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DATA MINING TECHNIQUES APPLIED TO INCREASING AIRCREW SITUATIONAL AWARENESS

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You can't connect the dots looking forward;
you can only connect them looking backwards.
So you have to trust that the dots will somehow connect in your future.

— Steve Jobs

Dedicado a Sachiko

ABSTRACT

Situation Awareness (SA) is a fundamental concept in the field of human factors in aviation. In the case of aircraft pilots, the most relevant models of SA focus on studying the individual perception of the critical aspects that influence decision making in complex and dynamic environments, i.e., during the flight. In this thesis, we have attempted to provide a comprehensive summary of the factors that surround information management in the cockpit of the aircraft, with special attention to the management of information in air navigation.

The research has tried to analyse existing SA models, which already take information management into account, and adapt their interpretation so that the parameters can be measured using Bayesian networks, ultimately intending to provide an estimation of SA.

Throughout the research, we have carried out experiments on different machine learning tasks, such as discretization, regression, clustering, and therefore we have improved our knowledge about how to process aeronautical data of various types.

We have managed data from several sources with multiple computer tools, using various types of databases, different information exchange formats, testing cloud environments, and successfully sharing information between different applications, including flight simulators. We have developed a set of tools for collecting data in simulated flights, to analyse them, and to estimate models (dynamic Bayesian networks) able of computing and online probability of the SA conditioned to the observations.

The thesis also contains the results of the situation awareness estimation.

RESUMEN AMPLIO EN ESPAÑOL

Motivación

La motivación de esta investigación es la convicción de que existe una relación muy sólida entre la conciencia situacional, conocida generalmente como SA (del inglés *Situational Awareness*) de los pilotos durante el vuelo y la gestión de la información de que disponen, tanto la proveniente de los instrumentos de la aeronave, como la de los documentos, listas de chequeo o aplicaciones informáticas a las que tienen acceso. Tradicionalmente se ha pensado que la seguridad de vuelo aumenta conforme lo hace la experiencia y el saber hacer de un piloto, pero lo cierto es que las estadísticas demuestran que muchos accidentes relacionados con el factor humano tienen como protagonistas a pilotos con alta experiencia en situaciones no especialmente peligrosas. Con el objetivo de poder detectar un potencial peligro latente y evitar accidentes en circunstancias de vuelo rutinarias, nos hemos planteado el reto de utilizar redes bayesianas para monitorizar vuelos simulados y tratar de generar una medida de la conciencia situacional basada en las actuaciones del piloto.

Objetivos

Los objetivos de la investigación se dividen en tres áreas principales. La primera área pretende producir un modelo de la SA de un piloto basado en el comportamiento observado, la disponibilidad de información aeronáutica y los métodos de presentación de información en la cabina. Los objetivos secundarios incluyen la adquisición de conocimientos teóricos relacionados con la SA, el análisis de los estándares de gestión de información aeronáutica y la construcción de un modelo que incorpore los diversos elementos estudiados de una manera lo más rigurosa posible.

La segunda área se centra en la implementación de un entorno de simulación para la realización de experimentos válidos, utilizando en la medida de lo posible las últimas tecnologías de gestión de información aeronáuticas, las cuales se encuentran en pleno proceso de estandarización de los diferentes elementos en que la información ha ido pasando del papel o la voz a formatos digitales durante las últimas décadas. Por último, la investigación pretende aplicar técnicas de aprendizaje automático para medir la SA y validar los modelos matemáticos propuestos, al tiempo que se identifican y estudian diferentes tipos de variables relacionadas con la SA, los factores humanos y la información aeronáutica.

Resumen por capítulos

Capítulo 1: Introducción

Además de la motivación, objetivos e hipótesis ya avanzados al inicio de este resumen, el primer capítulo de esta memoria contiene una breve descripción de los conceptos principales de los diferentes ámbitos en los que se ha trabajado en la tesis, con el objetivo de ofrecer definiciones básicas y el contexto suficiente para presentar las hipótesis, justificaciones y objetivos de la investigación.

Se enumeran a continuación las hipótesis sobre las que se ha centrado la investigación:

1. Los pilotos que realizan una adecuada gestión de la información en la cabina realizarán mejor sus tareas.

2. La SA de un piloto se puede medir como un conjunto de valores numéricos que proporcionan una estimación cuantitativa de la capacidad del piloto para percibir y comprender la información disponible durante un período de tiempo determinado.

3. La medición de la SA del piloto tiene un comportamiento probabilístico, y las técnicas de minería de datos, especialmente las redes bayesianas dinámicas (siglas Dynamic Bayesian networks (DBN) en inglés), pueden ser útiles para diseñar sistemas de medición de la SA en un entorno dinámico.

4. Se puede diseñar un sistema para evaluar la medición y el aumento de la SA de un piloto durante el vuelo mediante el uso de técnicas de aprendizaje automático para coordinar criterios deterministas que controlen la información mostrada en la cabina, asumiendo que el modelo de SA resultante tendrá una naturaleza probabilística relevante.

Capítulo 2: Conciencia situacional

El capítulo 2 pretende aportar, de forma rigurosa y autocontenida, los principales elementos que se han considerado vinculados entre el concepto SA y los factores de seguridad aeronáutica, fundamentalmente el factor humano. El capítulo trata de resumir un campo de estudio que es extenso, haciendo referencia a los principales autores que han contribuido a armar el cuerpo teórico alrededor del concepto de conciencia situacional.

Múltiples aspectos de la investigación se articulan en torno al modelo Endsley de conciencia situacional [40], que es ampliamente reconocido como el más influyente en la investigación de factores humanos relacionada con la seguridad de vuelo. Este modelo diferencia tres niveles de SA:

- La percepción de elementos en la situación actual (Nivel 1).
- La comprensión de la situación actual (Nivel 2).
- La proyección mental del estado futuro (Nivel 3).

El capítulo explica cómo estos niveles no siempre se mencionan explícitamente en la capacitación de pilotos y el diseño de aeronaves, a pesar del uso generalizado del concepto de SA en la aviación, por lo que usarlos para realizar un modelo de medida de SA no es una tarea fácil.

De entre otras áreas de conocimiento relacionadas con la temática que se han seleccionado, cabe destacar la metodología de gestión de riesgos operativos (siglas Operational Risk Management (ORM) en inglés), cuya aplicación se ha hecho habitual en los últimos años en los centros de operaciones aéreas, tanto civiles como militares.

Capítulo 3: Gestión de información de misiones de vuelo

El Capítulo 3 contiene una visión general de la gestión de información de misiones de vuelo, destacando la importancia de la iniciativa internacional para estandarizar la información aeronáutica inter-sistemas (siglas System Wide Information Management (SWIM) en inglés), pues hemos constatado durante la investigación su aplicabilidad a nuestros objetivos.

Fundamentos de la información de misión

Para familiarizar al lector con la información aeronáutica necesaria en la planificación de misiones de vuelo se ha incluido un apartado en el que se presenta una visión general de la estructura y contenidos de los principales sistemas de gestión de información utilizados por pilotos y otros agentes involucrados en las operaciones aéreas, quienes necesitan datos precisos sobre rutas, planes de vuelo, parámetros de aeronaves, configuraciones, etc.

- Sistema AIRAC: Según sus siglas inglesas Aeronautical Information Regulation and Control (AIRAC), antes de iniciarse el actual proceso de digitalización, la información se distribuía en papel en el marco de este sistema con ciclos de actualización cada 28 días, mediante publicaciones estandarizadas como el AIP (siglas Aeronautical Information Publication (AIP) en inglés), al que se dedica un subapartado del capítulo. Aunque este sistema sigue siendo relevante, ahora se está integrando en SWIM para modernizar y digitalizar el acceso a la información.

- SWIM: Se trata de una iniciativa internacional que a nivel europeo está coordinada por la agencia Eurocontrol y cuyo objetivo es facilitar el intercambio en tiempo real de información aeronáutica, de vuelo y meteorológica. Cabe señalar que una de las facetas más ambiciosas de esta iniciativa es la gestión de trayectorias de vuelo, la cual se menciona con frecuencia lo largo de la tesis.

Estándares de SWIM

SWIM facilita la interoperabilidad y estandarización a través de tres principales modelos de intercambio de datos:

- Aeronautical Information Exchange Model (AIXM): Modelo para datos aeronáuticos, como aeropuertos, rutas y restricciones de vuelo.

- Flight Information Exchange Model (FIXM): Gestiona principalmente información sobre planes de vuelo y trayectorias de aeronaves, para el seguimiento individualizado de los vuelos.

- Meteorological Exchange Model (WXXM): Es el estándar para datos meteorológicos. Se ha usado poco en la investigación, pero conviene que el lector conozca su existencia.

Estos estándares mejoran la calidad y eficiencia de la provisión de datos, habiendo sido posible realizar la tesis en gran medida gracias a ellos. Además, se trata de una iniciativa viva en la que resulta gratificante poder participar desde un punto de vista académico y no solamente como usuarios.

Impacto de SWIM en las operaciones de vuelo

El último apartado del capítulo trata principalmente dos aspectos de SWIM que nos parecen especialmente relevantes, por su impacto en la SA del piloto, no tanto por la medida efectuada en esta tesis, sino por el potencial futuro:

- Trajectory Based Operations (TBO): La iniciativa no está del todo madura, pero consideramos interesante dedicarle una cierta atención por la potencial faceta de permitir que los pilotos puedan en el futuro participar activamente en la gestión de trayectorias en colaboración con otros actores del tráfico aéreo, lo cual nos motiva también por lo que respecta al impacto en la SA.

- SWIM en las bolsas de vuelo electrónicas (siglas Electronic Flight Bag (EFB) en inglés): Estos dispositivos basados en tabletas son una puerta de entrada clave para que los pilotos accedan a los beneficios de SWIM, facilitando herramientas avanzadas para misiones específicas. Nosotros las vemos también como una plataforma viable en la que instalar una aplicación que monitorice la SA.

Capítulo 4: Redes bayesianas

Este capítulo ofrece una introducción a las redes bayesianas, centrándose en su aplicación en el contexto de experimentos realizados utilizando un simulador de vuelo y tratando de adaptar las explicaciones a un lector no familiarizado con la ciencia de datos. Se comienza explicando los conceptos básicos de los modelos gráficos probabilísticos y los gráficos dirigidos acíclicos, que son importantes para comprender cómo las redes bayesianas pueden realizar inferencia al mismo tiempo que ofrecen una representación gráfica comprensible.

Dentro del capítulo se proporciona la definición de red bayesiana como un gráfico acíclico dirigido que representa relaciones de dependencia entre variables, basadas en la propiedad local de Markov: una variable en una red bayesiana es condicionalmente independiente de sus no descendientes dado el estado de sus padres. Aunque se parte de la base de que no todos los lectores de la memoria considerarán accesibles los conceptos de este capítulo, conviene hacer hincapié en que esta propiedad es la que permite reducir la cantidad de dependencias necesarias para modelar y calcular probabilidades, haciendo de las redes bayesianas una herramienta muy útil para resolver problemas inabordables usando otras herramientas computacionales.

Seguidamente, se introducen otros conceptos básicos en la minería de datos, como son los algoritmos de inferencia y aprendizaje para redes bayesianas.

También se presentan las redes bayesianas dinámicas, que son una variante que permite sustanciar las metodologías de aprendizaje de datos dinámicos, incluso en tiempo real, necesarias para llevar a cabo la investigación.

Finalmente, se hace una introducción a la problemática de medir variables discretas y continuas en una misma aplicación y a las diferentes alternativas existentes en el campo de los modelos gráficos probabilísticos.

Capítulo 5: Construcción de un modelo para estimar la SA

Este capítulo expone el modelo diseñado en esta tesis para estimar la SA de un piloto. Nuestro modelo se basa en el modelo Endsley de SA, basado en la definición de tres niveles de conciencia situacional ya mencionados. En base a aclaraciones publicadas por Endsley, motivadas por discusiones entre expertos de factores humanos en aviación, se exponen una serie de proposiciones subyacentes al modelo, de las cuales derivan un conjunto de suposiciones que darán lugar a la definición de variables. Se enumeran a continuación las proposiciones con sus correspondientes suposiciones:

1. Los tres niveles de SA no son lineales:
    - No existe una relación numérica apriorística entre los niveles de SA.
    - Las estimaciones de los niveles de SA son independientes.
2. El modelo no puede considerarse simplemente como un modelo de procesamiento de información basado en datos:
    - El conocimiento experto proporciona rigor a la estimación.
3. Existe una clara distinción entre producto y proceso:
    - Interdependencia de producto y proceso.
    - El producto es la SA estimada.
    - El proceso se basa en una serie de valoraciones realizadas sobre parámetros de vuelo y acciones del piloto, tanto para controlar la aeronave como para gestionar la información.
4. El modelo de SA es cíclico y dinámico:
    - La SA depende del tiempo.
    - La SA se basa en actividades iterativas y continuas.
5. El modelo de SA tiene en cuenta el significado de los distintos niveles:

- El conocimiento experto contribuye a la relevancia de este significado.

6. El modelo de SA tiene en cuenta la memoria de trabajo:

    - Las personas con experiencia tienden a apoyarse en la memoria de largo plazo.
    - La simulación debe detectar las necesidades de la memoria de trabajo, en particular la de corto plazo.
    - La simulación debe permitir observar las interacciones de la memoria de trabajo, independiente de los niveles de SA.

Seguidamente se explica una evaluación basada en un sondeo realizado con pilotos instructores de vuelo, a quienes se preguntó sobre criterios operativos para realizar misiones desde el punto de vista de la gestión del ORM, con el objetivo de adquirir un mejor criterio para la definición de las variables.

Las variables se identifican en función de tres categorías principales: variables internas (parámetros observados referentes al piloto, como acciones de control), variables externas (como parámetros de la aeronave o datos del entorno) y variables de monitorización de la situación, entre las que se incluyen las derivadas del conocimiento experto. Finalmente se analizan los roles de la memoria en la estimación de la SA del piloto, especialmente la memoria de corto plazo, pues es la que tiene un valor prevalente para modelar la memoria de trabajo según nuestro enfoque y el diseño del entorno de simulación.

Capítulo 6: Implementación de un entorno de simulación

El Capítulo 6 describe la implementación del entorno que hemos elaborado durante la investigación, el cual permite volar con un simulador mientras se recopilan datos sobre variables relacionadas con el vuelo, incluidos los parámetros de la aeronave y las interacciones del piloto. El entorno de simulación consta de dos aplicaciones principales: *FlightApp* y *PostFlight*, ambas desarrolladas en JavaScript, PHP, HTML y CSS. Para almacenar los conjuntos de datos se utilizan bases de datos MySQL. *FlightApp* se conecta además con el simulador de vuelo mediante sockets.

Tras la realización de los vuelos, *PostFlight* se encarga de sincronizar los datos, realizar diversos tipos de cálculos y agregar conocimiento experto, lo que facilita la extracción y el análisis de datos después del vuelo, adaptados a las necesidades del aprendizaje mediante redes Bayesianas dinámicas.

El conjunto de datos generado por el entorno de simulación incluye más de cien variables, cuyo listado se proporciona en el Apéndice D. Para su mejor comprensión, las variables se han clasificado en los siguientes grupos:

- Situación del Avión: Parámetros que definen la posición del avión en diferentes ejes, considerando también la ruta del plan de vuelo esperado (altitud, coordenadas geográficas, distancia a waypoints, etc.).
- Parámetros del Avión: Parámetros básicos del avión como la potencia de los motores y los ángulos de cabeceo, alabeo y guiñada.
- Variables del Entorno: Condiciones ambientales que incluyen velocidad y dirección del viento, temperatura externa y presión atmosférica.
- Acciones del Piloto: Acciones del piloto para controlar el avión, principalmente los ajustes de altitud, velocidad y rumbo.
- Chequeos de Información: Acciones del piloto para revisar documentos en la bolsa de vuelo electrónica (siglas EFB en inglés), incluyendo una evaluación de la relevancia de la información consultada para el tramo actual y el siguiente tramo del plan de vuelo.
- Revisiones de Situación: Consultas del piloto para obtener información de posición, evaluadas además con respecto a la precisión de la navegación en base al conocimiento experto aportado.
- Plan de Vuelo: Información del plan de vuelo utilizada para comparar la ruta planeada con la trayectoria real del avión.
- Precisión o calidad de la situación: Variables que evalúan si la situación del avión es adecuada respecto al plan de vuelo, usando conocimiento experto incorporado para mejorar la precisión del análisis.

El capítulo también expone los métodos planteados en esta tesis para reducir el sesgo de la estimación de la SA, pues se ha adaptado la interfaz de usuario para detectar cuándo los pilotos necesitan verificar elementos de información clave durante el vuelo. La parte de la interfaz de usuario que posibilita al piloto controlar la aeronave trata de replicar un director de vuelo de avión comercial, mientras que la que permite acceder a la información aeronáutica y controlar la posición durante la navegación se asemeja a una EFB, procurando así reducir el sesgo de simulación.

Se describe la propuesta para monitorizar las interacciones del piloto y su recopilación de datos, especialmente enfocándonos en los niveles 1 (percepción) y 2 (comprensión) del modelo de Endsley de conciencia situacional. El enfoque planteado implica que el piloto realice acciones simples perturbando lo mínimo posible sus actividades de cabina, realizando un seguimiento de las interacciones con la interfaz, lo que proporciona información valiosa para la estimación de la SA sin los sesgos de cuestionario que introducen otras metodologías tradicionales como Situation Awareness Global Assessment Technique (SAGAT) y Situation Awareness Rating Technique (SART). Este enfoque permite además que, en caso de ser aplicado al diseño de una EFB, la medida pudiese ser llevada a cabo también en una aeronave real.

Capítulo 7: Análisis de trayectorias y situaciones

El Capítulo 7 se centra en el análisis de los datos de trayectoria de las aeronaves, con el objetivo de presentar el trabajo realizado en la búsqueda de bases para llevar a cabo la estimación de SA usando diversos tipos de datos aeronáuticos. Dichas actividades, aunque se vinieron desarrollando desde el principio de la investigación, se concretaron especialmente en una aplicación cuyos detalles se publicaron en un trabajo del año 2017 [97]. Dentro de este contexto, el capítulo explica de forma resumida las diferentes metodologías que se han usado en experimentos que involucran discretización de variables, regresión y métodos de agrupamiento (*clustering*), que han servido también para tener una visión más general de las posibilidades en el manejo de los datos disponibles, tanto del simulador desarrollado para esta tesis, como los datos que se han obtenido de otras fuentes.

Con respecto al experimento de discretización, que se publicó en el año 2015 [100], el capítulo muestra un extracto de sus resultados para ilustrar cómo mediante las métricas de discretización analizadas (BIC, Akaike, K2 y BDEu) se puso de manifiesto la limitada capacidad de las redes bayesianas dinámicas para manejar variables continuas, en base al enfoque utilizado en este primer trabajo. Para mejorar el rendimiento de la red bayesiana dinámica se recurrió en el siguiente trabajo [98] a combinar técnicas de regresión con la discretización, según se muestra en el apartado 7.3.

Seguidamente se muestran los fundamentos del trabajo sobre análisis de trayectorias mediante agrupamiento [102] y se explica que pese a no tener una aplicación directa sobre la estimación de la SA, en su momento sirvió para mejorar el conocimiento sobre este tipo de metodologías y sobre la información que se puede extraer de los diferentes formatos de datos de trayectorias en los que se ha trabajado durante la tesis.

Finalmente, el capítulo incluye un extracto del trabajo sobre Navegación Basada en el Rendimiento (Performance Based Navigation (PBN)) y una breve discusión acerca del impacto que la implantación de este tipo de procedimientos de vuelo está teniendo en la automatización de las labores en cabina, con el consiguiente impacto en la SA y su estimación.

Capítulo 8: Estimación de la conciencia situacional

Para explicar cómo se ha realizado la estimación de la SA, el Capítulo 8 se centra en el último experimento diseñado al efecto. En esta ocasión, se trata de analizar cómo los pilotos mantienen la precisión de la navegación durante los vuelos, en ocasiones sometidos a distracciones externas, mientras se analizan las variables derivadas de monitorizar su actividad. La investigación emplea el entorno de simulación explicado en el Capítulo 6 para integrar diversos datos de factores humanos y aplica metodologías de aprendizaje automático para interpretar estos datos, frente al resto de parámetros de vuelo y navegación también recogidos. En esta ocasión se ha recopilado un conjunto de datos de entrenamiento que consta de veintisiete vuelos simulados, para posteriormente probar los resultados con un conjunto de cuatro vuelos correctos y dos erróneos. El plan de vuelo escogido es el mismo que el empleado en el experimento PBN explicado en el Capítulo 7.

Este capítulo también contiene una discusión sobre la selección de variables y la adición de conocimiento experto, el cual ha servido para corroborar la medida de la SA realizada de forma no supervisada. Los resultados obtenidos indican estimaciones prometedoras de la SA, materializada en una medida de la probabilidad de que esté por debajo del nivel umbral adecuado. Los resultados han sido adecuados para todos los vuelos del conjunto de prueba, mostrando concordancia significativa con los vuelos correctos e incorrectos.

Conclusiones

En el Capítulo 9 se recogen las conclusiones de la investigación, proporcionándose una relación de contribuciones y limitaciones de la investigación, así como las posibles líneas de trabajo futuro.

Contribuciones

En esta investigación hemos trabajado para proporcionar un resumen completo de los factores que rodean la gestión de la información en la cabina de un avión, desde la perspectiva de su influencia en la conciencia situacional y la posibilidad de construir un modelo para proporcionar una medida utilizando redes bayesianas. Hemos resumido las contribuciones para resaltar que nuestra investigación ha puesto el foco en los siguientes temas:

- Introducción de SWIM y sus estándares: AIXM,FIXM y WXXM.

- Hemos prestado especial atención a la gestión de la información en la navegación aérea, los experimentos se centraron en vuelos de navegación instrumental comunes y con configuraciones estándar.

- Hemos seguido la evolución de PBN (siglas PBN en inglés), que es un concepto fundamental en la navegación aérea futura.

- Hemos realizado un estudio en profundidad del tema de la conciencia situacional, respaldado por una revisión exhaustiva de literatura científica. Basándonos en eso y en nuestra propia experiencia, hemos desarrollado un modelo para la estimación de la SA, aplicando las redes bayesianas para proporcionar un enfoque robusto y sistemático a este dominio complejo.

Por otro lado, una parte fundamental del trabajo ha sido el desarrollo de un entorno de simulación y de software adicional para explorar la interoperabilidad entre las fuentes de información aeronáutica y las herramientas de aprendizaje automático. En la memoria, especialmente en el Capítulo 6, se explican las características de este desarrollo y se proporcionan algunos detalles de la implementación, incluyendo el acceso a algunos elementos del código fuente producido.

A partir de estas actividades, concluimos que existen posibilidades muy interesantes para realizar simulaciones de vuelo con herramientas asequibles que podrían proporcionar a estudiantes e investigadores herramientas potentes y realistas para realizar trabajos en este ámbito. También cabe señalar la importancia de las bolsas de vuelo electrónicas como posibles plataformas para aplicar algunos resultados en el interior de la cabina de aeronaves en vuelos reales.

En paralelo, hemos analizado los modelos de SA existentes, que ya tienen en cuenta la gestión de la información y los hemos adaptado de tal manera que hemos podido diseñar un modelo específico de medición de la SA con redes bayesianas dinámicas, cuyos resultados experimentales muestran resultados prometedores. Consideramos que el uso de redes bayesianas es relevante, actualizado y un camino adecuado para futuras investigaciones en este campo.

Limitaciones del estudio

Nos parece conveniente señalar las limitaciones que hemos encontrado, en parte porque también nos marcan el posible camino a seguir en futuras fases de la investigación.

Sesgo de simulación

Debido al hecho de que utilizamos simulaciones para realizar los experimentos, existe un sesgo de simulación inherente, que por otro lado se ha analizado en cierta medida como parte de la investigación. Nuestro entorno de simulación es muy básico y no se puede comparar con un simulador de vuelo con certificación aeronáutica, pero ofrece la ventaja de que el diseño se ha podido adaptar a nuestra investigación y a las medidas relacionadas con factores humanos.

Tipos de misión estudiados

Nuestros experimentos se centran en un tipo de vuelo muy específico: Vuelos de navegación de aviones comerciales. Hemos realizado experimentos en dos fases de vuelo diferentes: En ruta y en la fase de salida instrumental posterior al despegue. La complejidad del vuelo simulado es media, lo que nos ha ayudado a validar el modelo de estimación de la SA porque pudimos centrarnos en situaciones específicas y de complejidad limitada.

Limitaciones de las redes bayesianas

Durante las diferentes fases de la investigación hemos trabajado para identificar y superar las limitaciones de las redes bayesianas, especialmente las relacionadas con los tipos de variables que pueden manejar. Hemos avanzado en el procesamiento de variables continuas, si bien en la presente memoria se puede observar que tuvimos dificultades para adaptar las redes a los tipos de datos que manejamos, especialmente cuando se trata de discretizar variables continuas.

Limitaciones en el modelado de factores cognitivos humanos

Nuestro enfoque para modelar los niveles de SA se basa en el análisis de las acciones del piloto y sus resultados en términos de medidas de la trayectoria o actitud de la aeronave. Somos conscientes de que existe una amplia área de estudio para investigar de manera más profunda los enfoques de los mecanismos cognitivos del ser humano y aplicar alternativas computacionales adoptadas por otros autores que están trabajando en este tema.

Trabajo futuro

Entre los muchos temas en los que consideramos que existe un campo de estudio interesante para seguir investigando, proponemos lo siguiente:

- En general, es necesario explorar la aplicabilidad de la inteligencia artificial al ámbito aeronáutico, particularmente a la luz de lo establecido por la Agencia Europea de Seguridad Aérea [2].
- Continuar realizando diferentes experimentos con diferentes alcances, para mejorar el modelo de SA.
- Continuar estudiando la aplicación de los principios de gestión de riesgos, no solo ORM.
- Explorar formas adicionales de realizar un análisis sistemático de la gestión de la información. Por ejemplo, aplicando principios de teoría de la información, donde hay espacio para un estudio aplicando redes bayesianas.
- Actualizar el entorno de simulación para conectarse a otros medios de simulación y mejorar la interoperabilidad con fuentes de datos adicionales.
- Ampliar la investigación a aviones tripulados remotamente.
- Explorar la utilidad potencial de las EFB en vuelos reales, no solo para alojar aplicaciones que brinden información, sino también para monitorizar potencialmente las actividades del piloto y poder detectar anomalías en el rendimiento para brindar advertencias. Ésta podría ser una aplicación práctica de esta tesis.
- Ampliar y mejorar el modelo para el cálculo de la SA en línea presentado en el Capítulo 8.

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ACRONYMS

ADS-B Automatic Dependent Surveillance-Broadcast

AENA Aeropuertos Españoles y Navegación Aérea

AI Artificial Intelligence

AIP Aeronautical Information Publication

AIRAC Aeronautical Information Regulation and Control

AIXM Aeronautical Information Exchange Model

AIS Aeronautical Information Service

API Application Programming Interface

ARINC Aeronautical Radio Incorporated

ARP Airport Reference Point

ATC Air Traffic Controller

ATM Air Traffic Management

BADA Base of Aircraft DAta

BIC Bayesian Information Criterion

BN Bayesian networks

CDM Collaborative Decision-Making

CFIT Controlled flight into terrain

CFQ Cognitive Failures Questionnaire

CNS Communications, Navigation, Surveillance

CRM Crew Resource Management

CSS Cascading Style Sheets

CSV Comma-separated Values

DAG Directed Acyclic Graph

DBN Dynamic Bayesian networks

EASA European Union Aviation Safety Agency

EFB Electronic Flight Bag

EIWAC ENRI International Workshop on ATM/CNS

EM Expectation Maximization

ENAIRE Spanish Airports and Air Navigation

ENRI Electronic Navigation Research Institute

ETD Estimated Time of Departure

FAA Federal Aviation Administration

FF-ICE Flight and Flow Information for a Collaborative Environment

FIR Flight Information Region

FIXM Flight Information Exchange Model

FMS Flight Management System

FPL Flight Plan

FSX Flight Simulator X

GANP Global Air Navigation Plan

GCS Ground Control Station

GML Geography Markup Language

GPS Global Positioning System

GUFI Globally Unique Flight Identifier

HMI Human Machine Interface

HTML Hypertext Mark-up Language

ICAO International Civil Aviation Organization

IEEE Institute of Electrical and Electronics Engineers, Inc.

IFR Instrument Flight Rules

IMC Instrument Meteorological Conditions

ISADS International Symposium on Autonomous Decentralized Systems

IWXXM Meteorological Information Exchange Model

JSON JavaScript Object Notation

LP Logarithm of probability

HMI Human Machine Interface

HBN Hybrid Bayesian network

MAP Maximum a Posteriori

MCAS Maneuvering Characteristics Augmentation System

METAR Meteorological Aerodrome Report

MLE Maximum Likelihood Estimator

NASA National Aeronautics and Space Administration

NavDB Navigation Database

NM Nautical Mile

NOTAM Notice to Airmen

ANSP Air Navigation Service Provider

ORM Operational Risk Management

PBN Performance Based Navigation

PGM Probabilistic Graphical Model

PHP PHP: Hypertext Preprocessor

RMI Radio Magnetic Indicator

RNAV Area Navigation

RNP Required Navigation Performance

SA Situation Awareness

SAGAT Situation Awareness Global Assessment Technique

SART Situation Awareness Rating Technique

SASWIM Service Assurance System Wide Information Management

SESAR Single European Sky ATM Research

SID Standard Instrument Departure

SIGMET Significant Meteorological Information

SQL Structured Query Language

SWIM System Wide Information Management

TAF Terminal Aerodrome Forecast

TBO Trajectory Based Operations

TCP Transmission Control Protocol

USAF United States Air Force

UAS Unmanned Aircraft System

WAMP Windows, Apache, MySQL, and PHP

WXXM Meteorological Exchange Model

XML Extensible Markup Language

Part I

INTRODUCTION

1 INTRODUCTION

1.1 Situation awareness and the challenges of flight safety

In the past, aircraft were less reliable, more complicated to handle, not very robust when operating in adverse conditions, and procedures were less developed. And their systems included very limited capabilities to manage information. In some models, to allow pilots to focus more on flying and making decisions, there were additional crew members, such as the flight engineer, the navigator, or the mission systems operator, particularly in the case of military aircraft.

Over time, both the reliability of the aircraft and the quality of the cockpit design have improved, training plans have been refined, the use of simulations is becoming generalised, and many cockpit tasks have been automated thanks to the application of electronics and computing. Accident rates have been reduced, and it seems that we are on the right path to reach a *zero accident* condition. However, accidents still happen, and the causes of most of them tend to remain in a grey zone between crew errors and Human Machine Interface (HMI) design. Therefore, challenges to flight safety remain, especially taking into account that the level of automation of tasks performed by the pilot is increasing substantially, in parallel with the volume of information related to the flight that is relevant to the pilot. Human factors experts, system designers, flight instructors, and pilots need to remain aware of the challenges posed by this situation, reducing automation bias, and ensuring that the pilot level of awareness is adequate to manage the assigned tasks.

1.1.1 Definition of SA

In the context of human factors applied to aviation, situation (or situational) awareness (SA) can be defined as the field of study concerned with quantifying the perception of the environment critical to decision-makers in complex and dynamic areas [49].

This term will be broadly explained and analysed in this dissertation, so it is important to point out from the beginning that the SA of flight crews usually depends on the knowledge and interpretation of a large number of variables with complex relationships, such as individual human factors, aircraft parameters, pilot control commands, interaction with air traffic controllers and other aircraft, or the management of information in the cockpit during flight.

1.1.2 The complexity of monitoring awareness

Even when the cockpit parameters can be measured, recorded and analysed, it is a great challenge to find a reliable way to know how they are interpreted by the pilot and therefore to establish how they affect SA, basically because they do not show deterministic dependencies. This is one of the reasons why BN and moreover DBN for time-dependant systems, are particularly applicable to this research.

The complexity of the task is increased by a technological context that favours an over-balanced increase in the sources of information to be managed by the pilot. However, there are potentially useful tools for monitoring cockpit activities through the use of EFB and a reliable relationship of flight data thanks to the implementation of SWIM, which are concepts that will be mentioned very often during this dissertation.

We already highlighted this complexity in our first published paper [100], where we proposed to explore the relationship between SA and cockpit information management, from our experience observing the difficulties found by military pilots flying complex aircraft or managing aircraft navigation in intricate routes or congested airspace, sometimes with short notice for mission preparation. We also identified the concern for complex information management in modern cockpits related to *automation bias*, as described Salas et. al. in [130], originating the danger of non-coherent judgments in complex electronic environments, which may emphasize some information when it is only part of the solution to managing the cockpit: "*the design of many high technology systems may encourage decision makers, including experts, to focus on the most salient, available cues and to make intuitive, heuristic judgments before they have taken into account a broader array of relevant cues and information*".

1.1.3 Proposing a model for measuring SA

In the previous subsections we have highlighted challenges and complexity, and we consider that an effective method to measure or monitor SA is not

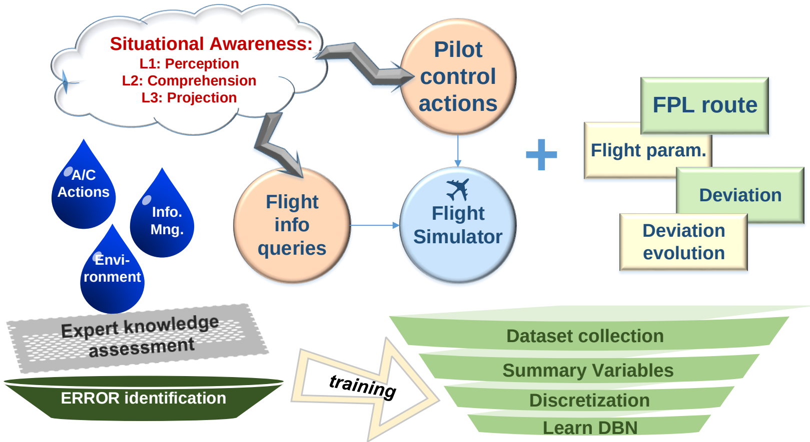


Figure 1.1: SA estimation and simulator parameters model.

possible with conventional offline tools, so we consider that there is a new field of research to perform a real-time measurement.

Over the years, we have implemented and updated a simulation environment that has been designed to take advantage of the interoperability benefits provided by SWIM and to monitor the parameters related to automation bias. The collection of a relevant dataset was also a priority and, together with the availability of multiple information sources, our goal has been to perform a robust training of a DBN and to optimise the development of real-time data mining techniques. Figure 1.1, which was already incorporated in our previous paper [101], illustrates the baseline model for constructing the simulation environment: collecting pilot control actions and flight information queries, because the SA estimation focusses on these sources. The datasets generated for each experiment repetition also contain route and deviation information. The summary and discretization of the variables was also performed when applicable, to increase the relevance of the collected data. Expert knowledge was added in some cases to allow the correct identification of human error and also to contribute to training the networks.

1.2 The digitalisation of flight information

The introduction of the first onboard computers back in the 1970s evolved to specific aircraft systems called Flight Management System (FMS) that gradually started storing digital information in avionics systems; therefore, the first databases were implemented inside aircraft computers. At first, the priority was to control the aircraft [26], since technology did not allow to consider a global approach to information management. In fact, for many years and even in the current times, the management of flight information in the cockpit has been paper-based. In this section, we will briefly review the key aspects of the process that leads to full digitalisation sponsored by the new technologies introduced by SWIM.

The question might arise as to whether this transition could be faster. It is mainly due to the predominant role of airworthiness and the conservative approach of airworthiness authorities that prioritise flight safety in terms of reducing the probability of system failure, versus the introduction of new technologies.

It could be discussed that flight safety is improved from different perspectives: either reducing system error probability, thus reducing non-human failure, or supporting the role of the pilot to prevent human failures that could lead to an accident. The compromise is not simple, and it is beyond the scope of this thesis to discuss the impact of airworthiness certification on the speed of digitalisation of flight information.

For many years, the digitised data were handled by specific equipment, being virtually unavailable, as data itself, to pilots, who could only have access to the results of calculations or computer operations. Very timid advances were made during the last years of the 20th century in the sense of making digital information available to operators. An example is [114], where it can be seen that the regulation contemplates the option of editing data. However, the level of interaction of the crew with the digitised data was still very reduced, even with the arrival of the EFB.

1.2.1 The Electronic Flight Bag

At the beginning of the 21st century, advances in portable computers and touch screens began to be significant, but reliability prevented the aerospace industry from incorporating them into the cockpit. However, regulators started to anticipate the arrival of portable computers in the cockpit and in 2003 the United States Federal Aviation Administration (FAA) published the first advisory circular [64] establishing the guidelines for a portable electronic device whose main purpose was the management of digital information in the cockpit: the EFB. It should be noted that the chosen name did not invite a technological revolution, and for several years the role of most EFBs was focused on replacing paper to make flight safer. Once again, safety was regarded in aviation more from the point of view of reducing technical failure than facilitating crew tasks, of course this is a simplification of the problem not to be discussed in this research.

But an event radically accelerated the adoption of EFBs in the cockpit: In early 2010, Apple Computers marketed the first *iPad* device, and it quickly became the de facto standard for EFBs globally, raising interest in the aeronautical community, that quickly became aware of the positive impact to flight safety [66] and the increase of SA, although the adaptation to the aircraft was not immediate [4]. A very interesting view of the industry perspective of this digitalisation process was published in 2012 as an academic paper [120] by staff from *Jeppesen*, the leading company in the provision of paper information, aeronautical databases and currently EFB software.

1.2.2 Digitalization on the ground

In parallel, technological advances at the beginning of the 21st century started preparing the way for an integral digitization of ground aeronautical information. The first edition of the ICAO Global ATM Operational Concept [29] was published in 2005, adopting SWIM as a key player to achieve air traffic integration.

SWIM was initially only for the ground, but it was very quickly noticed that the information it handles also affects the activities of the crew. With the arrival of Unmanned Aircraft System (UAS) the approach is changed in some way because the digital resources are more feasible to be integrated in the Ground Control Station (GCS), affecting both training and certification [149]. This offers a promising field of study in the future to apply the results of our work.

1.2.3 Information for cross domains

In an ideal situation, as already envisaged by SWIM, information management can be extended to support interoperability among aeronautical stakeholders: pilots, air traffic controllers, airlines, maintenance organisations, etc. But this goal is very difficult to achieve. EFBs are dominated by very powerful aerospace companies or very small developers for niche markets. In most cases, interoperability is not a priority, but it is important for this research to be able to collect data from different sources to support the performance of machine learning tools.

There is a lack of a market for companies that could deliver information services without competing with very different-sized companies, and this is slowing down the process of finding synergies in the two worlds. During this research, we have witnessed the following:

- Stable EFB business by some large companies.
- Slow evolution of the SWIM development and lack of easily available certified data to be exploited by EFB.

Our aim in highlighting this situation is to draw attention to the potential benefits of higher integration and also to provide context for the related work performed during the research. In Chapter 3 we will explain in more detail what kind of information is digitised, and in Chapter 6 we will provide details of how and with which sources, we have made use of this digital information.

1.3 Hypothesis and justification

The hypotheses of this thesis were already raised in the 2016 research plan and have not changed substantially, so they are reproduced below. Experience shows that problems related to human factors related to the pilot are among the causes of most accidents in an aircraft. Examples of these problems are poor internal crew coordination, lack of training, self-complacency, lack of resting time, or inadequate radio communications. This research focuses on the lack of availability of adequate and timely information required to make decisions at certain moments during the flight.

Therefore, the first hypothesis of this thesis is to consider that pilots who perform adequate information management in the cockpit will perform their tasks better.

The second hypothesis is based on considering that the SA of a pilot can be measured as a set of numerical values that provide a quantitative estimate of the ability of a pilot to have the right perception of the environment and to measure his or her level of comprehension of the available information [34], during a given period of time. To support this hypothesis, some practical methods to measure SA have been analysed, like the ones described by Endsley in [38].

The third hypothesis of this research is based on considering that the measurement of pilot SA has a probabilistic behaviour, and therefore data mining techniques, and especially DBN [106] [116], can be useful for designing systems that can learn how to measure the SA of a pilot in a dynamic environment, also combining additional deterministic factors such as aeronautical information management.

Finally, the fourth hypothesis can be seen as a combination of the previous ones, affirming that a system can be designed to assess the measurement and increase of the SA of a pilot during the flight, in terms of the availability of the right information necessary to make decisions, and the related measurements of the observed behaviour. This system can make use of machine learning techniques in order to coordinate the deterministic criteria that can control the information displayed in the cockpit, assuming that the resulting model of SA will have a relevant probabilistic nature.

1.4 Applicability of Bayesian networks

The applicability of artificial intelligence in the aviation context needs to be carefully tackled. However, there is already a roadmap established by European Union Aviation Safety Agency (EASA) [2]. Consequently, it is clear that there is a reasonable scope for applying the results of artificial intelligence, despite its eminently non-deterministic nature, to a field that is traditionally reserved for much more conservative approaches that require rigorous certification processes and that a priori rule out the use of this type of tools.

1.4.1 Suitability to satisfy the hypotheses

We have already mentioned DBN in sections 1.1 and 1.2, and now we will provide an explanation of the reasons that support the choice of this tool to process the datasets obtained after each simulated flight. The main theoretical explanation about Probabilistic Graphical Model (PGM) and, in particular, BN and DBN, is contained in Chapter 4. Before that, we consider it interesting to present a very brief introduction to provide more context to the hypotheses exposed in the previous section 1.3.

Based on the second hypothesis, we suggest that an EFB can be used to monitor the pilot's performance during the flight. In an environment with a large number of measured variables with dependencies among them, such as the one generated in the experiments that we performed, BN are specially appropriate for optimising calculations [79]. DBN are a particular case of BN, more suitable for dynamic systems [106], which reinforces the proposal that SA can be measured in real time. Therefore, we have selected several reasons to support the applicability DBN to this research:

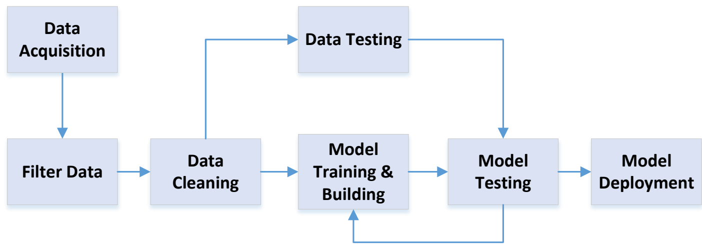


Figure 1.2: Machine learning generic process.

- Bayesian networks are especially appropriate when we have a large number of variables with dependencies among them.
- In real-time applications, DBN can explicitly represent temporal relations between measured variables.
- DBNs can be learnt from data and, at the same time, include expert human knowledge when available.
- Inference in DBN can be performed in a short time, even in the presence of a large number of variables and observations. This can be applied to assess SA in real-time.

We also have to take into account that inference is more efficient when values from variables in the past are available to predict the values of future variables, and this happens in our case. Thus, this procedure can be applied to assess SA in real time.

For the readers who may not be familiar with the way machine learning algorithms work, we have included figure 1.2, with the purpose of providing visual support to understand the different steps necessary to process the flight parameters and pilot actions, so that they can comply with the requirements of dynamic Bayesian networks.

1.4.2 Design of a method to measure SA

Bayesian networks are particularly suited for applications where a probabilistic relationship between different variables can be sought. As will be explained throughout this dissertation, we have created a model for the estimation of SA based on such relationships, taking into account the following:

DBNs are very effective in training systems with multiple variable dependencies and are usable for real-time applications. To achieve these goals, we have to make sure that our BNs are able to combine the following factors:

- Ability to learn from data.
- Incorporate expert knowledge when required.
- Integrate data from proven information management standards, such as SWIM.
- Compatibility with the proposed human factors models, to provide a systematic approach for managing cockpit information and pilot actions.
- Build a simulation environment that implements these factors.

1.5 Objectives

The objectives of this thesis, first established in the research plan presented in 2016, have been divided into three main areas. The first is to produce a model of the SA of a pilot, based on assessments of:

- Observed pilot behaviour.
- Pilot decisions.
- Availability and selection of aeronautical information.
- Methods and criteria used to present information in the cockpit or in an EFB.

To achieve this, the following secondary objectives were identified:

- Acquire an appropriate theoretical basis of the concepts related to SA, especially regarding to human factors: Pilot perception and comprehension, management of stressful situations during the flight and the relationship between the SA of a crew and observed behaviour, including study of real situations.
- Analyse and understand aeronautical information management standards and their influence on cockpit activities during flight, in order to focus on the relationship between the availability of information for the flight mission and the decisions made by the crew members.
- Build a model of the SA measurement that appropriately incorporates:
  - Theoretical concepts related to human factors.
  - Existing SA measurement tools.

  - The roles of aeronautical information management and EFB.

The second main area of this research is focused on the implementation of a simulation environment that provides the possibility of performing valid experiments. The design of this simulation environment was based on the following prerequisites:

- The environment includes the use of a PC-based flight simulator where flight missions can be simulated, a graphical interface to allow the pilot to access and visualise aeronautical information, and connections to software tools in charge of running machine learning techniques.

- Incorporate features into the simulator to reduce simulation bias, that is, identify and, if possible, characterise the differences between the SA of pilots using the simulation environment and the SA of corresponding real flight missions.

- The simulation environment is designed to compute and integrate the variables related to aircraft parameters, human factors and pilot behaviour, as well as aeronautical information databases and tools for SA measurement.

Finally, the third area of research has been the application of machine learning techniques to measure the SA of a pilot, and accordingly achieve the following proposed objectives:

- Develop and validate a theoretical model that relates the interactions and feedback between selected SA measurement techniques and the corresponding influence to/from pilot's behaviour.

- Identify and study the different types of variables related to SA, human factors, and aeronautical information, and characterise them from a probabilistic point of view.

- Identify the functions and processes related to these variables that fall into the field of study of this thesis, working to find the machine learning techniques that best match the purpose of the research.

- Perform the necessary experiments to validate the proposed mathematical models.

1.6 Methodology

In this research, we have tried to use a methodology as rigorous as possible with respect to the standard scientific methodology. The observation phase is based on years of experience of the researcher as a flight instructor, observing the behaviour of pilots with very different levels of proficiency, and also analysing the causes and contributor factors of helicopter incidents and accidents as a flight safety officer during several years. The hypotheses are already listed in Section 1.3, and will not be repeated here.

Conducting experiments has been prioritised during this research. The simulation environment is probably the main deliverable because a very relevant part of the data collected for the experiments is based on simulations. We have been very attentive to building models and experiments that reduce simulation bias as much as possible, taking into account that this is an academic work and that we did not have access to professional simulators, which, on the other hand, are not easy to modify in order to collect the SA related information that we targeted as part of our methods.

We have performed several main experiments, published in the corresponding papers, which will be introduced in Section 1.7 and explained in more detail in later chapters. The collection of data, a fundamental part of the experiments, has been complemented by an exhaustive analysis of different relevant data sources that will be explained in detail in Chapter 3. The simulation environment registers certain actions of the pilot and states of the system and exports them to data processing software tools that apply data mining and machine learning techniques for calculations related with SA estimation. The data, stored in different types of databases, have been analysed using a wide range of data analysis and machine learning tools.

Replicability of the experiments has also been taken into account in this research. The simulation environment has been designed to operate with a well-defined dataset, both as input and output. We have asked several volunteers, all professional and experienced pilots, to perform simulations, and there were no significant differences in the outcome of the experiment repetitions due to the subject who performed each simulation.

Finally, as has already been noted, the main experiments have been published in academic publications.

1.7 Associated publications

During the completion of this thesis, the following academic works have been published:

- Carlos Morales and Serafín Moral. "Discretization of simulated flight parameters for estimation of situational awareness using dynamic Bayesian networks". In: 2015 IEEE Twelfth International Symposium on Autonomous Decentralized Systems. IEEE. 2015, pp. 196–201.

  This was the paper which introduced the simulation environment, whose first version was finished just before publishing this work. Special emphasis is placed on discretization methods and the metrics that evaluate them for their use with DBN.

- Carlos Morales and Serafín Moral. "Modeling aircrew information management for estimation of situational awareness using dynamic Bayesian networks". In: Simulation Modelling Practice and Theory 65 (2016), pp. 93–103.

  This second paper is a resubmission of the previous one requested by the editor with the purpose of publishing it in an Impact Factor journal. More detail about the simulation modelling principles was added in this case.

- Carlos Morales and Serafın Moral. "Regression methods applied to flight variables for Situational Awareness estimation using dynamic Bayesian networks". In: Conference on Probabilistic Graphical Models. 2016, pp. 356–367.

  This paper was presented in a conference on probabilistic graphical models, and on this occasion we focused on testing regression algorithms with the same dataset as the one used in the previous experiment.

- Carlos Morales, Serafín Moral and Jaime Sanz. "Design of a software environment to support machine learning analysis of aircraft trajectories". In: EIWAC 2017, 5th ENRI International Workshop on ATM/CNS. 2017.

  During approximately three years, the focus of the research was shifted from SA estimation to the study of aircraft trajectories, with the aim of improving observation. But the activity of collecting relevant data for machine learning algorithms was challenging. We decided to explore different options to obtain structured datasets, and in the meantime, we decided that this was a good opportunity to build a companion application. The outcome was published in this article.

