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A Probabilistic Algorithm for Predictive Control With Full-Complexity Models in Non-Residential Buildings

JUAN GÓMEZ-ROMERO[1], CARLOS J. FERNÁNDEZ-BASSO[1], M. VICTORIA CAMBRONERO[2], MIGUEL MOLINA-SOLANA[3], JESÚS R. CAMPAÑA[1], M. DOLORES RUIZ[1], AND MARIA J. MARTIN-BAUTISTA[1]

[1]Department of Computer Science and Artificial Intelligence, Universidad de Granada, 18071 Granada, Spain
[2]Acciona Ingeniería, 28108 Alcobendas, Spain
[3]Data Science Institute, Imperial College London, London SW7 2AZ, U.K.

Corresponding author: Juan Gómez-Romero (jgomez@decsai.ugr.es)

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ABSTRACT Despite the increasing capabilities of information technologies for data acquisition and processing, building energy management systems still require manual configuration and supervision to achieve optimal performance. Model predictive control (MPC) aims to leverage equipment control–particularly heating, ventilation, and air conditioning (HVAC)–by using a model of the building to capture its dynamic characteristics and to predict its response to alternative control scenarios. Usually, MPC approaches are based on simplified linear models, which support faster computation but also present some limitations regarding interpretability, solution diversification, and longer-term optimization. In this paper, we propose a novel MPC algorithm that uses a full-complexity grey-box simulation model to optimize HVAC operation in non-residential buildings. Our system generates hundreds of candidate operation plans, typically for the next day, and evaluates them in terms of consumption and comfort by means of a parallel simulator configured according to the expected building conditions (weather and occupancy). The system has been implemented and tested in an office building in Helsinki, both in a simulated environment and in the real building, yielding energy savings around 35% during the intermediate winter season and 20% in the whole winter season with respect to the current operation of the heating equipment.

INDEX TERMS Model predictive control, simulation, control, building energy management system.

I. INTRODUCTION

Buildings account for more than one third of the worldwide primary energy consumption [1] and they are an equally important source of CO_2 emissions [2]. In western countries, non-residential buildings consume between 30-40% of the energy, mostly during the operational stage and by the HVAC (heating, ventilation, and air conditioning) systems [3]. These figures are expected to increase in the future due to inefficiency of aging infrastructures, impact of climate change in weather, and economic growth in China and India [4]. At the same time, technological advances offer great opportunities to achieve energy savings in new and old buildings. For the latter, the European Union issued in 2016 an update of the Directive on the Energy Performance of Buildings addressing the target of a 30% increase of energy efficiency by 2030 [5].

There are several complementary strategies to reduce energy consumption in existing buildings. Renovation works and retrofitting, making the most of affordable and clean sources, are essential, and to be effective, they must be accompanied by suitable operation protocols to optimize energy management [6]. As a matter of fact, selecting daily optimal setpoints for the HVAC equipment is estimated to lead to savings up to 35%, depending on the climate [7].

New approaches to building energy management systems (BEMS) offer interactive and real-time building monitoring and remote control, and provide support for simulation and optimization [8]–[10]. Still, a great deal of the decision-making is left to the operators, who must analyze available data, estimate energy demand, and propose control

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rules to be implemented in the BEMS. Common a priori control strategies include optimized start/stop of equipment, chiller and boiler optimization, adaptive control, and optimal energy sourcing [11].

In the last decade, several proposals for automating the generation of operational plans based on Model Predictive Control (MPC) have been presented [12], [13]. MPC uses a simulation model of the building to capture its dynamic characteristics and predict its response to alternative control scenarios. It pursues a (conflicting) dual target: reducing energy consumption thanks to pre-emptive control and anticipation of the building state while keeping users' comfort. By establishing a complete sequence of instructions for the building equipment –i.e. the (daily) operational plan–, it overcomes the limitations of homeostatic controllers, which cannot guarantee long-term optimal operation: the ahead time and the timespan of the control instructions can expand to several hours, leading to plans entailing more uncertainty –because of the use of forecasted building conditions (e.g. weather, occupancy)– and more complexity –because of the exponential increase of possible plans–, but also more efficient –because of the exploitation of the inertial effects of HVAC equipment.