- Carlos Morales and Serafín Moral. "Flight Trajectory Clustering: a framework that uses Planned Route data". In: 2019 IEEE Fourteenth International Symposium on Autonomous Decentralized Systems. IEEE. 2019, pp. 213–218.

  In parallel with the previous work, we collected a large dataset in cooperation with a MsC student in the context of a tutoring activity [91]. After finishing his master, the student was offered the possibility to publish the work, but we did not receive an answer, therefore, we decided to implement a *k-means* trajectory clustering algorithm with the dataset and publish this paper.

- Carlos Morales and Serafín Moral. "Assessment of Situation Awareness and automation in Performance-Based Navigation procedures". In: 2023 IEEE 15th International Symposium on Autonomous Decentralized System (ISADS). IEEE. 2023, pp. 1–6.

  After a pause in the progress for different reasons, we decided to update the simulation environment to incorporate specific functionalities to simulate a PBN flight, which is a concept of high importance in modern aviation, as will be explained in Section 2.3. With this final paper, we have collected a more refined dataset and improved the algorithms to calculate SA, with promising results.

1.8 Thesis outline

This dissertation is divided into three blocks: The first is an introduction that consists of four chapters in which we explain the state-of-the-art of the concepts studied and used in this research. These four chapters are the following:

Introduction
Chapter 1 contains a brief overview of the main concepts, with the aim of providing basic definitions and sufficient context to present the hypotheses, justifications and objectives of the research.

Situation awareness and safety factors in aviation
Chapter 2 seeks to provide, in a rigorous and self-contained manner, the main elements that have been considered to be linked between the SA concept and aeronautical safety factors, mainly the human factor, seeking to provide contributions from the most relevant researchers in the field of SA. The chapter

is ambitious in trying to summarise a field of study that is very extensive. However, areas of knowledge related to these topics are omitted. Among those selected, special mention is made of the ORM methodology, whose application has become common in air operations centres, both civil and military, in recent years.

Flight mission information management

The processes related to important technological changes in the aeronautical field are long due to the safety implications and high adoption costs by stakeholders. During the course of this thesis, over several years, we have assisted and to some extent contributed to various phases of the implementation of a number of information technologies that are briefly described in Chapter 3. Without these standards and a rigorous approach to cockpit information management, this thesis would be meaningless, so the reader is encouraged to give special importance to the contents of this section.

Bayesian networks

To conclude the introduction, in Chapter 4 we present a brief summary of the most relevant aspects of BN and the DBN that should be taken into account for this thesis. It includes a very brief overview of PGM, the Markov property, and the basics to understand inference and learning. A brief glimpse of the concepts of classification and supervised and unsupervised learning approaches is also included. Finally, there is an outlook of the methods to compute conditional probabilities in DBNs, which has been considered necessary to understand the approach of our last experiment.

Building a model for the estimation of SA

Chapter 5 tries to bring together the lessons learnt derived from the different approaches to SA introduced previously in Chapter 2, leading to the creation of a model specifically designed to adapt to the architecture and user interface of our simulation environment. Our model is closely based on Endsley's, and we have dedicated Section 5.2 to explain the principles of our implementation of the 3 SA levels. We also have intended to include other aspects, especially those related to short-term memory modelling, that we consider to be better developed in other models.

Implementation of a simulation environment

The simulation environment developed specifically for this research is probably our most relevant contribution, and Chapter 6 contains an overview of the criteria and methods employed for its development. To explain the process from the overarching objectives to its architecture, we have a specific section intending to summarise some software development details of the application used for performing experiments on real time. There are also specific details of the HMI design to describe how the model explained in the previous chapter has been put into practice, in order to reduce simulation bias.

This chapter also contains details about the datasets, including descriptions of the variables that have been generated during the flight simulations and the post-flight calculations.

Situation and trajectory analysis

Chapter 7 is dedicated to the explanation of an approach that is not directly included in the traditional models of SA estimation, but that has been merged into the main research line of the thesis: the analysis of aircraft trajectories. For us, it is very relevant to analyse the performance of the pilot, depending on the machine learning tools and computational capabilities applied. Therefore, we have carried out several experiments that are described in this chapter. We also provide more level of detail on the practical aspects of the information management technologies explained in Chapter 3.

Situation awareness estimation

To reach the end of the thesis contributions, we have chosen to explain in Chapter 8 details of the approach followed for the SA estimation: the selection of variables, specifying the training and testing datasets and the principles employed to design the estimation algorithm, with an extract of its outcome. Finally, the chapter ends with a discussion about the results and basic principles of the achievements and modelling options of the topic, which is central to our research.

The third block contains only Chapter 9, that briefly exposes a general discussion and conclusions of the research.

Finally, we have included several appendices to support understanding of certain key aspects of this thesis:

- Appendix A contains a brief overview of the AIRAC cycle. This is an aeronautical concept that we believe should be understood by the reader of this dissertation because it encompasses many aspects of the selection and update of information in the cockpit.

- Appendix B contains a brief description of the Notice to Airmen (NOTAM) contents, with examples. These "*notices*" or messages to pilots are considered a key aspect of the pilot SA, and since their implementation in the simulator does not follow standard methods to reduce bias, it has been decided to add this appendix.

- Appendix C contains a description of a survey that was carried out with several Instrument Flight Rules (IFR) instructor pilots to obtain information about specific aspects of ORM, focused on their experience, to evaluate its applicability to this research.
- Appendix D contains an extract of the datasets produced by the application, to support the explanations that can be found across the dissertation.
- Appendix E contains a compilation of code snippets that we have found particularly significant and that we have decided to share with the readers of the dissertation.

2 SITUATION AWARENESS AND SAFETY FACTORS IN AVIATION

This chapter has the objective of presenting a summary of multiple concepts related to human factors in aviation that have a direct impact on the concept of SA. The topic is very broad, covered by multiple researchers in the fields of psychology, airworthiness certification, cockpit designers, etc. Therefore, it cannot be said that we are presenting the state-of-the-art of this topic, but at least we conduct a literature survey with very varied sources, both in time and scope.

2.1 Common approaches to assess SA in aviation

2.1.1 Selection of relevant SA models

SA is a very relevant, widely known and studied concept in the field of human factors, more specifically in dynamic systems, and still more specifically in aviation, the field where it originated, probably being the paper of Martin L. Fracker, a captain of the United States Air Force (USAF), the seminal scientific publication to define SA back in 1988 [49]. In this thesis, the focus will be mainly set on aviation, mainly due to professional background-related reasons, although during the research it has been noticed that a significant body of literature, especially MSc. and PhD. thesis, applies many common concepts related to the most remarkable SA models, to other dynamic systems. Significant examples are Gommosani's thesis [61], which focusses on increasing SA in the bridge of ships performing merchant shipping operations, and Fischer's thesis [47], also in the context of maritime operations, which extensively applies dynamic Bayesian networks to the SA rating.

Focussing on the SA models themselves, regardless of the field of application, there are several models in the literature. The decision to opt for a specific model as the main reference has not been easy. However, there seems to be a consensus among human factors researchers to consider Endsley's model as the most relevant one. In addition, the prolific work of this author, with hundreds of publications and around 52,000 citations according to Google Scholar [63], helped us to make the decision easier. However, the same author offers a comparison between specific aspects of some models, suggesting a series of misconceptions and misunderstandings that are especially relevant to this research, and are thoroughly analysed in [42]. Especially relevant to our research is the observation contained in the mentioned paper on the linear character of the SA models. After thoughtful consideration, in the context of this research, it was decided to use the Endsley approach based on 3 SA levels, trusting that it is especially valuable to perform real-time estimations of SA using machine learning without intending to consider that some models are better than others.

The way in which memory is handled is a key topic where relevant differences appear depending on the SA model. Most researchers differentiate between working memory and long-term memory, although there seems to be a big difference in the way they establish relationships and dependencies among them. Endsley offers a very synthetic explanation of the common differences in the perspective that some authors show, regarding the role of these two types of memory in the cockpit [42] (Fallacy 6), although this is certainly not a consensus. It is particularly relevant to note that, depending on the author, the use of information in the cockpit with regard to memory is considered very different depending on the experience / skills of the pilot.

In the context of this thesis, it is very clear that memory is a relevant factor that can be attempted to quantify, and therefore it is very relevant for performing a real-time estimation of SA. However, given the complexity of the concept and provided that this falls mainly in the field of human factors, we will not attempt to build a model of memory. Instead, our simulation environment has been designed to monitor the frequency of information checks, which can be directly related to pilot workload and, more indirectly, to saturation of operator memory and the need to perform more information cues than expected, as will be explained in Chapter 6.

In the next sections, we will introduce the Endsley model, although its applicability to this research will be discussed in more depth in Chapter 5. There is also a section dedicated to SART and SAGAT SA measurement techniques. Although they are based on different modelling principles from those for which this research has focused its main focus, SART and SAGAT have been widely accepted in several areas of the aerospace industry for several decades; [125] offers a very interesting update of these techniques, including questionnaire examples that are used for human factor evaluations by institutions such as National Aeronautics and Space Administration (NASA) or FAA. We have also noticed that SART is specifically used by Spanish aerospace certification authorities to perform human factors evaluations.

2.1.2 Endsley's model of SA

The Endsley model of SA was first published in 1995 [40] and was slightly refined in 1996 [36]. The representation shown in Figure 2.1 is ubiquitous in research works in the field of human factors and is still easy to find, the same as the original or roughly unaltered, in many papers published nowadays. Therefore, we have decided to include it as it was originally published and emphasise the credit it deserves as probably the most relevant achievement in human factors research related to flight safety in the history of aviation at the time of writing this thesis.

The Endsley model differentiates three levels of SA:

- SA Level 1: Perception of elements in the current situation.
- SA Level 2: Comprehension of current situation.
- SA Level 3: Projection of future status.

It is relevant to note that in the field of aviation, these 3 levels are hardly referenced in handbooks or pilot training plans, despite the fact that the SA concept is widely used and known by aircrew. The purpose of this dissertation is not to discuss the approach to applying the research outcomes of human factors to pilot training plans or aircraft design. However, it should be noted that the same concept, SA, is used to refer to different realities depending on the context of use. This is a dilemma that has conditioned the research from the beginning, even considering that it is not feasible to provide a solution to everything. One of the main drivers of this investigation is to adapt as many elements of figure 2.1 as possible to the SA model built in this investigation and presented in Chapter 5, and furthermore to the simulator implemented to carry out this research and described in Chapter 6, Section 6.2.

This is a very brief introduction to the model, but we will dedicate Chapter 5 to expand the explanation and explain how we apply it to the SA measurement, including some insights to complementary models of human memory presented in Section 5.4, as well as a more detailed explanation of the practical aspects, in terms of SA measurement, derived from the key concepts introduced in the model: perception, comprehension, and projection.

2.1.3 Alternative models

In this subsection we summarise the most relevant SA models that can be considered alternatives or complements to Endsley's model, also trying to provide a first insight into their relevance in the field of aviation human factors

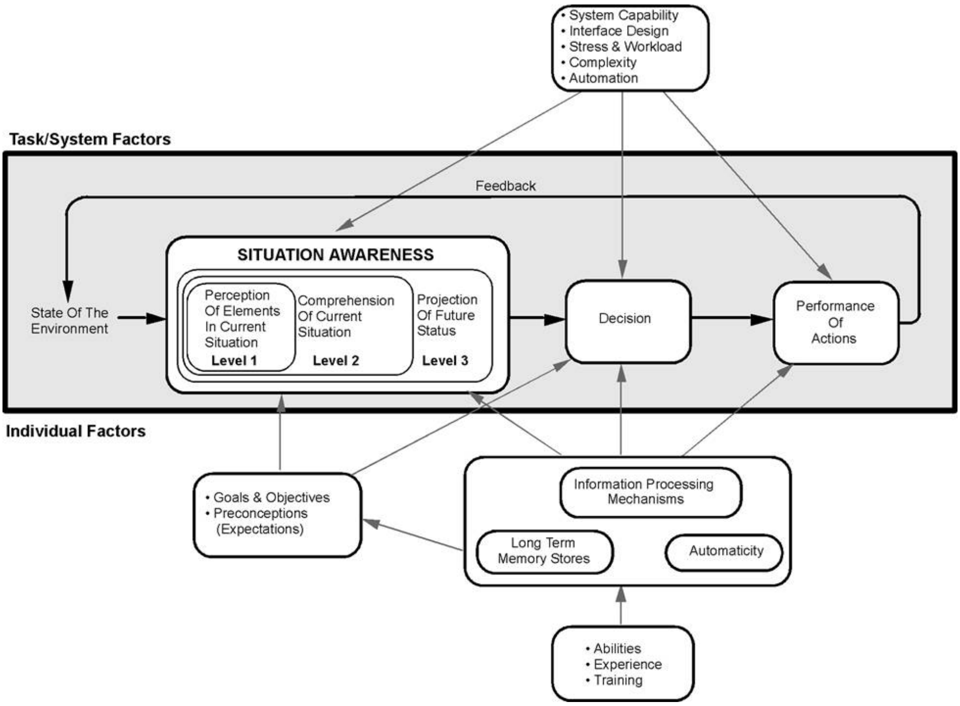


Figure 2.1: Endsley's model of situation awareness in dynamic decision making [40].

and the applicability to our research, which will be further analysed in Chapter 5. It should be noted that they are not intrinsically different between them, since they all derive to some extent from the seminal SA concept presented by Fracker[49]. They provide different methodologies or focus on different areas of human factors, so it can be understood that the differences, advantages, and disadvantages are not obvious for this research, given that our field of study is also focused on machine learning. During the years of research, we have been aware of the difficulty in tackling these differences and finding the best applicability to our purpose; actually in this chapter we are already acknowledging the fact that Endsley even describes these differences as fallacies or misinterpretations [42]. This has even made our research more interesting and motivating.

2.1.3.1 *Perceptual Cycle Model*

The Perceptual Cycle Mode has been analysed by different authors. The first approach is the one proposed by Adams et al. in 1995 [1], which is contemporary with the Endsley model. In this case, the focus is on the cognitive management of complex systems, which is a very similar approach to End-

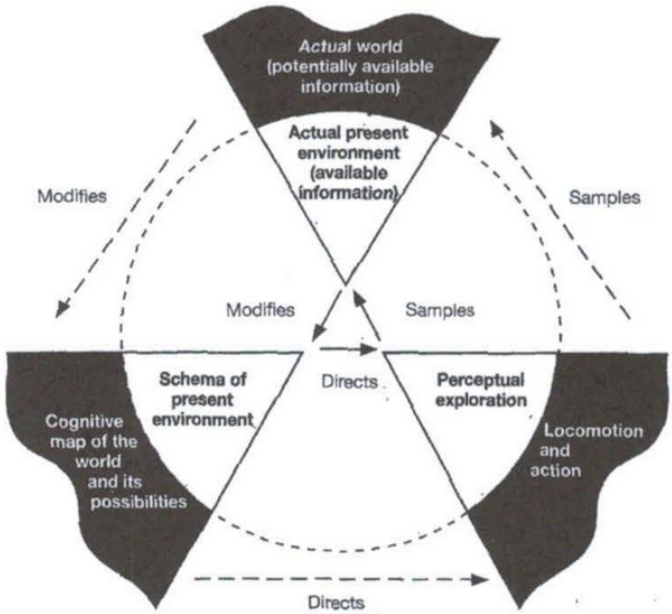


Figure 2.2: Adam's cyclical model of situation awareness [1].

sley's, but the main difference is presenting a linear relationship among the factors of the perception-decision-action loop, instead of the SA levels, as can be observed in Figure 2.2.

According to this model, also presented by Smith and Hancock (1995) [142], SA is defined as adaptive, externally directed consciousness, bridging the gap between seeing SA as either knowledge or process. This definition clarifies that SA is tied to external goals within the task environment, guiding behaviour towards achieving these goals. It is very important to take this into account, to avoid seeing SA as a result of an external process, therefore externally provided to the pilot. Articles related to this model also present the concept of *risk space*, which includes critical invariant relationships in the environment that inform decisions, ensuring safe and efficient performance [142], especially for aircraft navigation.

2.1.3.2 *Activity Theory Model*

This model was introduced in the mid-20th century by the psychologist Aleksei Leontiev. In modern times, different authors have applied it to aviation and computer interface design. We have chosen the model provided by Bedny and Meister in 1999 [12], basically because they are the first western authors to acknowledge Leontiev's contribution, and also because it applies to aviation situation awareness, emphasising the interaction between the pilot's cognitive processes and their environment. Similarly to other models, it views SA as part of a broader activity system where human actions are goal-directed and shaped by the external context. The authors also acknowledge the Endsley model and no significant additional contributions applicable to our research have been found.

2.1.3.3 *Distributed Situation Awareness Model*

This model was first published in 2008 by Salmon et al. [134] in the context of a research on energy distribution. The model is extended and its applicability to aviation is more evident after the work published in 2017 [133]. The main contribution of this model is to extend the concept of SA by considering it as a property of systems rather than individuals. Therefore, in aviation, apart from the pilots, other members of the team with a contribution to SA are identified: air traffic controllers, information providers and even automated systems. This model is particularly relevant for understanding how different components of an aviation system contribute to overall awareness and performance. It focusses on teamwork, communication, and coordination in shared environments, which in our research can be extrapolated in terms of information sharing and information management.

2.1.3.4 *Goal-Directed Situation Awareness Model*

This model, introduced by Stanton et al. in 2001 [146] and updated more recently [147], emphasises a systemic and interaction-focused approach, that is, it is more focused on the design of the system, aircraft systems, information resources, HMIs, etc. In contrast to Endsley's Model, it does not take into account to the same extent the individual's mental processing in relation to SA.

However, both models share many valuable parallelisms, with Endsley providing a clear framework for cognitive processes and Stanton offering insights into the systemic and interactional aspects of SA.

2.1.3.5 *Fracker's Model of Situation Awareness*

We will finally mention Fracker's model [50], since it is the predecessor of the ones described in the previous subsections, with the exception on Leontiev's, and it is undoubtedly the first author to not only define situational awareness [49], but to estate that it arises from matching incoming information to preexisting cognitive structures. It is our impression after a careful

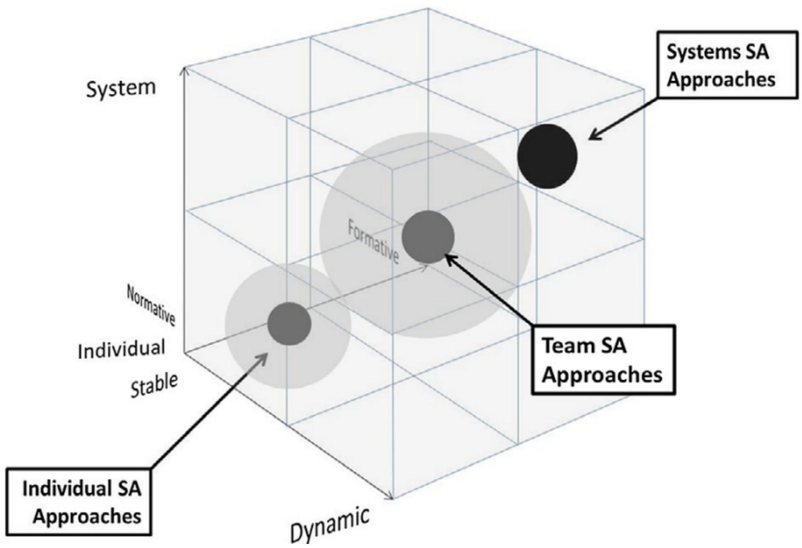


Figure 2.3: Different approaches to SA modelling, according to the Goal-Directed Model [147].

study of multiple sources on the topic, that what this model identifies as Mental Models (the fact that pilots use their mental representations of a situation to anticipate and interpret information from the environment), schema activation (the specific situations that trigger relevant schemas) and the Dynamic Interaction (seen as a continuous cycle of updating mental models as new information is processed) is the basis of the 3-level approach defined by Endsley a few years later and that we have adopted as the paradigm of the SA modelling.

2.1.4 Misconceptions about SA

In the domain of human factors in aircraft, the concept of SA has become very common. Many aircraft systems developers claim that their products increase SA. It is clear that in most cases they are right, and this research acknowledges that modern aircraft human interface assets and automation tools are a general contributor to increase pilot awareness. But after having studied the Endsley model in some detail, the question that arises then is if these developments are targeting the different levels of awareness in a balanced way. Our premise is that high SA is always desirable, but it does not entirely depend on the system working or being operated as designed, but rather on the ability of the pilot to form a correct mental image of the present and future situations. Consequently, a nuance arises that calls into question the effectiveness of modern information management systems in the event that the system fails. What if the data are wrong? If the SA is really high, this case is already discounted. A (good) pilot with the appropriate SA is always prepared so that this type of failure does not pose a safety problem. If the problem actually occurs, having had an adequate SA had already made the pilot to previously form a mental image of what was going to happen in case the phenomenon had occurred.

However, the concept of SA is not so simple to analyse, and as will be explained in Chapter 5, we should take into account the existence of certain misconceptions, such as those identified by Endsley in [42]. Based on the introduction of these fallacies and their refutations, in addition to the additional considerations set forth in the following work by Endsley [37], we enumerate a set of propositions that are useful to provide a better understanding of the model scope:

1. The three levels of SA are not linear.

2. The model cannot be considered as merely a data-driven information processing model.

3. There is a clear distinction between Product and Process.

4. The model of SA is cyclical and dynamic.

5. The model takes into account the meaning of different SA levels.

6. The SA model requires a dynamic integration of working memory and long-term memory.

We found that this type of reasoning to define SA offers a wide field of study to apply probabilistic methods to its estimation. We will return to these propositions in Chapter 5, in order to apply them to our model, while in Chapter 8 they will be treated indirectly when explaining how the model has been implemented in the last experiment. Still, we would like to anticipate the explanation for the first proposition, because it seems to be the one that Endsley finds prioritary when clarifying the model. The fact that three levels are defined and that Level 1 (perception) seems to be more basic than Level 2 (comprehension), etc., does not mean that a level needs to be fulfilled for the next one to show a good SA level. That is, even if the perception of elements of the situation is far from being good, the individual could have a good comprehension of the situation, for example due to experience, or even if not everything happening in a situation is understood by the pilot, the situation may be clear for the pilot, and the projection of the future state could be accurate. That is what we infer from the first proposition.

2.1.5 Common SA measurement techniques

There are different recognised SA metrics. One of them is the SART, which is often used by aeronautical certification authorities to obtain evidence of how HMI implementations affect SA. SART normally obtains the SA rating after analysing the reports completed by the operator (typically a test pilot). These reports provide assessments of how systems contribute to SA and can be filled during or after real or simulated flights. They are not intended to rate the SA of the user, and cannot be applied for real-time SA estimations because dedicated user actions are necessary to perform the evaluation.

SAGAT [36, 41] is another method, more specialised in flight operations than in aircraft system design, offering a wide variety of applications, such as the evaluation of flight training effectiveness. It is interesting to note that the wording of the 3 SA levels identified by Endsley is slightly different in [36] (1996), compared to [40] (1995) and listed in the previous section. It could be noted that the context of the later paper is focused on the measurement of SA rather than the previous year research, which was more focused on presenting the model.

Taking into account the context acquired after so many published research works and after these years of evolution in the aircraft cockpit design, integration of automation, etc., this is not an issue at all and provides a hint about how the SA levels can be interpreted depending on the method designed to measure SA.

2.1.5.1 *SAGAT: SA Global Assessment technique*

SAGAT usually consists of freezing a flight simulation and asking the crew to fill out a questionnaire on the relevant aspects of the mission. The answers are expected to reflect the degree of SA of the subject, usually based on the operator requirements at the three different SA levels previously described. SAGAT is a direct measurement of SA because it explores the perceptions of the operator rather than inferring them from behaviour that may be influenced by many other factors. SAGAT depends on the optimisation of the questions and the appropriate choice of simulation pauses to reduce the bias of the first two SA levels. However, this is not feasible at level 3 SA as freezing the simulation directly impacts the projection of the near future. We did not find references of

SAGAT being applied in environments where the simulation was not stopped. [150] shows some results applied to automatic driving simulations, an application with many parallelisms with aircraft SA, and confirms that the projection of the near future (Level 3 SA) obtains unsatisfactory results with SAGAT [39, 41].

2.1.5.2 *SART: SA Rating technique*

SART offers a different approach based on a self-assessment performed by the pilot, rather than an externally asked set of questions. It is clear that SART's approach is not applicable to our research because it is not feasible to pose a self-assessment or a questionnaire in real time during the flight. SART is designed to be implemented in a controlled environment with highly experienced pilots, usually test pilots or operators dedicated to system development and certification, to provide feedback on situation awareness for specific purposes.

SART has been used for many years, together with SAGAT, and its pros and cons are widely available in the literature, although the most relevant study is possibly the one developed by Endsley [38]. In environments were simulators or UAS remote flight consoles are used, the bias introduced by these techniques is smaller than in a real cockpit, according to Rebensky [125]. Therefore, it is interesting for potential future research lines to analyse how a small assessment, either based on direct questions or asking the pilot about subjective appreciations, could be beneficial to measure or even increase SA.

2.2 Operational Risk Management (ORM)

2.2.1 Introduction

ORM is a decision aid tool used in many flight operations environments, based on the application of risk management methodologies to operational risks, in our case flight operations. These are risks such as adverse weather, impact of unaccounted for factors on crew performance during the operation, inadequate rest periods, extended mission times, or demanding mission conditions.

To understand how standard risk management techniques are applied in aviation operational environments, we have a very valuable source of information in the FAA manual published ad hoc [113]. There are other sources of information focussing on military operations, such as the one with free access from the USAF [9].

Risk management has proven that analysis of uncertainty and the impact of uncertain events has very tangible results when accurate probabilities can be provided. In this sense, ORM is implemented in many operations centres, with a growing tendency to integrate probabilistic software tools in the dispatch process of missions. These probabilities could be applied to the design of SA using the BN analysis, although this falls out of the scope of this investigation.

2.2.2 ORM relation with SA

ORM and SA are closely related in the context of flight safety, although their applicability, if considered as success parameters, is different in mainly the moment of application: ORM is supposed to be applied consciously before the flight, in order to validate the decisions that surround clearance for a specific mission. On the other hand, SA is an individual state or mental condition, which is supposed to be kept high if operational risks have been adequately assessed. In this sense, although difficult to quantify, it could be inferred that an adequate ORM properly briefed to the crew will create favourable conditions to maintain high SA.

Both ORM and SA related methodologies can be considered to offer solutions to the same problems from different perspectives. In an effort to simplify, it can be said that ORM puts more emphasis in the organisational or procedural perspective, while SA is more closely related to human factors.

The Swiss Cheese model for risk analysis, first published by Reason in 1980 in the framework of psychology and human factors research, has developed over the years and has been adopted by ORM [124]. Figure 2.4 shows how this model takes into account different external and internal factors to explain the interaction of accident causes in complex systems.

The purpose of ORM is to establish a set of defences in an operational environment, based on the identification of vulnerabilities, mainly latent failures at managerial levels, intrinsic defects in the design of the aircraft, the flight procedure, etc., internal human factors of the pilot, among whose the model stresses the importance of individual psychological precursors and unsafe acts. Managing and mitigating these risks is clearly an effective strategy to enhance defences and reduce the probability of accidents. From this point of view, SA can be considered as a product of ORM.

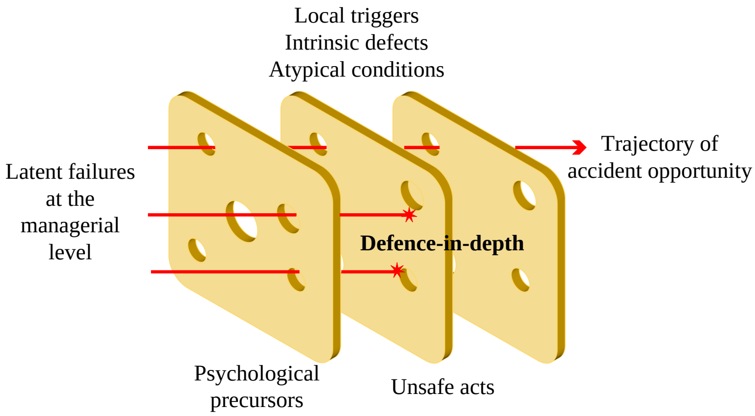


Figure 2.4: Reason's Swiss Cheese model for risk analysis [124]

2.2.3 Applicability of ORM to this research

Given the high number of parallelisms between both disciplines, we decided to carry out a survey that consisted of asking mission-related questions to several individuals familiar with ORM practices, with the intention of obtaining feedback related to their priorities to establish the most critical causes of error or their priorities to maintain a high SA during a flight similar to the one performed in the first experiment of this research. This approach emphasises the vision of SA as a product of risk management. The details of this part of the investigation are exposed in Section 5.2.

2.3 Performance-based navigation (PBN)

2.3.1 Introduction

PBN is a navigation concept in aviation that defines different types of routes and navigation methods, depending on the aircraft performance of its onboard navigation systems, rather than relying solely on ground-based navigation aids [10]. This approach was conceived at the beginning of the twenty-first century, in parallel with other processes of digitisation of navigation information and increase of air traffic volumes. It is designed to enhance the precision, efficiency, and flexibility of air navigation through its two main components:

- Area Navigation (RNAV): Chronologically speaking, this could be considered the precursor to PBN. RNAV procedures were at the beginning based on waypoints defined only in coordinates, located directly by Global Positioning System (GPS) or inertial systems, allowing the aircraft to fly directly between arbitrary points, rather than following flight paths between points defined by a radio-navigation aid based on a ground station. This allows for a more flexible airspace.

- Required Navigation Performance (RNP): RNP is a specific type of RNAV that adds a requirement for onboard performance monitoring and alerting. It ensures that the aircraft can navigate accurately within a defined airspace, with the crew being alerted if the navigation accuracy drops below the required level [31].

The implementation of PBN is one of the top priorities of the current Air Traffic Management (ATM) authorities, and in Europe, PBN is being implemented within the framework of Single European Sky ATM Research (SESAR), with the objective of meeting the increased requirements for airspace traffic capacity and flight safety. Thanks to PBN, airspace becomes more flexible, adapting routes to operational requirements without being tied to ground-based stations [31].

For pilots, PBN has several implications. The most important is probably the increase of automation in the cockpit, in some cases even compulsory according to the operational procedures of the company or unit. Before discussing automation bias in Section 2.4, in the following subsections we will explain briefly the background of the increase of automation, partly due to the increase in route calculations necessary to achieve PBN optimisation requirements.

2.3.2 Implications on route complexity of modern navigation

At the same time that automation spreads in aircraft systems, the complexity in navigation increases. In fact, the optimisation of the routes introduced by PBN brings as a consequence that some of their parameters can no longer be calculated or even understood by the pilot.

One of the main causes is the fly-by turn procedures, which, although they have existed for decades, were hardly used in commercial navigation until the arrival of PBN, where fly-by turns have replaced many fly-over turns. Figure 2.5 shows a schematic representation of both types of turns, which, although they may seem similar, have a great difference in terms of how to fly them accurately. While in a fly-over turn the pilot focusses the attention on flying towards the waypoint and, once over it, joining the outbound route as quickly as possible, in the case of fly-by the starting point of the turn is not so obvious as it depends on multiple factors. The advantages of fly-by turns are mainly two:

- They imply a slight savings of fuel and time, as the distance flown is shorter than in fly-overs.
- If they are executed with the appropriate means, the precision of the navigation is greater, as the desired route is known at all times. However, in fly-bys, just at the moment of passing through the vertical of the waypoint, there is a cone of confusion in which the pilot is responsible for recovering the reference and continuing with the departure within certain margins.

This topic involves a certain complexity and it is not our purpose to go into further details, other than the fly-by turn execution itself, which will be analysed in Section 7.6, and the approach to measure SA in PBN procedures, which we will start presenting in the next subsection.

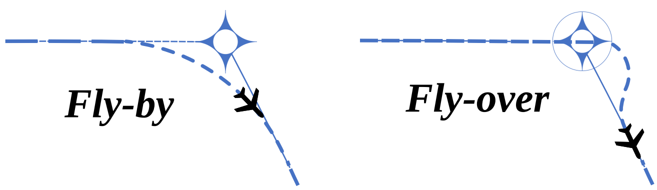


Figure 2.5: Fly-by turns are widely used in PBN vs. fly-over.

2.3.3 Consequences for automation and situation awareness

PBN introduces an unprecedented optimisation of congested airspaces, allowing the implementation of parallel routes, while fly-by turns provide shorter trajectories at the same time that the required precision is maintained [65]. Fuel consumption and airspace density are therefore improved [87], but one of the consequences is that the routes are no longer intuitive to pilots if they try to fly without using an automatic pilot.

PBN procedures often involve predefined paths and waypoints, and aircraft automation systems can follow these paths accurately. Pilots can engage autopilot modes to automate the lateral and vertical profiles of the flight. From a cognitive point of view, this is a big challenge for the pilot, since the focus tends to be on controlling the equipment that provides the automation rather than checking the accuracy of the flown trajectory, which is expected to be controlled by the machine. In our experiments, we have collected variables for both profiles (vertical and horizontal), although in the last one, which is explained in Section 7.6, we decided to estimate only the SA associated to horizontal trajectory variables and the aircraft parameters. Among the reasons for this decision are the following considerations highlighted by Barhydt and Adams [10]: Over-complexity in procedure design, including factors like the number of waypoints, chart clutter, and successive altitude constraints, that can contribute to pilot workload and confusion.

The results of these issues are some of the main challenges of this research: to decide how human factors are modelled in relation to navigation parameters [10]. Our approach will be explained in Chapter 5. But before that, we will present a very relevant concept closely related with the level of awareness of any individual working in an environment where automation is present: the automation bias.

2.4 Automation bias

On a general basis, automation bias refers to a phenomenon in which operators have a tendency to rely too much on automated systems, which may lead to reduced vigilance and potential errors when automation fails or does not work correctly. The concept was introduced in the 1990s in the context of new developments of HMI based on computers, digital displays and FMS [104, 135, 136]. After reviewing the literature, we have found that the problem persists over the years [85, 111, 137], with the disappointing and worrying fact that fatal accidents still occur. More updated models also mention the concept of *complacency* [55].

For this research, it has been recognised especially relevant to focus on considering a balance between accountability and double-checks performed by pilots, analysed in a context of high automation, and we have attempted to model this in our simulations.

Based on the fact that, in general, automation provides better levels of safety in air operations, on the other hand, it is important to analyse where the limits of these benefits are and to characterise them, with the intention of integrating into our model. We consider that it is still valid to take into account the outcome of the experiment performed by Mosier [104], indicating that pilots who show an internalised perception of accountability for their performance and the way they manage automation tend to make fewer mistakes because they establish better strategies for managing automation, mainly performing more double-checks.

The topic is not simple because, in modern aviation, the availability of automatic systems clearly impacts the accountability of pilots. This is still clearer in military aviation since modern aircraft sometimes prevent pilots from using the basic aircraft controls available in the past, forcing them to focus on the mission progress rather than on flying, and thus reducing their accountability about basic aircraft control.

In civil aviation, this has become very relevant in recent years. With the generalisation of PBN, as we explained in our paper [99], the level of automation goes beyond the pilot's ability to understand the reasons why the aircraft starts turning at a given moment. But this is not the only case where a high degree of automation can impact the ability of the crew to understand why the aircraft systems behave the way they do. We have selected several cases of study related to automation, deeply analysed by multiple experts because they caused great human losses, to offer a brief insight about the role of automation bias in the next subsection.

2.4.1 Cases of study

During our research, we have often checked statistics of real flights and analysed information about accidents where it was clear that the human factor and specially SA was a contributing factor [8, 71, 118]. In general, the easiest way to access accident reports in a simplified way is to check web repositories of accident statistics from a trusted source. We aim to to put certain focus on this kind of mishaps, since they have had some public significance, and carrying out an analysis of them allows drawing more attention of the reader.

In our case, we found that the Aviation Safety Network repository provided by the Flight Safety Foundation meets the requirements to perform this kind of analysis [8], and we have focused on three accidents:

Air France Flight 447 crash, 2009:

These are some excerpts from the analysis of the causes of the accident, available in entry 321502 of the database [8]:

- "*The occurrence of the failure in the context of flight in cruise completely surprised the pilots*".

- "*In the minute that followed the autopilot disconnection, the failure of the attempts to understand the situation and the de-structuring of crew cooperation fed on each other until the total loss of cognitive control of the situation*".

Lion Air Flight 610 crash, 2018:

This is the first accident with victims of a Boeing 737MAX, stored as entry 319547 of the database [8]. It should be noted that the Maneuvering Characteristics Augmentation System (MCAS) is a system designed to enhance the stability characteristics of modern aircrafts, and it involves certain automation on the way the pilot commands the control surfaces of the aircraft. The following are contributing factors to the accident, according to the published information:

- "*The absence of guidance on MCAS or more detailed use of trim in flight manuals and in flight crew training, made it more difficult for flight crews to properly respond to uncommanded MCAS*".
- "*The multiple alerts, repetitive MCAS activations, and distractions related to numerous Air Traffic Controller (ATC) communications were not able to be effectively managed*".

Ethiopian Airlines Flight 302 crash, 2019:

This is the second accident with victims of a Boeing 737MAX, stored as entry 319474 of the database [8]. Although the circumstances are very similar to those in the previous paragraph, given their great impact, both publicly and in the review of certain certification criteria, it has been considered appropriate to mention this accident. For the first time in the history of aviation it was acknowledged that an automation system (the MCAS) had been designed in such a way that operators (pilots) could not override an abnormal behaviour of the system in the event of a failure. It should be noted that, in the case of aircraft systems related to human factors, the design includes not only the implementation, but also the crew training and the design of emergency checklists. This could be identified as an additional type of automation bias [68, 128], but it is not the purpose of this thesis to perform this kind of contribution.

2.4.2 Main consequences of automation bias

We will end this chapter with a list of some error categories or in some cases of accidents that are more related to automation bias. These were already identified by Mosier in 1998 [104] and can be found to some extent in most of the scholar references related to SA that have been cited in this chapter:

- Mode confusion: this is a direct confusion about the automation itself, because the pilot fails to understand what control modes are really automated. Although it is more typical in the case of inexperienced pilots, mode confusion could affect any pilot if the workload is excessive or the SA is low for other reasons.

- Lack of manual flying proficiency: although not openly acknowledged, the fact that flight missions are being carried out with ever-increasing levels of automation means that pilots have fewer opportunities to maintain their skills in handling manual systems on a day-to-day basis. Although this problem can be mitigated with flight simulators, it comes at a cost both financially and in terms of working hours.

- Over-reliance on automated alerts: similar to the previous consequence, but on a cognitive level instead of a physical level. The fact that the pilot is used to trust automation on a day-to-day basis leads to an inability to detect that there is a malfunction, just because there is a belief that malfunctions should be automatically detected.

- Failure to monitor automation: this is the most dangerous consequence of automation, because the boundary between correct automation monitoring and a failure on this task is not very clear, since it depends on the situation. Therefore, it is a clear example of the importance of considering SA in the three levels identified by Endsley.

- Disengagement of attention: a particular case of the previous category, where the pilots not only stop monitoring essential aspects of the flight but for any reason their attention is disengaged, typically due to having to attend to an external factor. In the worst case, this situation could lead to a specific type of accident: a Controlled flight into terrain (CFIT). There are relevant studies [103] that deal with the causes of this type of accident that is often difficult to understand. There is an interesting resource in [140] to see the statistics and cause analysis of many accidents of this type.

3 FLIGHT MISSION INFORMATION MANAGEMENT

As stated in Section 1.5, one of the objectives of this thesis is to provide an assessment of the availability and selection of aeronautical information, given the key role of the related information management assets to be exploited by machine learning algorithms. At the beginning of the 21st century, the ICAO published Document 9750 [32], renamed as the Global Air Navigation Plan for Communications, Navigation, Surveillance (CNS)/ATM Systems since its second edition in 2002. In 2013, the fourth edition of the document introduced the concept of SWIM as a governance framework for standards, policies and processes related to aeronautical-related information, for the national authorities that act as Aeronautical Information Service (AIS) providers. In any case, the document and its related activities are generally known as the Global Air Navigation Plan (GANP). Since many years earlier, the same AIS providers had been delivering, nation by nation, a set of publications of aeronautical data, initially paper-based, more focused on providing critical aeronautical information to operators (pilots, controllers, etc.) with a systematic schedule and update system, widely known as the AIRAC system.

In this chapter we try to offer, in a very concise way, an overview of the contents, formats and organization of aeronautical information, and then outline how they are integrated into the more recent SWIM technologies, of which we will also briefly show their internal structure.

3.1 Fundamentals of mission information

3.1.1 Aeronautical information and its stakeholders

Despite the multiple factors that affect mission planning, whether a military tactical mission or a routine airline operation, the pilot needs to plan a flight route, calculate the required aircraft performance, and decide its configuration accordingly. There are multiple stakeholders around flight operations, and some of them require as much information as possible to optimise the performance of their products. Apparently, some years ago, one of these stakeholders mentioned during a meeting in the Eurocontrol headquarters that they needed to "swim in seas of data". This anecdote led to the adoption of the SWIM acronym, which stands for the international initiative designed to enhance the exchange of information among aviation stakeholders, allowing seamless and real-time sharing of aeronautical, flight and weather data between airlines, airports, air navigation service providers, and other aviation entities, promoting efficient and data-driven decision-making [29]. The SWIM standards will be explained in Section 3.2.

A list of these stakeholders is provided in [29], stressing that all can behave as both information providers and consumers:

- Aerodrome community;
- airspace providers;
- airspace users;
- ATM service providers (ASP);
- ATM support industry;
- International Civil Aviation Organization (ICAO);
- regulatory authorities; and
- States.

Seeing the level of ambition of the aeronautical community is an indication of the complexity of the SWIM initiative itself. It should be kept in mind that the concept was introduced to modernise air traffic management information and systems, and at the same time standardise them. The reality is that there were many different systems and processes for managing different types of ATM information, depending on the national authorities, aircraft manufacturers, information and service providers, etc. From the point of view of this research, we have studied the intents to overcome inefficiencies, redundancies, and inconsistencies of a multi-system approach and focused on using information from standardised sources with a modern approach for information management.

3.1.2 The AIRAC system

The AIRAC system is a data provisioning structure established by the ICAO to ensure that aviation information and data are distributed in a standardised and timely manner [6]. This subsection aims to provide an introduction to its features and its relationship with SWIM, while some details about its structure and content, especially those applicable to this research, are presented in Appendix A.

In a simplified way, the AIRAC system intends to distribute aeronautical information, with a similar scope as SWIM provides in digital format. Before the age of computers, all information required to support air operations was distributed by paper-based means, as the organisation of operational structures, airlines, air forces, etc. evolved, the AIRAC system was developed as an international initiative with certain key aspects to ensure timely information to support safe flight.

One of the main characteristics of the AIRAC system is that there are regular update cycles of aeronautical information every 28 days, which does not mean that all information is updated with this frequency; the stakeholders are expected to know what is updated and what is not. However, these cycles are mandatory, and this introduces a high workload to many pilots who are expected to be responsible for the validity of the information they consult during the flight. This, of course, has an impact on SA.

The basic aspects of the information products included in the AIRAC system are standardised worldwide, which can be seen as an advantage because the standardisation of information allows a methodical approach to information management. However, the reality is that information is not the same everywhere in the world and the pilot is expected to be aware of certain exceptions that could affect the way he/she manages information in the cockpit. As a baseline, the information provided includes updates to flight procedures, air traffic control routes, airport data, navigation aids, and other critical operational details. The main product of the AIRAC system is AIP, which will be introduced in the next subsection.

To support the timely access to information, the changes are published before their effective date, usually at least 42 days prior to the information items that should be replaced. This also adds certain complexity to the tasks of the pilots, that need to have awareness of when the information they possess will be valid. This requires a global coordination of international aviation authorities, airlines, and service providers. All of these stakeholders need to be coordinated to maintain harmonised and synchronised aeronautical information. Since SWIM was conceived, it was designed to adapt to the AIRAC system.

3.1.3 The Aeronautical Information Publications

The AIP is an essential document that contains aeronautical information for operations. It follows the AIRAC cycle and is published by or on behalf of a country's aviation authority. In the case of the USA it is published by the FAA, in the case of Spain it is published by the public entity *Enaire*, etc. At the time of writing this dissertation, the European Union has not yet established a mechanism to centralise the publication of aeronautical information, so it is the responsibility of each estate.

The structure, content and distribution of aeronautical information is established by the ICAO in the Document 8126 [30], titled the Aeronautical Information Services Manual. The AIP contains comprehensive information on flight procedures and facilities relevant to air navigation within the country's airspace and is employed as a primary source of information by pilots and other aviation personnel, such as flight planners. Below is a list of the most relevant elements contained in the AIP:

- Airport information: Layouts, available services, and operating hours.
- Airspace structure: Controlled airspace boundaries, flight rules, and designated altitudes.
- Navigation Aids: Locations and details of radio beacons, GPS systems, and instrument landing systems.
- Communication protocols: Frequencies and guidelines for air traffic control.
- Weather Services: Availability and types of meteorological data.

Figure 3.1 has been included to also provide an overview of how this information is distributed in within the AIP volumes.

One of the challenges often experienced by pilots, especially when they are not very experienced, is the difficulty of carrying the appropriate information in the cockpit. Although the situation has radically improved with the use of EFBs, it should be recognised that the digital format does not always mean that the information is more available. In fact, one of the main reasons why EFBs have become widely used in recent years is because the AIP paper folders are very bulky. Figure 3.2 is included to highlight the fact that for a middle-sized country like Germany, IFR pilots need 3 volumes (A4-sized) that contain almost a thousand pages. Of course, all this information does not need to be checked for a single flight, but the pilot has the obligation to keep access to

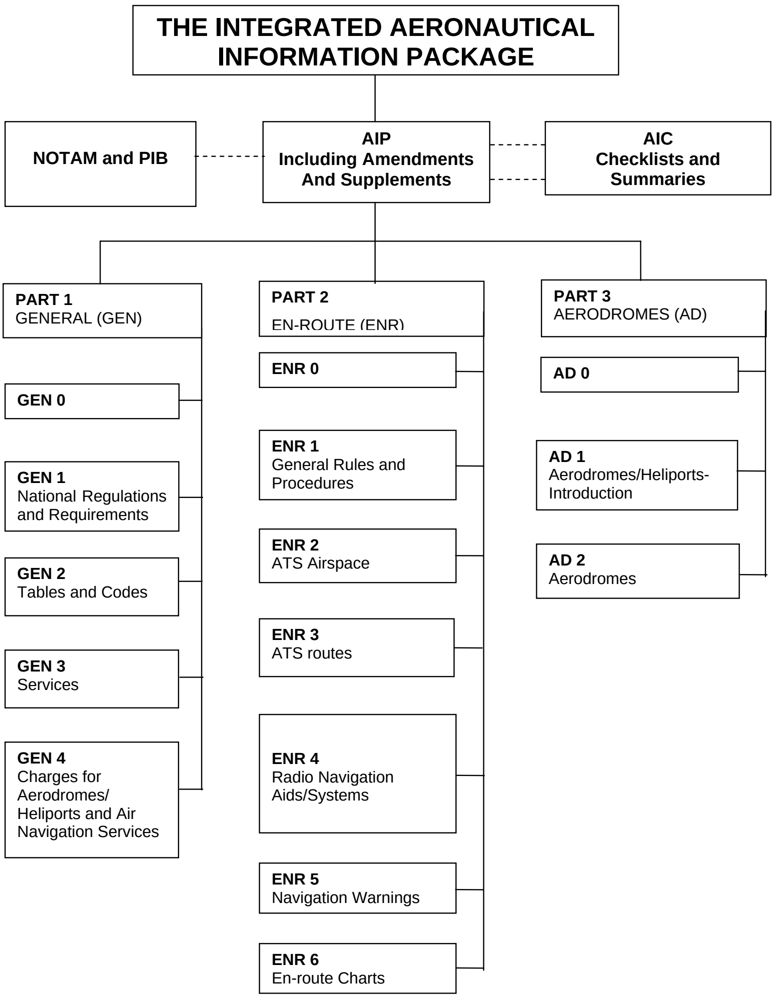


Figure 3.1: Flowchart of the AIP contents [145].

Figure 3.2: Paper folders for storing AIP or equivalent charts from Jeppesen [57, 76].

an updated set of information in every flight. This is really a burden for flight safety when the operations centre does not provide enough support for this task.

3.1.4 Flow of information and SA

We are now aware of the stakeholders related to aeronautical information management, but to better understand how the data can be used by machine learning tools, it is important to present an overview of the aircraft mission information flow.

As explained in the previous chapter, SA is a concept related to internal aspects of the subject, in this case the pilot. Therefore, when considering the impact of information management on the overall performance of the pilot, it is mandatory to take into account the type of mission. The current research does not intend to provide a holistic solution or answer to this challenge, and it has already been mentioned that our experiments focus on specific mission profiles, quite similar to the ones faced by airline pilots. However, despite the general complexity, it is important to bear in mind that one of the priorities of SWIM is aircraft trajectory management: The trajectory, either planned, in real-time during the flight or in debriefing analysis, contains the information to determine if the flight takes place in the desired airspace areas, if the deconfliction with other aircraft is successful, if the route meets the safety criteria according to the aircraft limitations, or if the route is efficient in terms of fuel and time.

The trajectory is in most cases a priority in mission development and the pilot is trained accordingly. That is why we dedicate special attention to the SA model related to trajectory management. Given the importance of the study of trajectories, we have decided to dedicate a large part of our research to their analysis, as will be explained in the chapter 7.

3.2 SWIM standards

In the previous chapters, we have introduced the concept of SWIM, whose role is of great importance in the standardisation of aeronautical information, both currently and in the medium / long term future. In this section, the standards that make up SWIM will be presented, providing some examples of the information that they bring together and that has been used as far as possible in the different experiments of this thesis.

The definition of SWIM provided by the ICAO states that it is a concept consisting of standards, infrastructure and governance that enable the management of ATM related information and its exchange between qualified parties through interoperable services [29].

In this section, we will provide a brief and general overview of the SWIM implementation, and then focus on the three standards that enable information sharing, since they are the main point of interest for our research in terms of accessing information to be used by our learning algorithms.

3.2.1 Background of SWIM implementation

The SWIM framework, as established by ICAO in the Document 10039 *Manual on System Wide Information Management (SWIM) Concept* [29] is shown in Figure 3.3, where it can be observed that the main elements of the scope of SWIM are:

- Information exchange services,
- Information exchange models,
- SWIM infrastructure,
- all of them under a common governance (right side of the figure).

On top of that, the SWIM-enabled applications exploit the information managed by this framework. It should be noted that although the figure does not show a representation of a pilot or cockpit of an aircraft, the approach of SWIM is perfectly compatible with the provision of information, even in real-time, to aircrews [78].

During the years of our research, we have been following the development of SWIM, both in terms of technical aspects and in terms of how SWIM-enabled

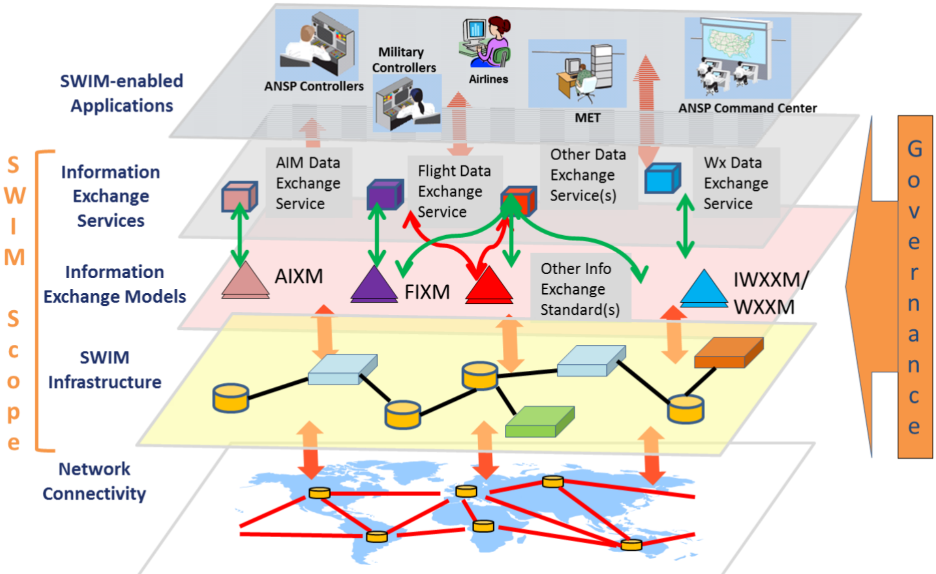


Figure 3.3: SWIM Global Interoperability Framework established by ICAO [29].

applications exploit it. We have realised that the adoption of this implementation is very slow, basically due to two reasons:

- The high standards of safety required by the aviation industry are translated into certification processes that are long, and in the particular case of SWIM the level of reluctance is high due to the great technological leap.

- SWIM implementation involves a multinational and multi-domain agreement, and its adoption does not have the same priority for all stakeholders. In any case, we have observed a general consensus on the need for digitisation and standardisation of flight information.

3.2.2 AIXM

AIXM is a data model based on the Geography Markup Language (GML), developed as a multinational initiative in the context of SWIM, with the purpose of enabling the exchange and provision of aeronautical information in digital format, within the scope of AIS, and therefore interconnecting systems from multiple aeronautical stakeholders. The implementation of such AIS information / data flows has become increasingly complex during recent years, as the number of interconnected systems also grows, involving many actors including multiple suppliers and consumers. There is also a growing need in the global ATM system for high data quality and cost efficiency [3].

In order to meet the requirements of this increasingly automated environment, the AIS is moving from the provision of paper products to the collection and provision of digital data. AIXM supports this transition by enabling the collection, verification, dissemination, and transformation of digital aeronautical data throughout the data chain, particularly in the segment that connects AIS with the next intended user. There are very relevant examples of efforts made by service providers, airspace authorities, and operators to achieve an increase in interoperability [88] and airspace optimisation thanks to the use of AIXM, and this technology continues its evolution to become the first-choice standard for aeronautical information. The following main information areas are within the scope of AIXM:

- Aerodrome/Heliport including movement areas, services, facilities, etc.,
- Airspace structures,
- Organisations and units, including services,
- Points and Navaids,
- Procedures,
- Routes,
- Flying restrictions.

AIXM takes advantage of established information exchange standards and supports the requirements of the aeronautical information system. The rest of this subsection will be dedicated to provide examples of Extensible Markup Language (XML) excerpts of messages, so that the reader can have a more accurate idea of how the aeronautical information is coded.

Listing 3.1 shows a fragment of an AIXM message that contains basic information about the *Der Minot International Airport* (USA) with the ICAO identifier *KMOT*. In this case, in addition to the *message id* and the *time stamp*, we can observe the Airport Reference Point (ARP) coordinates, provided with maximum precision, compared to the previous listing.

Listing 3.1: AIXM example: Runway surface information.

```
<aixm:AirportHeliport gml:id="uuid.1cdd625a-4502-4250-b310-f5d055978 37c">
  <aixm:timeSlice>
    <aixm:AirportHeliportTimeSlice gml:id="gid-636137529080339182">
      <gml:validTime>
```

```
            <gml:TimePeriod gml:id="gid-636137529080339183">
               <gml:beginPosition>2016-10-25T00:00:00</gml:beginPosition>
               <gml:endPosition indeterminatePosition="unknown" />
            </gml:TimePeriod>
         </gml:validTime>
         <aixm:interpretation>BASELINE</aixm:interpretation>
         <aixm:designator>KMOT</aixm:designator>
         <aixm:name>MINOT INTL</aixm:name>
         <aixm:locationIndicatorICAO>KMOT</aixm:locationIndicatorICAO>
         <aixm:ARP>
            <aixm:ElevatedPoint gml:id="gid-636137529080339184" srsName="
                urn:ogc:def:crs:OGC:1.3:CRS84" srsDimension="2">
               <gml:pos>-101.28231787946062 48.257406747191631</gml:pos>
            </aixm:ElevatedPoint>
         </aixm:ARP>
      </aixm:AirportHeliportTimeSlice>
   </aixm:timeSlice>
</aixm:AirportHeliport>
```

In the case of Listing 3.2, we provide an AIXM fragment that indicates the length (6351 feet) and width (100 feet) of a runway which has headings 80º and 260º (see these headings in the *designator* field).

Listing 3.2: AIXM example: Runway orientation and length information.

```
<aixm:Runway gml:id="uuid.f3a1c226-5b46-4f38-92f7-9e80853b28ab">
   <aixm:timeSlice>
      <aixm:RunwayTimeSlice gml:id="gid-636137529080339188">
         <gml:validTime>
            <gml:TimePeriod gml:id="gid-636137529080339189">
               <gml:beginPosition indeterminatePosition="unknown" />
               <gml:endPosition indeterminatePosition="unknown" />
            </gml:TimePeriod>
         </gml:validTime>
         <aixm:interpretation>BASELINE</aixm:interpretation>
         <aixm:designator>08/26</aixm:designator>
         <aixm:type>RWY</aixm:type>
         <aixm:nominalLength uom="FT">6351</aixm:nominalLength>
         <aixm:nominalWidth uom="FT">100</aixm:nominalWidth>
      </aixm:RunwayTimeSlice>
   </aixm:timeSlice>
</aixm:Runway>
```

The third message chosen as an example is a NOTAM, which is, as defined by the ICAO, a standardised message that aims to provide essential information to pilots and other personnel involved in flight operations, which cannot be published by other means, normally due to urgency or temporary affectation to flight operations [6]. NOTAM are a special type of message and are somewhat difficult to compare with other, more structured types of messages, basically because their scope is wider in terms of the type of information they contain, compared with more standardised messages, like the two previous examples. More information about the nature of NOTAM messages is included in Appendix B, with the aim of providing more context for the following example.

Listing 3.3 shows an XML fragment of a real AIXM NOTAM, where we can see fields like the affected Flight Information Region (FIR), which is the airspace region to which the publication is assigned. There is a field for coordinates (3° 18′ North / 2° 55′ West) and a radius (5 Nautical Miles), resulting in a circular sector, although the location is in this case also expressed with the airport identifier (*LEBB* is the ICAO identifier for the *Bilbao Airport* in Spain) to provide more context. Finally, the start and end timestamps indicate the effectiveness period of the notice.

Listing 3.3: AIXM example: NOTAM event.

```xml
<event:NOTAM gml:id="LOCAL_ID_20">
  <event:series>B</event:series>
  <event:number>4287</event:number>
  <event:year>2017</event:year>
  <event:affectedFIR>LECM</event:affectedFIR>
  <event:coordinates>4318N00255W</event:coordinates>
  <event:radius>005</event:radius>
  <event:location>LEBB</event:location>
  <event:effectiveStart>2017-09-04T13:05:00.000Z</event:effectiveStart>
  <event:effectiveEnd>2017-10-11T23:59:00.000Z</event:effectiveEnd>
  <event:publisherNOF xlink:title="LEANYNYX"/>
</event:NOTAM>
```

3.2.3 FIXM

FIXM mainly supports trajectory management, in the different stages of the mission, from planning and pre-flight coordination, to debriefing and analysis after the landing. It is used for the exchange of planned routes, actually covering the scope of the traditional flight plans. But it also covers the trajectory flown by aircraft, with ambitious applications like real-time trajectory negotiation, to support operations and airspace optimisation. A discussion about Air-Ground SWIM integration to achieve trajectory sharing and negotiation, and the specific role of FIXM in these topics is available in [90].

The importance of trajectory management will be discussed in more detail in Section 7.4, as a primary application of SWIM from the SA perspective in our research. In any case, during the years that this research was carried out, we did not only focus on SA modelling, and we tried to explore other applications and methodologies where trajectory analysis can support not only the SA estimation but also complement flight optimisation in general, and this was almost always done based on the information present inside FIXM messages.

In the current subsection, we introduce the main types of message and also provide some examples. The following is a list of the main FIXM messages defined by the SWIM manual [29]:

- Flight Planning: Flight Plan (FPL) standards messages, used by all pilots and air traffic controllers, are actually coded inside FIXM messages. Changes, delays, cancellations, etc. are also in this category.
- Flight Status: once the aircraft has been dispatched, flight status updates (e.g. departure and arrival times), as well as estimations and delays, are also coded using FIXM.
- Surveillance and Tracking: The aircraft position during the flight, either in real-time or after the operation, is one of the main assets of FIXM. An example is provided below.
- ATC clearances: These messages are exchanged to provide clearance or instructions from controllers to aircraft to support safe flight operations.
- Collaborative Decision-Making (CDM): CDM is a key concept in modern research on airspace sharing and optimisation because its messages focus on improving operational efficiency through collaborative data sharing between stakeholders, such as airlines, airports, and ATC.
- Airspace and Flow Management: This category is of special importance for pilots, and therefore for SA, because it contains messages related to airspace restriction, temporary flight restrictions, flow control instructions, re-routing, etc.

Listing 3.4 shows the basic information about a route in FIXM format:

- The departure airport is Barcelona (ICAO identifier LEBL) and the destination is Malaga (ICAO LEMG).
- Timestamps for estimated times of arrival and departure are included next to the identifiers.

- At first, we can see an XML field for the identification of the aircraft: an Airbus A-320 with registration number *EC-LQZ*.

Listing 3.4: FIXM example: departure, arrival, and aircraft information

```
<fx:aircraftDescription registration="EC−LQZ" wakeTurbulence="M">
  <fx:aircraftType>
    <fx:icaoModelIdentifier>A320</fx:icaoModelIdentifier>
  </fx:aircraftType>
</fx:aircraftDescription>
<fx:arrival>
  <fx:arrivalAerodromeOriginal xsi:type="fb:IcaoAerodromeReferenceType"
       code="LEBL"/>
  <fx:arrivalFixTime xsi:type="fb:ExtendedMultiTimeType">
    <fb:estimated timestamp="2018−10−10T16:44:00.000Z"/>
  </fx:arrivalFixTime>
</fx:arrival>
<fx:departure>
  <fx:departureAerodrome xsi:type="fb:IcaoAerodromeReferenceType" code="
       LEMG"/>
  <fx:departureFixTime xsi:type="fb:ExtendedMultiTimeType">
    <fb:initial timestamp="2018−10−10T15:30:00.000Z"/>
  </fx:departureFixTime>
</fx:departure>
```

Our last XML FIXM example is Listing 3.5, where we show a fragment of a message with an example of a single aircraft position point. The most basic information is position coordinates (*location* tag), altitude and speed. With this basic information, the trajectories are sampled, and the information is obtained to reconstruct the characteristics of the flight. These messages are based on aircraft equipment, known as Automatic Dependent Surveillance-Broadcast (ADS-B), that broadcast different types of data, although normally only the fields shown in this listing are released to the public.

Listing 3.5: FIXM example: Trajectory point

```
<fx:position positionTime="2018−10−10T16:40:13.000Z" source="ADS−B">
  <fx:actualSpeed>
    <fx:surveillance uom="KNOTS">469</fx:surveillance>
  </fx:actualSpeed>
  <fx:altitude uom="FEET" ref="MEAN_SEA_LEVEL">24450</fx:altitude>
  <fx:position xsi:type="fb:LocationPointType">
    <fb:location srsName="urn:ogc:def:crs:EPSG::4326">
      <ff:pos>40.5788 0.3390</ff:pos>
    </fb:location>
```

```
  </fx:position>
</fx:position>
```

3.2.4 WXXM

WXXM is an exchange model for the standardisation of meteorological data sharing between systems, in particular: weather reports, forecasts and observations. Meteorological Information Exchange Model (IWXXM) is a specialised subset focused strictly on the aeronautical domain, although both are initially defined within the SWIM scope [29]. For the purposes of this thesis, no distinction will be made between them, referring only to WXXM, since it is more generic.

The implementation of WXXM is not as mature as the other models because the standardisation of the information contained in the messages is more challenging [18]. Regarding this research, WXXM was not used for the purpose of modelling SA because it was considered that adding meteorological conditions as a factor in the pilot's decision would imply too much complexity to the SA model, and would complicate the implementation of the simulation environment. WXXM messages were however supported by the application developed in 2017 [97], including the three main aeronautical weather messages:

- Meteorological Aerodrome Report (METAR): This message is a report that explains the current or real-time conditions of the aerodrome weather. Normally, it is used to analyse the weather conditions of the departure aerodrome just before the flight. The message is designed to be understood by well trained operators, based on abbreviations and figures on a specific order.

- Terminal Aerodrome Forecast (TAF): This message is similar to a METAR, but it forecasts the expected weather conditions of an aerodrome or a terminal area. Crews normally use it to predict the meteorological conditions of the destination aerodrome and its surroundings before starting the flight.

- Significant Meteorological Information (SIGMET): Specific message issued for unusual or severe aeronautical weather information, normally in clear text, that needs to be disseminated for safety reasons.

Listing 3.6 shows an example of a METAR, where the clear text of the message is shown in the *description* tag, and then its components are repeated in specific tags for:

- Air temperature.
- Dew point temperature.
- QNH (reference air pressure).
- Surface wind (direction and speed).
- Visibility.

Listing 3.6: Example WXXM METAR

```
<gml:description>LEMD 042230Z 03001KT CAVOK 23/10 Q1020 NOSIG</
    gml:description>
<iwxxm:MeteorologicalAerodromeObservationRecord gml:id="LOCAL_ID_8"
    cloudAndVisibilityOK="true">
  <iwxxm:airTemperature uom="Cel">23</iwxxm:airTemperature>
  <iwxxm:dewpointTemperature uom="Cel">10</iwxxm:dewpointTemperature>
  <iwxxm:qnh uom="hPa">1020</iwxxm:qnh>
  <iwxxm:surfaceWind>
    <iwxxm:AerodromeSurfaceWind variableDirection="false">
      <iwxxm:meanWindDirection uom="deg">30</iwxxm:meanWindDirection>
      <iwxxm:meanWindSpeed uom="[kn_i]">1</iwxxm:meanWindSpeed>
    </iwxxm:AerodromeSurfaceWind>
  </iwxxm:surfaceWind>
  <iwxxm:visibility>
    <iwxxm:AerodromeHorizontalVisibility>
      <iwxxm:prevailingVisibility uom="[mi_i]">6.21</
          iwxxm:prevailingVisibility>
    </iwxxm:AerodromeHorizontalVisibility>
  </iwxxm:visibility>
</iwxxm:MeteorologicalAerodromeObservationRecord>
```

3.3 The impact of SWIM on flight operations

3.3.1 General considerations

Since its inception, SWIM has focused more on operations from the perspective of stakeholders closer to ground control centres, ATC and flow-control.

These technologies involved by SWIM are expected to have a great impact on the optimisation of air operations, which by definition are carried out under strict flight safety criteria, always involving correct situational awareness of the pilot.

For the development of our research, beyond the implementation of the simulator and the Bayesian network learning algorithms that will be explained in later chapters, it has been considered essential to be able to count on data exchange standards such as those described. Without their existence, little can be done to design robust systems that can calculate the SA associated with the management of information in the cockpit. We consider it is important to stress this idea so that the reader can understand the importance of AIXM, FIXM and WXXM for our research.

There are ongoing initiatives to bring the benefits of SWIM to the cockpit, providing information to the pilot, before the flight or in real-time, that can be used to increase SA in a tangible way. This is part of a very slow and gradual process in the context of the modernisation of airspace management, which in Europe is allocated in the context of SESAR, monitored by Eurocontrol [43], and in the USA in an initiative called *NextGen*, monitored by the FAA. Other nations like Japan are also very active in the implementation of SWIM, and in particular the *connected aircraft* concept [89], as will be explained in the next subsection.

3.3.2 Trajectory Based Operations

TBO is a broad concept; therefore, for the purpose of this research, we will focus on two initiatives that, in different ways, maintain the pilot in the loop of the information management process: CDM and Flight and Flow Information for a Collaborative Environment (FF-ICE). Figure 3.4 shows a proposed implementation [90] to explore the interoperability capabilities of SWIM in different layers of the stakeholder community involved in the management of the trajectory. The fact that the pilot is included in the decision loop proposed by CDM, with the purpose of optimising collaboration for the air traffic flow optimisation envisaged by FF-ICE should provide an indication of the extent to which SWIM enabled operational environments have the potential to change the way pilots operate, not only to control the aircraft, but also to participate in dynamic negotiation of trajectories.

SA should be limited not only to safety but also to optimisation of operation. In this sense, we explore the analysis of the trajectory to try to find a relationship between the pilot actions and the factors that impact the trajectory.

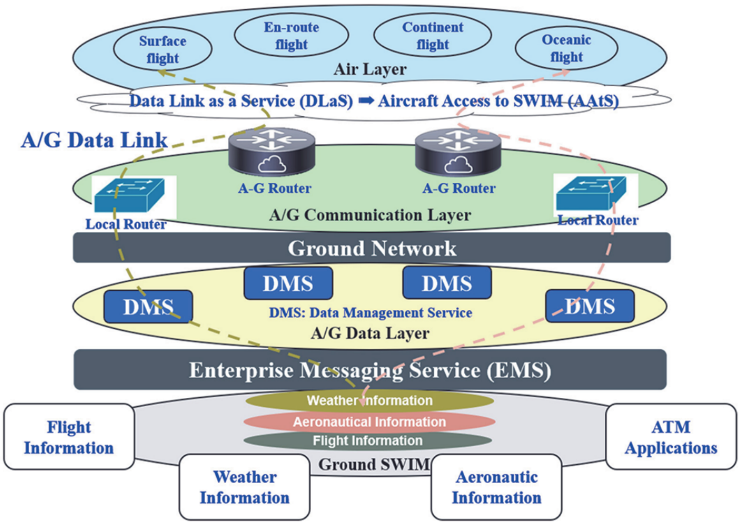


Figure 3.4: Air/Ground implementation of SWIM enabled TBO initiative to exchange information with the pilot [90].

3.3.3 SWIM in the Electronic Flight Bag

To finish this chapter, we will introduce in this subsection the idea that the EFB is probably the entry point to allow the pilot access to the advantages of SWIM, with certain independence to the technological level of other elements of the cockpit.

In modern cockpits of aircrafts, all three levels of SA are linked to how information is managed by the pilot. SWIM and its associated standards presented in Section 3.2, are likely to be widely implemented in EFBs in the future, at least when these devices are not exclusively fed with proprietary applications from specific companies.

This should imply that the initial approach of the EFB as a substitute for paper documents is expected to be overruled by applications that provide pilots with more powerful tools to extract relevant information from data. From our point of view, SWIM technologies applied to EFBs provide an added value in terms of SA because they offer the possibility of implementing applications tailored to the specific need of the mission that the pilot is going to fly. This is particularly important for military pilots, or pilots of aircraft that are demanded to fly different types of missions on a regular basis.

The certification requirements are also less exigent in EFBs than in the cockpit equipment. This is basically due to the fact that the responsibility of making an adequate use of the device and managing its possible malfunctions

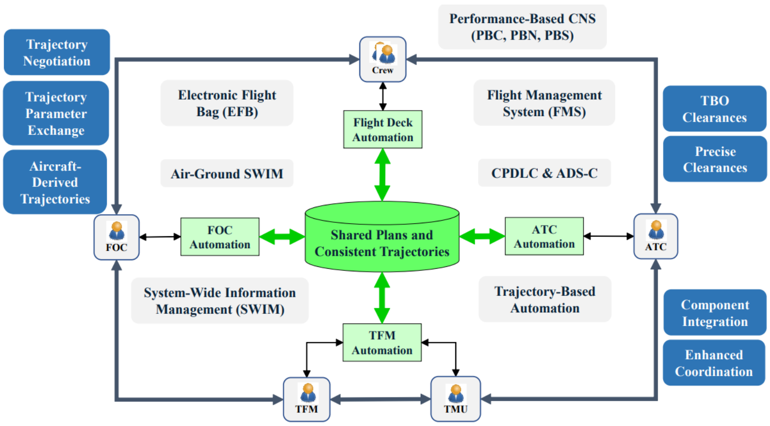


Figure 3.5: Implementation of SWIM enabled TBO initiative with EFB in the loop [89].

essentially relies more on the pilot. Therefore, it is feasible to update the applications installed in an EFB, making it a better option to implement the advances proposed by SWIM. Figure 3.5 shows the implementation proposed by the Electronic Navigation Research Institute (ENRI), where the the EFB integrates within the CDM ecosystem to enable the pilot to become an active stakeholder of the TBO concept, thanks to SWIM [88–90].

With these considerations, for the purpose of this research, we focus on analysing data relationships, especially exploring the interactions between data from different origins and standards within the EFB. The aim is to provide a systematic and robust approach to the management of information and to enable obtaining synergies on the information from combined data sources. It is also a target of this research to translate this concept into the information management methodology of the pilot in the cockpit, reflected in the way the user interface to perform information queries is implemented.

We have initially designed the simulation environment to handle FIXM and AIXM, for the moment with a limited scope, but we anticipate increasing the way information is exploited by these standards and also to add digital NOTAM and WXXM data to improve the simulation with weather and environmental factors. AIXM databases have been provided by Aeropuertos Españoles y Navegación Aérea (AENA), the official Spanish AIS provider.

4 BAYESIAN NETWORKS

This chapter presents a brief, general introduction to Bayesian networks, focussing on concepts more closely related to this research. Therefore, the main purpose is to explain the basics behind the Bayesian networks designed in the experiments that we carried out, where the main challenge was to adapt the data collected from the flight simulator. With this premise, we provide a general explanation of probabilistic graphical models and a few details about directed acyclic graphs, due to their importance in understanding how Bayesian networks perform inference. Given the dynamic nature of flights, we have used dynamic Bayesian networks as the basic modelling tool. These are briefly explained in Section 4.5. Finally, we briefly explain the basic principles that are behind our approach to overcome certain limitations of variables according to their continuous vs. discrete nature or their probability distribution when working with dynamic Bayesian networks.

4.1 Probabilistic Graphical Models

4.1.1 Definition and essential properties

PGM use graphs, i.e. non-linear data structures consisting of vertices and edges, to facilitate the representation and resolution of complex problems where uncertainty is modelled with the use of probabilistic dependencies [81].

The graphical structure encodes conditional independence properties. For instance, in a Bayesian network, a node is conditionally independent of its non-descendants given its parents.

These are the main properties of PGM [75, 116]:

- They offer an intuitive graphical representation and, unlike other data mining techniques, PGM provide the possibility to visualise variable dependencies intuitively, helping humans understand the relationships and dependencies between variables.

- Conditional Dependence: Given the conditional independence relationships encoded by a graph, the conditional probabilities associated with nodes given their parents/descendants are used to model the joint probability distributions of the variables that they represent.

- Modularity: The joint probability distribution of the variables of a PGM can be decomposed into more manageable sets, associated with a local structure in the graph. This offers key advantages in terms of the memory and computational power required to analyse the model.

- Inference: PGMs provide algorithms for efficient probabilistic inference, allowing the computation of marginal probabilities and conditional probabilities.

- Learning: PGMs also provide algorithms for learning the graph structure and conditional probability distributions from data.

4.2 Fundamentals of Bayesian networks

4.2.1 Directed Acyclic Graphs

Before defining a BN, it is important to note that it is PGM with a DAG, a directed acyclic graph, with a node for each of the variables of the problem. The network structure that defines the BN is a directed acyclic graph $G = (V, A)$, where each node $v_i \in V$ corresponds to a random variable X_i. Each element of the set of arcs A that join the nodes across the network is identified by the pair of nodes it connects: $a_{ij} = (v_i, v_j)$, for every $a_{ij} \in A$.

Being a DAG means that a Bayesian network:

- contains only directed arcs;

- does not contain any cycle, i.e. a sequence of arcs that starts and ends in the same node.

The fact of being directed clearly defines the sense of the probabilistic dependencies among the variables represented by the graph, whereas the acyclic nature enforces the hierarchical/dependency nature of the structure [75]. In the example DAG of Figure 4.2, it can be noted the following topological order of the nodes:

- A is defined prior to B and C;

- both B and C a prior to D;

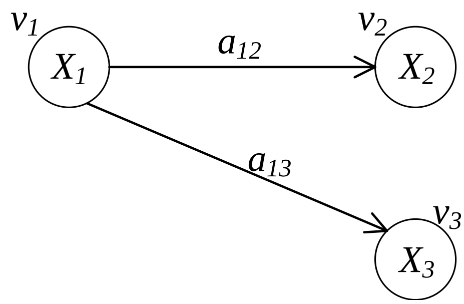


Figure 4.1: Basic representation of the elements of a Bayesian network.

- D is prior to E;
- this structure ensures that there are no cycles and dependencies are established in a specific order.

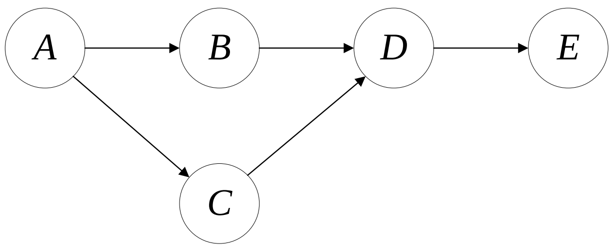


Figure 4.2: Basic example of a DAG.

4.2.2 Definition of Bayesian network

Suppose a finite set of variables [100] $\mathbf{X} = \{X_1, \ldots, X_n\}$, where each variable X_i takes its values on a set U_i. A generic value of the variable X_i is denoted as x_i. A BN is a model of independence relationships among these variables that defines a joint probability distribution for their values [79, 116].

BN for variables $\mathbf{X}$ is a directed acyclic graph G with a node for each variable $X_i \in \mathbf{X}$. A conditional probability $P(X_i|\Pi_i)$ is defined for each variable X_i given its parents Π_i in the network G. The graph represents (in)dependence relationships among the variables according to the d-separation principle [116] and, given these dependencies, the joint probability distribution for all the variables $P(\mathbf{X})$ decomposes as a product of the conditional distributions, as shown by Equation 4.1.

$$P(\mathbf{X}) = \prod_{i=1}^{n} P(X_i|\Pi_i) \tag{4.1}$$

4.2.3 Markov property in Bayesian networks

An important property of Bayesian networks is the local Markov property, which states that each node variable X_i is conditionally independent of its non-descendants (i.e. the nodes X_j for which there is no path from X_i to X_j) given its parents. Therefore, this property highlights the fact that children directly depend on their parents in a BN. However, observations propagate in all directions (direct and reverse arcs) changing the conditional probabilities of the nodes in the graph. A simple example of this is the application of the Bayes theorem to compute conditional probabilities of a node, given its child (see Equation 4.2),

$$P(X_1 \mid X_2) = \frac{P(X_2 \mid X_1)\, P(X_1)}{P(X_2)} \tag{4.2}$$

4.2.4 Inference in Bayesian networks

Inference in a PGM is the process by which conclusions are drawn from available data and knowledge, whether deterministic or probabilistic. Seen from a more practical point of view, inference techniques help to solve an existing Bayesian network, and thus obtain the desired result as quickly as possible. To achieve this, the probabilities of certain variables are updated, either based on observed evidence or using methods to calculate it, with exact or approximate computations. There are two basic types of inference. In both of them, it is assumed that we have a set of observations $\mathbf{O}$: $Y = y$ for some of the variables $Y \in \mathbf{X}$:

- **Conditional posterior probabilities:** In this case, we want to compute $P(X \mid \mathbf{O})$ for any variable X [116].
- **Configuration of Maximum Probability (MAP):** In this case, we have a subset of variables $\mathbf{Z} \subseteq \mathbf{X}$ and we have to compute the configuration of these variables with maximum posterior probability: $\arg\max_{\mathbf{z}} P(\mathbf{Z} = \mathbf{z} \mid \mathbf{O})$ [54, 115].

In this dissertation, we will concentrate on the computation of conditional posterior probabilities. For exact inference, these are the most relevant methods:

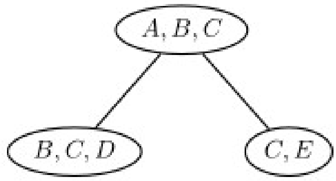


Figure 4.3: Example of clique tree.

- Belief Propagation (or Message Passing): An algorithm used in tree-structured networks where messages (probabilities) are passed between nodes to update beliefs [116].
- Variable Elimination: This method involves systematically summing out (or eliminating) variables from the joint distribution to compute marginal probabilities [138].
- Junction Tree Algorithm: Converts the Bayesian network into a tree structure (junction tree) and performs belief propagation on this tree. It is suitable for more complex networks [83]. Figures 4.3 and 4.4 show a Bayesian network and a possible equivalent clique tree corresponding to an example from [75].

In the case of approximate inference, these are examples of relevant methods:

- Monte Carlo methods: These methods use random sampling to approximate the posterior distributions. They are useful when exact inference is computationally infeasible. The two main procedures are based on importance sampling [131] and Markov chain Monte Carlo [141]. It is also possible to compute the intervals of posterior probability distributions [15].
- Numerical approximate methods and sparse data structures: These methods are based on the use of compact representations of conditional probability tables that need less parameters as probability trees [22], also being able to reduce the size of a representation by using approximate values.

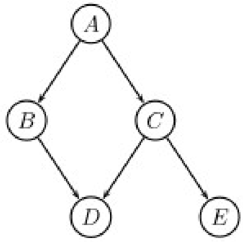


Figure 4.4: Example of Bayesian network to be analyzed with clique tree approach.

4.2.5 Learning Bayesian networks

The concept of learning a network refers to applying techniques of probability theory and graphical representation of PGMs to induce a Bayesian network from a dataset of observations. The idea is to construct BNs including their probabilistic relationships from data [109]. It has two parts: learning the structure and estimating the parameters.

The parameters are usually estimated by the maximum likelihood according to which the estimated value $\hat{\theta}_{ijk}$ of $P(X_i = x_k|\Pi_i = \pi_j)$ is given by

$$\hat{\theta}_{ijk} = \frac{N_{ijk}}{N_{ij}},$$

where π_j is a configuration (combination) of values of parents variables Π_i, and N_{ij} is the absolute frequencies of $\Pi_i = \pi_j$ in the dataset, while N_{ijk} are the absolute frequencies of $\Pi_i = \pi_j$ and $X_i = x_k$, simultaneously.

Bayesian procedures are more robust in practice [109] and usually a global sample size S is considered. The estimation of $P(X_i = x_k|\Pi_i = \pi_j)$ is given by:

$$\theta^*_{ijk} = \frac{N_{ijk} + S/(r_i.k_i)}{N_{ij} + S/r_i},$$

where k_i is the number of possible values of variable X_i and r_i is the number of possible configurations of parent variables Π_i.

The most challenging part when learning a BN is the qualitative part or learning the graph structure. One of the key concepts necessary to understand how this learning is performed is related to metrics. Metrics are score-type functions, that is, they measure the adequacy of probabilistic models [15, 74]. As an example, we will introduce the Bayesian Information Criterion (BIC) metric, although other like Akaike, K2 and BDEu will be referred in Chapter

7. The metrics favour models that describe well the observed data and have an small number of parameters.

BIC metric is defined as a simplification of the Laplace approximation to a function of $P(G|D)$, which is the joint probability function of the network G on the database D. An approximation is made using $\hat{\theta}$, the Maximum Likelihood Estimator (MLE) estimator of the model parameters, and is defined as follows:

$$\mathrm{BIC}(G|D) = \log(P(D|\hat{\theta}, G)) - \frac{\log N}{2} \dim G,$$

where $P(D|\hat{\theta}, G)$ is the probability of the data given the graph G with his maximum likelihood parameters, N is the number of cases in the dataset D, and $\dim(G)$ is the number of network parameters.

Learning the structure is done by searching the DAG optimising this score.

There are also learning algorithms that are not based on optimising a metric, but in doing a series of conditional independence statistical tests, as the Peter and Clark (PC) algorithm [144].

There are methods for learning BNs directly from structured data such as relational databases [58].

4.3 Fundamentals of dynamic Bayesian networks

4.3.1 Definition of dynamic Bayesian network

A DBN [106] is a particular case of BN with repeated measures of a basic set of variables $\mathbf{X}$ in different time instants (or time slices) $t = 1, \ldots, m$. It is assumed that the variables $\mathbf{X}$ on instant t are denoted as $\mathbf{X}_t$ and the value of X_i as X_{it} [100, 101].

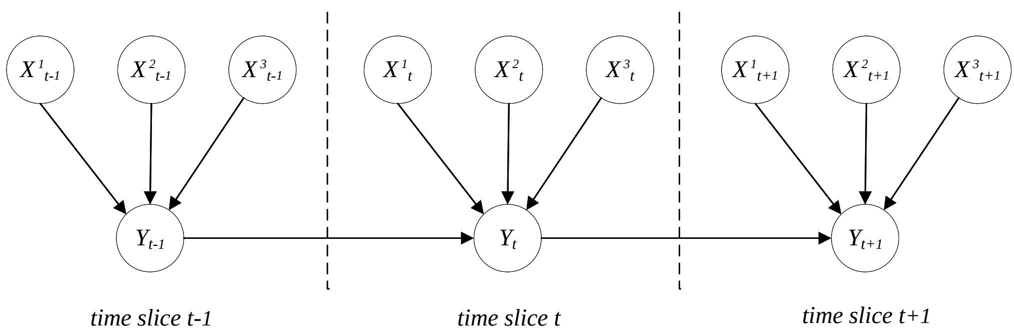


Figure 4.5: Example of dynamic Bayesian network.

4.3.2 Markovian and stationary assumptions in dynamic Bayesian networks

Two common assumptions are done for DBNs in order to reduce the computational complexity of the calculations associated with the model [106]:

- Markovian process assumption: Probabilities at a given time step depend only on the previous time step, i.e. the set of parents for each variable X_{it} is included in $\mathbf{X}_{t-1}$.

$$P(\mathbf{X_t} \mid \mathbf{X_{t-1}}, \ldots, \mathbf{X_1}) = P(\mathbf{X_t} \mid \mathbf{X_{t-1}}) \tag{4.3}$$

  A consequence is that the set of parents of variable Xit is always included in $\mathbf{X_t} \cup \mathbf{X_{t-1}}$.

- Stationary assumption: The transition probability between time steps is time independent, i.e. the conditional probability $P(X_{it}|\Pi_{it})$ is the same for any value of t. The process is therefore time-invariant:

$$P(X_{t+1} \mid X_t) = P(X_{t+k} \mid X_{t+k-1}) \quad \text{for all } t \text{ and } k \tag{4.4}$$

In some cases, dynamic networks also include variables X_{it} that depend on the variables $\mathbf{X}_t$ in the same time t [51].

In a dynamic Bayesian network there can be two types of arcs:

- Arcs connecting a node from $\mathbf{X}_{t-1}$ to a node of $\mathbf{X}_t$. This set of arcs conforms the inter-slice connectivity.
- Arcs connecting two nodes from $\mathbf{X}_t$: the nodes conforming to the intra-slice connectivity.

4.3.3 Inference and learning in dynamic Bayesian networks

Inference algorithms for hybrid Bayesian networks [132] are especially relevant for this research, as will be explained in later chapters. Inference in DBN can be done with the same algorithms as in general Bayesian networks. However, there are special problems for which we can apply special-purpose algorithms which take into account the special temporal characteristics of the variables. Temporal dependencies have such a nature that benefit from applying forwards-backward algorithms [106]. This will be the case for our problem of the online computations of a SA estimation, for which a fast algorithm will be developed in Chapter 8.

Concerning the approaches for learning the structure of a DBN from data, it is important to note that the intra-slice connectivity must be a DAG, and the inter-slice connectivity is equivalent to the variable selection problem [106]. One key aspect of DBN learning relies on assuming that intra-slice connections are fixed, reducing structure learning for DBNs to feature selection. Other approaches to learning in DBN emphasise the importance of model efficiency over data fitting [13].

In some cases, there are missing values, then Expectation Maximization (EM) method, based on iterative maximum likelihood or Maximum a Posteriori (MAP) estimates, is the most common method for learning DBNs as it provides an efficient way to find model parameters.

4.4 Bayesian classification for supervised and unsupervised learning

4.4.1 Definitions and relationships

Another important topic to cover in this brief introduction to Bayesian networks is classification. Classification usually is associated to supervised learning, i.e. we have an special class variable C and the objective is to build a model in which it is possible to compute the conditional probability of C given that the rest of variables (attributes) is observed: $P(C = c|Attributes)$. When the variable is continuous, the problem is called regression.

In the case of unsupervised classification, there is no observed class variable in the dataset and the objective is to find a partition of the data in homogeneous sets. Unsupervised learning can be thought of as finding patterns in data above and beyond what would be considered pure unstructured noise [59].

4.4.2 Overview of classification methods

As will be explained in later chapters, we have performed different types of classification, so this section aims to briefly explain the findings and some thoughts to better understand the reasons for the implementations carried out in this research.

For supervised learning, the availability of labels or well-indexed datasets has made available a bigger amount of algorithms that we have been able to test with our data: Linear regression and logistic regression.

In the case of unsupervised learning, the goal is to find hidden patterns without the aid of labels, which in the case of large datasets can be computationally costly and time-consuming. This limitation causes this approach to be reserved for specific applications where the computational effort is worth it. In our research, we performed an experiment [102], explained in more detail in Chapter 7.

In the following, we summarise the most relevant supervised and unsupervised classification methods:

- Supervised: Linear regression, logistic regression, decision trees, support vector machines, and Bayesian classifiers.
- Unsupervised: Clustering.

4.5 Hybrid Dynamic Bayesian Networks

One of the main problems associated with the modelling of flight data by means of PGMs is the fact that we measure continuous and discrete variables in each time instant. This poses an important problem, as we are in the case of a hybrid graphical model. In general, there are several possible approaches to work with continuous and discrete variables at the same time:

1. Discretise all continuous variables and work with discrete variables [14, 110].
2. Work with models able to consider continuous and discrete variables at the same time as mixtures of truncated exponentials [96, 127] or mixtures of polynomials [139].
3. Transform all the discrete parent variables of a variable Y into a continuous variable and consider that all the parents are always continuous. If a variable X takes values in $\{x_1, x_2, \ldots, x_k\}$, this can be done by transforming this variable into a variable X' such that $X' = j$ when $X = x_j$. Another more suitable approach can be to define a set of dummy $0-1$ variables: X_j $(j = 1, \ldots, k-1)$ with $X_j = 1$ if $X = x_j$ and $X_j = 0$, otherwise. If the original variable is bi-valued, both approaches are equivalent, but in other case, there can be differences, the second approach being more

general in most of the cases. Assume, for example, that we are computing the conditional probability of $P(Y|X)$ and that X is a variable taking 3 values: $\{x_1, x_2, x_3\}$. In all the models we are considering for continuous variables, the probability of Y will depend on X through a linear combination of the values of the parents. So, in the case of considering X' we will have a function like $f(X) = aX' + b$ with two parameters a, b. So we have that $f(x_2) - f(x_1) = f(x_3) - f(x_2) = a$. However, if two dummy variables X_1 and X_2 are defined, a linear combination of these variables will be $g(X) = a_1X_1 + a_2X_2 + c$, we have 3 parameters and the restriction disappears, now $g(x_2) - g(x_1) = a_2 - a_1$ and $g(x_3) - g(x_2) = -a_2$. In fact, $g(x_i) = a_1 + c, g(x_2) = a_2 + c, g(x_3) = c$ and we can fix an independent effect for each of the 3 values of the variable X.

When estimating the conditional probability $P(Y|\Pi)$ all the discrete variables are transformed into numerical ones by applying a transformation $\Pi' = T(\Pi)$, then the conditional probability $P(Y|\Pi')$ is estimated being $P(Y|\Pi = \pi) = P(Y|\Pi' = T(\pi))$. In our research, we have taken into account the nature of variable Y: If this variable is continuous, the conditional probabilities are estimated using linear regression and if it is discrete multinomial, logistic regression is used [70].

In this dissertation, we have considered approaches 1 (Chapter 7) and 3 (Chapter 8).

4.6 Limitations of variables working with dynamic Bayesian networks

The decision between using discrete and continuous variables has largely conditioned this research from the beginning. In fact, the first article published in 2015 is mainly dedicated to the discretization of variables [100], because at that time we assumed that using real-time DBN to analyse multiple continuous variables would be infeasible. In this section, we briefly explain how this topic has been approached at different stages of the research until reaching the solution used in the 2024 experiment whose results are presented in Chapter 8. The first subsection focusses on the comparison between regression approaches with continuous and discrete variables, while the second subsection focusses on presenting some brief considerations on the probability distributions of random variables for use with DBN.

4.6.1 Continuous vs. discrete variables

The high computational cost associated with DBNs that handle continuous variables or a mix of continuous and discrete variables has been well known since the beginning of DBN-related research [94]. In fact, there are relevant efforts to design BN that handle mixed variables, like the Hybrid Bayesian network (HBN) presented in [80].

In the context of learning Bayesian networks from mixed data containing both continuous and discrete variables, one way to avoid discretization is to directly model the continuous data without discretising it. However, this approach may be limited by the computational cost of using a more general parametric representation, such as certain families of probability densities. Another way to avoid discretization is to make simplifying assumptions, such as assuming all variables are discrete or all variables are continuous and normally distributed, but these assumptions might not accurately represent real-world domains with mixed data.

In this section, we will explain the limitations of (dynamic) Bayesian networks that affect this research more directly:

- The growth of computational complexity occurs as the number of variables in the network grows.
- The problems of handling continuous variables versus the loss of information when continuous variables are discretised.

The handling of these limitations has been one of the main focus of the research, which poses a challenge to perform inference in real-time, as could be intended to calculate SA during the flight. One of the models allowing exact inference algorithms is the conditional Gaussian network [82]. But it is limited in the sense that a continuous variable cannot be the parent of a discrete variable, and this situation makes it inappropriate for our case in which we have continuous and discrete variables measured over time, and a discrete variable may depend on continuous variables measured in the previous instant. Another possibility is to use mixtures of truncated polynomials or truncated exponentials, which allow the application of general propagation algorithms, though the complexity can be high. In this dissertation, we have considered an alternative approach:

- To convert all the variables into numerical ones and to consider general purpose tools for modelling the conditional probabilities: logistic regression for discrete variables and linear regression for continuous variables.

- As this model does not allow the application of general purpose propagation algorithms, we chose to develop special purpose ones, allowing a fast and exact computation, but that are specific for a particular case in which we have a given set of observed variables and an interest variable (the SA variable).

4.7 Other Graphical Models

There are more models that can be considered as PGMs. This is the case of undirected graphs [116], chain graphs (including directed and undirected links) [52], influence diagrams (including decision and utility nodes) [75], or sum-product networks [119]. Of them, influence diagrams could be useful in helping pilots make correct decisions in concrete situations. But in this work, we have not considered its use, leaving it for future work.

Decision trees [122] are also a common tool in decision-making environments, including some related to aviation operations. Although the way in which they are built and employed varies greatly. They can be considered as a variant of the general class of PGMs, but they are more useful in asymmetric decision problems.

Decision trees are PGM strictly speaking, but since they can be used for modelling probabilistic relationships based on data, it is important to note that there is a correspondence between them and influence diagrams [75]. Influence diagrams are considered a generalisation of Bayesian networks because they extend their basic structure to include decision making (including decision variables and utilities, apart from random variables). This relationship is exemplified in Figure 4.6.

This figure is relevant to understand that influence diagrams are considered a generalisation of Bayesian networks because they extend their basic structure to include decision making. Though we do not enter into the details of both models, it can be seen that influence diagrams are a more compact representation of a decision problem, allowing modularity and independence relationships, especially when the problem shows symmetry. In the example, it is considered that the utility does not depend directly on S, whereas this cannot be expressed with the decision tree.

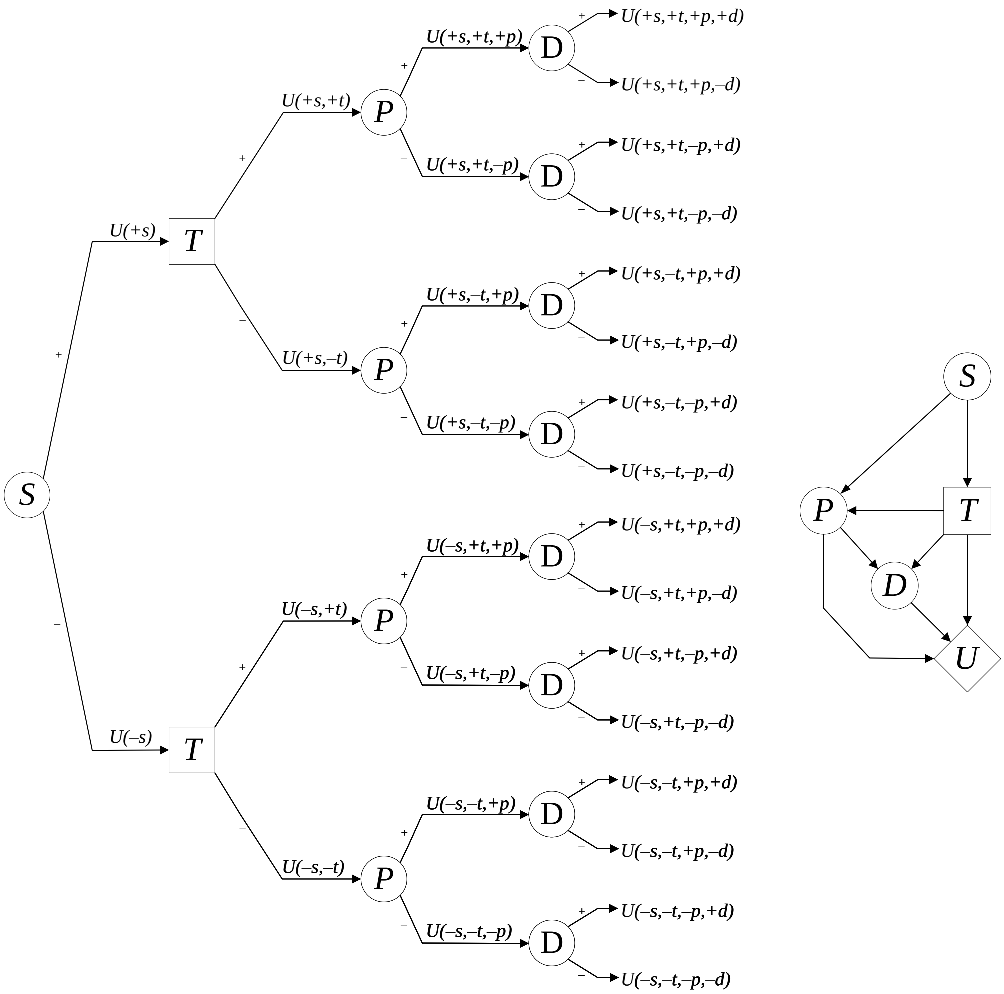


Figure 4.6: Example of decision tree and its associated influence diagram [75].