MPC is formulated as a combinatorial optimization problem, in which a search algorithm must find the best actuation plan, in terms of thermal comfort and overall building consumption, in a solution space including all the possible setpoint combinations for a given future period [14]. Nevertheless, most works tend to simplify the models (e.g. by reducing the model differential equations to linear combinations) or to reduce the search space (e.g. by limiting the control to a small part of the building equipment, and by incorporating manually-extracted expert knowledge). This results in short-scope, limited-extensibility and low-performance solutions involving a great deal of manual work

The departing hypothesis of our research work is that we can exploit the increasing capabilities of massive and parallel data processing technologies to run a large amount of simulations with full-complexity physical models and to assess multiple hypothetical control scenarios to obtain the appropriate setpoints in terms of efficiency and comfort. Availability of sensor data allows us to develop more accurate models, since data can be used for calibration, calculation of better predictions of relevant contextual factors (e.g. occupancy), and detection of control performance decline. At the same time, physical models are more interpretable and easier to extend; actually, we can use physical models and model development tools out of the box, such as TRNSYS, EnergyPlus or IESVE [15].

In the Energy IN TIME project,[1] we developed an advanced BEMS for optimized HVAC operation in non-residential buildings. This BEMS is powered by Big Data technologies, which provide support for massive data management for continuous model calibration, distributed execution of simulation software, accurate prediction of building conditions, and remote operation.

The core of the system is the intelligent operational plan generator (OPG) module, an MPC-like control scheduler supported by a cloud-based extension of the IESVE[2] simulation software. The OPG algorithm calculates an operational plan (OP) for a future period (typically the next day) after simulating hundreds of candidate plans under the forecasted state of the building (i.e. considering weather and occupancy estimations) in order to minimize energy consumption while guaranteeing occupants' comfort. Eventually, the OP setpoints are automatically applied to the equipment without direct involvement of the operator. To the best of our knowledge, this is the first proposal using an off-the-shell full-complexity model for predictive control.

In this paper, we describe the OPG algorithm design, implementation, and evaluation in the Sanomatalo commercial building located in Helsinki (Finland). The control strategies for this building focus on optimizing the air supply temperature setpoint and the airflow volume setpoints. The main contributions of this research work are the following:

- The OPG algorithm, based on probabilistic search, directly provides operational plans for HVAC equipment including on/off and numerical setpoint values that are directly applied through the BEMS –no additional translation from demand estimations into actions is needed.
- We extend the control horizon compared to usual MPC approaches. The OPG considers setpoints up to a 1-day period, which fits better to the usual building operation (e.g. the operator can validate control for the whole day) and offers more opportunities for longer-term energy saving policies.
- We use a full-complexity simulation model out of the box, decoupled from the optimization algorithm and directly interpretable by experts and operators. The simulation model self-recalibrates by using data directly measured from the building and runs on a cloud-based distributed version of IESVE.
- We carry out an evaluation of the system in the simulation environment and in the real building; in the latter case, over a longer period of time than related works (30 days), in line with the recommendations in [16].

Comparison with the base control, performed according to the International Performance Measurement and Verification Protocol (IPMVP) [17], yielded energy savings above 20%, with peaks above 40% at the end of the winter season.

The remainder of the paper is organized as follows. Next, we describe several related works, most of them centered in the use of simplified simulation models. In Section III, we describe the pilot building, the simulation model, and the evaluation methodology. In Section IV, we detail the design of the OPG algorithm and its features. Section V presents the

[1]The Energy IN TIME project (Simulation-based control for energy efficiency building operation and maintenance) was funded by the European Commission within the 7th Framework Programme in 2013-2017. See [66] for a brief description of the overall project results.

[2]https://www.iesve.com/VE2018

experimental setup and the results obtained in the simulation environment and in the real building compared to the baseline operation. In Section VI we discuss the contributions of our proposal in terms of energy savings and comfort achievement, as well as possible improvements to the system. Finally, we summarize the conclusions of the work and introduce prospective directions for future research.

II. RELATED WORK

MPC was introduced by Mahdavi in 2001 [18], and was initially used offline to derive an optimized control law from sensor measurements and simulations, and to validate predefined control strategies [19], [20]. Associated small-scale experiments, most of them carried out in the simulation environment, showed that the application of MPC can effectively accomplish a reduction in energy consumption [21]. Further studies characterized and performed a preliminary evaluation of HVAC-related energy management actions that can be exploited in MPC [22]: outside air economizer cycle, programmed start and stop lead time, load reset, and occupied time adaptive control strategy. Additionally, other authors emphasized the need for considering subjective comfort measures beyond indoor temperatures and humidity thresholds, such as predicted mean vote (PMV) [23].