4.8 Overview of other research that apply BN to SA estimation

Now that the concept of SA has been presented in Chapter 2 and the fundamentals of BN have been summarised in the previous sections of this chapter, before proceeding with the explanation of the SA measurement model in the next chapter, we will briefly include a reference to several research where we have found examples of approaches that use BN or DBN to measure SA.

4.8.1 Multi plan recognition and predictive situation awareness

The Ph.D. thesis published by Robert Suzić in 2006 [148] explores the use of BNs for situation awareness estimation in the context of tactical decision-making. It discusses how agent-based stochastic simulations can be used to fill conditional probability tables for BNs, which can be used for plan recognition and predictive situation awareness. The approach is different from the one used in our thesis, since it does not focus on the individual human factors behind SA, but has a multi-agent approach; therefore, its applicability to aircraft navigation monitoring is limited. It should be noted that when articles about SA were first published in the 1980s, they focused on tactical situations with high workload rather than routine phases of the flight [49]. The use of BNs presented in Suzić's thesis is not time dependent in the same way as our research: DBNs are employed to guess what planning agents were doing in previous periods of time.

4.8.2 Knowledge-based probabilistic modelling for situation analysis using the example of maritime surveillance

The approach presented by Yvonne Fischer in her Ph.D. thesis published in 2016 [47] is similar to ours, since it proposes to use DBNs to measure situation analysis. However, the model differs in the way it considers situations, as they are mainly presented as external semantic interpretations of sensor data. Therefore, although the purpose is similar, the SA modelling approach is different. The fact that Fischer's thesis is focused on maritime navigation instead of aircraft offers room for interesting comparison: the numerical tools used to analyse position information are similar, based on calculations with geographical coordinates, and we can see that k-means clustering is also employed for this purpose. On the other hand, vehicle speeds are very different, deeply affecting the way DBN should be designed in terms of time dependency, sample rate of data, etc.

4.8.3 Dynamic Bayesian network-based situational awareness and course of action decision-making support model

The article published by Kim and Lee in 2024 [77] proposes direct applicability of DBN to the SA estimation. It acknowledges that DBN are suitable to provide an estimation of uncertainty related to decision-making in dynamic environments. It also accepts the use of expert knowledge to overcome data availability or modelling limitations. However, the approach presented by the authors differs from our work because the context is different, based on tactical threat analysis. The parallelism is clear if the focus of the calculation are military pilots, but the nature of the threats proposed by Kim and Lee is very different from the ones found by an aircrew while navigating between two airports.

4.8.4 Situation Assessment in Aviation: Bayesian Network and Fuzzy Logic-based Approaches

The book by Raol et al. [123] deserves a special mention for several reasons: it is a publication from 2024, very recent at the time of finishing writing this thesis. Its content is closely linked to that of our thesis; it actually dedicates an entire chapter to the topic of situational awareness, explaining in detail the Endsley model, and mentioning the importance of information management.

In several chapters of the book, risk management is mentioned, but not from the ORM perspective. Instead, the book relates crew risk management with Crew Resource Management (CRM), which is a related concept but that has historically been linked to aircraft with multiple crew members. Nevertheless, we have found in the book contributions of CRM to single-pilot operation which could be applicable to our SA measurement model.

The main difference of the book with respect to our research is that it focusses on assessment instead of awareness, which is an aspect of the situation that is generally at a different level with respect to individual human factors (the awareness of the pilot). Situation assessment would be particularly applicable when modelling the overall system with multiple actors, such as other aircraft, controllers, flight operations centres, etc.

To address this operational and human factors approach, the types of Bayesian network resources proposed by the book are based on using fuzzy logic to handle the vagueness and imprecise information present in the assessed situations. The simulation environment presented in the book is not particularly focused on flight parameters and is not using a flight simulator in the same way that we propose. Instead, it uses different tools to simulate a combat environment where the situation can be assessed. Therefore, the Bayesian networks presented in the book, to perform fuzzy logic based on classification, are not dynamic.

Part II

CONTRIBUTIONS OF THIS THESIS

5 BUILDING A MODEL FOR THE ESTIMATION OF SA

In Chapter 2 we introduced the Endsley model for the estimation of SA, as well as some of the most relevant SA alternative models and rating techniques, like SAGAT and SART. Since the appearance of the first models to estimate SA, there has been a continuous effort in the field of aviation to develop different tools and rating techniques, as explained in [27].

Based on the available references, the Endsley model is clearly the most influential and offers the possibility to associate different flight factors, and therefore variables collected from our simulations, to different SA levels. That is the main reason why our model, presented in this chapter, follows Endsley's approach.

The first version of our model was published in [101] and we have attempted to update and evolve it during years of research, with three updates of the collected simulated flight datasets for the DBN training, and performing different iterations of discretization, intra-variable calculations, addition of expert knowledge, etc. to obtain a DBN that calculates the SA.

5.1 Primary assumptions of the model

The Endsley model [40] was introduced and analysed in Section 2.1, where we also identified a set of propositions based on scientific discussions found in the literature [42]. From these propositions, we define a set of primary assumptions that we consider to be underlying our model, trying to simplify the approach to measure SA and therefore build a simulation environment that is compatible with the complexity of the measurement.

Assumptions based on Proposition 1 "*The three levels of SA are not linear*":

- Neither the simulation environment nor the expert knowledge assume any numerical relationship between the three SA levels. When expert knowledge is provided, the considerations about SA level are based on practical insights and experienced understanding of the situations that the simulation is replicating, even when they are not explicitly documented in empirical data.

- When SA estimations corresponding to different levels are calculated, they shall always be stored in different variables, without pursuing that they follow any kind of pattern.

Assumptions based on Proposition 2 "*The model cannot be considered as merely a data-driven information processing model*":

- From the beginning of this research it was clear for us that the SA of the pilot is based on multiple factors, both environmental and individual, and although the ability to evaluate the information analysis of the pilot from the collected data has always been considered, expert knowledge seems necessary to provide a robust estimation of SA.

Assumptions based on Proposition 3 "*There is a clear distinction between Product and Process*":

- We aim to recreate the way in which Endsley's model explicitly describes the interdependence of SA as a product and the processes that create it, emphasising a circular relationship where SA influences information-gathering and interpretation.

- The product is the measured SA.

- The processes leading to the measured SA are a set of situation assessments based on measurable variables concerning the pilot actions, the aircraft position, the navigation environment, etc. These processes are limited in scope for the purpose of this research, but the model is intended to be scalable based on the available data and computing capabilities.

Assumptions based on Proposition 4 "*The model of SA is cyclical and dynamic*":

- The estimated SA shall be a time-dependent variable, as well as most of the measured variables that support the processes associated with the former assumption.

- The cyclical nature of SA is modelled implicitly in our model as a continuous and iterative set of activities to collect data samples that describe external changes in the situation of the aircraft and internal cognitive activities of the pilot.

Assumptions based on Proposition 5 "*The model takes into account the meaning of different SA levels*":

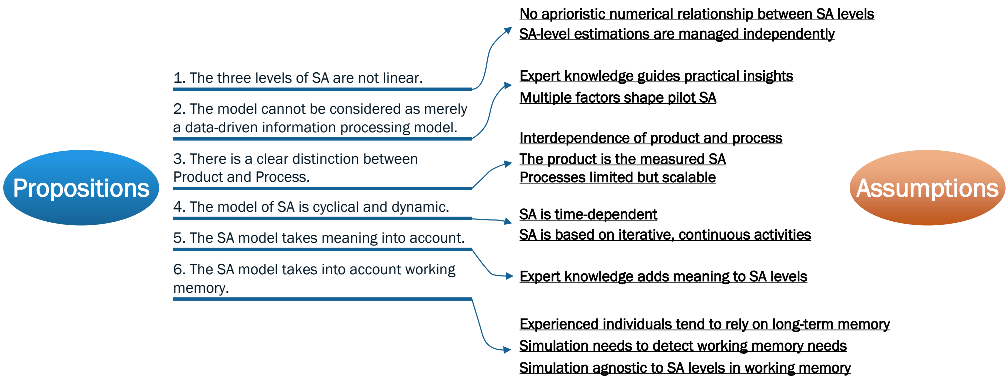


Figure 5.1: Overview of modelling primary propositions and assumptions.

- Following the modelling principles expressed by Endsley [42], we propose to increase the meaning of the different levels of SA, avoiding to regard them as simple queries of the situation. This is obtained with the addition of expert knowledge, which in our case has been integrated in the form of variables added to the dataset.

Assumptions based on Proposition 6 "*The SA model requires a dynamic integration of working memory and long-term memory*":

- Our model assumes that experienced individuals rely on schemas and mental models included in long-term memory to process and predict information, reducing reliance on working memory.
- The simulation environment will include specific elements to detect when the pilot needs to load information in working memory.
- The simulation environment shall be designed to be agnostic in terms of assigning better SA levels according to the use of working memory.

Figure 5.1 shows a schematic overview of the propositions and assumptions on which our model is based, that have been presented in this section.

5.2 Context-specific assumptions of the model

The assumptions in the previous section are relatively generic and cannot be used to identify a specific set of variables that serve as an indication for designing the simulation environment or for designing other essential aspects of the model, such as the processing tools for adapting simulated data to the algorithms or the mechanism for incorporating expert knowledge. For this reason, we conducted a survey that helped us obtain feedback from highly experienced professionals about the kind of variables that should be used to model information management and, therefore, should be collected in our simulation.

5.2.1 An ORM based survey to prioritize error avoidance

The principles of ORM were explained in Section 2.2. Since it is a standardised approach to understand and mitigate risks and factors that affect safety and situation awareness, we decided to conduct a survey to extract specific information about IFR flights, because this is the type of operation that the simulator developed in this thesis is aimed at reproducing.

During the preparation of the survey, we investigated examples of analogous activities using surveys aimed at detecting pilot errors in these types of flight operations. We understood that many approaches are based on a direct assessment of the pilot's cognitive capabilities. Examples like Zotov's 1997 thesis and subsequent works [154], as well as the Cognitive Failures Questionnaire (CFQ) [19] and its evolved versions [62, 152] provide methodical approaches to assess how human failures contribute to accidents. Although most of these previous investigations were based on self-report tools, we also found that they are evolving to also employ specific cognitive measurement devices; in fact, a related experiment had taken place within the same facility, involving researchers from the University of Granada [28].

5.2.1.1 *Design and validity of the survey*

It should be noted that when presenting the survey to the subjects, any reference to SA was deliberately omitted in order to avoid contaminating the results with assumptions about this term that are foreign to Endsley's model, and which pilots are usually unaware of. The survey was therefore orientated from the point of view of ORM risk management, a term that is tangibly related to SA and which allowed the questions to be given a more rigorous context.

The survey was carried out with the support of four active pilots who worked as flight instructors and were familiar with the principles of ORM. The survey did not mention SA directly to avoid an excessive bias of the subjects to consider that the parameter that is internal to the pilot should be a product of the survey, while it is in reality a product of risk management methodologies and associated tasks, either on the ground or in flight.

It is already explained in Section 2.2 that SA can be regarded as a product of ORM, therefore the purpose of the survey was to extract as much information as possible from these pilots on how this is performed. The intention was to apply the lessons learnt in the design of the simulator updates, to perform future experiments with better tools to measure SA. Participants were asked to complete a questionnaire that provided feedback on elements related to ORM and SA.

The validity of this survey is limited, as it has a very limited number of samples because the number of subjects available was very reduced and there were no resources to extend the survey to other subjects. However, the results are relevant for the purposes of the thesis because the questions included very specific and directed topics to detect causes of error during the flight, seen from the perspective of experienced instructors. We also included some control questions to evaluate the reliability and attention of the participants, for instance, asking about weather conditions in context where weather is not especially relevant.

In any case, the interest of the survey is more qualitative than quantitative, and the results showed a high degree of consensus, as will be explained in the next subsection, which was interpreted from our side as a reinforcement of our approach, as the answers provided an important overview of the criteria that should be employed to prioritise the simulation parameters to be monitored by the SA estimation, from a risk management perspective. A very brief extract of the answers is presented below, and more detail about the questions asked is provided in Appendix C:

- Always prioritise relative position to points in front of the route deviations.
- Pilots tend to consider that making errors in the handling of instruments is more risky than missing information.
- The practice of challenging situations and flight under adverse conditions should be performed in the flight simulator.

5.2.1.2 *Findings to be applied to the SA modelling*

The survey has interesting outcomes in the sense that it shows that pilots tend to prioritise the detection of their own operating errors, instead of deviations that could be due to other factors. This agrees with the risks derived from automation bias: When the pilot is focused on preventing his/her own errors, automation is regarded as a guarantee for a flawless operation, masking the capacity to detect deviation or malfunctions that the pilot could perceive under full responsibility. In the survey results, we have detected a prevalence of respondents to prioritise this kind of cues to reduce risks.

We need to establish which variables need more focus to analyse the types of error related to automation and issues with pilot prioritisation in automated tasks. If an error related to a high priority factor occurs, we have a higher probability of establishing that it was due to a lack of SA. The survey responses provide information on the subjects' priorities, and this information is valuable because it is used to build the model on automation bias. There are multiple types of bias that affect human factors in aviation and therefore have a direct impact on SA, but the most relevant for our study is automation bias, which was analysed in depth for the first time by [104], although other authors highlight aspects more related to the type of operations that we simulate and our approach to automation, Meyer's thesis being a very valuable source of information in this regard [92]. In particular, our efforts to build the model have taken into account two concepts clearly identified:

- Decision bias, which refers to a tendency to make decisions based on cognitive factors other than the merits of the decision.
- Confirmation bias, which is the tendency to search for, interpret, favour, and recall information in a way that confirms one's preexisting beliefs or hypotheses.

As we explain below, variable selection intends to collect data that reflect that the pilot is relying too much on automation and pays more attention to past mistakes, rather than noticing deviations that are still unnoticed. This is how we model this part of the pilot's behaviour.

5.2.2 SA model key factors

This is a very important part of this dissertation. In the years that we have conducted this research we have not found a clear model example of key factors for modelling SA as a general approach. Of course, we have checked SART and SAGAT examples because they remain widely used and we have clear ideas about the main aspects that influence any SA model, which are orientated by the SA levels defined by Endsley:

- Good perception of the environment, driven by a well-designed cockpit, adequate training to instruct the pilot on how to make a correct use of the aircraft systems, and a good preparation of the mission that allows the pilot to be able to focus the attention on the right information sources.

- Adequate comprehension of the situation, which is more intimately related to the pilot's internal factors that enable the mental processes that allow understanding what is happening in the cockpit. At this point, memory starts taking a relevant place in the conformance of an adequate SA:
  - Short-term or working memory is related to the cognitive state of the pilot, which allows us to take into account relevant information that was perceived seconds or minutes before it was needed.
  - Long-term memory is related to the experience or training outcomes that provide the pilot with background elements to manage an adverse situation.
- A correct projection of the near future is somehow less tangible because it is a human being's capacity to anticipate what is going to happen. This is not magic or an intuition, and from a scientific point of view this projection needs to be related both with external factors to the pilot (training, workload, etc.) and internal factors, both positive (accountability, discipline, adaptability, diligence, focus, etc.) and negative (inflexibility, obstinacy, etc.), which are present in pilots, as in other human beings.

The three levels, as previously explained in this chapter as one of the primary assumptions, do not have a linear relationship. During our long investigation, we have come to the conclusion that they also do not show fixed dependency patterns, but they rely on multiple factors that cannot be listed exhaustively, but are well known and mentioned in the literature. Figure 5.2 provides a visual representation of the framework and the interacting factors involved in the SA of the pilot, showing that there are grey areas in the interactions between the different levels.

Situation awareness and its three levels occupy a central position within the framework, while the contributing factors are not confined to fixed locations on the way they interact with this central construct. Overarching this structure is information management, or more specifically, the information checks performed by the pilot, which reflects and influences the interactions between these elements. Therefore, according to our approach, information management has a predominant role in the SA of a pilot and therefore needs to be especially considered.

Consequently, the distinctive aspect of our model is based on the following proposition:

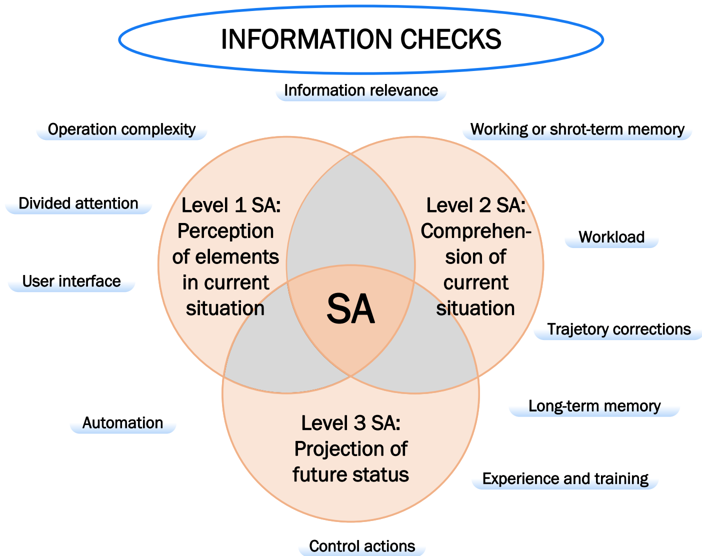


Figure 5.2: Predominant role of information management in the SA model.

Modelling assumption 1 *The three levels of Situation Awareness (perception, comprehension, and projection) are interconnected with the manner in which a pilot accesses and uses the information available in the cockpit of an aircraft.*

5.3 Identification of variables

After presenting the assumptions that have supported building a model for the SA estimation, this section goes a step further into the identification of variables. It should be noted that during our thesis we have learnt from experience, and in the first experiments we selected, in some cases generated, variables without having a fully consistent model. Due to the complexity of the topic, it was not possible to create an accurate model from the beginning, so the task of building the model and identifying the associated variables has been iterative along the research. After this clarification, we will now present a set of variable categories that we consider to be required for the SA measurement when following our approach based on information management monitoring.

Figure 5.3 is included to provide an overview of the variable types that we have identified to support our model. The main grouping has been done based on three categories that will not necessarily be reflected in the datasets

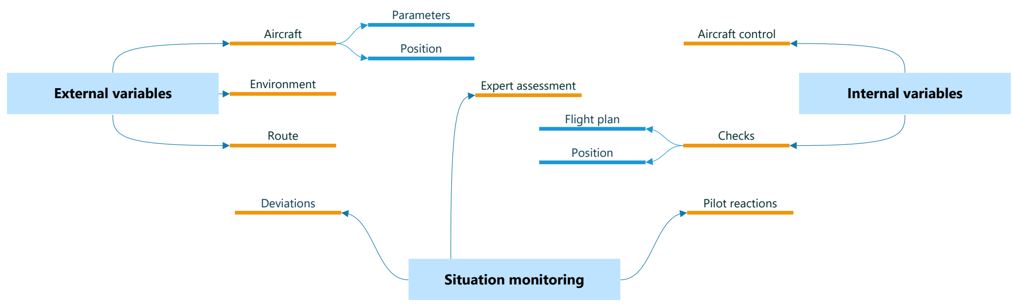


Figure 5.3: Basic variable groups according to our proposed model.

of the experiments that will be presented in the next chapter, but they have been included here for clarity:

- Internal variables: They refer to the observed parameters of the subject of the experiment, that is, the pilot, so the objective is to characterise the control actions on the aircraft, the management of information, and, as far as possible, the reactions of the pilot to the situations that occur during the simulation.

- External variables: These variables are not obtained by focussing on the pilot, but by collecting data from his/her environment, mainly the relevant available aircraft parameters, as well as information on the route the aircraft is flying and the route it is expected to fly. Environmental parameters may also be included in this group, such as weather, interactions with the ATC, etc., always depending on the characteristics of the experiment to be carried out.

- Situation monitoring: These are the most specific variables depending on the experiment or the SA parameters to be measured. In this group, we also include the expert knowledge provided after the simulations, variables included to provide an interpretation of the situation. More information will be provided in Section 6.4.

In the next Chapter 6 we will offer more details about these categories and the actual variables generated in the context of our specific experiments.

The research has been conducted using simulations, and one advantage of having implemented the simulation environment is that it has allowed us to collect variables with considerable flexibility. When designing the experiments and modelling the datasets, we have intended that a potential applicability to real flights could be feasible, so we assume that not all types of data can be accessed. In fact, it is unrealistic to think that flight data can be extracted from aircraft systems in real time during the flight if these systems have not been designed for this purpose. For this reason, the figure of the EFB becomes very relevant for this thesis, since we see in this type of device a possibility of access the data by our tool during a real flight and, of course, during a simulation.

5.4 Considerations about the memory model

Throughout our research, the pilot's memory model has been one of the most challenging aspects when designing the simulator in a way that provides meaningful variables. The way memory is modelled is crucial for relating the levels of perception and comprehension and it is very sensitive to the individual characteristics. This section provides some reflections showing how we consider that memory should be modelled to enable reflecting its impact on SA in the dataset.

5.4.1 The roles of short-term and long-term memory in SA estimation

Numerous studies have identified concepts such as working memory, attention, inhibition, and expertise as significant factors in the determination of offline and online SA measures [21]. It needs to be clarified that working memory is closely related to short-term memory but not identical. Short-term memory refers to the temporary storage of information for a brief period, typically around 15-30 seconds, while working memory, for the purposes of our research, involves not just the storage but also the manipulation of information by the pilot, as a dynamic process that involves organising and using information in real-time cognitive tasks. In order to simplify the modelling, which involves the design of the user interface, definition of variables, processing algorithms, interpretation of results, etc., we will treat them as equivalent, referring primarily to short-term memory.

On the other hand, long-term memory, for the purposes of modelling within this research, is related to the pilot's experience and skills developed by training, professional knowledge, and individual skills. It is challenging to model these attributes, and we have not designed any specific methodology to measure these behaviours. We believe that focussing on the measurement of short-term memory parameters is more feasible and allows for clearer results. Therefore, the measurement of long-term memory is carried out indirectly, basically implicit within the contribution of expert knowledge.

5.4.2 References for the working memory modelling

For the first experiments, the memory model for the simulator design was extracted directly from Endsley's model [36, 39]. Endsley identified capacity constraints related to working memory because it can hold and manipulate only a limited amount of information at a time. Apart from that, information in working memory degrades unless it is already encoded into long-term memory, which usually can be associated with experience and training, apart from individual skills.

More recent studies with objectives similar to our study, also in the field of human factors in aviation, have addressed the memory model. In the research conducted by Cak [21] and by Causse [23], working memory performance was studied with the focus set on measuring tasks that target the visuospatial component of airline pilots that fly a simulated mission with a high level of demand. In both cases, they used special equipment to record Functional Near-Infrared Spectroscopy, as a way to monitor prefrontal brain activity of the subjects, providing insight into the neural mechanisms involved during piloting and neuropsychological tasks. The results indicate that offline SA measures are better correlated with working memory and expertise, while online SA was better predicted by expertise and divided attention [21]. This result confirms our observations in the sense that during online SA measurements, subjects that perform poorly when relying on tasks related to working memory tend to have a higher probability of lower SA.

In contrast, after analysing the results of Volz et al. [151] we confirmed our assumptions in the sense that calculation is a difficult skill that relies on working memory and requires the pilot to synthesise various variables and then properly use them to receive an accurate output. From this perspective, one way to monitor working memory is through tasks that require participants to temporarily store and manipulate information. With this approach, we avoid using neuroimaging techniques, which could be feasible for simulated flights, but we find difficult to implement in a real cockpit, with current technologies, especially for pilots flying without helmet.

5.4.3 Implementation in our simulator and possible validity for real flights

For analysing the pilot's memory management, the application interface needs to be designed to allow monitoring when each query is made, in order to collect data indicating how frequently the pilot has used the information, and thus be able to interpret whether the information necessary to carry out the mission was in the short- or long-term memory. This simplification has bias, but we consider that it is not excessive in terms of making an effective measurement of SA.

We do not envisage to use eye-tracking devices to monitor the information checks. Therefore, the HMI implementation needs to allow monitoring the frequency of the checks, as we will explain in the next chapter. During the different experiments, we have considered several variables to synthesise situation awareness, which limits the possibilities.

During the various experiments of our research, we have refined the selection of variables that allow us to recognise whether the flight is being carried out correctly, as well as to collect the pilot's situational awareness, in view of the frequency and time accuracy of the checks. We consider that depending on the pilot's experience and the workload at each moment of the flight, a series of preliminary conclusions can be drawn about the nature of the SA. Table 5.1 summarises our approach to interpret the meaning of performing frequent queries on certain aspects of the flight that we can monitor. The qualitative ratings shown in this table are those that have been taken into account when providing expert knowledge after the flight.

	High-experienced pilot		**Limited-experienced pilot**	
	Affordable workload	**Excessive workload**	**Affordable workload**	**Excessive workload**
Flight plan	Routine checks	Challenges due to overload	Self assurance	Struggles with overload
Track deviation	Effective corrections	Delayed adjustments	Slow reactions	Risk of errors
Relative position to next waypoint	Smooth navigation	Reduced accuracy	Confirm position location	Risk of confusion
Moving map: position only	Quick situation assessment	Recovery of awareness	Understanding the situation	Potential disorientation
Moving map: accumulated track	Strategic use	Issues with data integration	Struggles with assessment	Overwhelmed
Instrumental procedure chart	Proficient interpretation	Avoid losing focus	Basic interpretation	Risk of misinterpretation
Airway chart	Efficient use for planning	Struggles with details	Needs basic assessment	High likelihood of errors

Table 5.1: Suggested interpretations of reasons associated to frequency of checks.

5.4.4 Conclusions of the modelling approach

We will now summarise the modelling approach and offer some conclusions for the sake of clarity. Our research has been long and has consisted of several experiments. From the beginning, we tried to follow the Endsley model, but as the years passed, we realised that the interpretation of the model is widely accepted but seems not to be understood by a significant number of researchers. We became aware of this approximately in 2017 after reading two significant articles by Endsley [37, 42].

In this chapter, we have presented a set of assumptions based on the clarifications offered by Endsley. We found them very useful to generate the set of propositions presented in Section 5.1 and summarised in Figure 5.1. To contribute to the generation of the actual variables, we performed a survey with experts not familiar with our research, that is the ORM survey presented in Section 5.2, to transition from this abstract level to a more concrete one.

Our conclusions are as follows.

- Modelling SA is very challenging, and even prestigious authors make mistakes when interpreting the concept, to the point that Endsley published an article to refute some fallacies.
- It is necessary to distinguish between situation assessment and situation awareness, which is more focused on the subject.
- Estimating SA requires a robust model for the subject's memory. We consider that our approach is mature, but offers significant room for improvement.

6 IMPLEMENTATION OF A SIMULATION ENVIRONMENT

This chapter focusses on the implementation of the simulation environment that collects data from the simulated flights. Throughout the research, significant effort has been dedicated to develop this environment in a way that a pilot can fly a simulated mission with a user interface familiar to a real aircraft while we collect SA related data intending to affect as little as possible the pilot's activity, with the purpose of reducing simulation bias. We explain the principles of the design and provide figures with screenshots of the environment. The chapter also contains a description of the application developed to perform post-flight processing, as well as some information about the produced dataset. Appendix D includes some lists and additional information on some datasets used.

6.1 Overview

The first version of the simulation environment was presented at Eurocontrol's SWIM Masterclass 2014. Since then, it has been used for several experiments and has been updated, mainly to adapt the user interface for the collection of different variables. In addition to the main application used to perform the simulated flights, there is an application that generates the main database, as well as different functions that have been implemented over the years in different programming languages. It is worth highlighting the post-processing tools in R, as well as the programming of Bayesian networks, which was initially done in Java in the Elvira environment [25], and later using Python.

6.1.1 Main objectives of the simulation environment

The simulation environment collects sample datasets of flight-related variables, both aircraft parameters and pilot interactions with the application. In a later stage, the collected data are synchronised, and a first stage of expert knowledge is added to assess the accuracy of the navigation.

The main objective is to analyse the correlation between variables, emphasising the influence of information management on crew performance, and

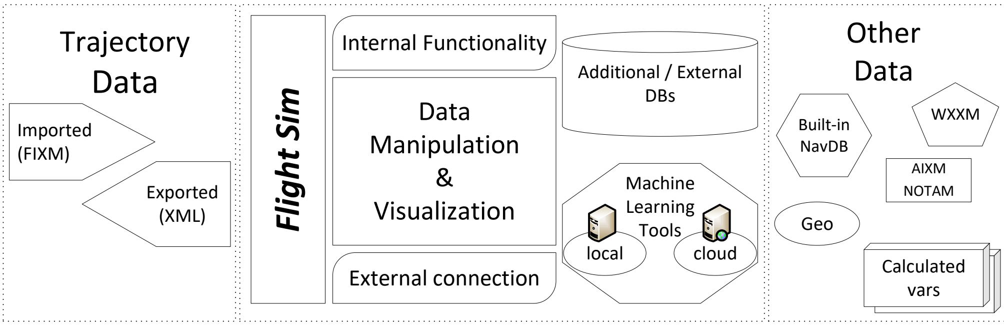


Figure 6.1: Overview of the simulation environment.

train Bayesian networks to learn an estimation of SA based on the accuracy of navigation versus the actions performed by the pilot.

Another objective is to exploit the functionalities of standardised data formats, mainly SWIM, both by importing data and generating them in interoperable formats, although this has been done to a lesser extent.

A derived goal is to test the potential utility of EFB not only to host applications that provide information but to potentially monitor pilot activities and be able to detect performance anomalies to provide warnings. This would be a practical application of this thesis.

Figure 6.1 was originally included in one of our published articles [97] and shows an overview of the functional blocks of the simulation environment, which we summarise below.

- Imported FIXM: We implemented parsing of flight plans in FIXM format to enable the preparation of flights with conventional flight plans and navigation routes. The data necessary to interpret these routes was previously loaded in AIXM format in the built-in Navigation Database (NavDB).

- An external flight simulator software was connected to our application to enable the execution and control of simulated flights.

- AIXM aeronautical information was used to interpret the flight plan and to provide information about the route, waypoint, and Special Use Airspaces information to the pilot during the flight. We also introduced limited capabilities to import weather data in WXXM format, although it was not used for the SA estimation.

- We implemented several database connections to access data from external sources, both in the local machine and on cloud servers. In these cloud servers, we also installed instances of R to run machine learning algorithms.

- The moving map to show the route, aircraft position and other information requested by the pilot used geographical information, especially coastlines, downloaded from the US National Geophysical Data Centre (NGDC) site [107].

- The data collected during every experiment repetition was stored in a local database, which was later used to perform post-flight transformations to the stored variables, to provide formatting to the data according to the needs of data mining software tools. In this stage, we also generated summary variables and combinations of variables.

- Our post-flight application also included functionalities for data filtering and visualisation, both numerical and graphical, of the stored data.

6.1.2 Architecture of the implementation

In the previous subsection we have briefly explained the functional blocks of the environment. We will now provide a description of its architecture.

The environment consists of two main components:

- *FlightApp*: A web application connected to a flight simulator for experiment repetition and data collection.

- *PostFlight*: A post-simulation web application with functionalities to represent, select, transform, and export data, with special attention to interoperability with data mining tools.

They are both coded in JavaScript, PHP: Hypertext Preprocessor (PHP), Hypertext Mark-up Language (HTML) and Cascading Style Sheets (CSS), running over Windows, Apache, MySQL, and PHP (WAMP) server and connected with sockets to a Windows-based flight simulator. The parameters of the environment and the recorded dataset are stored in the databases provided by the server.

Fig. 6.2 shows the architecture of the simulation environment and the technologies selected for the implementation. Most data exchanges are performed with XML files or data streams that are either SWIM compliant or can be adapted to be interoperable with SWIM services and applications with little source code modifications. Technologies are open-source when possible, and the environment could be adapted to run in different operating systems, including mobile devices, if required in the future.

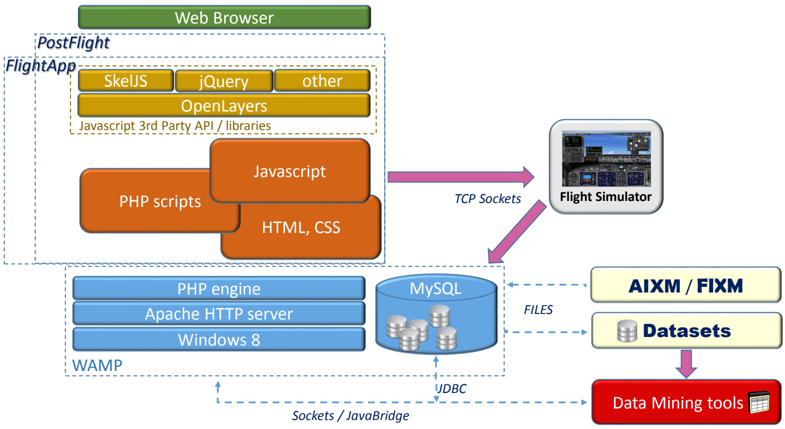


Figure 6.2: Simulation environment architecture and its applied technologies.

6.1.3 The flight simulator and the connection to the environment

The flight simulator is certainly an essential component of the simulation environment, and to carry out the experiments, we have used Microsoft Flight Simulator X (FSX). It should be noted that this software was released by Microsoft in 2006 and is no longer supported by this company. However, as of 2024 the tool is widely used in the amateur flight simulator community and is available in the Steam Platform [93], although the updates are very limited and the risk of obsolescence is high. For this reason, in 2016 we started using Lockheed Martin's Prepar3D [86], which is a properly maintained tool, with a more professional approach, internally based on FSX architecture. In any case, we decided to continue using FSX due to the shorter loading times and because it is still fit for purpose.

The connection between the flight simulator and the application that we developed to establish a user interface with the pilot is a commercial product called FSUIPC [33], and is compatible with older and recent versions of Microsoft Flight Simulator, as well as all existing versions of Prepar3D.

FSUIPC provides access to the memory positions of the flight simulator where we can read and write multiple parameters of the simulation. Therefore, the position of the aircraft, flight controls, engine settings, environmental and weather parameters, etc. can be controlled externally. This is a very powerful approach to conduct simulated flights because the flight simulators mentioned above have a considerable degree of realism. Figure 6.3 shows an example of these parameters.

Offset	Size	Use	FS Read	FS Write
030C	4	Vertical speed, copy of offset 02C8 whilst airborne, not updated whilst the "on ground" flag (0366) is set. Can be used to check hardness of touchdown (but watch out for bounces which may change this).	Ok-Intl	N/A
0310	8	Timer (double float, elapsed seconds including fractions, adjusted each 'tick' – i.e. 1/18th sec). See also 0368	Ok-Intl	No
0318	4	Pressurisation cabin altitude at present (feet, 32-bit integer)	?-SimC	No
031C	4	Pressurisation cabin altitude set goal (feet, 32-bit integer)	?-SimC	No

Figure 6.3: Example of FSUIPC memory position offsets to access flight simulator parameters [53].

FSUIPC supports Lua programming language scripting to interact with the flight simulator. We have included in Appendix E samples of the code that we implemented at both ends, using Transmission Control Protocol (TCP) sockets in a client-server implementation: Lua in the simulator and PHP on our application. We set up a communication channel between the two sides, where one end (FSUIPC as interface to FSX) sends and receives flight simulator parameters and data, and the other end (the interface to our applications written in PHP) sends control commands and receives data from the simulator.

6.1.4 Other software development resources

To develop the simulation environment, we have used several third-party libraries or resources. We summarise the most relevant:

- SkelJS was chosen in 2014 as a web application framework for developing the main user interfaces of the environment. We also used an updated version of the framework in 2017 for the trajectory analysis environment that will be explained in Chapter 7, Section 7.4. SkelJS was deprecated in 2018, so at the time of writing this dissertation it was no longer available, but still some relevant information about its technical characteristics is available on this website [129].

- Fontawesome was selected to provide icons for the user interface to make it more user-friendly and because this resource includes aircraft designs [48].

- OpenLayers was our choice as an open source JavaScript library to create dynamic and interactive maps [112]. This was a relevant choice as a main component of the simulation environment because a lot of the data handled in the environment need to be represented on a map.

- We used a third party Javascript library to calculate the distance and bearing between latitude and longitude points [105].
- Apart from the AIXM data that we used to integrate navigation waypoints, routes, etc. in the application, we used Navigraph as a navigation data service to obtain additional data with worldwide coverage [108].

6.2 An application for performing experiments on real time

To perform flight simulations, we developed an application and named it *FlightApp*. The intention when the HMI of *FlightApp* was developed to emulate an EFB and provide the user with basic autopilot controls of the flight simulator and a customisable interface to access a selection of aeronautical information necessary for the flight.

6.2.1 Overview of the user interface

In order to reduce simulation bias, the number of elements in the user interface of *FlightApp* related to SA measurement are minimised. There are no questionnaires or simulation pauses to perform the assessments. The pilot is expected to load a flight, the aircraft will be placed on the runway and with easy commands the take-off and navigation can be performed. We would like to mention that a significant effort was made to implement a parser of FIXM FPL messages, so that any route could potentially be loaded into the simulator using standardised flight plans. This is shown in Figure 6.4: On the left of the interface there is a drag & drop area where the user can release the XML flight plan and press the "Parse FIXM FPL" button. The summary of the parsing outcome is shown to the user and an initial dataset is created and stored in the local database, containing the route information. The route points are shown on the map, as can be observed in the right area of the figure. In the background, once the flight plan is parsed and the route is defined, we open a socket connection between *FlightApp* and the FSX instance which is running on the same computer, so both applications start exchanging data, as described in Section 6.1.

Once the flight plan has been successfully added, the pilot can start flying the aircraft. Using the characteristics of the FSUIPC application, we implemented a flight initializer that places the aircraft in the right runway and

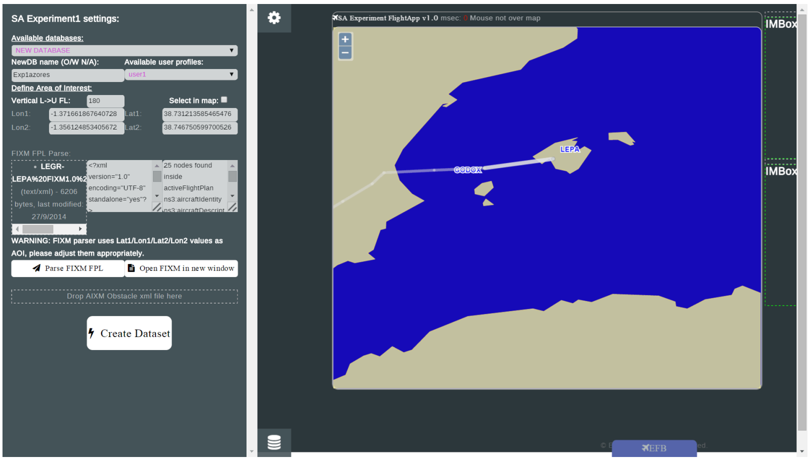


Figure 6.4: FlightApp 1.0 flight plan parser and database management detail.

configured for take-off, so that the pilot does not have to perform pre-flight checks and can concentrate on the flight tasks that we aim to monitor during the experiment. Figure 6.5 shows the flight control section of *FlightApp* on top of a reproduction of a typical flight director of a real Airbus aircraft used by pilots on semi-automatic flights, which is the flight condition that we aim to replicate in the simulation. It can be noted in the figure that similarly to real aircraft, the pilot can control the speed, heading, and altitude of the aircraft by inputting the desired values, and the aircraft will modify the power settings and flight surfaces positions to follow the pilot's commands. Therefore, when we mention pilot control actions throughout this dissertation, we are basically referring to the interactions with this part of the user interface.

To finish this subsection, we provide Figure 6.6 to show how the elements are distributed inside the user interface:

- The left section, with the header "SA Experiment settings", is used before starting the flight to ensure the load of the appropriate dataset and confirm the positioning of the aircraft. The FIXM flight plan does not need to be loaded each time because the dataset generated after loading the message can be reused for different flights.

- The flight controls mentioned previously are in the lower part of the central area of the figure.

- On top of the flight controls there is a map which can be used to visualise the flight route and / or the flown track, as well as the aircraft. This map is empty by default.

Figure 6.5: Flight Control Unit comparison: FlightApp 2.0 implementation (top) vs. Airbus type [45] (bottom).

The right side of the interface is dedicated to the interaction with information sources:

- Flight Log: This is an essential information source for most pilots, who check it frequently to ensure that they are following the planned route.
- Buttons to visualise information on the map: These buttons show information in the map that is automatically hidden after a few seconds. This is a feature of our simulator that allows us to measure when the pilot checks the information on the map.
- Information about the next leg: This box was included in the PBN experiment to help the pilot calculate the turning point.
- Buttons to check situation with respect to any point of the procedure: We added a button for each waypoint of the experiment route to measure if the pilot needs to check the relative position of the aircraft to points, other than the next waypoint.
- Radio Magnetic Indicator (RMI): In the second version of the application we decided to incorporate this aircraft navigation instrument that combines a magnetic compass with directional information from navigation aids, to encourage the pilot to use different information sources.

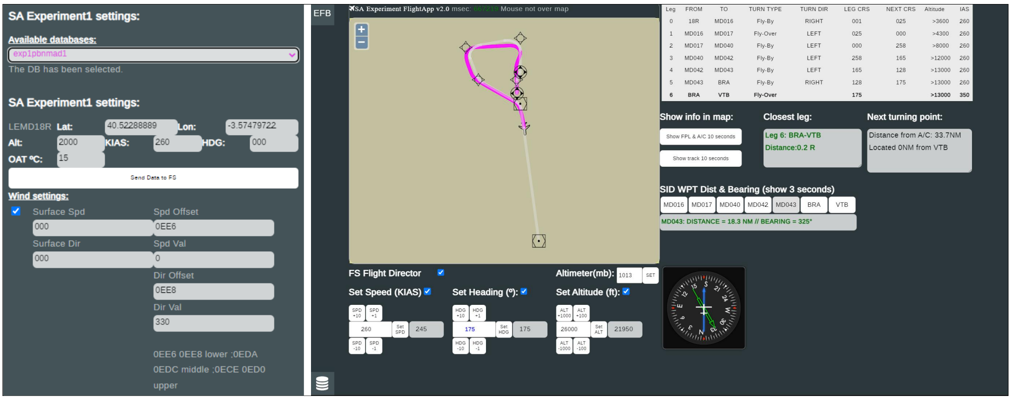


Figure 6.6: General view of the user interface of FlightApp 2.0.

Figure 6.7: FlightApp 1.0 incorporates an EFB dedicated user interface for document queries.

6.2.2 Implementation related to information management

We have explained in detail that our approach to measure SA is based on monitoring how the pilot performs information checks. For that reason, the user interface of the application was designed not only to offer several ways for the pilot to perform the checks, but also to register the most relevant interactions of the user to be analysed after the simulation.

In the first version of *FlightApp* we incorporated some functionalities of an EFB. Figure 6.7 shows a composition of the user interface that was designed: In the bottom of the screen, the pilot had a set of buttons with links to different documents: the Navigation log, enroute charts, procedure charts, etc. It should be noted that the configuration of these buttons was performed using an XML file and that the application allows a high degree of flexibility to configure the appearance and contents of this EFB. The interactions with the EFB were recorded in the Structured Query Language (SQL) database. Apart from the EFB, in the figure we can observe that the map allowed the representation of route points and special use airspaces. The navigation log, consisting of a table with the route legs and their main parameters, is also shown in the figure.

Figure 6.8 has been included to depict the approach followed in the early experiments concerning the modularity of information management. At that stage of the research, we decided that the pilot would have a set of modules with different information items that could be dragged from the right area and

Figure 6.8: FlightApp 1.0 user interface focused more on information modularity.

dropped in the main workspace, so that the pilot would decide which information asset, which we called IMBox, would be used to obtain data necessary to perform the flight. Among these IMBoxes, we implemented tools to draw the FPL in the map, a selector to search for airspaces, navigation aids, etc.

To contribute to this prioritisation of information management monitoring, we decided to place the flight director collapsed on the right area of the interface. The figure shows how the screen looked when the flight director was expanded.

Another aspect that we would like to mention is the different approaches followed depending on the experiment to present the navigation log. This is shown in Figure 6.9, where it can be observed that the appearance of the navigation log changed from *FlightApp 1.0* to *FlightApp 2.0*. The change consisted in offering a less saturated appearance to avoid interpretation errors and to offer an automatic mechanism to highlight the leg that is being flown at each instant. This decision was made because the purpose of the more recent interface is to allow the pilot to focus on the calculations related to the turns to perform the PBN experiment that will be explained in the next chapter, Section 7.6.

Wpt1FIXMName	Wpt1FIXMType	Wpt1Lat	Wpt1Lon	Wpt2FIXMName	Wpt2FIXMType	Wpt2Lat	Wpt2Lon	LegAirspeedVal
LEGR	airport	N37°11.32'	W003°46.63'	BLN	Fix	N38°09.15'	W003°37.50'	undefined
BLN	Fix	N38°09.15'	W003°37.50'	YES	Fix	N38°21.65'	W002°21.17'	350.0
YES	Fix	N38°21.65'	W002°21.17'	TOSTO	Fix	N38°21.85'	W001°56.17'	350.0
TOSTO	Fix	N38°21.85'	W001°56.17'	OLPOS	Fix	N38°43.62'	W001°20.53'	350.0
OLPOS	Fix	N38°43.62'	W001°20.53'	BEGOX	Fix	N39°04.15'	W000°46.32'	350.0
BEGOX	Fix	N39°04.15'	W000°46.32'	LASPO	Fix	N39°16.95'	W000°32.66'	350.0
LASPO	Fix	N39°16.95'	W000°32.66'	ORVUS	Fix	N39°19.90'	E000°25.88'	340.0
ORVUS	Fix	N39°19.90'	E000°25.88'	GODOX	Fix	N39°22.36'	E001°24.64'	340.0
GODOX	Fix	N39°22.36'	E001°24.64'	LEPA	airport	N39°33.10'	E002°44.33'	340.0

Leg	FROM	TO	TURN TYPE	TURN DIR	LEG CRS	NEXT CRS	Altitude	IAS
0	18R	MD016	Fly-By	RIGHT	001	025	>3600	260
1	MD016	MD017	Fly-Over	LEFT	025	000	>4300	260
2	MD017	MD040	Fly-By	LEFT	000	258	>8000	260
3	**MD040**	**MD042**	**Fly-By**	**LEFT**	**258**	**165**	**>12000**	**260**
4	MD042	MD043	Fly-By	LEFT	165	128	>13000	260
5	MD043	BRA	Fly-By	RIGHT	128	175	>13000	260
6	BRA	VTB	Fly-Over		175		>13000	350

Figure 6.9: Evolution of the navigation logs from FlightApp 1.0 (top) FlightApp 2.0 (bottom).

6.3 Elements related to SA estimation bias reduction

When we designed the application user interface, we performed a comparison of SART and SAGAT, two methodologies that have been extensively used in this context since the early days when they were introduced by Endsley [38]. In both approaches, dedicated actions of the pilot are required in order to rate SA, with an inherent bias on the situation in the cockpit and therefore on the measurement. These two methodologies are designed to be used on the ground and should be excluded from real flight applications in order to avoid crew distractions with potential safety risks. That's why in our implementation we opted for an approach according to which the subject does not have to perceive that his/her SA is being measured.

6.3.1 Role of the EFB in the bias reduction

In the previous section, we briefly explained the implementation of the EFB functionality in *FlightApp*. Our final goal would be to collect relevant information for SA estimation without disturbing the cockpit activities, even in a real flight, trying to capture the pilot's perceptions without relying on behaviour inference from questionnaires or reports, as SART and SAGAT do. This is proposed to be achieved using the EFB as a pilot activity monitor, avoiding any simulation stops and opening the door for applying this method in real flights. An EFB typically hosts the information that the pilot needs during the flight: aircraft flight manuals, normal and emergency procedures, maps and navigation charts, mission checklists or flight plans. Many EFB obtain aircraft position, altitude, and speed information during flight, and some of them even receive aircraft status data.

With appropriate monitoring software, an EFB may be able to provide a lot of valuable information to produce a SA estimation without the questionnaire bias. The connection with the simulator provides additional parameters apart from the EFB monitoring, and as a result the SA estimation on this investigation is performed using aircraft and environment data from the flight simulator.

In summary, the approach of this research is that a partial SA rating can be obtained from the analysis of the EFB usage because there should be a reflection of the SA in the way the pilot makes use of managed information. Therefore, by analysing how an EFB is used to provide information, it should be possible to obtain indicators of the SA of its user at the three different SA levels. It is not necessary to ask the pilot to take any action related to SA rating in order to perform the evaluation if the relevant parameters are monitored.

6.3.2 Enhanced monitoring of SA levels 1 and 2

Our approach to increase the collection of data related to Endsley levels 1 (perception) and 2 (comprehension) is based on adapting the user interface to detect when the pilot needs to check key information items during the flight. We have opted for a simple approach based on forcing the pilot to perform a simple action each time he/she wants to monitor certain flight or mission parameters. In order to avoid complicated biometric detection system setups with doubtful applicability to real flights, we have decided to make some information disappear from the interface a few seconds after the pilot requested it. In this way, we can have more reliable information about the information that the pilot perceives during the flight (level 1). Furthermore, by analysing the frequency with which the pilot requests the same information, as well as assessing the coherence between the situation at each moment, the information requested, and the control actions executed, we have elements to conjecture whether the pilot has understood the information (level 2). We are confident that this approach does not contradict any of the SA modelling assumptions of Chapter 5.

Figure 6.10 shows how we have implemented the user interface in *FlightApp 2.0* by the means if buttons to hide information in five data items:

- **Show Nav Log 10 seconds**: The navigation log is necessary for the pilot to have an overview of the route and the most important information that needs to be compared against the cockpit indicators.

- **Show FPL & A/C 10 seconds**: This button shows the route and the position of the aircraft on the map.
- **Show track 10 seconds**: This button shows on the map the path that the aircraft has travelled from the start of the flight until the moment the query is made.
- **Show TP Info 5 seconds**: In this particular case, TP is the abbreviation for the turning point, and this control lets the pilot read the distance at which the aircraft is located from the next turning point. We consider that monitoring the interaction of the pilot with this information is particularly relevant to assess the SA.
- **SID WPT Dist & Bearing (show 3 seconds)**: a set of buttons is located under this banner, one for each waypoint of the flight procedure used for this experiment. When pressed, the text box below the buttons shows the bearing and distance to the selected waypoint, and the RMI adds a graphical indication pointing to the waypoint. This can be seen in Figure 6.10.

For level 1 SA (perception of data), the focus is on recording which information is requested by the pilot. Level 2 SA (comprehension of meaning) requires more attention to the actions performed by the pilot after receiving the information, either aircraft control actions or new information queries. Level 3 SA (projection of the near future) needs more complex analysis, as it depends on the subject's experience and attitude (subjective projection), as well as it demands a more comprehensive comparison between information queries, control actions, the aircraft flight path and the planned navigation route, in order to discover a reflection of the subjective projection on the dataset. In this case, it is highly valuable to detect pilot errors or inaccuracies, either navigation errors or unnecessary information queries and correction actions, mainly because pilot errors are very relevant clues of low level 3 SA.

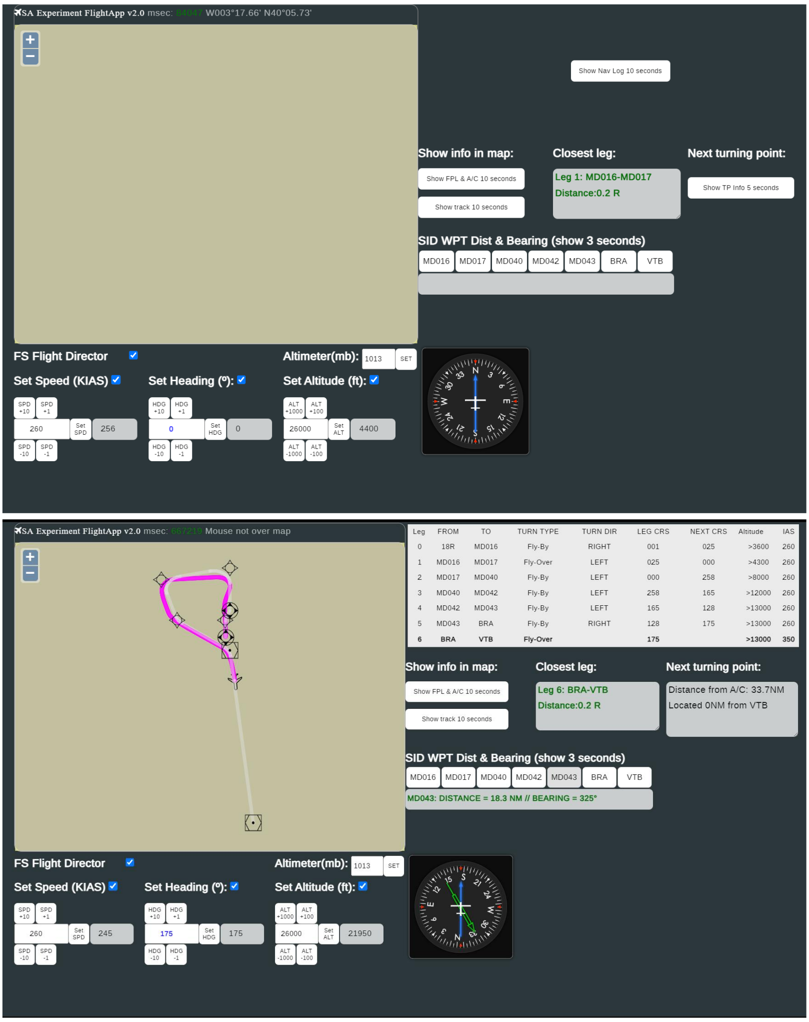


Figure 6.10: FlightApp 2.0 user interface with hidden information sources (top) vs. all shown (bottom).

6.4 An application for summarising data and adding expert knowledge

6.4.1 Description of *PostFlight* application

Once the flight simulation is performed, a dataset with the flight parameters and the pilot interactions with *FlightApp* is stored. We decided to develop an independent application to extract the data, as well as a set of summary variables resulting from post-flight calculations. Since these calculations can be improved or modified in the future, having an independent application enables us to generate several datasets for the same flight, allowing the possibility of having multiple versions of the post-flight analysis of a flight. We have named this application *PostFlight* and it was developed using the same tools as *PostFlight*, explained in Section 6.2.

The user interface of *PostFlight* is shown in Figure 6.11: The flight dataset is identified by the start time and a suffix indicating the experiment. Once the flight is selected, if the summary table already exists, there is a button to select either a reading operation of the existing table or writing a new table. The user can then press a button to start the processing. After processing is performed, the flight route and the flight path are shown on the map. The user can click on the map points to preview the information that has been stored in the database. It should be noted that we chose to store the data in XML format. Different colours in the points indicate if the information is related to aircraft parameters or pilot actions, either control over the aircraft or information checks.

At earlier stages of the research, we also developed a more advanced visualisation tool inside of this application to generate three-dimensional plots of multiple variables once synchronised, but we decided to remove this feature because the plotting capabilities of R and Python are more powerful.

Together with *PostFlight* we also implemented a socket-based functionality to communicate with Matlab and a Java bridge to run applets. The latter was used particularly to run Java-programmed Weka classifiers [16, 17], although the use of Weka was discontinued in favour of R and Python. In Appendix D we have included some screenshots of the databases and a table in Section D.2, where a list with the most relevant variables generated by the application is provided.

Figure 6.11: *PostFlight* map representation and user interface.

6.4.2 Variable synchronization and summary variables in *PostFlight*

Synchronising variables is required to use DBN because the network requires that clear relationships between variables at different time steps are accurately modelled, providing temporal consistency and adequately capture temporal dependencies of the variables. In our case, this topic is particularly important because the initial dataset stores asynchronous pilot actions, and we need to avoid temporal ambiguities. The tool is also in charge of generating some variables that add information, based on expert knowledge, about the temporal validity of the pilot's actions, especially in order to determine which actions are priority in case of overlap.

Among all these modifications, special attention should be paid to summary variables. They are needed because DBN typically use only one-time step to learn the network from former times, and that has an impact on the propagation of time-dependant information through the network: flight data is sampled every 5 seconds in this experiment, which is in general a very short time lapse in front of the duration of flight manoeuvrers and air navigation segments. In order to maintain the influence of relevant long-term information, it is necessary to create new variables that maintain the history of certain parameters along appropriate time periods; these are called summary variables.

Some of the summary variables in the dataset are created by simply accumulating variable values. Others are the result of a combination of variables, acting as counters of coincidences in the values of variables, and requiring more complex expert knowledge.

6.4.3 Creation of post-flight variables: the dataset

The simulation environment settings were adapted to test different discretization criteria for variables. In the case of the first experiment, all the repetitions consisted on a flight from Granada (LEGR) to Palma de Mallorca (LEPA) airport, in a twin-engine jet. The dataset was composed of samples taken every 5 seconds that include flight parameters (aircraft position, attitude, environmental data, etc.), pilot control actions (values of heading, speed and altitude flight director settings) and selected data of information management actions (time reference and identification of documents opened in the EFB, identification, range and bearing of AIXM checked waypoints with their time reference) recorded by *FlightApp*. *PostFlight* application synchronised all these data with their appropriate time references and aircraft position along the planned route, according to the flight plan. It also added performance variables that compute different aspects of the queried AIXM entities versus the aircraft and the FIXM flight plan at each time step. The result was a dataset that contained 80 variables, continuous and discrete.

Although it is not required by DBN to establish categories among the variables in order to learn their relationships, the dataset variables have been tagged. The following groups have been identified for the sake of improving the understanding of the variables and to facilitate the detection of unexpected relationships:

- Aircraft situation (AS): These are parameters that contribute to define the position of the aircraft in the different axes, also taking into account the flight plan route that the aircraft is expected to fly. Parameters like aircraft altitude, geographic coordinates, distance to flight plan waypoints, etc. are included in this group.

- Aircraft parameters (AP): They may be directly or indirectly set by the pilot and their value can typically be checked in an aircraft instrument. These parameters may vary or oscillate without human intervention due to aerodynamics and thrust force momentum. At this stage of the research, only engine power settings and aircraft pitch and bank angles are included in the dataset.

- Environment variables (EV): The current list includes wind speed and direction, external ambient temperature, and atmospheric pressure.

- Pilot actions (PA): These include actions to control the aircraft. For this experiment, only autopilot actions have been recorded, including those to set the altitude, speed, and heading of the aircraft. This approach provides relevant data on the pilot's intention to control the aircraft, without the simulation bias associated with manual control.

- Information checks (IC): These are pilot actions to check the documents included in the EFB. This category also contains some variables with *a priori* incorporated expert knowledge to evaluate whether the information checked by the pilot is relevant for the current or the next leg (or segment) of the flight plan route. More details are provided in section 6.4.

- Situation checks (SC): These are based on pilot queries to obtain information about the position of the aircraft, based on a simulation of navigation instruments. Additional SC variables are calculated after the flight with enhanced context information about the anticipation taken by the pilot to perform these queries.

- Flight plan (FP): These variables contain flight plan information and are used to compare the flight path with the expected route.

- Situation accuracy or quality (SQ): Including expert knowledge applied to AS and FP variables, to assess if the aircraft situation is suitable with respect to the flight plan or other factors related to the desired aircraft trajectory.

7 SITUATION AND TRAJECTORY ANALYSIS

To carry out this research, we have designed several experiments within the framework of SA estimation, in which trajectory analysis has always been present, based on the model explained in Chapter 5. Therefore, according to our approach, the pilot's SA and the trajectory that the aircraft flies are closely related. That is why we conducted several experiments combining both topics, and the reasons are summarised in the first section of this chapter.

The following sections briefly explain the main experiments, that is, those that have been published in conferences or journals. The chronological order is maintained and the approaches used and the results obtained in each case are presented, so the reader is asked to take this chronological context into account when finding aspects that were subsequently improved. The last experiment, with the final results of the thesis, has not been included in this chapter because Chapter 8 has been dedicated exclusively to it.

The first experiment, presented in Section D.2, deals with the discretization of the data in our first experiment. At that time, we prioritised good computational efficiency, which was clearly better with discrete variables. The variables were discretised, and linear regression was used in the learning of Bayesian networks. Section 7.3 focusses on regression, introducing criteria for handling continuous variables. After regression, another experiment with the use of k-means clustering algorithms was proposed to handle and classify multiple trajectories. We decided not to limit ourselves to using external datasets, but rather built an environment that was capable of using a SWIM service to collect these trajectories. This environment is shown in Section 7.4. The following Section 7.5 presents the results of the experiment to group flights using k-means clustering. The chapter ends with the experiment published in 2023, the predecessor of the last experiment in the thesis. It was already mentioned in Section 2.3 that PBN is a concept that is becoming widely established in aeronautical navigation, and in Section 7.6 we explain how we carried out an experiment using this type of navigation.

7.1 The importance of trajectory analysis

Situation awareness is mainly a concept of human factors and can be studied in terms of how the pilot interacts with the stimuli received from the cockpit. In order to go one step further and understand better the root causes of the indications and the information that the pilot has to manage during the flight, it is relevant to study the aircraft trajectory since it can be considered a product of the pilot's good or bad performance. The goal is to extract the relevant information contained in the data collected from the simulations, in accordance with the machine learning tools that we propose to use. It should be noted that all the trajectories analysed in this research refer to IFR flights, and their characteristics cannot be immediately extrapolated to other types of operations.

7.1.1 Characteristics of an acceptable trajectory

Considering the implementation of classifiers and aiming to provide valuable expert knowledge, it is relevant to establish criteria to determine to what extent a trajectory is acceptable or not. This task is by no means evident. The first approximation is to consider that a good trajectory is one that does not deviate from the planned route. This is for us the main indicator and, therefore, some of the variables where this research focusses are indicators that the path flown corresponds to the planned trajectory. However, there are multiple factors that can force or recommend that a pilot deviates from the initially planned route, and this cannot be associated with a low SA. Some examples are listed below:

- The ATC directs the pilot to a waypoint outside the planned trajectory.
- Due to operational reasons, the pilot decides to prioritise other tasks and accepts a reduction in the trajectory precision, consciously assuming responsibility for this deviation.
- The trajectory needs to be modified due to weather conditions.
- The trajectory needs to be modified due to interaction with other aircrafts or due to last-minute information acquired just before the flight, typically in a NOTAM, that was not properly taken into account during the pre-flight planning stage.

7.1.2 Characteristics of an inadequate trajectory

In the former paragraph, we have explained that there are multiple reasons that can justify that a trajectory deviation does not imply that there has been a SA reduction. Therefore, additional effort is required to find collectable data that could confirm that a deviation is associated with low SA. Therefore, the focus turns to human factors. It is important to note that during a routine phase of the flight the pilot does not always have to pay full attention to the trajectory, since the situation is under control and he/she is the one who decides to reserve concentration resources for more critical phases of the flight.

From this perspective, it is important to define other parameters that reflect the consequences of a low SA in the trajectory, considering not only the aircraft positions but also the pilot actions, as explained in Chapter 5 when we presented the model used to measure SA. Some examples of an inadequate trajectory are listed below:

- Erratic or excessive changes in the attitude of the aircraft.
- Pilot corrections that do not correspond to the deviation of the aircraft.
- Pilot actions that do not correspond to the information received after an information check.
- Information checks that are irrelevant or could provide misleading information, according to the situation in which the cue was executed.

7.2 Discretization of variables experiment

The first experiment was the most challenging because it included the creation of the simulation environment described in Chapter 6. The results were published at the Service Assurance System Wide Information Management (SASWIM) workshop during the 2015 International Symposium on Autonomous Decentralized Systems (ISADS)[100]. This was relevant because this Institute of Electrical and Electronics Engineers, Inc. (IEEE) symposium is the most relevant academic forum that combines SWIM and aviation human factors, in particular SA, to our knowledge.

7.2.1 The Available Data and Basic Model

As a result of a flight, we have a set of variables $\mathbf{X}$ that are measured in different instants or time steps $t \in T$. The variables measured in time t are denoted by $\mathbf{X_t}$. The variable $X_i \in \mathbf{X}$ measured at instant t is denoted by X_{it}. It is important to note that some of the variables are continuous and some are discrete. The model we are going to consider is a dynamic Bayesian network, in which the parents of each variable X_{it} are selected from the variables $\mathbf{X_{t-1}}$ measured in the previous instant. The parents of a variable X_i will be denoted as Π_i. The first approach for a correct modelling of a flight is based on discretising the continuous variables and using a fully discrete DBN.

7.2.2 Discretization requirements of DBN

The simulation environment developed for this experiment produces discrete and continuous variables to characterise the position of the aircraft and the actions of the pilot. From the beginning of the research we were aware that Bayesian networks, and therefore DBN, have issues for handling continuous variables. Although DBN can work with continuous variables to some extent, there are limitations related to the distributions that can be attached to continuous variables and the difficulties associated with computing with a conditional probability of a discrete variable conditioned to continuous ones. Some possible solutions are based on the use of the mixture of truncated exponentials model [126] or to discretise continuous variables. In the experiment, we performed the discretization of the data and assessed its characteristics and performance. The first step was to setup and test the discretization thresholds and analyse their performance in terms of BN learning from data, as explained below.

If X_i is a continuous variable taking values on U_i we will assume that U_i is an interval $[a^i, b^i]$ (i.e. there is always a minimum possible value a^i and a maximum value b^i). A discretization of this variable is a finite partition of $[a^i, b^i]$ in a finite set of subintervals $r^i_j = [a^i_j, b^i_j)$, $j = 1, \ldots, k_i$. Then the possible values of the discretised variable X^d_i will be the finite set of intervals $R^i = \{r^i_1, \ldots, r^i_{k_i}\}$. A probability distribution P for this variable will be a mapping $P : R^i \to [0, 1]$ such that $\sum_{j=1}^{k} P(r^i_k) = 1$. In our approach, this probability distribution will be considered as an approximate density of the original continuous variable X_i. This density will be constant in each interval r^i_j and the total density of the interval will be $P(r^i_j)$, that is, the associated density about X_i will be:

$$f(x) = \frac{P(r^i_j)}{b^i_j - a^i_j} \tag{7.1}$$

where r^i_j is the interval containing x ($x \in [a^i_j, b^i_j)$).

For this experiment, we defined five discretization templates, with a different number of thresholds adapted to the nature of the continuous variables handled, according to the following criteria:

- THRESHOLDS_min: Minimum set of thresholds for the trivial solution of the DBN learning process, established with expert knowledge.
- THRESHOLDS_10: Discretization with 10 thresholds, concentrated for each variable in the most probable intervals or in the simplest error cases during the flight.
- THRESHOLDS_20, THRESHOLDS_50 and THRESHOLDS_100: 20, 50 and 100 thresholds, to increasingly detect human errors, cover the most probable intervals and the full scope of the variables.

The values of the interval limits were provided by an expert trying to select meaningful thresholds for relationships with other variables: for example, THRESHOLDS_10 includes only thresholds that generally imply a hazardous situation according to standard flight procedures as described in [73], such as flying outside the airway. The other threshold templates were designed to increasingly identify flight conditions that are generally associated with different levels of pilot skill. On the other hand, we also introduced an automatic procedure to discover a discretization from data, without the need for expert knowledge.

7.2.3 Learning a Model

Given a discretization of each continuous variable, the dependence model is learnt using the techniques for Bayesian networks learning [109]. We assume that we have a set of data with the measurement of variables in several flights $\mathcal{D} = \{\mathcal{D}_i\}_{i=1}^{m}$. Each $\mathcal{D}_i$ contains the measurement of all the variables $\mathbf{X}_t$ in several times during a flight (at constant time steps). Learning is based on metrics that measure for each variable X_i the suitability of Π_i as its set of parents given the observed data $\mathcal{D}$. For all of them, it is necessary to compute for a variable X_i and a set of parents Π_i, the values N_{ijk} which are the frequencies in the data $\mathcal{D}$ for which X_i takes the value x_k in time t given that parents Π_i take the combination of values number j in time $t-1$. It is assumed that there are l_i different values for the variable X_i (this number is finite since all variables have been discretised) and h_i possible combinations of the values of the parents. Also, $N_{ij} = \sum_{k=1}^{l_i} N_{ijk}$ and $N = \sum_j N_{ij}$.

Under these conditions, the selected scores for each variable and parents are the following:

- BIC information criterion:

$$\mathrm{BIC}(X_i, \Pi_i, \mathcal{D}) = \sum_{j=1}^{h_i} \sum_{k=1}^{l_i} N_{ijk} \log \frac{N_{ijk}}{N_{ij}} - (1/2) h_i (l_i - 1) \log(N)$$

- Akaike information criterion:

$$\mathrm{Akaike}(X_i, \Pi_i, \mathcal{D}) = \sum_{j=1}^{h_i} \sum_{k=1}^{l_i} N_{ijk} \log \frac{N_{ijk}}{N_{ij}} - h_i (l_i - 1)$$

- K2 metric (usually the logarithm of this value is computed):

$$\mathrm{K2}(X_i, \Pi_i, \mathcal{D}) = \prod_{j=1}^{h_i} \prod_{k=1}^{l_i} \frac{\Gamma(l_i)}{\Gamma(l_i + N_{ij})} \Gamma(1 + N_{ijk})$$

- BDEu metric (usually the logarithm of this value is computed):

$$\mathrm{BDEu}(X_i, \Pi_i, \mathcal{D}) = \prod_{j=1}^{h_i} \prod_{k=1}^{l_i} \frac{\Gamma(s)}{\Gamma(s + N_{ij})} \frac{\Gamma(s/l_i + N_{ijk})}{\Gamma(s/l_i)}$$

  where s is a parameter (the global sample size) usually in the interval $s \in [1, 10]$.

BDEu was chosen because it was a common metric used to learn graphical models; however, we found that it has some learning issues in our case. The particularity of our datasets is that when learning the parents of a variable X_i it often occurs that for each time step t the variable X_{it} is very similar to the same variable $X_{i(t-1)}$ in the previous time step. In some cases, they have the same value almost within the whole sequence, with very few exceptions in which there is a change. This produces that BDEu does not work well, and increasing the number of parents always increases the score. To avoid this, we modified the BDEu score by changing s/l_i by s/l'_i, where l'_i is the number of $k = 1, \ldots, l_i$ where $N_{ijk} > 0$.

Once a metric is selected, the set of parents of a variable is learnt trying to find for each variable X_i the set of parents Π_i that optimises the score. For that we used a greedy search method [109] that starts with an empty set of parents, and in each step it considers all the sets of parents obtained from the current one, by adding a non-parent variable or removing a parent variable, changing the set of parents to the one with the highest score, while there is an improvement of the score of the current set of parents. After the set of parents is learned for each variable, the parameters for each conditional probability are estimated with the Laplace correction [109].

7.2.4 Learning a Discretization

In the former subsection, we have considered scores when the discretization is fixed. When we want to learn the intervals to discretise continuous variables, these scores have to be updated. Given the hypothesis assumed about the densities associated with a discretization (see Equation (7.1)), this can be achieved by adding to the scores (in case of K2 and BDEu to the logarithm of the expressions we have given) the following value for each variable X_i that is discretised:

$$-\sum_{j=1}^{k_i} N_{ij} \log(b_j^i - a_j^i) \tag{7.2}$$

This value corresponds to the logarithm of the probability of the actual values of the variables (without discretization) conditioned on the fact that the variable value is in the interval $[a_j^i, b_j^i]$: N_{ij} cases and each, and assuming a uniform probability in the interval, the probability is $\frac{1}{b_j^i - a_j^i}$.

With this complement, we have a score for a graph and a discretization. As discretizations are finer, the original scores have a tendency to be lower, while this complement increases, so the addition of the two tries to find optimal discretizations balancing the two parts.

As the intervals limits for variable X_i can be any values in the interval $[a^i, b^i]$, there is a risk of overfitting the model by producing very small intervals just around the actual values of the variables. To avoid this problem, we computed all the values of a given variable X_i and considered that the possible interval limits are the middle points between two actual values of the variable.

Theoretically, we should learn a couple given by a graph and a discretization maximising the score. As this was very time consuming, we applied an approximate and faster procedure consisting on optimising the discretization assuming an empty graph (where variables do not have parents) and then to learn a graph structure considering that this discretization had been fixed. Thus, each variable is discretised with independence from the discretizations of the other variables.

The search for a discretization of the variable X_i starts with a discretization in which the interval $[a^i, b^i]$ is divided into two parts with equal frequency. Then the procedure is repeated while there are improvements in the score: Each actual interval is tested to be split into two parts with equal frequency, and when there are no improvements dividing intervals, then each interval is tested to be merged with the consecutive interval on its right.

7.2.5 Testing a Model

Once a temporal model is learnt, we can test how good the model is at predicting the measures of variables $\mathbf{X}$ in a new flight. We assume that we have a measurement of the variables $\mathbf{X}_t$ for a finite set of time steps $t \in T$. The idea is to compute $\sum_{t \in T} \log(P(\mathbf{X}_t|M))$, where M is the learnt model, that is the Logarithm of probability (LP) of the measurements obtained in the new flight, given the model M that has been learnt. This computation is done starting with a value of $LP = 0$ and then for each t, considering each variable X_{it} and the observed values of its parents Π_{t-1} in the previous time interval $\Pi_{t-1} = \pi_{t-1}$. With these values and the conditional probability of the variable given its parents, we can select a discrete probability P_i for the value of the variable. We differentiate two situations:

- If X_i is discrete and $X_{it} = x_i$, then we add $\log(P_i(x_i))$ to LP.
- If X_i is continuous and $X_{it} = x_i$ where x_i belongs to interval r^i_k, then $\log(P_i(r^i_k)) - \log(b^i_k - a^i_k)$ is added to LP.

The higher the results LP, it should be assumed that the model M has better predicted the values of variables $\mathbf{X}_t$. Alternatively, if we are interested only in a subset $\mathbf{Y} \subset \mathbf{X}$ of variables (for example, the variables describing pilot actions) we could compute this value, but repeating the computation of LP only for the variables in that subset.

7.2.6 Results of the discretization experiment

During this experiment, we recorded 10 simulated flights performed by 3 experienced pilots with different backgrounds (fighter, transport, and helicopter) and the DBN training was performed with all the different combinations: for every discretization template and for the automatic learning of thresholds, we trained 1 network with 9 flights, and then checked how that network can predict the measures of the remaining flight (the one that was not used to train the network). This was repeated 10 times. Each time, a different flight was selected for testing and the remaining nine flights for learning, as in 10-fold cross-validation. The experiment aims to compare how the discretization templates affect the score of the DBN training and to determine the discretization strategies that should be followed in further stages of the research.

Table 7.1 shows the performance of the different scores with the five discretization templates using a 10-fold cross-validation. Each value presented is

Score	THRES_min	THRES_10	THRES_20	THRES_50	THRES_100	LEARNED
BIC	$-9.919 \cdot 10^5$	$-8.663 \cdot 10^5$	$-8.200 \cdot 10^5$	$-7.424 \cdot 10^5$	$-6.613 \cdot 10^5$	$-5.312 \cdot 10^5$
Akaike	$-9.920 \cdot 10^5$	$-8.662 \cdot 10^5$	$-8.200 \cdot 10^5$	$-7.424 \cdot 10^5$	$-6.612 \cdot 10^5$	$-4.876 \cdot 10^5$
K2	$-8.633 \cdot 10^5$	$-5.993 \cdot 10^5$	$-5.055 \cdot 10^5$	$-3.768 \cdot 10^5$	$-2.965 \cdot 10^5$	$-5.015 \cdot 10^5$
BDEu	$-8.820 \cdot 10^5$	$-6.538 \cdot 10^5$	$-6.109 \cdot 10^5$	$-5.712 \cdot 10^5$	$-5.090 \cdot 10^5$	$-5.308 \cdot 10^5$

Table 7.1: LP values in a 10-fold cross validation

the sum of the LP values for 10 repetitions of the experiment. Higher LP values indicate better performance. The discretization templates go from a very crude one using a minimum set of intervals to a very fine one including 100 intervals.

According to these criteria, K2 was the best score to determine the graphical structure of our model. BIC and Akaike scores produce very similar results with expert discretization, but Akaike showed better results when discretization is learnt. K2 score is better than the BDEu score and this improvement increases with the number of intervals. This somewhat contradicts the general belief that BDEu is a better justified score than K2 [109] from a theoretical point of view (for this reason, nowadays BDEu is much more used in practical applications than K2).

In addition, as the number of intervals increases, the predictions of the values of the variables improve. Theoretically, if the number of intervals is too high, then the performance should deteriorate. In this case, this optimal number of intervals was not surpassed in our experiments. We believe that the results of the experiments can be explained taking into account the following facts:

- There are many continuous variables, and we always subtract the logarithm of the interval width, which favours small intervals. We think that if the performance of the model is measured taking into account the pilot actions, then the result could have been different, as many of the actions are discrete variables.

- In our case, each variable X_{it} is very similar to $X_{i(t-1)}$. So it can be predicted with high accuracy when $X_{i(t-1)}$ is a parent of X_{it}. This favours the use of small intervals. This was also due to the fact that the variables were measured every 5 seconds. Larger time steps would reduce this tendency. At that time of the research, we could foresee that a heterogeneous discretization, as in [80], would improve the results, without using too many intervals. The idea is that each variable X_{it} could be discretised with small intervals in the proximity of $X_{i(t-1)}$ and with large intervals when the value of X_{it} is quite different from the value of the same variable in previous intervals.

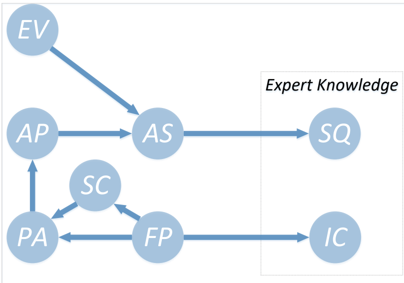
A possible approach that was taken into consideration to improve the results consists in adding an artificial variable Y_{it} that is an estimation of X_{it} as a linear combination of variables in previous time $\mathbf{X}_{t-1}$ (in the simplest case, we could have the estimation $Y_{it} = X_{i(t-1)}$). Then we consider the error variable $E_{it} = X_{it} - Y_{it}$, which is the variable to be discretised. The parents of this variable would be also learnt from the set of variables in the previous timestamp.

The parents of X_{it} will be E_{it} and Y_{it} and the value is obtained deterministically as: $X_{it} = E_{it} + Y_{it}$. We foresee that it will not be necessary to consider a large number of intervals to discretise E_{it} and that only around 0 would be necessary to define small intervals.

The automatic discretization was better or similar to the discretization provided by the expert in all scores except K2 for a high number of intervals (50 or 100). The number of intervals of the learnt discretization was always less than 50. In any case, the best results are for K2 with 100 intervals with expert knowledge. This does not mean that automatic discretization is useless, because it should also be taken into account that manually providing a high number of intervals for all the continuous variables is a tedious task and that expert knowledge is not always available.

Also, the score we used to validate a model favoured small intervals, which explains why a large number of intervals can provide better results than an automatic procedure. In any case, this only happened for the K2 score, and the automatic procedure was better or very similar to the fixed discretizations for all the other scores. Furthermore, automatic discretization showed room for improvement in the following ways:

- Try to find a couple given by a graph and a discretization optimising the score, without the simplification we applied consisting of learning the discretization for the empty graph and then learning the graph considering the obtained discretization.
- As the best results are obtained with a large number of intervals, fix a high number of intervals beforehand and then learn the best discretization given this number of intervals.
- Combine different scores for the discretization and learning of the graph. For example, using the Akaike score to learn the discretization which provides finer discretization results, and then using K2 to learn the network structure.



AS	Aircraft Situation	19
AP	Aircraft Parameters	4
EV	Environment Variable	4
PA	Pilot Action	21
IC	Information Check	37
SC	Situation Check	14
FP	Flight Plan	9
SQ	Situation Accuracy or Quality	11
119 variables, sampled every 7 seconds, 10 flights with durations from 54 to 64 minutes.		

Figure 7.1: The dataset variables categories and their main expected dependencies, used for the regression experiment.

7.3 Regression experiment

This is the second experiment we conducted using the same simulation environment explained in Chapter 6 and the results were published at the 2016 International Conference on Probabilistic Graphical Models (PGM) [98]. The simulated flights were the same as those used for the previous experiment, but in this case we improved the post-flight expert knowledge based on the lessons learnt from the previous work explained in Section D.2.

7.3.1 Overview of the expert knowledge

The dataset used for the experiment included several types of variables that were generated with several tools. The variables categories mentioned below were introduced in Section 6.4 and their acronym meanings and dependencies are shown in Figure 7.1. Among these variables, there are two different types of expert knowledge: SQ variables contain *a priori* expert knowledge not particularised to any particular flight, based on general assumptions of compliance with standard flight quality criteria. Their discrete values indicate whether the aircraft is too separated from the expected flight path or the required altitude.

On the other hand, IC variables have also been produced integrating *a priori* expert knowledge, but in this category the assessment is particularised to the planned route and should be adapted if the flight plan is modified. This expert knowledge consists of different discrete variables that rate the information checked by the pilot in terms of relevance, that is, the query performed by the pilot is relevant according to the instant when it happens and it contains information that is necessary to ensure flight safety; and exclusiveness, i.e., the query provides information that can more or less be obtained from other sources.

Different values of IC variables are expected to indicate from beneficial to distractive queries, whereas SQ values will indicate deviations based on the impact on flight safety. In both cases, the applied expert knowledge was causal and did not require knowledge of the future development of the flight to provide an SA estimation, even in real time.

7.3.2 Summary variables

The DBN considered for the regression experiment, and in general for the rest of the research, are such that each variable depends only on the variables in the previous time (Markov condition). In order to alleviate this restriction and to introduce dependencies from a full time interval, we created summary variables that contain information about what happened in the past.

At the time of this experiment, the focus was on quantifying the regression improvements, rather than optimising the summary variables, so these were kept relatively simple and no significant increase in model performance was expected from them. Therefore, they basically perform a calculation of the average error of the aircraft position (SQ variables) and the expert assessment about relevance and exclusiveness of pilot information queries (IC variables). These averages were calculated for the total flown time, and for the last two and four minutes of flight, at each time step. As explained in Chapters 6 and 8, different approaches were used for subsequent experiments.

7.3.3 Dataset variable groups from the perspective of SA levels

For the regression experiment, we used the following criteria concerning variable modelling with regard to Endsley levels for the SA estimation [36]:

- Level 1 SA - Perception of elements in the environment: The measurement of perception-related variables was focused on navigation information management, expecting a low simulation bias, as discussed in [101]. Dataset IC and SC variable types are expected to contain information about level 1 SA because the contain information about the monitoring real-time pilot activities related to the retrieval of navigation information.
- Level 2 SA - Comprehension of the current situation: The most common approach to measure level 2 SA is based on techniques like SAGAT [38]

that rely on obtaining direct and explicit feedback from the subject. As already discussed in our previous work [101], when the pilot behaviour is monitored in real time, the assessment on the pilot's comprehension of the situation is preferably inferred from his/her actions rather than from a conscious feedback. Therefore, variable types IC, SC, PA (containing pilot actions) and AS, AP, EV, FP, SQ (containing aircraft situation / condition) were considered at the time to be related to level 2 SA.

- Level 3 SA - Projection of the near future: One of the most important conclusions that we extract from Endsley's model is that pilots with correct SA not only perceive and comprehend, but are also able to predict the future flight evolution. This cannot be reduced to associating good SA to the absence of errors or inaccuracies of the crew. Specially in high workload situations, pilot actions should be more focused on avoiding future problems rather than fixing past mistakes. At the moment of carrying out this experiment, we associated SA Level 3 to the expert knowledge variables incorporated after the simulation, in that case SQ and IC.

7.3.4 Computation of regression

In previous experiments [101], the results showed an improvement in performance when the number of intervals in the discretization was increased. The problem we faced at that time is that most continuous variables are such that their value in time t is a small variation of their value in previous time $t-1$. In later experiments, we modified the sample rate, as will be explained in Chapter 8. However, in 2016 we considered it to have been more reasonable to discretise the differences $X_{it} - X_{i(t-1)}$. In the paper [98], we went a step forward, first trying to make a numerical estimate of each continuous variable X_{it} using linear regression and variables in previous time as predictors. In this way, the variable $X_{i(t-1)}$ was considered as a possible predictor of X_{it}. Data manipulation was performed with the R package `bestglm`. As the number of predictors was very high and to avoid overfitting, the number of variables in regression was limited to a maximum and the best model was chosen with BIC criterion. In our case, the maximum number of predictors was selected to be 4. This number of variables proved to be enough to produce good estimates and, although `bestglm` has a procedure to determine the optimal number of variables, if this maximum was not limited, the procedure turned out to be very time consuming given the large number of measured variables of this particular experiment. In all cases, the most important variable that acted as a predictor of X_{it} was $X_{i(t-1)}$ with a regression coefficient close to 1.0.

Concerning the introduction of artificial variables Z_i, assume that we have predicted X_t by means of a linear combination $a + b_1 Y^1_{t-1} + \cdots b_k Y^k_{t-1}$, then our model includes in time $t-1$ the deterministic variable $Z_{i(t-1)} = a + b_1 Y^1_{t-1} + \cdots b_k Y^k_{t-1}$. The values of this variable can be computed with the values of other variables at the same time.

Then in time t we add another variable, the error variable: $E_{it} = X_{it} - Z_{i(t-1)}$. Once the regression is computed, the dataset is expanded by including the artificial variables Z_{it} and E_{it}: $Z_{it} = a + b_1 Y^1_t + \cdots b_k Y^k_t$, $E_{it} = X_{it} - Z_{i(t-1)}$.

With the expanded dataset, we estimate the model structure in the following way:

- Each variable Z_i is a deterministic variable depending on other variables over the same period of time, by its linear equation.
- Each continuous variable X_{it} is a deterministic variable equal to the sum of the artificial variable in the previous period $Z_{i(t-1)}$ and the error variable of the same period E_t.
- Each error variable E_{it} is discretised with the procedure of the above subsection and its set of parents is computed by optimising the score with a set of parents $\Pi_{i(t-1)}$ selected from variables in previous time, in the same way that was done with continuous variables in the previous approach.

It is important to remark that though E_{it} is computed from X_{it} and $Z_{i(t-1)}$, in the model it is considered that E_{it} is random and that X_{it} is the sum of $Z_{i(t-1)}$ and E_{it}. This is the usual assumption in regression models, where it is assumed that a variable of interest is the sum of a deterministic function (in our case, the value of $Z_{i(t-1)}$) and a noise (in our case E_{it}), although in the data the noise or error is computed by measuring the difference between the real value and the value of the deterministic function.

In classical regression, it is assumed that the variable E_i is Gaussian and independent of the rest of the variables in the problem. In our case, we do not assume this hypothesis and consider that E_i is a variable that can depend on any variable in the previous period. We do not consider either that the errors are Gaussian, learning a generic distribution through the discretization and conditional probability estimation.

In the regression problem, discrete variables X_i can also be an explanatory variable, with values $0, 1, \ldots, l_i - 1$ with l_i the number of elements of variable X_i. We also compute a discretization for variables Z_i and continuous variables

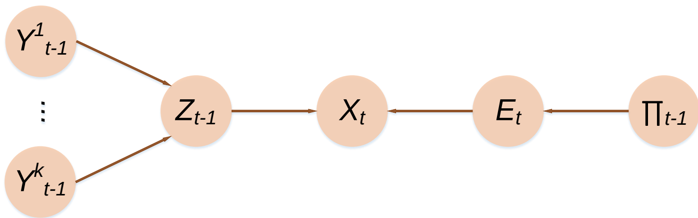


Figure 7.2: Regression model for the estimation of pilot actions.

X_i. These discretised variables can be parents of any discrete or error variable. The complete model is represented in Fig. 7.2.

7.3.5 Testing a Model

In this subsection, we present the improvements of the regression experiments [98], compared to the results of the model tests only based on discretization [100]. Once a model is learnt, its performance is measured using new observations of variables $\mathbf{X}$ in a new flight. Assume that we have a measurement of the variables $\mathbf{X}_t$ for a finite set of time steps $t \in T$. The idea is to compute the LP, $LP = \log(P((\mathbf{X}_t)_{t\in T}|M)) = \log(P(\mathbf{X}_{t_0})) + \sum_{t\in T\setminus\{t_0\}} \log(P(\mathbf{X}_t|M, \mathbf{X}_{t-1}))$, where M is the learnt model and $t_0 \in T$ is the initial time.

If only discretization is used, then we start with $LP = 0$ and for each t and for each variable X_i in this interval we add the following values to LP: first we compute the observed values of its parents in the former time interval $\Pi_{t-1} = \pi_{t-1}$, with these values and the conditional probability of the variable given its parents, we can select a discrete probability P_i for the values of this variable in time t. Then

- If it is discrete and $X_{it} = x_i$, then we add $\log(P_i(x_i))$ to LP.
- If X_i is continuous and $X_{it} = x_i$ and x_i belong to the interval r^i_k, then $\log(P_i(r^i_k)) - \log(b^i_k - a^i_k)$ is added to LP.

In the case of using linear regression, the computation is done in a similar way, but first we have to compute the values of instrumental variables Z_i (linear combinations) and E_i (error variables). Then, we take into account that variables Z_i and continuous variables X_i are considered deterministic variables and then their true value is predicted with probability one (given the other measured and error variables). So, these variables add a value of $\log(1.0) = 0.0$ to LP. We have to apply the above computations only to discrete variables and to error variables, with the same procedure that was employed to discretise continuous variables.

The higher LP results for model M than for model M', it should be assumed that the model M has better predicted the values of variables $\mathbf{X}_t$ than model M'.

If we are interested only in a subset $\mathbf{Y} \subset \mathbf{X}$ of the variables (for example, the variables describing pilot actions), we could compute this value, but adding the computation of LP only for the variables in that subset or the corresponding errors in the case of continuous variables with the regression model.

7.3.6 Results of the variable regression experiment

We have carried out a series of experiments in which we have repeated the learning of the model with 9 flights and tested it with the remaining one, as in 10-fold cross-validation. We report the results of LP for the different discretizations and the regression model in the following experiments:

- Experiment 1: All variables are used in the model and LP is measured for all variables.
- Experiment 2: The summary and expert knowledge variables are not used and LP is only measured for pilot actions.
- Experiment 3: All variables are used in the model and LP is measured only for pilot actions, including consulting information (PA and IC variables).

When regression is not used, the discretizations we have tested are provided by the expert. Experiments for learning discretizations without regression are reported in [101] and are not better than the results obtained with a large number of intervals. In the LP model the error variable is not known in advance, and therefore the intervals have to be learnt with the procedure shown in the previous subsection. Other continuous variables are also discretised with the automatic method, but these discrete variables can only appear as parent variables.

The results of these experiments are given in Tables 7.2, 7.3, and 7.4, respectively.

From the analysis of this part of the experiments we extracted the following facts:

- Without regression: using a large number of discretization intervals is better, also with the extra variables added, and when we focus on pilot

Score	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regression
BIC	−9.300e5	−6.690e5	−5.699e5	−6.360e5	−5.676e5	−2.475e5
Akaike	−9.310e5	−6.682e5	−5.655e5	−4.271e5	−5.075e5	−2.450e5
K2	−9.305e5	−6.694e5	−5.653e5	−4.188e5	−3.602e5	−1.989e5

Table 7.2: LP values for the estimation of all variables and using summary variables.

Score	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regr. w/o
BIC	−1.408e5	−1.034e5	−9.680e4	−1.034e5	−9.280e4	−2.162e4
Akaike	−1.398e5	−1.021e5	−9.235e4	−8.082e4	−8.966e4	−2.378e4
K2	−1.409e5	−1.032e5	−9.330e4	−7.886e4	−6.548e4	−2.184e4

Table 7.3: LP values for the estimation of pilot action variables, without using summary variables.

actions. This is in accordance with the previous discretization experiment. This is due to the fact that in our model we assume that the density is constant in each interval of the discretization and then $-\log(r_i)$ is added to the likelihood where r_i is the length of the interval to which the value of X_i belongs. This factor has a great impact and gives rise to a preference for larger discretizations with smaller a_i values.

- Using regression plus discretization is always better than just discretization. The differences were several orders of magnitude better than with models that are smaller in size than the large discretizations, although we did not perform statistical tests. Here, the impact of using a high number of intervals is not so important, as only error variables are involved in the likelihood computation and the values of these variables are concentrated around 0 (in contrast with initial variables that have their values distributed in a large domain).

- Regression benefits from the use of summary variables and expert knowledge; however, the differences were not very important. In the case of

Score	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regr. w/
BIC	−1.408e5	−1.034e5	−9.680e4	−1.034e5	−9.280e4	−2.109e4
Akaike	−1.398e5	−1.021e5	−9.235e4	−8.078e4	−8.974e4	−2.281e4
K2	−1.409e5	−1.032e5	−9.330e4	−7.886e4	−6.548e4	−2.148e4

Table 7.4: LP values for the estimation of pilot action variables, using summary variables.

discretization, the use of summary variables did not change the results of the experiments.

- There were no meaningful differences between using the different scores: when focussing on the regression model, the model learnt with K2 was better at estimating all variables (experiment 1) but BIC was the best when learning only the pilot actions (experiment 2).

7.4 Trajectory analysis environment

In this section, we review some aspects of the development of a software environment that was implemented to exploit SWIM data. This work was presented at the 2017 ENRI International Workshop on ATM/CNS (EIWAC) workshop [97]. In this phase of the research, our purpose was to explore a line of work based on providing more relevant sources of aeronautical data that could be reused in other experiments or by other researchers. Part of the data obtained with this project was applied to the clustering experiment, which will be explained in Section 7.5.

7.4.1 Overview of the developed environment

As explained in the abstract of the article [97], we designed and implemented a software environment that was able to import real and simulated aircraft trajectory data, in combination with aeronautical information from different sources. User interfaces and functionalities were implemented to facilitate interoperability with machine learning and data mining tools. The intended applicability of the environment included research on ATM and airspace optimisation, test and validation of algorithms related with aviation engineering, operational criteria, or other related fields where the analysis of aircraft trajectories is relevant. The software environment was designed to support the use of SWIM standards, exploiting their advantages in terms of information availability, data robustness, and synergies with advanced computing software tools. The implementation included the import of real data on aircraft trajectories, aeronautical weather reports, airspace information and NOTAM. Figure 7.3 shows the different blocks of the implementation.

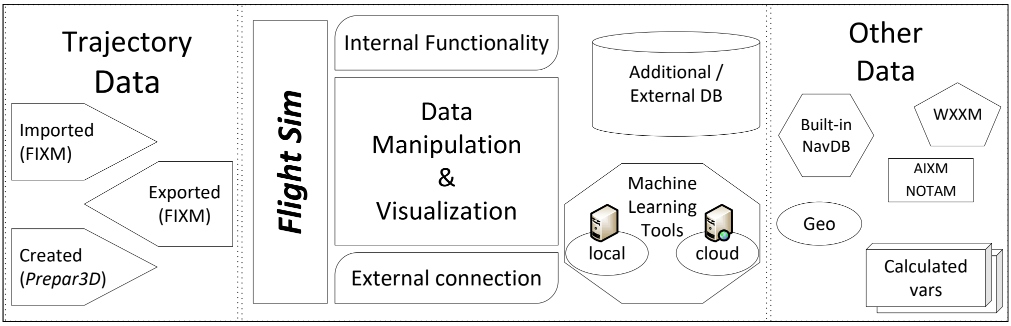


Figure 7.3: Environment Diagram [97]

7.4.2 SWIM data exploitation

Using the *SnowFlake Laminar* platform [143] we were able to access different types of aeronautical information in SWIM standards formats, both XML and JavaScript Object Notation (JSON). The most relevant ones are the following:

- Flight trajectory data in FIXM standard: Retrieval of real-time route trajectories by aerodrome pair, by a specific area of interest, or by the Globally Unique Flight Identifier (GUFI) present inside the Aircraft FPL identifier XML tag.

- NOTAM data in the AIXM standard: Retrieval of Aerodrome and Enroute NOTAM information by FIR or ICAO code.

- Weather data in WXXM standard: Retrieval of Aerodrome METAR, TAF and enroute SIGMET information in real time.

- Aeronautical data in AIXM standard: Retrieval of airspaces, navigational points, waypoints, aerodrome, and regulatory data.

SWIM data for test and development were also provided by ENRI. It should be noted that there are not many SWIM data sources available, so getting the data was an important part of the development.

The application was developed in 2017, but shortly thereafter the services available in *Laminar Data* changed ownership and became unavailable for our purposes. At the time of writing this dissertation, the *Laminar Data Hub Application Programming Interface (API)s* can be accessed on a different website [24] and the functionalities are slightly different.

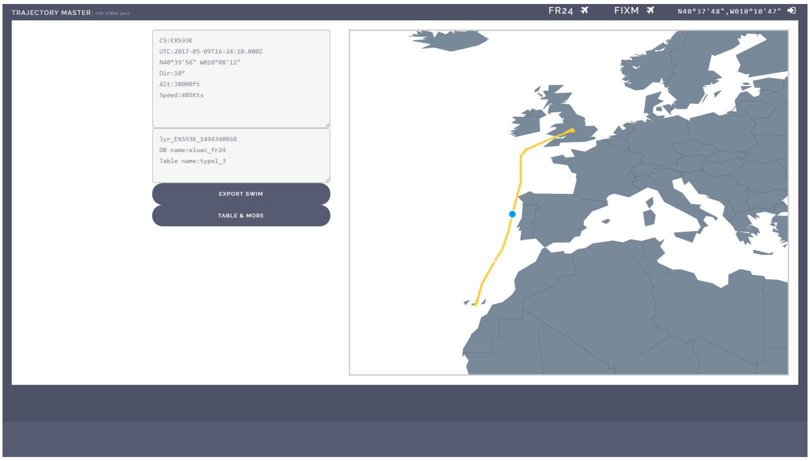


Figure 7.4: User interface after loading one flight.

7.4.3 User interface and data visualisation

In this section, we will provide examples of the functionalities implemented and the user interface that we developed for this purpose. Figure 7.4 shows the basic window displaying one imported flight on the right side of the screen and the basic data on the import on the left side.

It should be noted that the website template used for this application is an updated version of the one used to develop the simulation environment explained in Chapter 6, based on *SkelJS*.

Figure 7.5 shows the user interface implemented to retrieve trajectories that had previously been stored in a SQL database. These data items are parsed keeping all relevant data fields to make them available to machine learning tools (this corresponds to the hexagon in Figure 7.3, which also reflects that interfaces with cloud-based databases were also put in place.

Figures 7.6 and 7.7 have been added to highlight that certain operations of flight trajectories batch loading were also supported by the tool, for instance, getting flights by ICAO aerodrome identifier pairs, i.e., loading flights between two specific airports in the former, or the load of a batch of flights with the same flight number executed on different dates, as can be observed in the latter. Appendix D Section D.2 contains more information about this dataset.

Figure 7.7 Flight history for British Airways flight BA59.

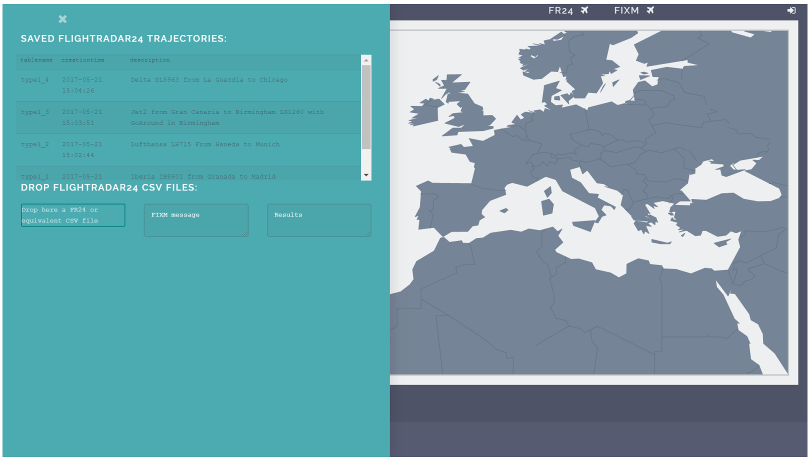


Figure 7.5: User interface to retrieve saved trajectories.

Figure 7.6: Example of flight trajectories batch selected by the designators of origin and destination airports.

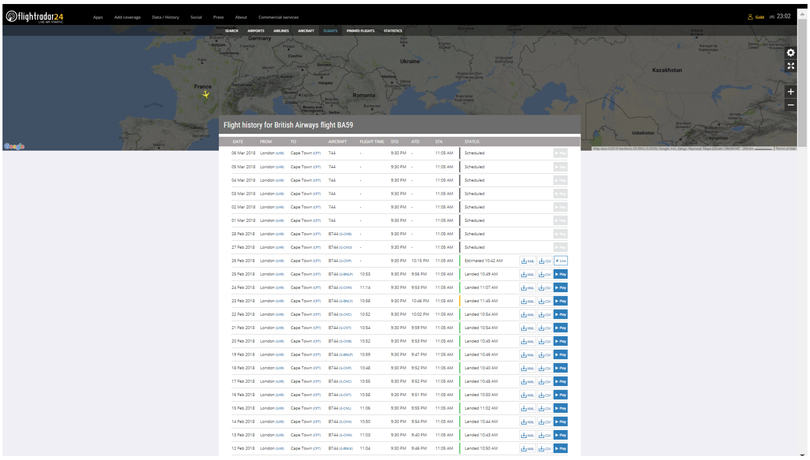


Figure 7.7: Example of flight trajectories batch selected by flight number.

7.4.4 Other functionalities

During the development of the application described in this section, we also implemented other functionalities related to data management. Figure 7.3 shows several components that we will briefly explain:

- Access to built-in navigation databases: We installed a navigation database with a structure similar to the standard AIRAC system (see Section 3.1 and Appendix A) with multiple types of waypoints and georeferenced data related to navigation and airspaces [108], which combined with the JavaScript library to calculate distances and bearings between latitude/-longitude points [105], facilitated the use of other data.

- Cloud Droplets: We used a cloud-based solution [69] to test implementations with improved data accessibility and availability. Reducing the dependency on a physical computer helped us automate data collection, so that we could download real-time information about flights at specific moments.

- Big data: We used solutions available at that time [67] to test the applicability of big data algorithms and technologies to our research, although we did not obtain any relevant results.

7.5 Trajectory Clustering experiment

In this section, we explain the trajectory clustering experiment that was carried out in 2018-19, first in the context of the supervision of a MsC thesis of the student Pedro Méndez [91] and later presented at the 2019 SASWIM workshop [102]. The paper focused on the application of k-means clustering to aircraft trajectory classification.

7.5.1 Mathematical background of the paper

The k-means clustering algorithm minimises the sum of squared Euclidean distances between data points and the mean vector of their assigned cluster. Given a dataset with n elements or observations that need to be partitioned in k distinct, non-overlapping clusters, two conditions are established for these clusters [102]:

$$C_1 \cup C_2 \cup ... \cup C_k = \{1, ..., n\}$$

meaning (7.5.1), that each observed element belongs to a cluster.

$$C_k \cap C_{k'} = \emptyset$$

for all $k \neq k'$, meaning that the clusters are non-overlapping.

A measure $W(C_k)$ is defined to quantify the difference between the observations assigned to the k-th cluster. Therefore, the principle behind the clustering strategy is as follows:

$$\underset{C_1,...,C_k}{\text{minimize}} \left\{ \sum_{k=1}^{K} W(C_k) \right\}$$

This means that the sum of the differences between the observations within each cluster is minimised. In k-means clustering it is assumed that the initial observations are vectors x_i of numerical values $x_1 = (x_{i1}, \dots, x_{ip})$. Then, the function to be minimised is the mean of the squared Euclidean distances between the observations assigned to each cluster and the mean vector inside each cluster.

$$W(C_k) = \frac{1}{\mid C_k \mid} \left\{ \sum_{i \in C_k} \sum_{j=1}^{p} (x_{ij} - m_{kj})^2 \right\},$$

where $m_k = (m_{k1}, \dots, m_{kp})$ is the mean vector of the observations assigned to the cluster k. Through an iterative process, the k-means algorithm minimises the sum of these distances until the value of the equation stabilises.

The process starts with an arbitrary assignation of individuals to clusters, and then repeat two steps until there are no changes: compute the mean values in each cluster and assign each individual to the cluster minimising the distance to its mean.

This approach supports route classification because it involves preprocessing trajectory coordinates and flight plan data to obtain additional variables that support unsupervised trajectory classification, which was achieved in a computationally efficient way, especially because the algorithm provides a way to substantially reduce the calculations related to geospatial data measurements, especially distance calculations.

Figure 7.8 shows an example of a FPL message that indicates the SID procedure name (BLN2C), the code of the waypoint that defines the end of the procedure (BLN) and the name of the airway where the departure procedure ends (UN865). This is normally the amount of data that is published on a commercial aircraft trajectory, and with these data it would be challenging to deduce the procedure from the raw trajectory downloaded in FIXM. Furthermore, in many cases, this information was not published, so it is necessary to design a trajectory classification system that does not take into account the textual information of the route if the flow of trajectories is to be investigated.

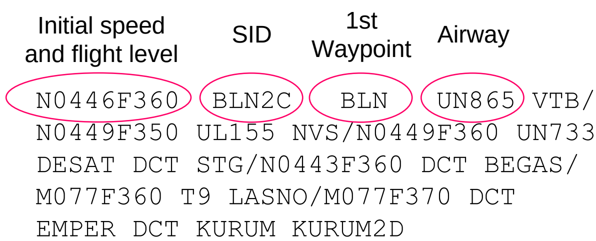


Figure 7.8: Example route text of a flight plan message.

7.5.2 Overview of the results and applicability to this research

The purpose of the experiment was to classify a dataset of approximately 2500 trajectories of commercial aircraft departing from Malaga airport according to their instrumental departure procedure. We had two objectives: On the one hand, we intended to classify each trajectory according to the end point of the procedure because this is normally the most important information for departure flow control. In addition, we tried to deduce the intermediate crossing points of the procedure from the trajectory. The analysis was performed to reduce the dependency on textual information about the route, mainly by clustering the sequences of coordinate points.

The results according to the first objective are summarised in Table 7.5, which shows the outcome of applying k-means clustering with k=8. The paper [102] also includes a discussion of the different results depending on the value of k. It should be mentioned that no specific expert knowledge was required to achieve promising results in trajectory classification and the results we obtained with this methodology offered an efficient way to classify trajectories according to their SID. In this case, the unsupervised algorithm is helpful to detect the flown SID just from a few geographic point samples, with very high computation optimisation. It is recognised that some classification errors will occur, for instance, flights with SID PIMOS will be classified within the same cluster as those of SID BLN, which is normal because they are both very similar. We are aware of such limitations of the clustering approach, and in case we may use this methodology again in the future, we should resort to additional techniques to obtain more reliable results.

Table 7.5: k=8 clustering results compared with SID points.

	1	2	3	4	5	6	7	8
BLN	395	2	0	71	1873	2	0	6
GALTO	0	0	0	0	1	0	1	0
MAR	0	0	0	0	0	0	2	0
NESDA	0	0	0	0	0	23	0	0
PEPAS	0	44	0	0	0	217	0	0
PIMOS	1	0	0	0	100	0	0	0
ROLAS	0	0	0	0	0	151	0	0
SVL	0	0	36	0	72	0	7	0
TARIK	0	0	0	0	0	3	0	0
ULPEP	0	0	0	0	0	25	0	0
VIBAS	0	1	0	0	5	0	0	0

Figure 7.9 shows a map representation of the classification with the 2500 trajectories, classified according to their route using an unsupervised method that did not require expert knowledge and with fairly accurate results. More details about the dataset are provided in Appendix D.

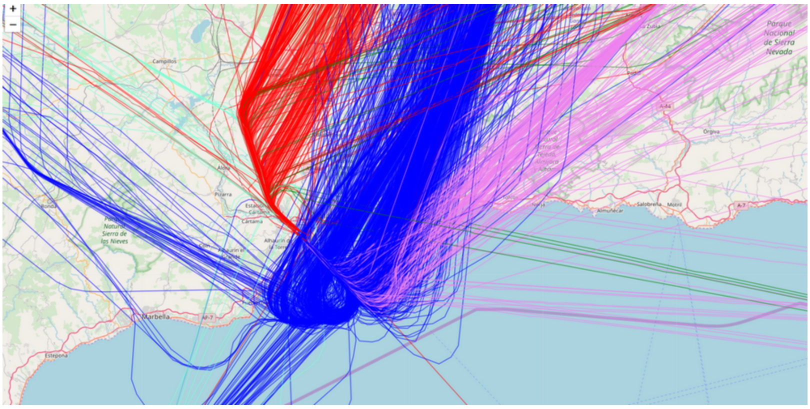


Figure 7.9: Graphical representation of the clustering results applied to group trajectories by flight procedure.

Concerning the second objective, what we tried to achieve was to deduce the accuracy of the flown trajectory compared to the published procedure using k-means clustering. Given the limitations of the sampling rate in the dataset, the error in the distance calculation prevented obtaining a reliable measurement, although we considered that the results could be improved by applying interpolation. However, we did not continue this approach to avoid diverting attention from the thesis objectives. Figure 7.10 shows the following:

- The diagram on the left of the figure is the published procedure.
- The red-lined path of the figure on the right is the trajectory representation from the aeronautical database.
- The green lined path of the figure on the right is the deduced trajectory for a specific flight.

As explained, the results that we achieved were enough to determine the procedure with good accuracy, but not to assess the precision of the flight path, therefore we decided not to use them for the SA estimation.

We resorted to this approach because at that point in the investigation we were looking for alternatives to analyse large amounts of data and apply the trajectory analysis to the SA calculation. Although the results are promising and in line with other research consulted [5, 11, 35, 56, 84], we decided not to continue with this approach because, as will be explained in Chapter 8, we have achieved better results with an approach based on a smaller set of variables.

However, the applicability of k-means clustering is still relevant to provide classification tools, and can be used to produce intermediate variables and

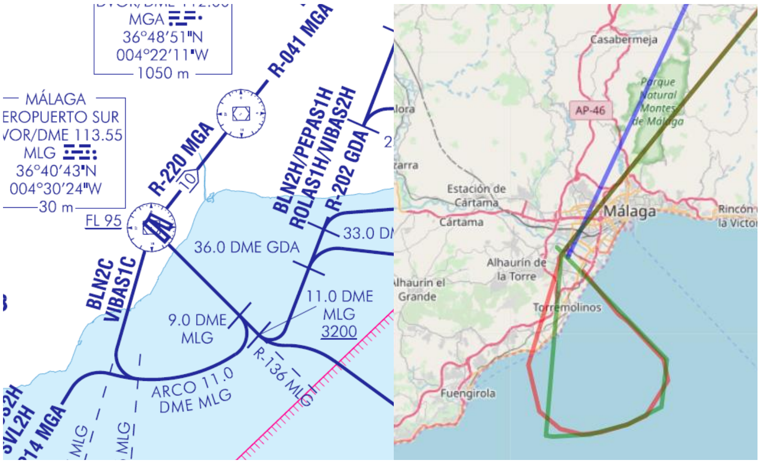


Figure 7.10: Comparison of published SID procedures of Malaga airport vs. deduced points using clustering analysis on the dataset.

potentially feed the DBN, but in our article [102] we already identified the need to perform some kind of preprocessing to improve the accuracy of the clustering results.

7.6 PBN experiment

Following the activities carried out in 2018 and 2019, there was a pause in the research, as efforts were devoted to other tasks, including progress in the programming of EFB applications that are not applicable to this thesis. However, we continued to consider appropriate approaches to measure SA, taking into account that the flights for which the initial simulator was designed are becoming less common. After a conversation in 2021 with an active pilot who had recently received specific training for PBN procedures, our attention was caught to learn about the high degree of automation of these operations. In 2022 we devoted the activities to get familiar with PBN flight procedures, receiving specific training provided by Eurocontrol [153].

7.6.1 PBN relationship with BADA

The concept of PBN, already introduced in Section 2.3, is very complex with other concepts that we have studied in previous years, such as BADA which is an initiative of Eurocontrol to provide aviation stakeholders with large amounts of performance data that can be used by data scientists and that we also analysed [44]. While BADA and PBN serve different primary purposes, they are closely related in supporting performance-driven air navigation. One one hand, BADA provides aircraft performance models, offering accurate data on various aircraft characteristics, such as fuel consumption, climb and descent rates, and speed profiles of many aircraft models. This data helps to predict and manage aircraft trajectories for air traffic controllers and decision support systems, that is the reason why at some point of the research we studied the link with trajectory management and PBN.

In 2018 we accessed the BADA database and made some test calculations based on aircraft performance data that could have a relationship with SA calculation. Although not directly applicable to any specific aspect of the SA model, the activity supported the PBN experiment.

7.6.2 PBN relationship with trajectory analysis

From a perspective focused on trajectory analysis, PBN provides a specification of the navigation performance required of aircraft to fly particular airspace routes, highlighting the required accuracy, integrity, and continuity. Additionally, deeper into the relationship between advanced trajectory management and human factors related to PBN, we found it relevant to design an experiment that could help us complement the SA estimation carried out in previous activities, while enriching the SA model with a more complex approach to automation.

The fly-over and fly-by turn procedures were introduced in Section 2.3, being the latter more generally used in PBN modern navigation. In our paper [99] we analyse the basic characteristics of PBN procedural turns and explain that the pilot is unable to mentally perform the calculations required to maintain the required lateral precision of the aircraft during navigation. Therefore, the use of computation and automation is more necessary than in previous navigation approaches, and thus we redesigned the simulator, as explained in Chapter 6. We used as an example a fly-by turn, illustrated in Figure 7.11.

The outcome of the paper [99] showed room for improvement in terms of the accuracy of the SA estimation and we decided to carry out a final experiment, which is explained in Chapter 8.

This was explained in our paper presented during SASWIM 2023 [99], where we provided an example with the focus on the parameters necessary to perform a fly-by turn, which is normally one of the most significant novelties of PBN for the pilots who start flying these procedures because they cannot cal-

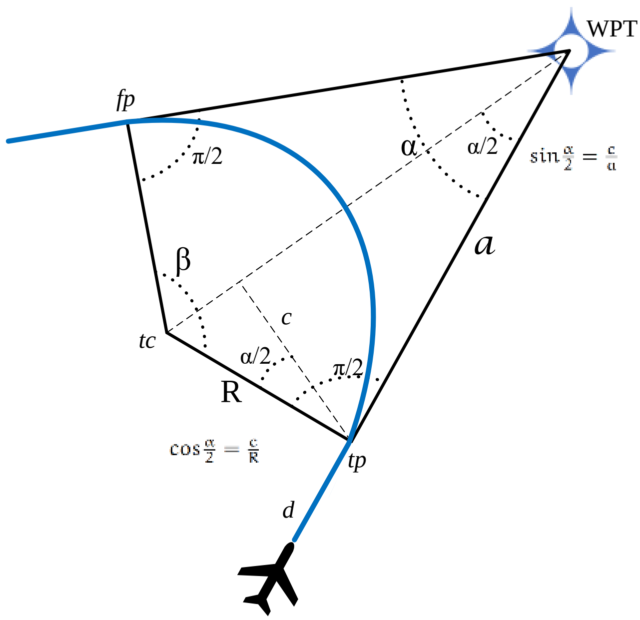


Figure 7.11: Analysis of a fly-by turn to calculate the turn anticipation a [99].

culate the turn anticipation mentally with the precision required by RNP and need to rely on computers and automation. In conventional flight procedures, the turn anticipation is the parameter that defines the moment when the pilot starts a turn, with respect to a route parameter, normally the next waypoint, and is generally easy to calculate as a function of the aircraft speed.

As can be observed in Figure 7.11, the turn anticipation a of a fly-by requires a more complex calculation to determine it:

- *tp*: aircraft turning point, where the turn begins.
- *d*: distance from the aircraft to the turning point. This information will be provided to the pilot in the user interface.
- *R*: turn radius, calculated with the following formula and approximation for mental estimation by the pilot, $R = \frac{V^2}{g \tan\theta} \approx \frac{[V_{NM/min}]^2}{9}$, where θ=25° is the aircraft bank selected for our simulation. V is the speed of the aircraft (dimensionless) and $V_{NM/min}$ is the speed in Nautical Mile (NM) per minute.
- β: turn angle.
- α: angle between the leg courses, related to β as $\alpha = 180 - \beta$.

- *a*: turn anticipation $a = \frac{R}{\tan\frac{\alpha}{2}}$, deduced from the triangles shown in Figure 7.11, where $\sin\frac{\alpha}{2} = \frac{c}{a}$ and $\cos\frac{\alpha}{2} = \frac{c}{R}$.

In the paper [99] we extracted the following considerations that were used for the design of the third experiment user interface, which will be explained in Section 7.6:

- The turn anticipation *a* is especially relevant for the experiment because it indicates to the pilot when the fly-by turn needs to start. The calculations show that it is not feasible for the pilot to mentally calculate *a*. We acknowledge this as a novelty aspect of fly-by points, because when flying other types of procedures, the turning reference to the pilot was normally to overfly a reference or to start the turn based on a previously calculated turn anticipation.

- It is important to note that the calculated value of anticipation depends proportionally on the speed of the aircraft and that the aircraft speed depends on the wind speed, which has not been included in the calculations. The turn should be flown with a constant radius. This mainly depends on aircraft speed, bank angle, and wind. In general, there is no instrument in the aircraft to indicate the correctness of the turn radius, apart from the moving map, which becomes a challenge for the pilot who is not using automation.

- Consequently, what we provide in the user interface is the distance d to the turning point *tp*, and the turn anticipation a is provided for information, but we do not expect it to be the main reference to start the turn.

Of course, the pilot can always check the distance to any waypoint and decide which ones of the information sources available will be consulted to start the turn, and this is our objective with the experiment when we collect the interactions with the user interface and distance you to the turning point which is specially collected as a variable of the dataset, to be contrasted with the control actions.

7.6.3 Expert knowledge applied to the experiment

For this experiment, we also included some variables that contain post-processing of data, like integration, differentiation, and correlation of accumulated differences, with the aim of adding expert knowledge to the already present variables that record the compliance of the actual track with the desired path. Figure 7.12 shows a plot of several variables collected from a flight of the dataset, where it is possible to identify situations where pilot errors or deviations (highlighted in red) occur mainly due to early or late turns and are also associated with excessive differences between the route course. Some tags indicate expert observations that may be added in the future, in case of adopting a supervised training approach.

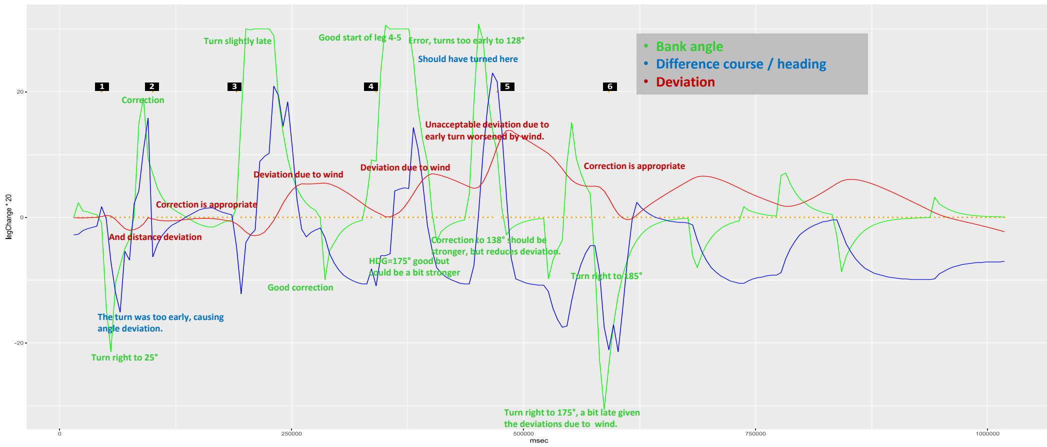


Figure 7.12: Representation of expert knowledge added to a flight of the dataset [99].

Based on these indications from expert knowledge, we also designed flights for the test dataset which will be presented in the next chapter in the framework of the last SA estimation experiment.

8 SITUATION AWARENESS ESTIMATION

We went through a lengthy process to create the simulation environment and its associated configurations that have enabled us to perform the different experiments with acceptable realism, collect multiple variables related to human factors and data of different natures, as explained in Chapter 6. The discretization, regression and clustering experiments explained in Chapter 7 were useful to become familiar with the data and apply the basic machine learning methodologies.

To conclude this research, we decided to carry out a final experiment based on a PBN flight using a similar setup to the one used for the paper presented to the SASWIM 2023 workshop [99].

This chapter is dedicated to explaining with detail the criteria used to select variables in different experiments, focusing on the last one, where we selected a more reduced set of variables with the expectation of getting a better idea of the most significant ones. A model to estimate the pilot's SA taking into account the actions and how he/she reacts to the environment is proposed which is an auto-regressive hidden Markov model [20, 95] with asymmetry in the dependence of the variables [121] and combining discrete and continuous variables.

We have reduced the experiment to the SA related to the trajectory (horizontal SA), measuring only the variables related to it. But we could consider other types of SA as the vertical SA related to aircraft altitude. Even, we could have several types of SA measured at the same time, with some assumptions about the probabilistic relationships among them: for example, it seems reasonable to assume that the different types of SA are not independent.

8.1 Description of the mathematical model

The model considers a set of variables $\mathbf{X}_t$ measured in different instants during a flight. Apart from them, there is a hidden variable S_t with is the SA of the real pilot with two possible values: *Positive* and *Negative*. The set of measured variables $\mathbf{X}_t$ is divided into two subsets: $\mathbf{X}_t = \mathbf{A}_t \cup \mathbf{O}_t$, where $\mathbf{A}_t$ represents the variables measuring the pilot actions (for example, the time from the last check of a given parameter and $\mathbf{O_t}$ contains all the other variables that are observed, for example, the horizontal deviation from the given route. The main assumptions of the model are as follows:

- The variable S_t behaves as a homogeneous Markov chain: the probabilities of the instant S_t depend on the value of the same variable in the previous instant S_{t-1}. It is assumed that there is an inertia and if the pilot SA is positive or negative in one instant, then it has a tendency to be in the same state in the next instant. So two parameters are necessary:

  $$P(S_t = +|S_{t-1} = +) = \alpha, \ P(S_t = -|S_{t-1} = -) = \beta,$$

  where α, β are two values in $[0, 1]$ and close to 1. The probabilities of changing the state are:

  $$P(S_t = +|S_{t-1} = -) = 1 - \beta, \ P(S_t = -|S_{t-1} = +) = 1 - \alpha.$$

  In our experiments, we have used the values $\alpha = 0.99$ and $\beta = 0.98$, as we think that there is more probability of correcting a deficient SA than of worsening a correct SA.

- The variables in $\mathbf{X_t}$ are conditionally independent given $\mathbf{X_{t-1}}$ and S_t, i.e. the conditional probability of the join variable $\mathbf{X_t}$ is the product of all the conditional probabilities of the individual variables $Y \in \mathbf{X_t}$.

- Each variable in $\mathbf{O_t}$ depends only on the variables in $\mathbf{X_t}$ in the previous state, i.e. it depends on the values of the actions of the pilot and the observed variables in the previous state. The dependence will be homogeneous, i.e. will not depend on the variable in the previous state. They do not depend on the state of the hidden variable S_t. The conditional probability $P(\mathbf{O_t}|\mathbf{X_{t-1}})$ is not estimated as it will be proved to be irrelevant for the online computation of S_t given all the observations.

- Each variable Y in $\mathbf{A_t}$ will depend of the pilot SA, S_t, and of the variables $\mathbf{X_{t-1}}$ in previous step. The dependence is asymmetric depending on S_t:
  - If the SA is positive, then each variable Y in $\mathbf{A_t}$ will potentially depend on all the variables $\mathbf{X_{t-1}}$. The dependence will be different when Y is discrete and when Y is continuous. In both cases, the variables in $\mathbf{t-1}$ we have defined have always numerical values, so we can apply numerical operations to the values of these variables. In the case of a continuous variable we have considered that the value of Y is obtained from variables in $\mathbf{X_{t-1}}$ by linear regression:

$$Y = \alpha_0 + \sum_{X \in \mathbf{X_{t-1}}} \alpha_X X + \epsilon,$$

where ϵ is a Gaussian random variable with mean 0.

In the case of Y being a discrete variable, we consider that the dependence is modelled by multinomial logistic regression. If Y takes the values $\{1, \ldots, k\}$, then it is assumed that

$$P(Y = j | \mathbf{X_{t-1}}) = \frac{e^{\alpha_{0,j} + \sum_{X \in \mathbf{X_{t-1}}} \alpha_{X,j} X}}{1 + \sum_{i=1}^{k-1} e^{\alpha_{0,i} + \sum_{X \in \mathbf{X_{t-1}}} \alpha_{X,i} X}}$$

for $j = 1, \ldots, k-1$, while,

$$P(Y = k | \mathbf{X_{t-1}}) = \frac{1}{1 + \sum_{i=1}^{k-1} e^{\alpha_{0,i} + \sum_{X \in \mathbf{X_{t-1}}} \alpha_{X,i} X}},$$

where $\alpha_{0,i}, \alpha_{X,i}$ are real valued parameters.

In the experiments, we have estimated the parameters of this model using `scikit-learn` package for Python [117] and a set of flights considered to be correct as data (the pilot has a good SA in every moment). We always have added an l1 penalty for the estimation of the parameters. With this penalty, instead of computing the parameters maximizing the logarithm of the likelihood of the data, a penalty of the sum of the absolute values of the parameters is added to this log-likelihood: the log of the likelihood of the data minus the sum of the absolute values of the alpha parameters is maximized. The effect of this penalty is that the models are more sparse and some of the parameters are 0, giving rise to a variable selection (variables with non-zero parameters).

– If the SA is negative, the procedure is completely analogous to the former case, but with one important difference: each variable $Y \in \mathbf{A_t}$ will depend only on the same variable in the previous instant Y', i.e. $P(Y|\mathbf{X_t}) = P(Y|Y')$. The intuition behind this is as follows: for example, the course selected by the pilot in a given instant will always depend on the course selected in the previous instant (it will have a tendency to be the same with some variations), but if the SA is negative, then it will not react to the other environment variables and therefore will be independent on them. The estimation procedures will be exactly the same as when the SA is positive but considering only $\{Y'\}$ instead of $\mathbf{X_{t-1}}$.

The general structure of the temporal Bayesian network representing the relationships is depicted in Figure 8.1.

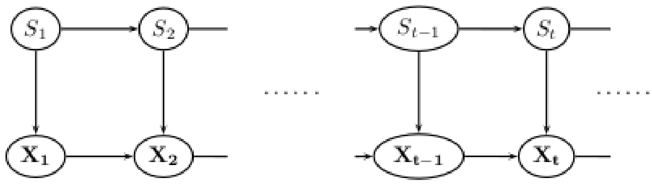


Figure 8.1: The structure of the dynamic Bayesian network.

The computation we want to carry out is $P(S_t|\mathbf{X_1}, \ldots, \mathbf{X_t})$ as an online estimation of the probability of the pilot's SA given the observed variables. For this aim, we have to take into account the following,

$$P(S_t|\mathbf{X_1}, \ldots, \mathbf{X_t}) \propto P(S_t, \mathbf{X_1}, \ldots, \mathbf{X_t}),$$

being the proportionality constant independent of the concrete value of S_t. We also have:

$$\begin{aligned} P(S_t, \mathbf{X_1}, \ldots, \mathbf{X_t}) = \sum_{x=+,-} P(S_t, S_{t-1} = x, \mathbf{X_1}, \ldots, \mathbf{X_t}) = \\ \sum_{x=+,-} P(S_{t-1} = x, \mathbf{X_1}, \ldots, \mathbf{X_{t-1}}).P(S_t, \mathbf{X_t}|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}, S_{t-1}) = \\ \sum_{x=+,-} P(S_{t-1} = x, \mathbf{X_1}, \ldots, \mathbf{X_{t-1}}).P(S_t, \mathbf{X_t}|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}) \propto \\ \sum_{x=+,-} P(S_{t-1} = x|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}).P(S_t, \mathbf{X_t}|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}). \end{aligned}$$

Again, in the last proportionality, the constant is $P(\mathbf{X_1}, \ldots, \mathbf{X_{t-1}})$, which is independent of the value of S_t and the value $S_{t-1} = x$. We continue with last expression:

$$\begin{aligned} \sum_{x=+,-} P(S_{t-1} = x|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}).P(S_t, \mathbf{X_t}|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}, S_{t-1} = x) = \\ \sum_{x=+,-} P(S_{t-1} = x|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}).P(S_t|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}, S_{t-1} = x). \\ P(\mathbf{X_t}|\mathbf{X_1}, \ldots, \mathbf{X_{t-1}}, S_{t-1} = x, S_t). \end{aligned}$$

Now, we have that $P(S_t|\mathbf{X_1},\ldots,\mathbf{X_{t-1}},S_{t-1}=x)=P(S_t|S_{t-1}=x)$ and $P(\mathbf{X_t}|\mathbf{X_1},\ldots,\mathbf{X_{t-1}},S_{t-1}=x,S_t)=P(\mathbf{X_t}|\mathbf{X_{t-1}},S_t)$ given the independence relationships assumed in our model (see Figure 8.1). So,

$$\sum_{x=+,-} P(S_{t-1}=x|\mathbf{X_1},\ldots,\mathbf{X_{t-1}}).P(S_t|\mathbf{X_1},\ldots,\mathbf{X_{t-1}},S_{t-1}=x).$$

$$P(\mathbf{X_t}|\mathbf{X_1},\ldots,\mathbf{X_{t-1}},S_{t-1}=x,S_t)=$$

$$P(\mathbf{X_t}|\mathbf{X_{t-1}},S_t)\sum_{x=+,-} P(S_{t-1}=x|\mathbf{X_1},\ldots,\mathbf{X_{t-1}}).P(S_t|S_{t-1}=x).$$

Now, we have that $P(\mathbf{X_t}|\mathbf{X_{t-1}},S_t)=P(\mathbf{A_t}|\mathbf{X_{t-1}},S_t).P(\mathbf{O_t}|\mathbf{X_{t-1}},S_t)$, given the conditional independence assumptions of variables in $\mathbf{X_t}$, and $P(\mathbf{O_t}|\mathbf{X_{t-1}},S_t)=P(\mathbf{O_t}|\mathbf{X_{t-1}})$ as the observed variables do not depend on S_t given $\mathbf{X_{t-1}}$. As this expression does not depend on S_t,S_{t-1}, finally

$$P(S_t|\mathbf{X_1},\ldots,\mathbf{X_t})\propto P(\mathbf{A_t}|\mathbf{X_{t-1}},S_t)\sum_{x=+,-} P(S_{t-1}=x|\mathbf{X_1},\ldots,\mathbf{X_{t-1}}).P(S_t|S_{t-1}=x).$$

And this will be the expression used in our computations, as $P(S_{t-1}=x|\mathbf{X_1},\ldots,\mathbf{X_{t-1}})$ is the same amount computed in the previous time, $P(S_t|S_{t-1}=x)$ are the transition probabilities for the hidden variable, and $P(\mathbf{A_t}|\mathbf{X_{t-1}},S_t)=\prod_{Y\in\mathbf{A_t}} P(Y|\mathbf{X_{t-1}},S_t)$ are the probabilities we have estimated from correct flights data. The exact values of the conditional probabilities are computed by normalizing the values of the right side of the above expression, so that the conditional probabilities for the different values of S_t add to one.

The expression has two parts:

$$P(\mathbf{A_t}|\mathbf{X_{t-1}},S_t),$$

the evidential part, and

$$\sum_{x=+,-} P(S_{t-1}=x|\mathbf{X_1},\ldots,\mathbf{X_{t-1}}).P(S_t|S_{t-1}=x),$$

the prior part depending of the SA in previous time step and the changes due to the hidden Markov chain of SA states. We are updating the prior hidden probabilities of a correct/incorrect SA by multiplying these probabilities by $\prod_{Y\in\mathbf{A_t}} P(Y|\mathbf{X_{t-1}},S_t=+)$ and $\prod_{Y\in\mathbf{A_t}} P(Y|\mathbf{X_{t-1}},S_t=-)$, respectively. To the difference of $\log\left(\prod_{Y\in\mathbf{A_t}} P(Y|\mathbf{X_{t-1}},S_t=+)\right)-\log\left(\prod_{Y\in\mathbf{A_t}} P(Y|\mathbf{X_{t-1}},S_t=-)\right)$, will be called the evidential value of the actions. If it is greater than 0, the probability of a good SA will increase, and if it is lower than 0, this probability will decrease. These values are also computed online in our experiments.

We will also compute the individual variable responsible for a decreasing in the probability of a good SA: if for a variable $Y \in \mathbf{A_t}$, we have that $P(Y|\mathbf{X_{t-1}}, S_t = +) > P(Y|\mathbf{X_{t-1}}, S_t = -)$, then the observation of this variable will give rise to an increasing on the probability of a correct SA. However, if $P(Y|\mathbf{X_{t-1}}, S_t = +) < P(Y|\mathbf{X_{t-1}}, S_t = -)$, this produces a decreasing on this probability. So, we can also monitor the variables that are responsible for a low SA: those variables for which,

$$-\frac{P(Y|\mathbf{X_{t-1}}, S_t = +)}{P(Y|\mathbf{X_{t-1}}, S_t = -)} < \alpha, \tag{8.1}$$

where $\alpha < 1$ is a given threshold. In our experiments, we have selected $\alpha = 0.5$. In that case, we have reported $Y \in \mathbf{A_t}$ as a pilot action that does not respond adequately to the environment variables.

8.2 Selection of variables

Throughout our research we have used variables from various sources, both by importing external data and by generating variables through our simulator. In some of our experiments, we have used datasets with a high number of variables, sometimes even more than one hundred. However, the approach adopted for this last experiment has prioritised the reduction of the number of variables, although this has been carried out by integrating a previous processing that sometimes provided variables that are the result of calculations from different sources.

These variables have been selected to focus on the horizontal deviation from the route. In previous experiments, we came to the conclusion that attempting to estimate SA simultaneously to vertical (or altitude) and speed errors would be too complex to validate this algorithm. After all, as explained in previous works [99, 102], the horizontal error is normally the most relevant in terms of ensuring the safety of the flight, so the SA calculation is more relevant. For altitude errors, the pilot generally has more means to check if the aircraft is in a safe condition.

The extension of this approach to other types of SA or even to the study of several types at the same time does not present important conceptual or theoretical challenges, only it makes the process of variable selection and measurement more complex. So, in this first evaluation, we have selected a simple model, which at the same time is the most relevant from our point of view.

It also remains to be considered which are the variables that optimise the algorithm performance. As explained below, the selected variables appear to

Var name	Type
dscrTimeWPTCheckCurrLeg	Action
dscrTimeWPTCheckNxtLeg	Action
dscrTimeNavlogCheck	Action
dscrTimeMapCheck	Action
dscrTimeTrackCheck	Action
dscrTimeMapClick	Action
dscrPBNdeviationIntegrCorr	Action
angdifSCl	Action
angdifHCl	Observation
bank	Observation
dscrPhase	Observation
discrSettingNextHdg	Observation
PBNlegPercent	Observation
PBNLegChange	Observation
PBNdeviation	Observation
PBNleg	Observation

Table 8.1: List of variables selected for the SA experiment DBN.

be sufficient to provide an estimation of SA with reasonable accuracy. For example, this model only takes into account the actions of the pilot. We came to the conclusion that the SA estimation does not really benefit from computing multiple variables based on navigation or aircraft parameters, so only the most relevant have been included in the dataset. The selected $\mathbf{A_t}$ variables are listed in Table 8.1 and explained in the next subsection.

8.2.1 Variables of the experiment

In this subsection, we explain in some detail the 16 variables selected for this last experiment. Table 8.1 shows whether the algorithm considers them Actions A_t or Observations O_t, and then we will divide them according to other criteria. The first group with those that focus on collecting the position of the aircraft with respect to the route, especially with regard to the horizontal attitude, since the altitude is not taken into account. The second group could be considered to include variables that more closely reflect human factors, especially activities related to information management in the cockpit. It should be noted that these two groups are only relevant for the purposes of presentation in this report and have no impact on the computation.

- **PBNleg**: This is the route leg, as defined by the flight procedure. The pilot is expected to know in which leg the aircraft is flying at every instant.
- **PBNlegPercent**: This variable has been created for the experiment and represents the completion percentage of each leg for every sample.
- **PBNLegChange**: This variable acts as a flag to indicate every leg change. It's generated from the changes in *PBNleg*.
- **dscrPhase**: This variable has been created for the experiment, based on the relative position of the aircraft with respect to each leg and its turning points. It has 4 different values, as can be seen in Figure 8.4:
  1. Outbound: After flying a waypoint, when the turn is finished, the aircraft flies to the next waypoint. The attention of the pilot is usually focused on establishing the course to the next waypoint, although there he/she will also check that the outbound trajectory from the last point is correct.
  2. Inbound: The aircraft is approaching to the next waypoint. The pilot does not consider the previous one because the focus is normally shared between maintaining the right trajectory and getting ready to the turn.
  3. Prepare to turn: Now the pilot's attention should focus on monitoring the distance to the next turning point. The deviation from the trajectory does not have to be corrected because it is more important to start the turn in the right moment.
  4. Turning: During the turn, the pilot loses several references about the right deviation from the trajectory, so the map is the most reliable one. The pilot is supposed to just maintain the turn, because the turn radius of the procedure is established by the procedure designers in accordance to aircraft performances, especially the speed. However, external factors like the wind could cause a deviation. In summary, checking the horizontal position on the map is basically the only way to provide awareness about the deviation.
- **PBNdeviation**: This is the most relevant variable regarding the accuracy of the position. After all, the essence of a PBN flight is related to the

pilot's responsibility to maintain a defined maximum horizontal separation from the route. For this simulation, the acceptable threshold is 1 NM. In the user interface, there is a colour code with green for deviations lower than 0.3 NM, yellow until 1 NM, and red when the deviation is higher than 1 NM, which is considered to be unacceptable for a good flight.

- **bank**: This is the angle between the aircraft's vertical axis and the earth's vertical plane, containing the aircraft's longitudinal axis. This angle is a result of the autopilot commands and should be less than 20° in module. Otherwise it gives information that the pilot has ordered a rough correction.

- **angdifHCl**: This angle is a computation of the difference between the closest leg bearing and the aircraft's heading. It gives indication of the accuracy of the aircraft's attitude.

- **angdifSCl**: This angle is a computation of the difference between the closest leg bearing and the heading selected by the pilot. It gives indication of the accuracy of the heading selected by the pilot.

- **discrSettingNextHdg**: This is a binary variable that indicates if the pilot is likely to have a heading setting related to the closest leg or the next leg of the flight. It helps to indicate on which leg the pilot is focusing the attention.

The next group of variables corresponds to discretised values of check times, to obtain a reference of how often the pilot performs a particular check. The simulation environment records the milliseconds since the last check, but it was considered that a discretised value, inversely proportional to the time elapsed since the last check, is more significant for the DBN. Therefore, the values of some of these variables are shown in Figure 8.2 and have the following meaning:

- 4: The last check was performed less than 3 seconds ago.

- 3: The last check was performed between 3 and 20 seconds ago.

- 2: The last check was performed between 20 and 60 seconds ago.

- 1: The last check was performed between 60 and 180 seconds ago.

- 0: The last check was performed more than 180 seconds ago.

It should be noted that, by design of the simulation environment, the indications disappear 3 seconds after they are shown, forcing the pilot to click to see the information again. With this strategy, our aim is to monitor as closely as possible which and when information is more valuable to the pilot.

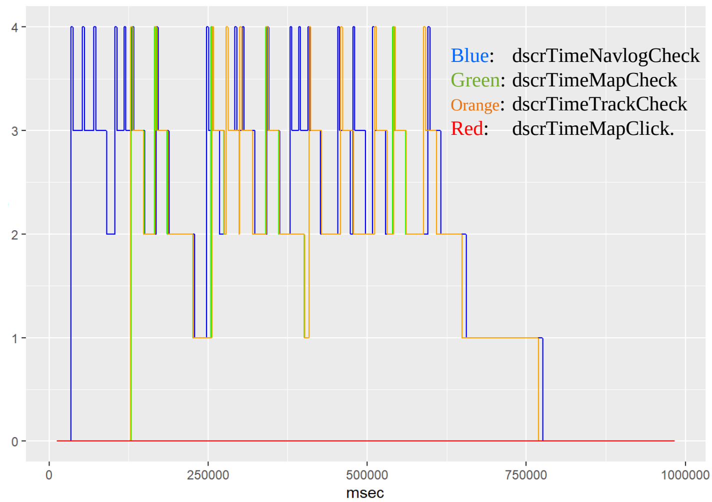


Figure 8.2: Example of one flight where several discrete variables register pilot checks.

- **dscrTimeNavlogCheck**: Time elapsed since the last check of the textual navigation log.
- **dscrTimeMapCheck**: Time elapsed since the last check of the aircraft position on the map.
- **dscrTimeTrackCheck**: Time elapsed since the last check of the aircraft track (i.e. dots showing the path that the aircraft has flown since take-off) in the map.
- **dscrTimeMapClick**: Time elapsed since the last click on a waypoint in the map, to confirm its name.
- **dscrTimeWPTCheckCurrLeg**: Time elapsed since the last check of information related to the current flight leg.
- **dscrTimeWPTCheckNxtLeg**: Time elapsed since the last check of information related to the next flight leg.

These last two variables have been designed to get information about the focus of attention of the pilot, whether it is centred on the current leg or on the next one. It could be very significant whenever an error appears, to know if the pilot's information cues were focused on the right leg.

Concerning the group of variables just described, it could be argued that checking the map provides more information to the pilot, but potentially have a negative impact on the SA. In general, a pilot who only requires textual information and the conventional instruments to fly shows a better knowledge of the route than a pilot who needs to check the position in the map continuously. This statement is in any case arguable, since modern aircraft systems offering moving map representations offer very valuable information to the pilot for the sake of safety. In any case, for the SA calculation of this experiment, the variables related to these checks have not been weighted or manipulated to imply this.

- **dscrPBNdeviationIntegrCorr**: This variable summarises a computation of the integration of the time in which the aircraft has been subject to a deviation with respect to the route. The meaning of its values is the following:
  - 0: The error is small or happened for a very short time.
  - 1: It may take longer to make, but the error is small (< 0.8 NM).
  - 2: The error has already reached 0.8 NM, but its accumulation is not yet excessive.
  - 3: The error has already reached 0.8 NM, and its accumulation is excessive (it does not appear in the figure).

8.2.2 Training and test datasets

For the training dataset, we have performed 27 simulated flights. All of them correspond to the same route, as explained previously. All flights have errors in a certain amount, but the accuracy of horizontal route maintenance is similar to the one found in real flights flown by professional pilots without using autopilots.

Figure 8.4 shows the map horizontal route, where it can be seen that sometimes the pilot makes mistakes that cause a deviation from the route.

Figure 8.5 shows miniature map representations of the 27 flights used for the training dataset. Some of them are almost perfect in terms of the precision of lateral navigation, while others have deviations that can typically occur when pilots have low SA and may deviate from the route. An effort has been made

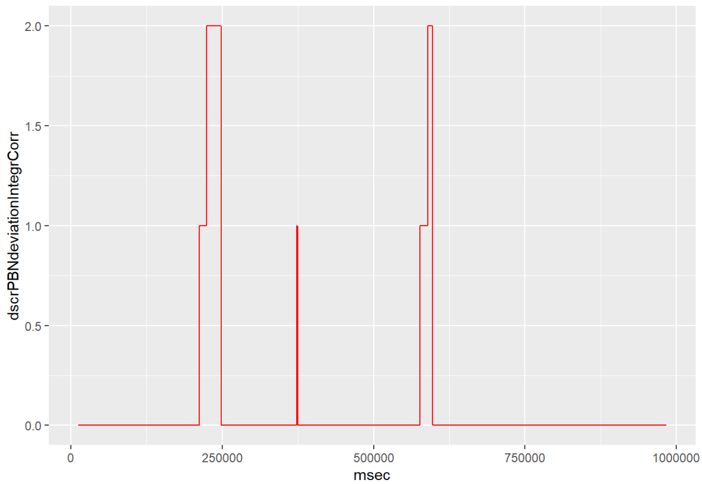


Figure 8.3: Example of the variable **PBNDeviationIntegrCorr**.

to generate simulated flights for this training dataset in realistic conditions and without dangerous situations.

Concerning the test dataset, a total of 6 flights have been generated and used to test the SA calculation. Two of them are good in terms of precision and maintaining a correct SA, and four are erroneous, since the pilot makes mistakes that are translated into unacceptable errors in the precision of the route. In terms of the context of the simulation, the methodology consisted basically in performing the flight with external distractions. More details about the interpretation of the results shown by the test dataset are provided in Section 8.3

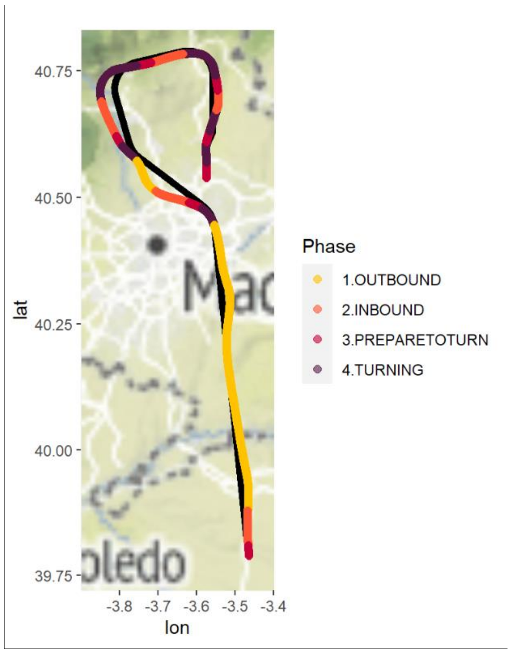


Figure 8.4: Map representation of one training flight with inaccuracies in horizontal position.

Figure 8.5: Map representation of the 27 flights used for the training dataset.

8.3 Results of the SA estimation

8.3.1 Principles of the estimation

The algorithm is based on the model described in Section 8.1 and for the last experiment of this research, we have used the variables explained in Section 8.2. It only computes the SA associated to pilot errors in maintaining the horizontal deviation from the route, not because of the algorithm itself, but due to the selection of variables already explained. This is a positive characteristic because the algorithm is independent of the type of error to compute.

The algorithm has several outcomes, which are enumerated below and will be further explained.

- SA probability.
- Estimation evidence value.
- List of critical variables associated with low SA probability.

Furthermore, we have generated expert knowledge to provide an insight of the precision of the results in the case of the four erroneous flights, especially assigning a SA level to the instants where the pilot makes obvious mistakes, so that the low SA probability and especially the variable that causes it can be checked.

8.3.2 Overview of the two good test flights

We start this explanation reviewing the outcome related to the two correct flights of the test dataset. There are two graphs for each flight: one to show the SA probability and another for the estimation evidence value; these are Figures 8.6 and 8.7. Since the accuracy of the pilot flying these two flights was good, there were no deviations with respect to the planned route and the information checks were timely, according to the navigation needs and with adequate timing, there are no reasons to assume that the pilot had a low SA during any instant of the flight. In fact, the pilot was consciously making an effort to maintain good awareness at all three levels, based on an attitude of maintaining high concentration and making an effort to accurately fly the simulation. This translates into a high probability of SA in all instants of both flights, as shown in Figure 8.6, where we can observe that the probability is clearly above the defined threshold (see Section 8.1).

Figure 8.7 shows a calculated variable that we have named as an estimate evidence value, which does not take into account the inertia that exists on the SA, i.e., it tends to be in the same state from one state to the next, and therefore are more stable, but they indicate when something is being done in a positive or negative way, so can potentially complement the SA probability values if required. However, for the two good flights, they do not contain any relevant information, which is a good sign. We will provide more details about the interpretation of this variable when we analyse the figures of the four erroneous flights.

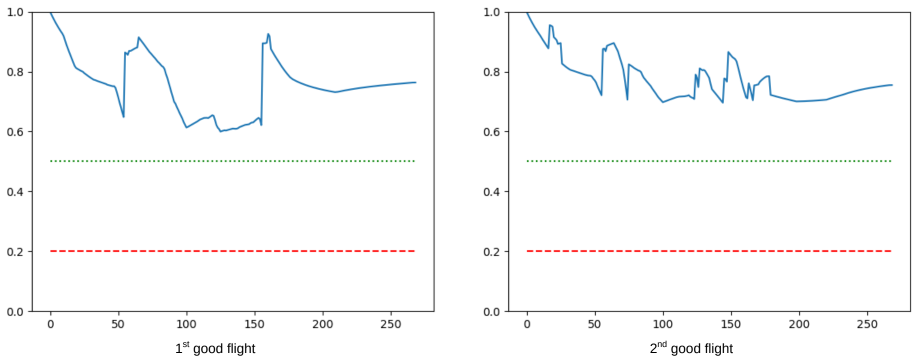


Figure 8.6: SA probability of the two good flights of the test dataset.

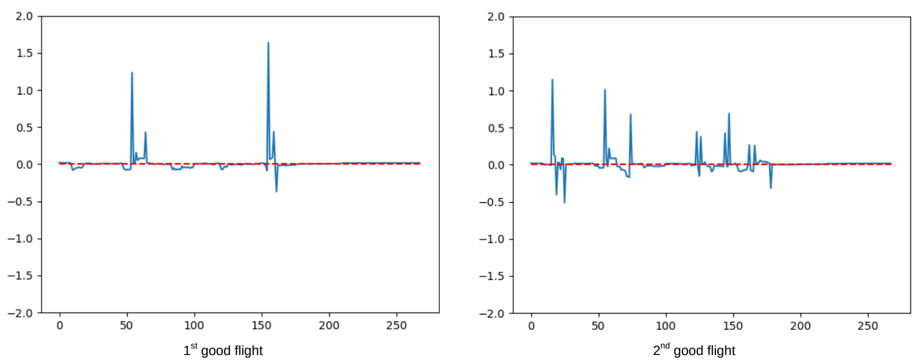


Figure 8.7: Estimation evidence value of the two good flights of the test dataset.

8.3.3 Interpretation of the results achieved for the erroneous test flights

This subsection presents in a graphical and summarised manner the observations and calculations carried out to contrast and validate the results of the SA estimation, including the addition of expert knowledge. As explained previously, the test dataset contains four erroneous flights. These simulations were carried out in an environment where the pilot was distracted by external factors, which although not the same as in a real flight, can be assimilated, for instance, to interruptions of flight calculations to answer ATC requests, low SA of navigation tasks due to high workload related to other mission constraints, or distractions due to crew members having conversations that have little to do with tasks that provide high SA, etc.

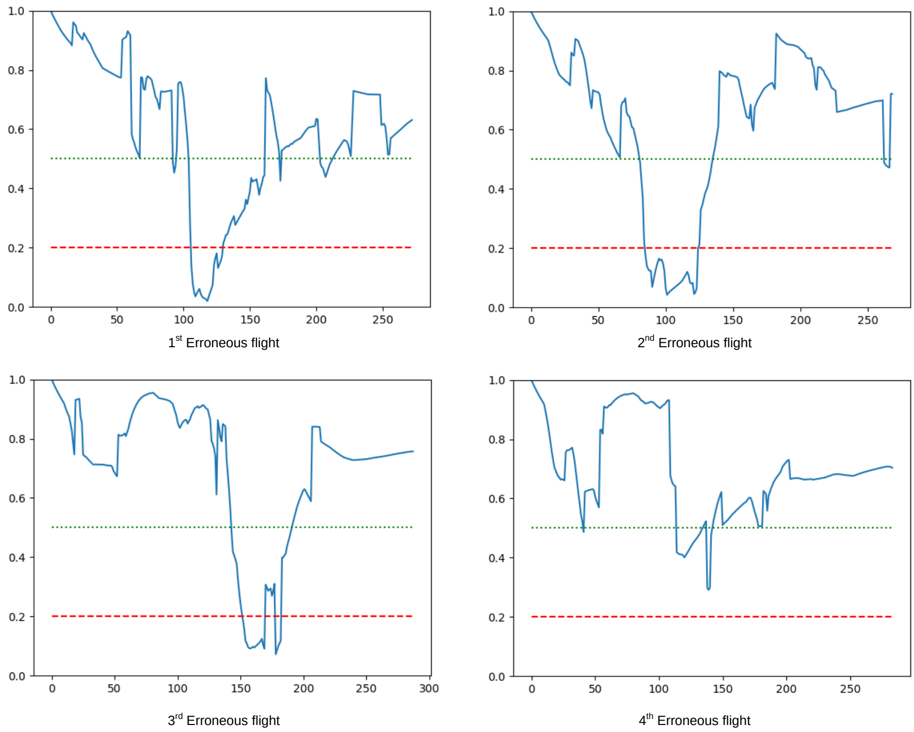


Figure 8.8: SA probability of the four erroneous flights of the test dataset.

These situations that distracted the pilot were not continuous, so they only happened at certain moments of the flight, and we will reason in this subsection, using data from different sources, that our algorithm is accurate detecting low SA instants and identifying the variables that caused the erroneous situation. Figures 8.8 and 8.9, respectively, contain the graphical representation of the SA probability and the estimation evidence values of the four erroneous flights. We can now observe that the SA is far from acceptable on all these flights, but we need to understand when it is acceptable or not, and why.

Figure 8.10 again shows the erroneous flights: in red the PBNdeviation, in blue the number of critical occurrences, and in cyan their criticality at each time slice, not affected by the criticality threshold.

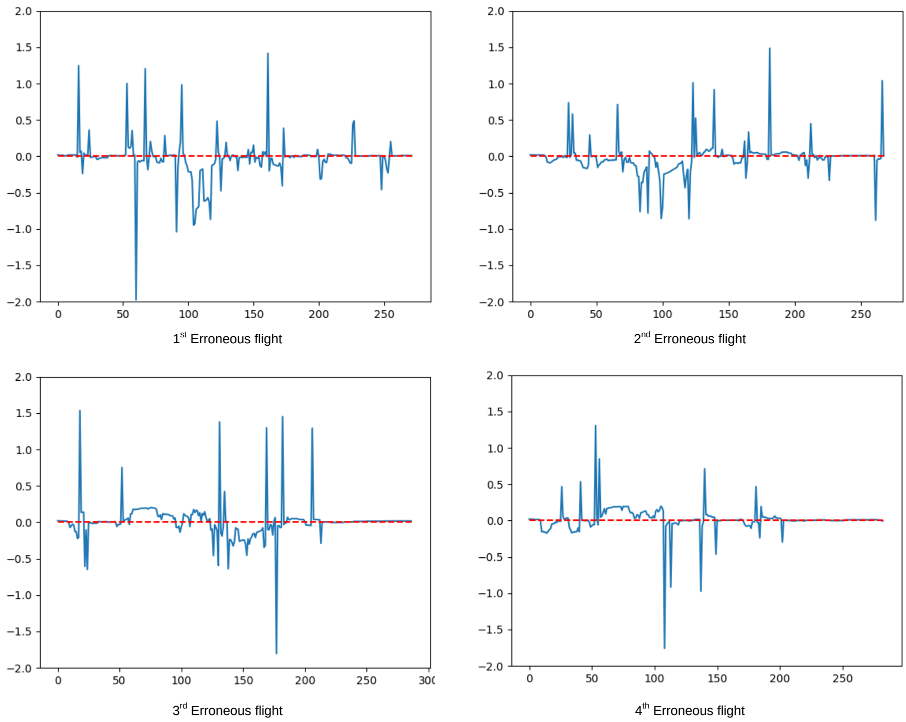


Figure 8.9: Estimation evidence value of the four erroneous flights of the test dataset.

It is important to note that the algorithm is designed to highlight when the actions A_t of the pilot do not respond normally to stimuli based on the observed variables Observations O_t (introduced in Section 8.1), so after performing a correction to the criticality threshold, the appearance of critical occurrences (dark blue) confirms that the low value of SA is due to a low situation awareness of the pilot.

To continue with the assessment of the SA, we generated an additional variable which is not part of the dataset that registers the most probable SA level responsible for the low awareness of the pilot. This is performed incorporating expert knowledge and the Python source code is provided in the Github repository [60] explained in the Appendix E.

Figure 8.11 shows in green and for the four erroneous flights, the SA level considered to be the main cause of the low SA in green. This assessment on the SA level is still not well supported and has spurious values on all flights, but it should be noted that during the times when there is a clear diversion from the route, the assessment is maintained in Level 3 (projection of the near future), which is consistent with our expectations.

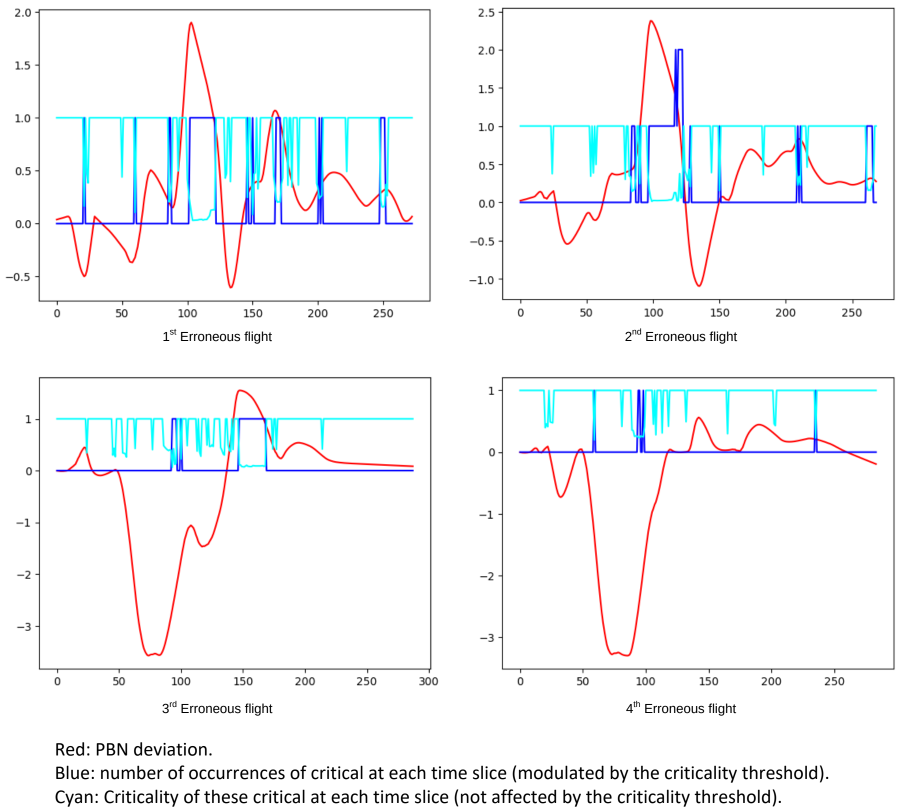


Figure 8.10: Erroneous flights and their criticality levels.

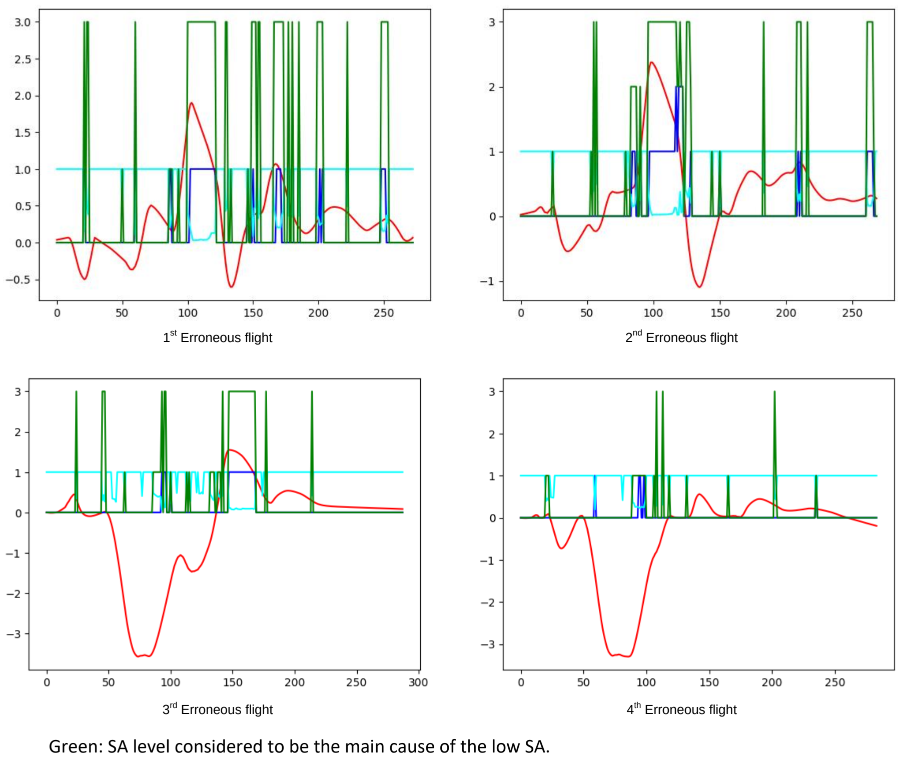


Figure 8.11: Erroneous flights with SA level according to the model.

Expert knowledge is based on checking which action variable is causing the criticality. At the current stage of expert assessment, only the following variables are considered: dscrTimeNavlogCheck, dscrPBNdeviationIntegrCorr, dscrTimeTrackCheck, dscrTimeWPTCheckCurrLeg and dscrTimeWPTCheckNxtLeg. For each one of them., a weight is assigned to a SA level to be considered a main or a contributor factor. That is, depending on the action that the pilot is performing, we consider that it variably affects the pilot's perception, comprehension, or projection. This assignment is available in the code uploaded to the mentioned Github repository.

flight	time	var	type	p goo	p bad
flight 4	246	dscrPBNdeviationIntegrCorr	d	0.02069	0.16049
flight 4	247	dscrPBNdeviationIntegrCorr	d	0.02729	0.16049
flight 4	248	dscrPBNdeviationIntegrCorr	d	0.03396	0.20180
flight 5	22	dscrPBNdeviationIntegrCorr	d	0.08788	0.20180
flight 5	44	dscrTimeMapCheck	d	0.19370	0.48942
flight 5	45	dscrTimeMapCheck	d	0.23722	0.48942
flight 5	55	dscrTimeNavlogCheck	d	0.04871	0.10346
flight 5	62	dscrPBNdeviationIntegrCorr	d	0.07461	0.16049
flight 5	79	dscrTimeMapCheck	d	0.22231	0.48942
flight 5	147	dscrPBNdeviationIntegrCorr	d	0.05013	0.16049

Table 8.2: Excerpt rows from the critical values file.

Table 8.2 contains an excerpt with several rows of the critical values file, which is available in the Github repository. These rows indicate the variables that are considered responsible for the SA reductions. The variable name is identified and two numerical values are calculated, with the quotient of the first value between the second being what indicates the intensity (the closer to 0 the more intense) with which the anomaly is occurring, as indicated in Equation 8.1.

In Figure 8.12 we observe several variables. The first row of graphs indicates the value of the SA estimation, which in some instants falls below the acceptable threshold, indicating that the error in the flight was due to a low awareness of the pilot. The following row of graphs combines a representation of the route deviation (in red), the time slices where we find a concentration of critical findings (in dark blue), and their corresponding criticality level (in cyan). The most relevant aspect is that the low SA corresponds with unacceptable route deviations. With these parameters alone we could not really discern if the route deviation was really caused by a low SA. That is why we needed to resort to a parameter that we named *criticality threshold*.

Figure 8.12 has been included to provide an overview of all the graphs that we have described for the four erroneous flights altogether, now with an additional row where the reader can also see the map view of the route and observe the deviations that the flight suffered in these erroneous flights, which were mainly due to a lack of concentration of the pilot, who either forgot to start the turn at the right time or made a mistake when starting the turn too early. These are errors that can occur with some frequency to real pilots who fly an instrumental navigation manually.

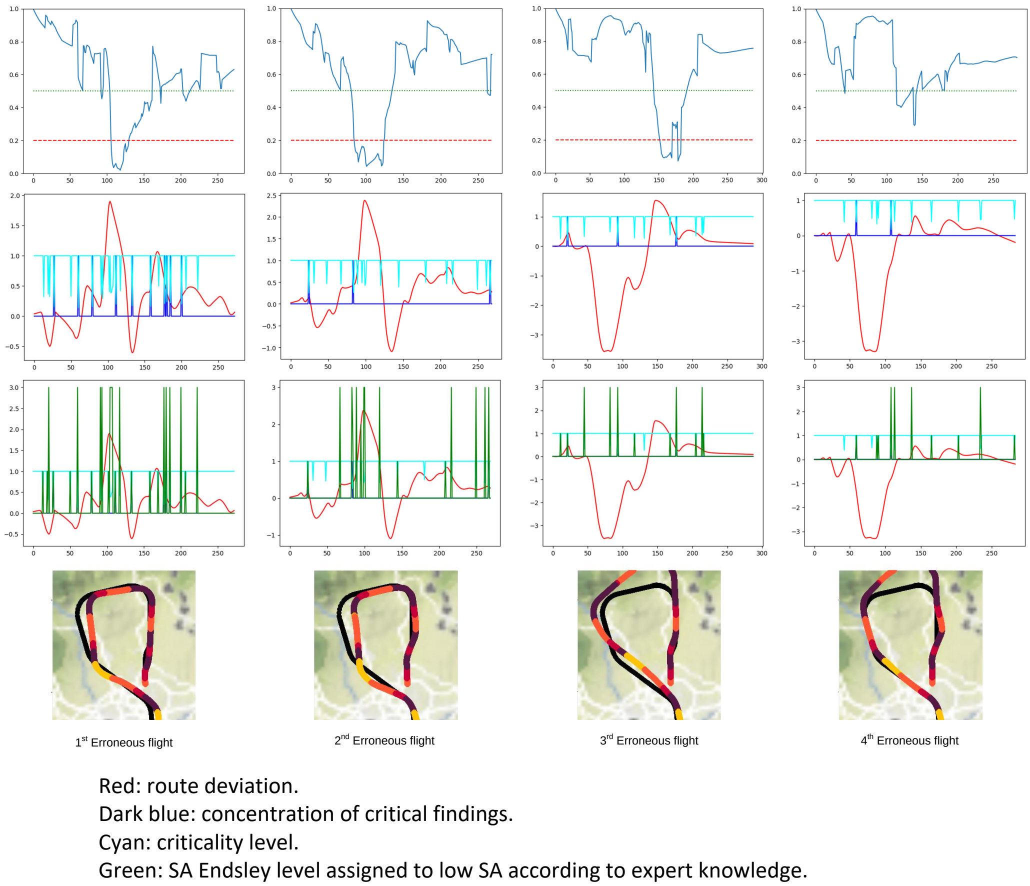


Figure 8.12: Overview of erroneous flights comparing SA estimation (first row) with other parameters.

We finally include in this subsection, for comparison purposes, Figures 8.13 and 8.14 that contain the graphs of criticality and expert knowledge corresponding to the two good flights, so that the reader can compare them with those of the erroneous flights previously described. It seems clear for us that

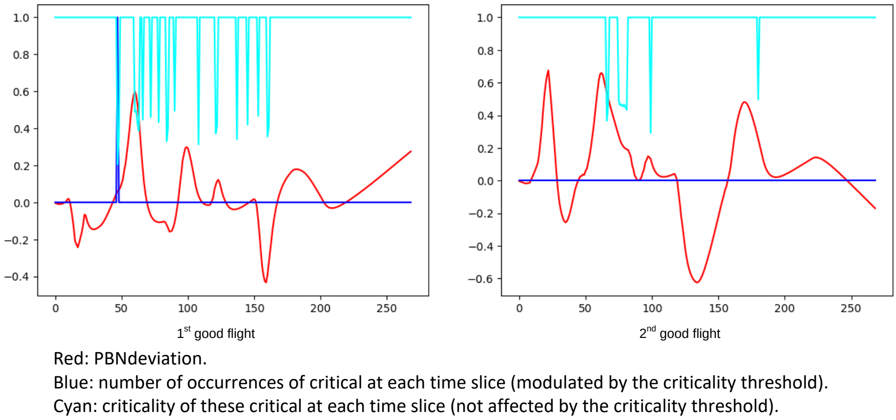


Figure 8.13: Good flights and their criticality levels.

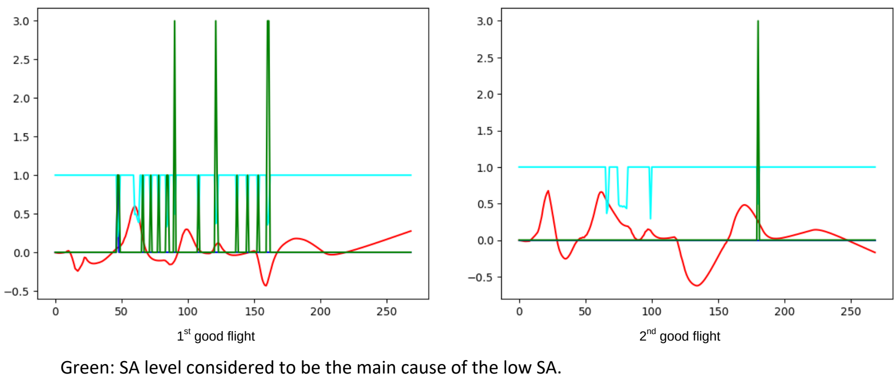


Figure 8.14: Good flights with SA level according to the model.

in these cases the values of the criticality indicators are much less persistent, and that the SA level assessment never remains at level 3 to indicate the causes of SA drops, which gives us encouraging results that our algorithm is capable of detecting the pilot's lack of concentration.

8.4 Future Work

We have presented a procedure to compute the SA online that is effective in a reduced setting. In the future, we plan to improve the SA model in several directions:

- To enlarge the experimental setting including more learning and test flights.
- To consider more variables and more SA modalities (horizontal SA, vertical SA, etc.) considering that there can be dependence among the different SA types.
- To improve the modelling procedures, by allowing more general models apart from logistic and linear regression, perhaps by defining instrumental variables.
- To consider the hidden SA values as missing values and to estimate their probabilities from flights by algorithm EM or variational procedures.
- To integrate the online SA computation in our simulation environment.

Part III

GENERAL DISCUSSION AND CONCLUSIONS

9 CONCLUSIONS AND FUTURE WORK

9.1 Contributions

In this research, we have worked to provide a comprehensive summary of the factors that surround information management in the cockpit of an aircraft, from the perspective of their influence on situation awareness and the possibility to build a model to provide a measure of SA uding Bayesian networks.

We have focused on the following topics:

- Introducing SWIM and its standards: AIXM, FIXM and WXXM.
- We paid special attention to the management of information in air navigation, the experiments focused on common IFR flights with standard settings.
- We have followed the evolution of PBN, which is a fundamental concept in future air navigation.
- We conducted an in-depth study of the topic of Situation Awareness, supported by a review of a substantial body of scientific literature. Based on that and on our own experience, we developed a model for SA estimation, leveraging Bayesian networks to provide a robust and systematic approach to this complex domain.

From these activities, we conclude that there is a very promising field of study, derived from the digitisation of aeronautical information management, which is still not very mature, so there is much room for research.

We have developed a simulation environment and additional software to explore interoperability between aeronautical information sources and machine learning tools:

- The initial version, available in 2014, already provided the possibility of connecting to a flight simulator and collecting variables.
- Later we developed code in languages specific for machine learning, first using R for and Elvira, and later we migrated to Python. We have performed experiments on discretization, regression, and clustering, and

also have implemented different reporting tools to analyse and visualise the results.

- We have developed code to process aeronautical data of various types: programming the data parsers for acquiring AIXM and FIXM, we connected to Eurocontrol's BADA.

- We have developed code to implement an EFB on a tablet. Although this is not strictly inside of the thesis, it is related to the research, for a future implementation of the SA estimation. This is a potential application of the research.

From these activities, we conclude that there are very interesting possibilities to perform flight simulations with affordable tools that could provide students or university researchers with very valuable and realistic tools to perform their work.

In parallel, we have analysed existing SA models, which already take information management into account, and we have adapted them in such a way that we have been able to design a specific SA measurement model whose experimental results show promising results. We consider the use of Bayesian networks to be relevant, up-to-date, and a suitable path for further research in this field.

9.2 Limitations of the study

9.2.1 Simulation bias

Due to the fact that we used simulations to perform the experiments, there is an inherent simulation bias, which, on the other hand, has been analysed to some extent as part of the research. Our simulation environment is very basic; it cannot be compared to a real flight simulator, but it offers the advantage that the design can be tailored to human factors research and to analyse specific information cues.

9.2.2 Scope of the mission types studied

Our experiments are focused on a very specific type of flight: IFR flights of commercial aircraft. We have performed experiments in two different flight phases: enroute and SID. The complexity of the simulated flight is relatively low, but this has contributed to validate the SA estimation model because we could focus on specific situations and information cues.

9.2.3 Limitations of Bayesian networks

During different phases of the research, we have worked to overcome the limitations of Bayesian networks, especially those related to the types of variables that they can handle. We have made progress in processing continuous variables. However, we can observe that we had difficulties in adapting the networks to the very varied types of the data we collected.

9.2.4 Limitations on the modelling of human cognitive factors

Our approach to model the SA levels is based on the analysis of pilot actions and their results in terms of aircraft trajectory or attitude measurements. We are aware that there is a large area of study to investigate in a deeper way the cognitive mechanisms of the human being and apply alternative computational approaches adopted by SA scholars.

9.3 Future work

Among the many topics in which we consider there is an interesting field of study to continue researching, we propose the following:

- In general, it is necessary to explore the applicability of Artificial Intelligence (AI) to the aeronautical field, particularly in light of what is established by EASA [2].
- Continue to perform experiments of different with different scopes, to improve the model of SA.
- Continue studying the application of risk management principles, not only ORM.
- Explore additional ways to perform a more systematic analysis of information management. For instance, applying information theory principles, where there is room for a study applying Bayesian networks.
- Update the simulation environment to connect to other simulation assets and improve interoperability with additional data sources.

- Explore the potential utility of EFBs in real flights, not only to host applications that provide information but also to potentially monitor pilot activities and be able to detect performance anomalies to provide warnings. This could be a practical application of this thesis.
- Expand the research to remotely piloted aircrafts, both with regard to the SA measure and the management of information.
- Enlarge and improve the model for online SA computation presented in Chapter 8 along the lines of Section 8.4.

Part IV

APPENDIX

A OVERVIEW OF THE CONTENTS OF THE AIRAC SYSTEM

A.1 Introduction

The structure of the AIRAC system, introduced in Section 3.1, is defined by the ICAO Annex 15 [6] and the dissemination of information is supported by the national authorities by means of the AIP. The AIRAC cycle is very relevant for pilots and for all stakeholders involved on the execution of air operations. Traditionally, the information was distributed in paper, but there is a de-facto standard maintained by several industries to provide a data model for related databases, initially developed by the Aeronautical Radio Incorporated (ARINC) in 1975. That is the ARINC-424 specification [7], that defines how the data contained in AIRAC cycles is structured for electronic navigation systems, and is typically used to define the database structure of aircraft FMS. The standardized update cycle of the AIRAC system is 28 days, but the most relevant exception are the NOTAM that have their own validity and update criteria to meet urgency needs.

A.2 General structure

The AIRAC system contains a wide range of aeronautical data critical for flight operations and air navigation. The data typically included in the AIRAC updates are:

Aerodrome/Heliport Information:

- Airport and heliport names, locations, and codes.
- Runway details (dimensions, surface type, lighting).
- Taxiway layouts.
- Parking and docking procedures.
- Operational hours and available services.

Airspace Structure:

- Airway routes.
- Controlled and restricted airspaces.
- Air traffic service routes.
- Flight information regions (FIRs).
- Special use airspace (SUAs).

Navigation Aids and Services:

- Locations and frequencies of VORs, NDBs, ILS, and other navigational aids.
- Details on communication frequencies.
- Radar services and coverage areas.
- Surveillance systems and procedures.

Flight Procedures:

- Standard instrument departures (SIDs).
- Standard terminal arrival routes (STARs).
- Instrument approach procedures (IAPs).
- Holding patterns and en-route procedures.
- Noise abatement procedures.

Obstacles and Terrain:

- Information on obstacles affecting air navigation (e.g., tall buildings, towers).
- Terrain data relevant to flight operations.

Air Traffic Management:

- ATC procedures and protocols.
- Coordination procedures between different air traffic control centers.
- Minimum safe altitudes and flight level allocations.

Regulatory Information:

- Temporary and permanent changes to regulations affecting air navigation.
- NOTAMs (Notices to Airmen).

Meteorological Information:

- Meteorological service locations and their services.
- Details on significant weather phenomena affecting flight safety.

Flight charts:

- En-route charts.
- Approach plates.
- Flight procedures charts.
- Aerodrome/Heliport diagrams.

B NOTAM MESSAGES: NATURE, STRUCTURE AND EXAMPLE

B.1 Nature of the NOTAM information

This appendix has been included to provide more context about NOTAM messages introduced in Section 3.2, basically because they have such a wide scope of contents that the structure of the information is not comparable to other AIXM messages. The nature of the information published by means of a NOTAM is very varied:

- Restrictions affecting airspaces, e.g. obstructions, special use due to public events, military operations or exercises.
- Limitations or incidences affecting communication or navigation aids.
- Temporary information about aerodrome services or facilities (runways, taxiways, supplies, etc.).
- Severe weather-related information (although weather information has other dedicated messages for normal situations).

The NOTAM are published only by the designated authorities:

- National aviation authorities: For example, the FAA in the case of the United States and EASA in the case of the European Union, although the latter does not have all competences, since some of them may be retained by the member states.
- Air Navigation Service Provider (ANSP): FAA in the case of the United States. In the European case, Eurocontrol is very linked to ANSPs, but the competences are maintained by national agencies, like Enaire in the case of Spain.

In any case, it is important to note that NOTAMs can be consulted in several official repositories [72] that ensure the completeness and correctness of the information they contain.

B.2 Structure and example of the NOTAM messages

The structure of a NOTAM message is standardised to ensure clarity and consistency, facilitating the task of the pilot or other user to understand the information contained. Typically, the structure of the message has the following contents:

- Header: Contains an identificator and the type of message with respect to the NOTAM: new, replacement or cancellation message.
- Body: Contains the details of the event or situation that needs to be reported to the air operators.

There is a compromise in the standardisation of the body to ensure a good balance between clarity, i.e. a well-structured and standardised message, and the accuracy of the message to the real situation that needs to be reported, and the fact that NOTAM are composed by thousands of human beings across the world. Typically, the body includes the information structured in the following order:

- A brief explanation, in clear text, of the situation or change being reported.
- Duration of the event: The start and end dates and times of the event need to be clearly stated in the body. The keywords "effective" and "expiration" are normally used to ensure proper understanding.
- Location of the event: Either using coordinates or standard ICAO codes. If the location is relative to a position, standardised wording is also used to express the distances, bearings and altitudes.

We have included figures B.1, B.2 and B.3 published by the United States FAA [46] in this appendix to provide an example that clearly shows the structure and where the information can be found in the message.

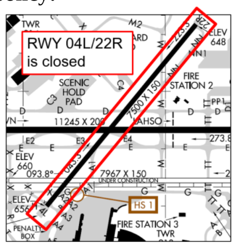
FAA

ICAO NOTAM Format Example

The example NOTAM depicts Runway 04L/22R Closed at Chicago O'Hare International Airport (ORD). ORD is located within the Chicago ARTCC (KZAU) Flight Information Region (FIR). The effective time for the NOTAM is June 23, 2021 from 1700 to 2300z**.**

Below is a sample NOTAM using the draft FAA ICAO NOTAM policy**:**

B0667/21 NOTAMN
Q) KZAU/QMRLC/IV/NBO/A/000/999/4159N08754W005
A) KORD<Location>
B) 2106231700<From>
C) 2106232300<To>
D) <Schedule>
E) RWY 04L/22R CLSD
F) <Lower Limit>
G) <Upper Limit>



Elements of the ICAO NOTAM

Q) A qualifier line, which contains coded information, coordinates, and radius for area for the automated filtering of NOTAMs

A) The ICAO location indicator of the aerodrome or FIR in which the facility, airspace, or condition being reported is located

B) Effective date/time (UTC)

C) Expiration date/time (UTC)

D) Schedule (optional)

E) NOTAM text field is the condition in which the NOTAM is being issued or put into force.

F) Lower altitude limit (Used with Airspace NOTAMs)

G) Upper altitude limit (Used with Airspace NOTAMs)

Below is the same sample NOTAM using the current Domestic NOTAM policy:

!ORD 06/001 ORD RWY 04L/22R CLSD 2106231700-2106232300

Series

In the ICAO format, NOTAMs are organized by Series, with each Series covering a specific NOTAM condition.

- The Series is the first element of the NOTAM, followed by the NOTAM Number.
- NOTAMs are numbered consecutively by Flight Information Region (FIR), and series beginning with S0001 each year. The FAA will utilize 13 different series for NOTAMs.

Figure B.1: ICAO NOTAM Format Example pg. 1 [46]

FAA

The NOTAM series replaces the keywords previously used in the current domestic format.

Series	NOTAM Type	Domestic NOTAM Subject
B	Aerodrome Maneuvering Areas	RWY, TWY
C	Published Services	COM, WX, ATC
D	Special Activity Airspace	SAA
E	Airspace Events and Activities (PJE, Gliders etc.)	PJE
G	Airways and Air Traffic Services Routes	
H	Regulatory (TFR, Security) NOTAMs	FDC, CARF
I	Apron/Ramp and Facilities	APN
J	Obstructions (Crane, BLDG, Non-FCC Tower)	OBST
K	FCC Obstructions (ASR assigned)	OBST
N	Ground-Based Navigational Aids	NAV
R	Field Condition (TALPA) NOTAM	RWY
V	Published Instrument Procedures	IFP
Z	Satellite Based Information	GPS

Note: Series may be updated with final publication of the 7930.2, Notice to Airmen Policy order.

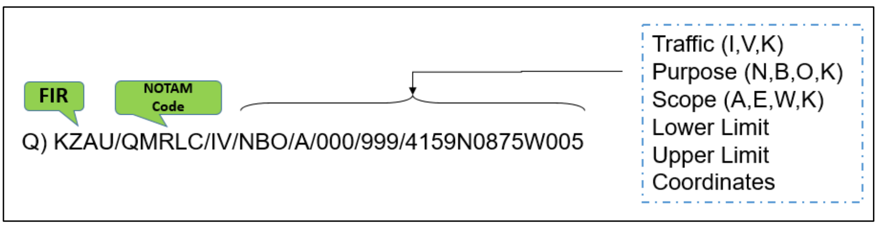
Action

The Action indicates the type of NOTAM. The example is a new NOTAM and is classified as a **NOTAMN**.

Action	Type of NOTAM
NOTAMN	Contains new information
NOTAMR	Replaces previous NOTAM
NOTAMC	Cancels previous non-auto cancel NOTAM

The Qualifier "Q" Line Explained

Q) A qualifier line, which contains coded information, coordinates, and radius for area for the automated filtering of NOTAMs



FIR

The first element of the qualifier line is the Flight Information Regions (FIR) In CONUS, FIR identifier is ARTCC identifier. This example uses KZAU as the FIR.

Figure B.2: ICAO NOTAM Format Example pg. 2 [46]

FAA

NOTAM Code

The second element of the qualifier line is the NOTAM code. The NOTAM Code forms the basis upon which NOTAM qualifiers TRAFFIC, PURPOSE, and SCOPE are determined for inclusion in Item Q) of the NOTAM Format, in addition to defining the abbreviated plain-language text which appears in Item E). All NOTAM code groups contain a total of five letters and the first letter is always the letter Q. The second and third letters identify the subject, and the fourth and fifth letters denote the condition of the subject being reported. The example uses **QMRLC** as the NOTAM code.

Traffic

This qualifier relates the NOTAM to a type of traffic and allows retrieval according to the user's needs. Depending on the NOTAM subject and content, the qualifier field TRAFFIC may contain the combined qualifiers. This example displays **IV** as the Traffic.

Traffic	Type of Traffic
I	Instrument Flight Rules (IFR)
V	Visual Flight Rules (VFR)
K	NOTAM is a Checklist

Purpose

The qualifier relates a NOTAM to certain purposes (intentions) and thus allows retrieval according to the user's requirements. Depending on the NOTAM subject and content, the qualifier field PURPOSE may contain combined qualifiers. This example displays **NBO** as the Purpose.

Purpose	Purpose description
N	NOTAM selected for the immediate attention of aircraft operators
B	NOTAM selected for pre-flight information briefing
O	NOTAM concerning flight operations
M	Miscellaneous NOTAM; not subject for briefing, but is available on request
K	NOTAM is a Checklist

Scope

The scope qualifiers are used to categorize NOTAMs. Depending on the NOTAM subject and content, the qualifier field SCOPE may contain combined qualifiers. This example uses **A** as the scope.

Scope	Scope Description
A	Aerodrome
E	Enroute
W	Navigation warning
K	Checklist

Lower Limit and Upper Limit

The lower and upper limit field applies mainly to airspace related NOTAMs. Most aerodrome-related information, qualifier scope 'A', refers to ground installations for which the insertion of lower/upper limit is not relevant. Therefore, such NOTAMs must include the default values of 000/999.

Figure B.3: ICAO NOTAM Format Example pg. 3 [46]

C ORM SURVEY

C.1 Overview

The survey was carried out in March 2017 after the results of the first two experiments were analysed and it became clear that a refined set of variables was necessary to improve the results of the SA estimation. This appendix shows an extract of the questions included in the survey and some basic statistics to illustrate which options are given priority by the subjects. The survey was completed by only 4 people, but because all of them were experienced helicopter IFR instructors, the outcome was considered relevant in terms of identifying qualitative information to prioritise the collection of variables.

The tables included in the following pages show that the questionnaire presented three different situations that the subjects needed to assess.

The first situation was referred to flight preparation, and the questions identified items to be collected to fly an instrumental flight departure, which is the type of procedure that we later selected for the PBN experiment performed in 2022. With respect to the second situation, in general, the main concern of the pilots was maintaining altitude, but for our research the most interesting outcome was that the comments were orientated towards having updated information, whether in electronic or digital format, and focussing attention in the next route leg. For both of them, the responses were rated from 1 to 10 to measure the relevance of each answer, although all the numerical values are merely intending to support the qualitative assessment.

Finally, the last situation was set on an Instrument Meteorological Conditions (IMC) flight, which implies adverse weather conditions for helicopter pilots, and was specifically orientated to receive feedback about which information was most demanded for each flight phase. The most relevant outcomes are highlighted in the text, but we do not provide numerical data. For us, the most important finding was related to the pilots' concern about making mistakes during turns, and this also influenced the design of the PBN experiment that we designed a few years later.

SITUATION 1: When preparing for an IFR flight, what information do you need to collect for the instrument departure, based on the different conditions exposed?

Acronyms:
CAVOK: cloud and visibility OK
CTA: Airport Control Area
IMC: Instrument Meteorological Conditions
TMA: Terminal Manoeuvring Area

		CAVOK in summer	CAVOK in winter	Low-level fog and CAVOK at higher altitude	Medium probability of IMC and inexperienced copilot	High probability of IMC in winter, at night, highly experienced copilot	
Cloud ceiling at departure airport	#1				10	10	
	#2	0	0	2	6	8	
	#3	6	7	10	9	9	
	#4	5	7	10	10	10	
	Av.	3,67	4,67	7,33	8,75	9,25	6,73
Probability of precipitation	#1				10	9	
	#2	0	3	3	6	8	
	#3	8	9	10	10	10	
	#4	8	9	10	10	10	
	Av.	5,33	7,00	7,67	9,00	9,25	7,65
Freezing level	#1				10	10	
	#2	2	4	5	8	9	
	#3	7	10	10	10	10	
	#4	6	10	10	10	10	
	Av.	5,00	8,00	8,33	9,50	9,75	8,12
NOTAM of the departure TMA/CTA	#1				9	8	
	#2	6	6	7	7	8	
	#3	9	9	9	9	9	
	#4	10	10	10	10	10	
	Av.	8,33	8,33	8,67	8,75	8,75	8,57
NOTAM of the departure airport	#1				9	8	
	#2	6	6	7	7	8	
	#3	9	9	9	10	9	
	#4	10	10	10	10	10	
	Av.	8,33	8,33	8,67	9,00	8,75	8,62
Maximum climb gradient that I will be able to maintain	#1				9	9	
	#2	5	5	7	7	9	
	#3	9	10	10	9	9	
	#4	10	10	10	10	10	
	Av.	8,00	8,33	9,00	8,75	9,25	8,67
Reference speeds for takeoff and climb	#1						
	#2	4	4	5	7	7	
	#3	9	9	9	9	9	
	#4	10	10	10	10	10	
	Av.	7,67	7,67	8,00	8,67	8,67	8,13
	Average	6,62	7,48	8,24	8,92	9,10	

Figure C.1: Situation 1 presented in the ORM survey.

SITUATION 2: During an IFR flight, in the final sections of the airway or at the beginning of the STAR, with the environmental conditions described in each column of the following table, indicate how relevant you consider it to be to know the data expressed in the different rows:

		VMC	IMC with no risk of icing or thunderstorms	IMC with low risk of icing	IMC with high risk of icing	Presence of thunderstorm cores on the route	
Relative position to the last route waypoint	#1	5	6	8	9	9	
	#2	2	4	6	8	9	
	#3	7	8	9	9	9	
	#4	7	8	9	10	10	
	Av.	5,25	6,50	8,00	9,00	9,25	7,60
Relative position to the next route waypoint	#1			8	9	9	
	#2	3	5	7	9	10	
	#3	8	9	9	9	10	
	#4	8	9	10	10	10	
	Av.	6,33	7,67	8,50	9,25	9,75	8,30
Lateral deviation from the route	#1						
	#2	1	3	5	7	9	
	#3	8	9	10	10	10	
	#4	10	10	10	10	10	
	Av.	6,33	7,33	8,33	9,00	9,67	8,13
Radio frequency of next control center	#1						
	#2	2	4	7	9	10	
	#3	9	9	10	9	9	
	#4	8	9	9	9	9	
	Av.	6,33	7,33	8,67	9,00	9,33	8,13
Time to next route waypoint	#1			8	8	8	
	#2	0	1	2	3	4	
	#3	8	9	9	9	9	
	#4	10	10	10	10	10	
	Av.	6,00	6,67	7,25	7,50	7,75	7,03
Altitudes of airway waypoints	#1	5	6	8	10	10	
	#2	5	7	8	10	10	
	#3	9	9	9	9	9	
	#4	10	10	10	10	10	
	Av.	7,25	8,00	8,75	9,75	9,75	8,70
Altitudes of STAR waypoints	#1	5	6	8	10	10	
	#2	5	7	8	10	10	
	#3	9	9	9	9	9	
	#4	10	10	10	10	10	
	Av.	7,25	8,00	8,75	9,75	9,75	8,70
	Average	6,39	7,36	8,32	9,04	9,32	

Figure C.2: Situation 2 presented in the ORM survey.

SITUATION 3: Information relevant when making an assessment for IFR flight in IMC

Probability of being assigned a specific SID: 8

Knowing in advance the times when I will be transferred from the frequency from taxiing to the end of the SID:

Knowing the runway visual range for takeoff: 7

Knowing the height of the cloud ceiling for takeoff: 10

Knowing the height of the cloud ceiling for touchdown: 10

Knowing which phases of the flight will be in IMC: **SID**: 9 AWY: 7 STAR: 7 **APP**: 9

If you could have statistical information about your errors or inaccuracies in flight, what information would be most relevant in each case? (Please try to give a relevance value based on a compromise between the severity of the error or inaccuracy and the probability/frequency with which it usually occurs to you)

Takeoff and initial climb:

V1/V2/VBROC calculations: /

Maximum climb slope/variometer calculations: 8/

Forgetting to raise landing gear: /

Forgetting to turn on anti-ice: 7/

Changing radio frequency too early: /

Changing radio frequency too late: /

Turning late: /

Turning early: /

Turning to the wrong side: 10

Other: /

SID:

Turning late: /

Turning early: /

Turning to the wrong side: /

Incorrect radio frequency input: /

Incorrect VOR frequency input: 7/

Incorrect GPS coordinate input: 7/

Selecting an inappropriate source in the RMI: /

Selecting too high an altitude in the FD: /

Selecting too low an altitude on the FD: /

Forgetting to set the altimeter: 8/

Forgetting to turn on the anti-ice: /

Other: **Importance of knowing presence of icing conditions**.

Figure C.3: Situation 3 presented in the ORM survey (page 1).

AWY:

Lateral deviation from the route: /

Maintaining an inappropriate altitude: 7/

Miscalculating the GS: /

Entering a wrong radio frequency: /

Entering a wrong VOR frequency: /

Entering a wrong GPS coordinate: /

Selecting an inappropriate source on the RMI: /

Forgetting to make a radio call: 7/

Forgetting a fuel check: /

Other: 7: having to fly lower than minimum airway altitude in VMC /

STAR:

Turning late: /

Turning early: /

Turning to the wrong side: /

Misreading the STAR chart: /

Misreading the Nav chart: /

Misreading the kneeboard: /

Miscalculating the rate of descent: /

Starting to descend too late: /

Misinterpreting a DME distance: /

Misinterpreting a GPS distance: /

Other: 7: carry outdated charts/

FINAL COMMENTS

Please write comments here on information relevant to the SA during the flight, especially if you feel that it has not been mentioned enough during the questionnaire:

1. **Check that we carry all necessary charts, including alternate airports, and that they are updated. If you carry an EFB, prepare a backup, as with the GPS.**

Please write comments here on information relevant to the ORM assessment before the flight, especially if you feel that it has not been mentioned enough during the questionnaire:

1. **Charts updated.**
2. Adequeste crew rest.

Figure C.4: Situation 3 presented in the ORM survey (page 2).

D DATASETS

Several datasets have been used in this thesis, either generated from simulations, provided by third parties or downloaded from the internet. It has been attempted to use as many types of the data sources explained in chapter 3 as possible, with the aim of integrating real and simulated data from different sources in order to perform the experiments applying data mining techniques to identify patterns that could lead to the quantification of SA. Table D.1 shows an overview of some of the main datasets used during the research, followed by a summary of the experiments, explaining how the datasets were used and how variables were created or imported, and also how they were employed.

Dataset	Origin	Experiment used
AIXM	Provided by ENAIRE	Discretization
FIXM FPL	Provided by ENRI	-
BADA	Provided by Eurocontrol	-
Discretization data	Generated by PostFlight	Discretization
Regression data	Generated by PostFlight	Regression
Clustering data	Laminar Data platform	Clustering

Table D.1: Overview of the datasets used in this thesis.

D.1 Discretization experiment data

This experiment is explained in section D.2

D.1.1 AIXM dataset

An AIXM dataset was provided in 2014 by ENAIRE (the Spanish air navigation manager and air navigation service provider). It contained navigation information that we used to create the routes once the flight plans to carry out the experiment were parsed. It also contained special use airspaces that

Table	Action							Rows
airspace_1409	☆	Browse	Structure	Search	Insert	Empty	Drop	498
airspace_1409vertex	☆	Browse	Structure	Search	Insert	Empty	Drop	239,268
atsroute_1409	☆	Browse	Structure	Search	Insert	Empty	Drop	1,513
designatedpoint_1409	☆	Browse	Structure	Search	Insert	Empty	Drop	2,888
navaidsystem_1409	☆	Browse	Structure	Search	Insert	Empty	Drop	266

Figure D.1: Overview of the tables in the AIXM dataset provided by ENAIRE.

we managed to represent in the map. Below we include some captures to illustrate the database structure and the data types of these data.

General information about airspaces is stored in a specific table, in this case named *airspace_1409*. These airspaces include zones of significant importance for the pilot that are often translated into flight restrictions. See Figure D.2.

SHAPE_Leng	SHAPE_Area	LON1	LAT1	LON2	LAT2	VERTEX_COUNT
8.06874575764e-001	5.00092326142e-002	-1.79347249	42.66163500	-1.49930500	42.87836351	73

Figure D.2: Detail of an airspaces table example register.

Each airspace is modelled as a polygon, whose vertex coordinates are stored in the *airspace_1409vertex* table. See Figure D.3.

ID_AIXMxyz_1409	IDENT_TXT	LON	LAT	VERTEX_NUMBER
79	LER146	-4.62074067	39.40648151	6

Figure D.3: Detail of an airspace vertex table example register.

The ATS routes, in most cases, also known as airways, are modelled by lines made of segments, whose endpoint coordinates are stored in the *atsroute_1409* table. See Figure D.4.

LON1	LAT1	ALT1	LON2	LAT2	ALT2
3.13124278	39.11769056	-999999	3.14780917	38.29362694	-999999

Figure D.4: Detail of an ATS route segments endpoints table example register.

The *designatedpoint_1409* table contains some relevant points for navigation. Many of them are special points of the ATS route that need to stand out, for example, because they require special action from the pilot. See Figure D.5.

NAME	REMARKS_TX	LASTMOD_DA	IDENT_TXT	NAME_TXT	LAT_TXT	LONG_TXT	DATUM_CODE	TYPE_CODE
MOGIL	PURPOSE: B-31, UN-859 NOTES: BDRY FIR BARCELONA/A...	0000-00-00 00:00:00	MOGIL	MOGIL	380755N	0031207E	WGE	ICAO

Figure D.5: Detail of a designated points example register.

The *navaidsystem_1409* table contains the position coordinates of all the navigation aids of the dataset coverage area. A navaid, short for navigation aid, is a radio-frequency device on the ground that aircraft detect in order to obtain flight position references. See Figure D.6.

IDENT_TXT	CAT_CODE	CHANNEL_TX	LAT_TXT	LONG_TXT	DATUM_CODE
BLN	-	109X	380909,0582N	0033730,2424W	WGE

Figure D.6: Detail of a navigation aid table example register.

D.2 Regression experiment data

In this subsection we include, on the next page, a table in which can be found the complete list of variables that were used for the regression experiment, as well as the type of data in which they were stored in the corresponding database. We have also include very summarized information about the discretization thresholds, which were discussed in Section D.2, so that the reader can have an idea of the numerical ranges of the variables that we handled in the first two experiments (discretization and regression).

A column of the table is also including the type of variable, according to the high-level classification that was presented in Section 6.4 and whose main expected dependencies are shown in Figure 7.1.

TYPE	VAR NAME	TYPE	Thresholds	
AP	pitch	double(10,2)	-41.74	11.94
AP	bank	double(10,2)	-31.35	31.48
AP	ThrottleAvg	double(5,2)	0	100
AP	thr68y78y88y93y98	int(11)	0	5
AS	msec	bigint(20)	7400	3867751
AS	FSXlat	double(15,10	37.19	39.74
AS	FSXlon	double(15,11	-3.79	2.76
AS	alt	double(10,1)	31.5	35012
AS	hdgT	double(5,1)	0	360
AS	hdgM	double(5,1)	0	360
AS	vs	int(5)	-5483	11350
AS	ias	int(5)	61	355
AS	ts	int(5)	61	525
AS	gs	int(5)	61	548
AS	mach	double(6,3)	0.091	0.894
AS	closestleg	int(11)	1	2
AS	distacleg	double(12,8)	0	25.77
AS	distaclegside	varchar(8)	L	R
AS	distaclegstart	double(12,8)	0.036	63.41
AS	distaclegend	double(12,8)	0.1	62.48
AS	distaclegendsecondstas	int(11)	1	2102
AS	aclegaltdiffft	double(10,1)	0	28970
AS	aclegalthighlow	varchar(8)	L	H
EV	windSpd	int(5)	0	25
EV	windDir	int(5)	0	359
EV	pressure	int(5)	1012.9	1013.1
EV	OATemp	int(5)	-54	14.5
FP	closestlegstartlat	double(12,8)	37.18	39.38
FP	closestlegstartlon	double(12,8)	-3.78	1.42
FP	closestlegendlat	double(12,8)	38.15	39.56
FP	closestlegendlon	double(12,8)	-3.65	2.74
FP	closestlegairspeedknots	int(11)	0	350
FP	closestlegairspeedmach	double(12,8)	0	0.616
FP	closestleglength	double(12,8)	16.5	62.5
FP	closestlegbearing	double(12,8)	7	89
FP	legaltft	double(10,1)	1860	31000
SC	psclat	double(12,8)	0	39,57
SC	psclon	double(12,8)	-3.87	2.76
SC	pscdistance	double(12,8)	0	136.1
SC	pscbearing	int(11)	0	360
SC	psccoincidentnameleg	int(11)	0	1
SC	psccoincidentnamelegwpt	int(11)	0	1
SC	psccoincidentpositionleg	int(11)	0	1
SC	psccoincidentpositionlegwpt	int(11)	0	1
SC	pscdisttoclosestlegstart	double(12,8)	0	154
SC	pscdisttoclosestlegend	double(12,8)	0	109
SC	pscdisttonextlegend	double(12,8)	0	108
SC	pscbearhdgdiff	double(12,8)	-180	180
SC	pscbearlegbeardiff	double(12,8)	-180	180
SC	pscjam	int(11)	0	1
SQ	discrdistacleg	int(11)	0	1
SQ	discraltdiff	int(11)	0	1
SQ	discrDistACLegAccum	int(11)	0	113
SQ	discrDistACLegAvgGlobal	int(11)	0	1
SQ	discrDistACLegAvg20	int(11)	0	1
SQ	discrDistACLegAvg40	int(11)	0	1
SQ	accumConsecDiscrDistACLeg3orMoreDisc0	int(11)	-999	0
SQ	discrAltDiffAvgGlobal	int(11)	-999	0
SQ	discrAltDiffAvg20	int(11)	-999	0
SQ	discrAltDiffAvg40	int(11)	-999	0
SQ	accumConsecDiscrAltDiff3orMoreDisc05	int(11)	-999	0

TYPE	VAR NAME	TYPE	Thresholds	
IC	efbjam	int(11)	0	1
IC	efbcontentHorRelThisLeg	int(11)	-999	0
IC	efbcontentHorRelNextLeg	int(11)	-999	0
IC	efbcontentHorRelLastLeg	int(11)	-999	0
IC	efbcontentHorExcThisLeg	int(11)	-999	0
IC	efbcontentHorExcNextLeg	int(11)	-999	0
IC	efbcontentHorExcLastLeg	int(11)	-999	0
IC	efbcontentAltRelThisLeg	int(11)	-999	0
IC	efbcontentAltRelNextLeg	int(11)	-999	0
IC	efbcontentAltRelLastLeg	int(11)	-999	0
IC	efbcontentAltExcThisLeg	int(11)	-999	0
IC	efbcontentAltExcNextLeg	int(11)	-999	0
IC	efbcontentAltExcLastLeg	int(11)	-999	0
IC	efbcontentHorRelThisLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorRelNextLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorRelLastLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorExcThisLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorExcNextLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorExcLastLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltRelThisLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltRelNextLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltRelLastLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltExcThisLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltExcNextLegAvgGlobal	int(11)	-999	0
IC	efbcontentAltExcLastLegAvgGlobal	int(11)	-999	0
IC	efbcontentHorRelThisLegAvg20	int(11)	-999	0
IC	efbcontentHorRelNextLegAvg20	int(11)	-999	0
IC	efbcontentHorRelLastLegAvg20	int(11)	-999	0
IC	efbcontentHorExcThisLegAvg20	int(11)	-999	0
IC	efbcontentHorExcNextLegAvg20	int(11)	-999	0
IC	efbcontentHorExcLastLegAvg20	int(11)	-999	0
IC	efbcontentAltRelThisLegAvg20	int(11)	-999	0
IC	efbcontentAltRelNextLegAvg20	int(11)	-999	0
IC	efbcontentAltRelLastLegAvg20	int(11)	-999	0
IC	efbcontentAltExcThisLegAvg20	int(11)	-999	0
IC	efbcontentAltExcNextLegAvg20	int(11)	-999	0
IC	efbcontentAltExcLastLegAvg20	int(11)	-999	0
PA	kollsman	int(5)	1013	1018
PA	actionhdgval	int(11)	-999	360
PA	actionhdgsel	int(11)	-1	0
PA	actionspdval	int(11)	-999	350
PA	actionspdsel	int(11)	-1	0
PA	actionaltval	int(11)	-999	35000
PA	actionaltsel	int(11)	-1	0
PA	actionfdsel	int(11)	-1	0
PA	actionaltset	int(11)	-999	1019
PA	jamhdgval	int(11)	0	1
PA	jamhdgsel	int(11)	0	1
PA	jamspdval	int(11)	0	1
PA	jamspdsel	int(11)	0	1
PA	jamaltval	int(11)	0	1
PA	jamaltsel	int(11)	0	1
PA	jamfdsel	int(11)	0	1
PA	jamaltset	int(11)	0	1
PA	discaltsetting	int(11)	0	3
PA	accumActionHdgValChange	int(11)	0	55
PA	percentActionHdgValChangeLast20	int(11)	0	55
PA	percentActionHdgValChangeLast40	int(11)	0	55

Figure D.7: Variables of the Regression Experiment

D.3 Trajectory Clustering experiment data

For this experiment we collected 2520 FIXM messages, each one of them corresponding to the trajectory of a commercial flight departing from Malaga Costa del Sol airport (ICAO designator LEMG), although not all these flights were completely flown, which also contributed to testing the algorithm. This airport was selected because we were familiar with its departure procedures and due to its high density of traffic and because the geometry of the SID, avoiding a city very close to the east of the airport, and a range of mountains with high elevation relatively close to the airport, in the north, seems challenging in terms of turns, making it not so simple for the pilots to fly these procedures when there is a high load of traffics.

We parsed the FIXM flight messages using the application developed for SASWIM 2017 and the result was loaded in a SQL database, in two tables: one with a row for each flight and one with a row for each sampled point, which had a total of 373.441 records, which means that on average each flight was summarized in 148 samples.

Figure D.8 shows the fields found in the FIXM messages schematically [97]. Below is a short description of the fields parsed for each flight, and Figure D.9 contains a table with samples of data to support the understanding of its contents.

- flight_id: Correlative index to identify the flight (generated in the app).
- flight_ident: IATA flight designator (aka. flight number).
- flight_ident_num: Index provided by the data source.
- arr_arpt_icao: Identifier of arrival airport.

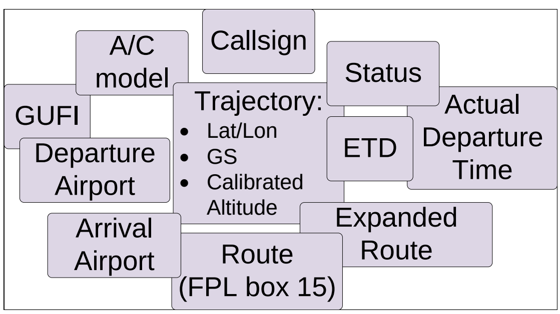


Figure D.8: FIXM schematic of the fields found in the trajectories downloaded for the Clustering experiment.

- etd_timestamp_sec: Estimated time of departure (timestamp format).
- etd_timestamp_flag: Estimated Time of Departure (ETD) flag without relevant information.
- etd_hour: Estimated time of departure (decimal format).
- take_off_found: Flag to confirm take off.
- rwyName: Departure runway identifier.
- rwyLon: Departure runway longitude coordinate.
- rwyLat: Departure runway latitude coordinate.
- dist_rwy_to_first_traj_point: Distance from the departure runway to first trajectory point.
- dist_dept_arpt_first_point: Distance from the departure ARP to first trajectory point.
- dist_dept_arpt_last_point: Distance from the departure ARP to last trajectory point.
- dist_arr_arpt_first_point: Distance from the arrival ARP to first trajectory point.
- dist_arr_arpt_last_point: Distance from the arrival ARP to last trajectory point.
- FPLSID: Planned SID designator, when known.
- FPL_first_wpt: Designator of first route waypoint (deduced by our application).
- ac_model: Aircraft model designator.
- 15 sets of the following fields, to summarize the route of the planned departure procedure:
  - dpx.lon: Longitude coordinate of departure procedure.
  - dpx.lat: Latitude coordinate of departure procedure.
  - dpx.type: Text designator of the departure procedure (SID + its designator).
  - dpx.name: Name of SID point closest to this point.

- dpx.dst_closest: of SID point closest to this point.
- dpx.dst_rwy: Distance of point to departure runway.
- dpx.brg_rwy: Bearing from point to departure runway.

It should be noted that we implemented an algorithm that detected the departure procedure flown in each flight and inserted it in the flight descriptor, as a sequence of 15 points. This was done to facilitate the comparison between the planned flight route and the actual flown path, for the initial phase of the flight,m which was the focus of the experiment (approximately the first 10 minutes of flight after the take-off).

flight_id	flight_ident	flight_ident_num	arr_arpt_icao	etd_timestamp_sec	etd_timestamp_flag	etd_hour	take_off_found	rwyName	rwyLon	rwyLat	dist_rwy_to_first_traj_point	dist_dept_arpt_first_point	dist_dept_arpt_last_point	dist_arr_arpt_first_point	dist_arr_arpt_last_point	FPLSID	FPL_first_wpt	ac_model	dp1.lon	dp1.lat	dp1.type
880	U27182	135	EGGP	1532460300	1	21,4	Y	13	-4,512594	36,684536	3,42	1,49	390,78	1005,15	612,94	N	BLN	A319	-4,51259	36,68454	RWY
881	FR6653	152	EGPH	1532456700	1	20,4	N	13	-4,512594	36,684536	2,31	1,64	885,98	1159,38	272,57	N	BLN	B738	-4,51259	36,68454	RWY
883	BA2719	131	EGKK	1532460840	1	21,6	Y	13	-4,512594	36,684536	3,13	1,24	515,76	906,51	387,59	N	BLN	A319	-4,51259	36,68454	RWY
884	HV6118	158	EHAM	1532456664	1	20,4	Y	13	-4,512594	36,684536	3,52	1,48	1010,48	1090,43	7,03	N	BLN	B738	-4,51259	36,68454	RWY
885	EI889	142	EICK	1532458380	1	20,9	Y	13	-4,512594	36,684536	2,31	1,13	714,24	941,92	226,38	BLN2C	BLN	A320	-4,51259	36,68454	RWY
886	U26058	135	EGGD	1532462400	1	22	N	13	-4,512594	36,684536	2,27	1,6	376,98	889,67	511,03	N	BLN	A320	-4,51259	36,68454	RWY
887	U22410	135	EGGW	1532461800	1	21,8	N	13	-4,512594	36,684536	1,84	1,1	477,31	945,53	462,58	N	BLN	A320	-4,51259	36,68454	RWY
888	SK584	158	EKCH	1532456820	1	20,5	Y	13	-4,512594	36,684536	2,33	0,92	1122,93	1533,39	338,45	N	BLN	A319	-4,51259	36,68454	RWY
890	W64412	141	LBSF	1532460720	1	21,5	Y	13	-4,512594	36,684536	3,28	1,75	837,14	1711,79	677,88	N	PEPAS	A321	-4,51259	36,68454	RWY
891	QS1153	164	LKPR	1532457540	1	20,7	Y	13	-4,512594	36,684536	3,32	1,68	1133,04	1383,59	14,9	N	PEPAS	B738	-4,51259	36,68454	RWY
892	EI589	142	EIDW	1532461440	1	21,7	Y	13	-4,512594	36,684536	3,03	1,44	784,99	1011,33	265,9	N	BLN	A321	-4,51259	36,68454	RWY
893	U28616	135	EGKK	1532462100	1	21,9	Y	13	-4,512594	36,684536	2,57	0,81	780,58	906,31	134,42	N	BLN	A20N	-4,51259	36,68454	RWY
894	SU2529	168	UUEE	1532461260	1	21,7	N	13	-4,512594	36,684536	2,71	2,11	754,48	2767,47	1862,93	N	PEPAS	B738	-4,51259	36,68454	RWY
895	AY1676	154	EFHK	1532466660	1	23,2	Y	13	-4,512594	36,684536	3,64	1,62	324,6	2266,09	1990,22	N	BLN	A321	-4,51259	36,68454	RWY
898	SK4308	158	EFHK	1532485497	1	4,4	N	31	-4,485825	36,665408	2,25	1,59	161,38	2266,96	2125,57	N	BLN	A20N	-4,48583	36,66541	RWY
899	SK6204	158	EKCH	1532485305	1	4,4	N	31	-4,485825	36,665408	2,52	1,89	187,12	1533,61	1360,29	N	BLN	A20N	-4,48583	36,66541	RWY
900	VY2608	175	LEBB	1532486969	1	4,8	Y	31	-4,485825	36,665408	2,78	1,12	246,43	408,4	159,54	N	BLN	A320	-4,48583	36,66541	RWY
901	FR4047	152	EKCH	1532487480	1	5	Y	31	-4,485825	36,665408	2,18	1,02	190,73	1533,6	1356,28	N	BLN	B738	-4,48583	36,66541	RWY
902	D85070	124	EKCH	1532487508	1	5	Y	31	-4,485825	36,665408	3,38	1,65	175,94	1533,58	1369,12	N	BLN	B738	-4,48583	36,66541	RWY
903	YW8260	176	GEML	1532488494	1	5,2	Y	31	-4,485825	36,665408	1,58	0,24	108,96	125,04	6,83	N	BLN	AT72	-4,48583	36,66541	RWY
904	UX1039	173	LFPG	1532486760	1	4,8	Y	31	-4,485825	36,665408	3,03	1,34	458,27	852,17	387,83	N	BLN	B738	-4,48583	36,66541	RWY
912	D85140	124	EPWA	1532490600	1	5,8	Y	31	-4,485825	36,665408	3,24	1,29	260,22	1788,97	1486,44	N	PEPAS	B738	-4,48583	36,66541	RWY
913	FR5945	152	EGHH	1532488211	1	5,2	N	31	-4,485825	36,665408	1,96	1,25	539,5	860,64	331,31	N	SVL	B738	-4,48583	36,66541	RWY
914	FR2524	152	ESGG	1532491980	1	6,2	Y	31	-4,485825	36,665408	3,2	1,11	137,2	1612,57	1479,2	N	BLN	B738	-4,48583	36,66541	RWY
915	FR7045	152	EIDW	1532490180	1	5,7	N	31	-4,485825	36,665408	2,75	2,17	477,6	1008,96	546,33	N	BLN	B738	-4,48583	36,66541	RWY
916	DL270	144	KJFK	1532492580	1	6,4	Y	31	-4,485825	36,665408	3,59	1,72	170,9	4162,12	3975,85	N	SVL	B752	-4,48583	36,66541	RWY
918	D85000	124	EGKK	1532490000	1	5,7	Y	31	-4,485825	36,665408	3,44	0,76	512,53	905,8	390,82	N	BLN	B738	-4,48583	36,66541	RWY
919	QR156	163	OTHH	1532496300	1	7,4	N	31	-4,485825	36,665408	1,87	1,14	170,72	3436,28	3224,65	N	ULPEP	B788	-4,48583	36,66541	RWY
920	UX1011	173	LFPG	1532496600	1	7,5	Y	31	-4,485825	36,665408	2,07	1,14	150,34	852,31	699,9	N	BLN	B738	-4,48583	36,66541	RWY
921	SN3734	161	EBBR	1532498280	1	8	Y	30	-4,480531	36,679575	2,73	1,25	180,61	1009,01	830,92	N	BLN	A320	-4,48053	36,67958	RWY
922	TB3262	150	EBBR	1532497882	1	7,9	Y	30	-4,480531	36,679575	2,86	1,63	221,6	1009,06	793,59	N	BLN	B38M	-4,48053	36,67958	RWY
923	TB3832	150	EBOS	1532498804	1	8,1	Y	31	-4,485825	36,665408	3,69	1,77	103,27	976,4	871,53	N	BLN	B38M	-4,48583	36,66541	RWY
924	FR6139	152	LIRF	1532499390	1	8,3	N	30	-4,480531	36,679575	2,24	1,9	230,53	1051,15	772,06	N	ROLAS	B738	-4,48053	36,67958	RWY
925	U22734	135	LIMC	1532498160	1	7,9	Y	30	-4,480531	36,679575	2,64	1,29	298,77	958,19	611,69	N	PEPAS	A319	-4,48053	36,67958	RWY
926	U28602	135	EGKK	1532500200	1	8,5	N	30	-4,480531	36,679575	1,95	1,58	102,85	905,16	801	N	BLN	A320	-4,48053	36,67958	RWY
927	ST4115	167	EDDG	1532500140	1	8,5	N	30	-4,480531	36,679575	2,49	2,19	152,23	1180,75	1024,58	N	BLN	A319	-4,48053	36,67958	RWY
929	FR2591	152	EDDB	1532500740	1	8,7	N	30	-4,480531	36,679575	1,66	1,29	104,51	1432,38	1333,84	N	BLN	B738	-4,48053	36,67958	RWY
930	U23956	135	LFPG	1532500980	1	8,7	N	30	-4,480531	36,679575	1,63	1,24	242,5	851,79	614,33	N	BLN	A320	-4,48053	36,67958	RWY
931	W63190	141	LROP	1532501097	1	8,7	Y	30	-4,480531	36,679575	2,73	1,53	289	1895,85	1545,83	N	ROLAS	A320	-4,48053	36,67958	RWY
932	D8515	124	EFHK	1532500860	1	8,7	N	30	-4,480531	36,679575	1,85	1,47	139,39	2266,53	2141,34	N	BLN	B738	-4,48053	36,67958	RWY
933	TO3161	163	LFPO	1532501520	1	8,9	N	30	-4,480531	36,679575	1,91	1,54	353,4	831,84	483,3	N	BLN	B738	-4,48053	36,67958	RWY
934	VY3068	175	GCLP	1532502900	1	9,3	N	31	-4,485825	36,665408	3,82	3,31	197,9	837,24	620,86	N	PIMOS	A320	-4,48583	36,66541	RWY
935	HV6652	158	EHEH	1532503500	1	9,4	Y	13	-4,512594	36,684536	3,77	1,73	134,99	1066,33	929,4	N	BLN	B738	-4,51259	36,68454	RWY
936	U21924	135	EGCC	1532501940	1	9	Y	30	-4,480531	36,679575	2,97	1,67	359,74	1008,52	649,08	N	BLN	A320	-4,48053	36,67958	RWY
938	591	110	LOWW	1532499300	1	8,3	Y	13	-4,512594	36,684536	3,63	1,43	249,54	1437,71	1151,01	N	BLN	A320	-4,51259	36,68454	RWY
939	VY2986	175	LFBD	1532504220	1	9,6	Y	13	-4,512594	36,684536	3,32	1,25	286,07	539,58	252,38	N	BLN	A320	-4,51259	36,68454	RWY
940	DY4222	157	ESSA	1532504100	1	9,6	N	13	-4,512594	36,684536	2,01	1,29	271,88	1925,99	1686,82	N	BLN	B738	-4,51259	36,68454	RWY
941	U27958	135	EHAM	1532504040	1	9,6	Y	13	-4,512594	36,684536	3,17	1,45	305,1	1090,53	788,29	N	BLN	A319	-4,51259	36,68454	RWY
942	PF2934	150	EGBB	1532505720	1	10	N	13	-4,512594	36,684536	2,37	1,71	291,64	961,79	667,54	N	BLN	B737	-4,51259	36,68454	RWY
943	TB3516	150	LFPO	1532503560	1	9,4	Y	13	-4,512594	36,684536	3,27	1,5	621,12	832,58	187,21	N	BLN	B738	-4,51259	36,68454	RWY
944	FR4469	152	EGNX	1532506140	1	10,2	N	13	-4,512594	36,684536	3,63	3,13	230,19	989,3	755,56	N	BLN	B738	-4,51259	36,68454	RWY
945	BA2713	131	EGKK	1532504820	1	9,8	Y	13	-4,512594	36,684536	1,92	0,99	500,17	906,48	402,59	N	BLN	A319	-4,51259	36,68454	RWY
947	U23112	135	EGSS	1532501100	1	8,8	N	31	-4,485825	36,665408	3,61	3,06	895,83	954,48	52,79	N	BLN	A319	-4,48583	36,66541	RWY
949	HV6116	158	EHAM	1532502900	1	9,3	Y	30	-4,480531	36,679575	1,86	1,36	917,7	1089,85	123,6	N	BLN	B738	-4,48053	36,67958	RWY
950	HV5022	158	EHRD	1532506140	1	10,2	Y	13	-4,512594	36,684536	2,21	0,82	454,32	1062,26	600,02	N	BLN	B737	-4,51259	36,68454	RWY
951	351	104	EDDL	1532506140	1	10,2	Y	13	-4,512594	36,684536	2,24	1,16	675,99	1106,49	434,21	N	BLN	B738	-4,51259	36,68454	RWY
952	EI583	142	EIDW	1532508000	1	10,7	N	13	-4,512594	36,684536	2,84	2,23	402,65	1011,95	619,88	N	BLN	A333	-4,51259	36,68454	RWY
953	LS558	159	EGNT	1532506980	1	10,4	Y	13	-4,512594	36,684536	2,93	1,63	556,42	1115,33	561,22	N	BLN	B738	-4,51259	36,68454	RWY
956	FR2575	152	EHEH	1532510100	1	11,3	N	13	-4,512594	36,684536	4,14	3,68	240,45	1066,61	835,09	N	BLN	B738	-4,51259	36,68454	RWY
957	FR9902	152	EICK	1532507940	1	10,7	N	13	-4,512594	36,684536	2,33	1,66	670,06	942,3	332,86	N	BLN	B738	-4,51259	36,68454	RWY
959	TO3165	163	LFPO	1532511840	1	11,7	Y	13	-4,512594	36,684536	2,87	0,91	244,64	832,63	592,48	N	BLN	B738	-4,51259	36,68454	RWY
961	LS1204	159	EGBB	1532507940	1	10,7	Y	13	-4,512594	36,684536	4,16	2,47	757,22	962,14	203,02	N	BLN	B738	-4,51259	36,68454	RWY
962	BE1678	135	EGHI	1532509980	1	11,2	N	13	-4,512594	36,684536	4,32	3,86	674,07	878,94	196,3	N	BLN	E195	-4,51259	36,68454	RWY
964	VY8184	175	LFPG	1532513400	1	12,2	N	13	-4,512594	36,684536	1,91	1,18	111,49	852,54	736,83	N	BLN	A320	-4,51259	36,68454	RWY
965	LS1406	159	EGSS	1532511300	1	11,6	N	13	-4,512594	36,684536	2,26	1,58	556,66	956,33	394,82	N	BLN	B734	-4,51259	36,68454	RWY
967	U26756	135	EGAA	1532510400	1	11,3	Y	13	-4,512594	36,684536	3,24	1,67	861,41	1084,96	237,3	N	BLN	A320	-4,51259	36,68454	RWY
969	EW9537	156	EDDL	1532517420	1	13,3	Y	13	-4,512594	36,684536	2,62	1,04	171,49	1106,41	940,85	N	BLN	A320	-4,51259	36,68454	RWY
970	LS810	159	EGCC	1532511000	1	11,5	N	13	-4,512594	36,684536	2,34	1,67	747,82	1010,46	266,83	N	BLN	B752	-4,51259	36,68454	RWY
971	KL1038	151	EHAM	1532511000	1	11,5	Y	13	-4,512594	36,684536	3,7	1,6	987,11	1090,47	42,96	N	BLN	B738	-4,51259	36,68454	RWY
972	D85052	124	ESSA	1532518080	1	13,5	N	13	-4,512594	36,684536	2,35	1,69	104,02	1925,86	1821,24	N	BLN	B738	-4,51259	36,68454	RWY
974	TK1306	159	LTBA	1532510100	1	11,3	Y	13	-4,512594	36,684536	2,3	1,43	1169,77	2014,4	533,4	N	TARIK	A321	-4,51259	36,68454	RWY
975	BA2715	131	EGKK	1532513580	1	12,2	Y	13	-4,512594	36,684536	3,37	0,73	878,82	906,3	9,75	N	TARIK	A320	-4,51259	36,68454	RWY
976	FR7055	152	EIDW	1532518200	1	13,5	N	13	-4,512594	36,684536	2,18	1,49	327,61	1011,41	698,12	N	BLN	B738	-4,51259	36,68454	RWY
978	LX2115	164	LSZH	1532519400	1	13,8	N	13	-4,512594	36,684536	1,96	1,25	376,73	1015,31	643,12	N	BLN	A320	-4,51259	36,68454	RWY
979	SU2621	168	UUEE	1532519280	1	13,8	N	13	-4,512594	36,684536	2,88	2,29	448,51	2767,42	2246,12	N	PEPAS	B738	-4,51259	36,68454	RWY
980	FR2334	152	EHAM	1532520420	1	14,1	N	13	-4,512594	36,684536	3,25	2,69	239,61	1090,71	855,43	N	BLN	B738	-4,51259	36,68454	RWY
981	VY2655	175	LEST	1532522280	1	14,6	N	13	-4,512594	36,684536	3,88	3,36	139,71	444,33	307,08	N	SVL	A320	-4,51259	36,68454	RWY
982	SK6354	158	ENGM	1532520900	1	14,3	Y	13	-4,512594	36,684536	2,6	1,02	204,45	1693,28	1493,62	N	BLN	A20N	-4,51259	36,68454	RWY
983	DS1434	151	LSGG	1532520540	1	14,2	N	13	-4,512594	36,684536	1,98	1,28	337,06	856,71	527,39	N	BLN	A320	-4,51259	36,68454	RWY
984	D85072	124	EKCH	1532518800	1	13,7	Y	13	-4,512594	36,684536	3,69	1,45	682,52	1533,24	870,62	N	BLN	B738	-4,51259	36,68454	RWY
985	D85100	124	EDDM	1532523060	1	14,9	N	13	-4,512594	36,684536	2,71	2,1	202,83	1201,8	966,79	N	PEPAS	B738	-4,51259	36,68454	RWY
986	VY8366	175	EHAM	1532521260	1	14,4	N	13	-4,512594	36,684536	2,91	2,31	446,29	1090,62	637,45	N	BLN	A320	-4,51259	36,68454	RWY
987	0B4026	114	LIMF	1532519220	1	13,8	Y	13	-4,512594	36,684536	4,08	2,76	667,63	889,71	109,36	N	BLN	B735	-4,51259	36,68454	RWY
988	D85110	124	EDDL	1532523240	1	14,9	N	13	-4,512594	36,684536	2,19	1,51	256,02	1106,38	868,41	N	BLN	B738	-4,51259	36,68454	RWY
990	LS606	159	EGNX	1532521500	1	14,4	N	13	-4,512594	36,684536	4,38	3,95	337,93	989,79	646,73	N	BLN	B733	-4,51259	36,68454	RWY
991	VY2612	175	LEBB	1532522880	1	14,8	Y	13	-4,512594	36,684536	2,63	1,06	311,29	409,25	94,24	N	BLN	A320	-4,51259	36,68454	RWY
992	D85022	124	ENGM	1532517480	1	13,3	Y	13	-4,512594	36,684536	3,41	1,48	961,38	1693,29	675,72	N	BLN	B738	-4,51259	36,68454	RWY
993	VY6210	175	LIRF	1532525040	1	15,4	N	13	-4,512594	36,684536	1,97	1,26	174,79	1049,58	840,6	N	ROLAS	A320	-4,51259	36,68454	RWY
995	U28608	135	EGKK	1532524860	1	15,4	Y	13	-4,512594	36,684536	3,08	1,45	124,66	906,54	778,69	N	BLN	A320	-4,51259	36,68454	RWY
996	VY2122	175	LEBL	1532525760	1	15,6	Y	13	-4,512594	36,684536	3,19	1,33	158,54	481,9	298,14	N	PEPAS	A320	-4,51259	36,68454	RWY
997	FR4613	152	EDFH	1532522280	1	14,6	N	13	-4,512594	36,684536	1,72	0,95	492,6	1063,93	601	N	BLN	B738	-4,51259	36,68454	RWY
998	SK6026	158	ESMS	1532524500	1	15,3	Y	13	-4,512594	36,684536	2,44	0,84	158,71	1558,67	1411,26	N	BLN	A20N	-4,51259	36,68454	RWY
1000	FR2563	152	ENTO	1532518320	1	13,5	N	13	-4,512594	36,684536	2,16	1,48	1144,61	1615,13	384,66	N	BLN	B738	-4,51259	36,68454	RWY
1002	BT678	150	EVRA	1532526398	1	15,8	N	13	-4,512594	36,684536	4,48	4,05	488,41	2095,28	1516,57	N	PEPAS	BCS3	-4,51259	36,68454	RWY
1003	FR2157	152	EGBB	1532523660	1	15	Y	13	-4,512594	36,684536	2,81	1,39	759,17	961,62	218,37	N	BLN	B738	-4,51259	36,68454	RWY
1004	SN3736	161	EBBR	1532524200	1	15,2	N	13	-4,512594	36,684536	3,67	3,13	569,83	1010,07	432,05	N	BLN	A320	-4,51259	36,68454	RWY
1005	UX1037	173	LFPG	1532524440	1	15,2	Y	13	-4,512594	36,684536	2,25	1,37	695,8	852,62	136,75	N	BLN	B738	-4,51259	36,68454	RWY
1008	TB3658	150	EBAW	1532528905	1	16,5	N	13	-4,512594	36,684536	2,64	1,99	363,45	1023,78	662,59	N	BLN	E190	-4,51259	36,68454	RWY
1009	AZ91	155	LIRF	1532528280	1	16,3	N	13	-4,512594	36,684536	1,87	1,14	464,72	1049,64	479,7	N	ROLAS	A320	-4,51259	36,68454	RWY

Figure D.9: Sample of data for flight descriptors used for the Clustering Experiment

E CODE SAMPLES

E.1 Repository for code samples and reports

We have set up a GitHub repository [60] where we have uploaded some source code samples and several reports generated by our applications.

E.2 Code snippets of the communication with the flight simulator

Listing E.1 shows the Lua server code running in the flight simulator side, receiving the parameters that govern the flight simulator from the external application.

Listing E.1: Server on the flight simulator side, to receive parameters (control actions) into the simulator from the application.

```
-- The SOCKET module is built into FSUIPC, but is not active until "
    required"
local socket = require("socket"); -- require "loads" the library
-- Change the host name to the name of the PC running this Server
-- The "localhost" name only serves local clients
local host = "127.0.0.1";
-- The port must match the port selected in the client and not clash with
     others.
local port = "8384";
local server = assert(socket.bind(host, port));
local ack = "\n";
while 1 do
   print("server: waiting for client connection...");
   local control = server:accept();
      control:settimeout(2);
   if control ~= nil then
      print("server: client connected!");
      while 1 do
            local command = control:receive('*a');
                  print ("server: Command just received: ");
            if command == nil then
```

```
                  print("server: client disconnected");
                  break
            end
            print("server: "..command);
                  (loadstring(command))();
      end
   end
      control:close();--close connection (don't confuse with closing socket)
end
```

Listing E.2 shows the PHP client code running in the application, sending messages with the command selected by the user each time there is an action in the application. These messages follow the format indicated in FSUIPC documentation [53], where it can be observed that virtually all the internal parameters of the simulated aircraft are assigned by a memory position and offset status definition, so that they can be read or written to provide almost full control of the simulator to an external application like the one developed in this research.

Listing E.2: Client on the application side, to send parameters (control actions) to the simulator.

```
<?php
$SocketFSUIPCMessage = $_GET ['FSUIPCMessage'];//Sintax to retrieve the
    message as PHP parameter.
$host='localhost';
//socket_create => Creates and returns the socket resource.
$socket=socket_create(AF_INET,SOCK_STREAM,SOL_TCP);
//Communication port to be used by the socket:
$puerto=8384; //Port needs to be the same as LuaServer.

/*socket_connect=>Starts a connection to the $host address via $socket
    resource.*/
$conexion=socket_connect($socket,$host,$puerto);

if($conexion)
      {socket_write($socket,$SocketFSUIPCMessage,strlen(
          $SocketFSUIPCMessage));
      echo "Successful connection. Sending: ".$SocketFSUIPCMessage;
   }
      else
      {
      echo "\n Unable to make TCP connection. Port: ".$puerto;
   }
socket_close($socket); //closing resource $socket.
```

```
echo " y llega al final del PHP cliente";
?>
```

Listing E.3 shows the Lua client code running in the flight simulator side, periodically sending the aircraft's parameters to the application where the HMI is implemented. In this code it can be observed how the data is read from the simulator using the FSUIPC message format, the numeric values are converted or re-scaled according to the FSUIPC documentation, and then the information is formatted as a Comma-separated Values (CSV) message that is transmitted to the application using a TCP socket.

Listing E.3: Client on the flight simulator side, to send parameters from the simulator to the application.

```
-- ****************************************************
-- clientaiviewer.lua *** FSUIPC lua Client that sends below selected FSX
     flight parameters to the server.
-- High level description:
--    *Open the socket with appropriate IP and Port
--    *Send a message (could be the XML header, if necessary)
--    *Endless while
--      -Collect data from FSX
--      -Send via socket
--      -Pause (vary time to change sample rate)
--    *Close socket

-- *Updated 31-05-2013
-- ****************************************************

-- In case of problems, check the computer IP with CMD ipconfig

-- WAMP localhost settings:
local host, port = "127.0.0.1", 4545

local socket = require("socket")
local tcp = assert(socket.tcp())

tcp:connect(host, port);
--note the newline below
tcp:send("socket established, also you could write the XML header here once\n");

while true do
   -- note the elapsed mSecs count now so can provide relative mSec
       timing column
   time0 = ipc.elapsedtime()
```

```
-- Loop until our Flag 0 is set (by assigned FSUIPC control)
while not ipc.testflag(0) do

   -- Set the timestamp for this loop
   time = ipc.elapsedtime() - time0

   -- Read all the data we want from FSUIPC
               -- 8 bytes -> DD (double precision signed decimal, e.g.
                   lat /lon)
               -- 4 bytes -> SD (single precision signed decimal, e.g.
                   pitch, bank, heading)
               -- 4 bytes -> UD (unsigned decimal, e.g. gs, tas, ias)
               -- 2 bytes -> readUW (unsigned int, e.g. mach)
               -- 2 bytes -> readSW (signed int, e.g. VS)
               -- 1 byte -> UB (unsigned byte, e.g. hour, min, sec)

   hour, min, sec, hourZ, minZ = ipc.readStruct(0x238, "5UB")
   gs, tas, ias = ipc.readStruct(0x02B4, "3UD")
               gs = (gs * 3600) / (65536 * 1852)
               tas = tas / 128
               ias = ias / 128

   lat, lon, alt, pitch, bank, hdgT = ipc.readStruct(0x0560,"3DD", "2
       SD", "1UD")
               lat = lat * 90 / (10001750 * 65536 * 65536)
               lon = lon * 360 / (65536 * 65536 * 65536 * 65536)
               alt = alt * 3.28084 / (65536 * 65536)
               pitch = pitch * 360 / (65536 * 65536)
               bank = bank * 360 / (65536 * 65536)
               hdgM = hdgT - (ipc.readSW(0x02A0) * 65536)
               hdgM = hdgM * 360 / (65536 * 65536)
               hdgT = hdgT * 360 / (65536 * 65536)
                     --heding adjustments
                     if (hdgT > 360) then
                     hdgT = hdgT-360
                     end
                     if (hdgM > 360) then
                     hdgM = hdgM-360
                     end
                     if (hdgT < 0) then
                     hdgT = hdgT+360
                     end

                     if (hdgM < 0) then
```

```
                        hdgM = hdgM+360
                        end
            mach = ipc.readUW(0x11C6)
                  mach = mach / 20480
      vs = ipc.readSW(0x842)
                  vs = vs * -3.28084
            --added on 25-09-2014:
            windSpeed = ipc.readUW(0x0E90) --no need convertion
            windDirection = ipc.readUW(0x0E92)
                  windDirection = windDirection * 360 / 65536
            pressure = ipc.readUW(0x0EC6)
                  pressure = pressure / 16
      OATemp = ipc.readSW(0x0E8C)
                  OATemp = OATemp / 256
            kollsman = ipc.readUW(0x0330)
                  kollsman = kollsman / 16
            Throttle = {}
      Throttle1 = ipc.readSW(0x088C)
                  Throttle1 = Throttle1 / 163.84
            table.insert(Throttle, Throttle1)
            Throttle2 = ipc.readSW(0x0924)
                  Throttle2 = Throttle2 / 163.84
            table.insert(Throttle, Throttle2)
            Throttle3 = ipc.readSW(0x09BC)
                  Throttle3 = Throttle3 / 163.84
            table.insert(Throttle, Throttle3)
            Throttle4 = ipc.readSW(0x0A54)
                  Throttle4 = Throttle4 / 163.84
            table.insert(Throttle, Throttle4)
            EnginesNumber = 2
            EnginesNumberRead = ipc.readUW(0x0AEC)
            -- this if prevents from obtaining a strange number of
                engines from FSX, so default will be 0
            -- if an aircraft #Eng != 2 but we can read it, we will
                assume it has 2 engines
            if (EnginesNumberRead > 0) and (EnginesNumberRead < 5) then
                  EnginesNumber = EnginesNumberRead
            end
            ThrottleAvg=0;
            for eng = 1, EnginesNumber do
              ThrottleAvg = ThrottleAvg + Throttle[eng]
            end
            ThrottleAvg = ThrottleAvg / EnginesNumber
      -- but only log this time IF we aren't in an FS menu, or loading scenery
      –– (check the "ready–to–fly" flag word at 3364)
```

```
        -- and provided we are not paused (flagged at 0264)
        if (ipc.readUW(0x3364) == 0) and (ipc.readUW(0x0264) == 0) then
          -- write a CSV line to the open file
          tcp:send(string.format("%d,
                %02d:%02d:%02d,%02d:%02d,%02.6f,%03.6f,%.1f,%.2f,%.2f,%03.1f
                    ,%03.1f,%d,%d,%d,%d,%.3f,%d,%d,%d,%d,%d,%.2f",
                 time,hour,min,sec,hourZ,minZ,lat,lon,alt,pitch,bank,hdgT,hdgM,vs,
                     ias,tas,gs,mach,windSpeed,windDirection,pressure,OATemp,
                     kollsman,ThrottleAvg))
        end
        -- every 5 seconds, due to server saturation & AIViewer performance
            decrease:
        ipc.sleep(500)
    end
end
tcp:close()
```

Listing E.4 shows the PHP server code running in the application, receiving the messages, parsing the CSV stream and converting it into an SQL query to insert the aircraft parameters into a database.

Listing E.4: Server on the flight simulator side, to send parameters from the simulator to the application.

```
<?php
//Websockets: https://code.google.com/p/phpwebsocket/
$dbName=$_GET['dbName'];
$flightTableName=$_GET['flightTableName'];
include("../Connections/conexGeneric.php");
$link=Conectarse($dbName);

$samples_per_second=1;

ob_implicit_flush();
function workaround() {
  if (!defined('MSG_DONTWAIT')) {
   define('MSG_DONTWAIT', 0x40);
   return 1;
  }
 }
 workaround();

define('ENOTSOCK', 88); /* Socket operation on non-socket */
define('EDESTADDRREQ', 89); /* Destination address required */
define('EMSGSIZE', 90); /* Message too long */
```

```
define('EPROTOTYPE', 91); /* Protocol wrong type for socket */
define('ENOPROTOOPT', 92); /* Protocol not available */
define('EPROTONOSUPPORT', 93); /* Protocol not supported */
define('ESOCKTNOSUPPORT', 94); /* Socket type not supported */
define('EOPNOTSUPP', 95); /* Operation not supported on transport
    endpoint */
define('EPFNOSUPPORT', 96); /* Protocol family not supported */
define('EAFNOSUPPORT', 97); /* Address family not supported by protocol
     */
define('EADDRINUSE', 98); /* Address already in use */
define('EADDRNOTAVAIL', 99); /* Cannot assign requested address */
define('ENETDOWN', 100); /* Network is down */
define('ENETUNREACH', 101); /* Network is unreachable */
define('ENETRESET', 102); /* Network dropped connection because of reset
     */
define('ECONNABORTED', 103); /* Software caused connection abort */
define('ECONNRESET', 104); /* Connection reset by peer */
define('ENOBUFS', 105); /* No buffer space available */
define('EISCONN', 106); /* Transport endpoint is already connected */
define('ENOTCONN', 107); /* Transport endpoint is not connected */
define('ESHUTDOWN', 108); /* Cannot send after transport endpoint
    shutdown */
define('ETOOMANYREFS', 109); /* Too many references: cannot splice */
define('ETIMEDOUT', 110); /* Connection timed out */
define('ECONNREFUSED', 111); /* Connection refused */
define('EHOSTDOWN', 112); /* Host is down */
define('EHOSTUNREACH', 113); /* No route to host */
define('EALREADY', 114); /* Operation already in progress */
define('EINPROGRESS', 115); /* Operation now in progress */
define('EREMOTEIO', 121); /* Remote I/O error */
define('ECANCELED', 125); /* Operation Canceled */

// Set time limit to indefinite execution
set_time_limit (0);

/*socket_create=>Creates and returns a socket resource.*/
$socket=socket_create(AF_INET,SOCK_STREAM,0);

//127.0.0.1 -> accept only from local host
//w.x.y.z (valid local IP) -> accep only from this network

$direccion=0;
$puerto=4545;//chosen port number. Needs to be the same in Server and
    Client sides.
```

```
/*socket_bind=>Binds the name given in $direccion to the socket described
     by $socket.
This has to be done before establishing a connection
using socket_connect() o socket_listen().*/
socket_bind($socket, $direccion,$puerto);

socket_listen($socket);//indication to listen to incoming connections
    once the socket is created.

$tamano=2048;
$i=0;
$cliente= array();
$numclientes=1;//Wait to 2 clients (2 connections)
while($i<$numclientes)
{
      $cliente[$i]=socket_accept($socket); //Blocks waiting for a client
          connection
      // $client is an array of "connections that identify each of the
          clients"
      $i++;
}
$i=0;

$clientesvivos=true;
$k=0;
while($clientesvivos){
      while($i<count($cliente) && $clientesvivos)
      {  if(($buffer=socket_read($cliente[$i], $tamano))) //leemos
          mensaje del cliente
            {$k++;

       if($k==$samples_per_second)
       {
          $flightparam=explode(",",$buffer);

          $query1="insert into ".$dbName.".".$flightTableName." ";
                   $query2="insert into `".$dbName."`.`latest` ";

                   $query1.="(msec,time,Ztime,FSXlat,FSXlon,alt,pitch,bank,hdgT,
                       hdgM,vs,ias,ts,gs,mach,windSpd,windDir,pressure,
                       OATemp,kollsman,ThrottleAvg) ";
             $query1.="VALUES (";
                   $query2.="(msec,time,Ztime,FSXlat,FSXlon,alt,pitch,bank,hdgT,
                       hdgM,vs,ias,ts,gs,mach,windSpd,windDir,pressure,
                       OATemp,kollsman,ThrottleAvg) ";
```

```
            $query2.="VALUES (";

         $j=0;
            while($j<count($flightparam)-1)
            {
          $query1.="'".$flightparam[$j]."',";
                     $query2.="'".$flightparam[$j]."',";
          $j++;
         }
         $query1.="'".$flightparam[count($flightparam)-1]."')";
         $query2.="'".$flightparam[count($flightparam)-1]."')";
                  $resultado = mysqli_query($link,$query1);
            if (!$resultado){echo mysqli_error($link);}
                  $resultado = mysqli_query($link,$query2);
            if (!$resultado){echo mysqli_error($link);}
         $k=0;

      }//end if $k
           }
           $i++;
      }
      $i=0;
}//end while
//@socket_close=>close socket resources provided by the client
@socket_close($cliente1);
@socket_close($cliente2);

socket_close($socket);
mysqli_close($link);
?>
```

Finally, Listing E.5 shows and excerpt of PHP code to create a SQL query that creates the table where the aircraft parameters will be inserted. This code has been included to provide a better understanding of the data structures handling and the data characteristics, complementing Appendix D

Listing E.5: The table that stores aircraft parameters is created with this SQL query.

```
$queryAuto1="CREATE TABLE `".$dbName."`.`flight".$flightdate."`";
$queryAuto1.=" (`ID_flight` INT( 11 ) NOT NULL AUTO_INCREMENT PRIMARY
    KEY ,";
$queryAuto1.="`msec` BIGINT UNSIGNED NOT NULL,";
$queryAuto1.="`time` TIME NOT NULL,";
$queryAuto1.="`Ztime` TIME NOT NULL,";
$queryAuto1.="`FSXlat` double(15,10) NOT NULL,";
```

```
$queryAuto1.="'FSXlon' double(15,11) NOT NULL,";
$queryAuto1.="'alt' double(10,1) NOT NULL,";
$queryAuto1.="'pitch' double(10,2) NOT NULL,";
$queryAuto1.="'bank' double(10,2) NOT NULL,";
$queryAuto1.="'hdgT' double(5,1) NOT NULL,";
$queryAuto1.="'hdgM' double(5,1) NOT NULL,";
$queryAuto1.="'vs' int(5) NOT NULL,";
$queryAuto1.="'ias' int(5) NOT NULL,";
$queryAuto1.="'ts' int(5) NOT NULL,";
$queryAuto1.="'gs' int(5) NOT NULL,";
$queryAuto1.="'mach' double(6,3) NOT NULL,";
$queryAuto1.="'windSpd' int(5) NOT NULL,";
$queryAuto1.="'windDir' int(5) NOT NULL,";
$queryAuto1.="'pressure' int(5) NOT NULL,";
$queryAuto1.="'OATemp' int(5) NOT NULL,";
$queryAuto1.="'kollsman' int(5) NOT NULL,";
$queryAuto1.="'ThrottleAvg' double(5,2) NOT NULL) ENGINE = MYISAM;";

$resultado = mysqli_query($link,$queryAuto1);
       if (!$resultado){echo mysqli_error($link);}
```

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