In contrast, current MPC-powered BEMS are not limited to only apply a plan elicited from expert knowledge and confirmed suitable after simulation. They can dynamically generate control instructions by searching an operational plan that, according to the simulation model, satisfies the expected energy demand while minimizes consumption. Nevertheless, the calculation of the fitness of a plan by simulation is computationally expensive [24].

Bianchini *et al.* [25] addressed this issue by replacing the full model of the building by a simplified linear model. The linear model is afterwards solved by using different heuristics that reduce the search to a computable mixed integer linear programming (MILP) problem. Although this solution considerably reduces the capability of the algorithm to find unknown solutions, it proved to yield good results in a simulation environment when tested for a delimited section of the building. Different proposals using linear and non-linear programming, having different degree of complexity, application scope, evaluation comprehensiveness and achieved energy savings, can be found in the literature, in particular for non-residential buildings [26]–[34].

Similarly, MPC solutions have been successfully applied to optimize the use of different energy sources in buildings with mixed supply systems [35]–[37] and to achieve distributed control [38], [39] –enabling extensions to minimize communication between network components [40]. To increase the capabilities for solution diversification, other search techniques have been applied to optimization in MPC, such as genetic algorithms [41]–[43] and particle swarm optimization [44]. To address the stabilization of the control process, nonlinear MPC solutions with varying horizon have been proposed [45].

As an alternative to MILP and related techniques, Katsigarakis *et al.* [46] created a surrogate building model by applying Machine Learning techniques. This surrogate model is automatically learnt from pre-computed outcomes of the real model by using a regression technique (e.g. support vector machines), and optimization with it is significantly faster than in MILP. Unfortunately, it can be inaccurate or unfeasible if the building state is difficult to model; i.e. when the control scope is too broad, there are too many outputs to estimate, or the variables have complex interdependencies. Analogously, Casals *et al.* used Bayesian networks to simplify the simulation model of a subway station, obtaining good prediction accuracy [47]. Their system does not provide long-term operation plans –and consequently, it does not optimize HVAC operation–, yet it achieves considerable energy savings in ventilation and lighting systems –thanks to the use of sophisticated Computer Vision techniques for real-time occupancy estimation. Manjarres *et al.* trained a predictive black-box model using Random Forests that reproduces the daily behavior of the building and replaces the physical model of the building; however, the control strategies are limited to switching on and off the HVAC systems [48]. Kontes *et al.* created a surrogate model with support vector machines (SVM) to optimize radiator operation with similar promising results [49].

A subsequent problem of MPC is the accuracy of the simulation model, particularly if a simplified version is required [50]–[52], or if there is uncertainty in the expected building conditions; e.g., weather forecast and occupancy estimations [53]–[55]. In this regard, Kwak *et al.* proposed exploiting parallel co-simulation, which is the execution of several simulation models under different conditions to minimize the errors due to uncertainty in input data and unexpected occupancy variations. The authors implemented a general-purpose enthalpy controller that generated control signals starting 15 and 30 minutes later [56], and a daily controller [57]. For the combination of the simulation models –in EnergyPlus and MATLAB–, they used the Building Controls Virtual Test Bed (BCVTB) suite. The system was tested during one day in severe weather conditions in a real building, showing energy savings around 2% in the best case.

III. MATERIALS AND METHODS

A. SANOMATALO BUILDING AND PILOT AREA

Sanomatalo[3] (Sanoma house, ‘house of the press’) is a multi-purpose building situated in Helsinki and inaugurated in 1999. It was designed by Jan Söderlund and Antti-Matti Siikala, featuring a double glass façade with a steel frame structure to reduce the need for heating. In its 9 floors and 8227,56 m^2, it houses the offices of the Sanoma media group and offers 2 floors of covered public space. The building is managed by Caverion,[4] a Finnish construction and maintenance company.

[3]https://sanoma.fi/en/sanoma-house/

[4]https://www.caverion.com/

(a)

(b)

FIGURE 1. **Sanomatalo building: (a) general view; (b) detail of the façade (source: FUNIBER for the Energy IN TIME project).**

The building is connected to the district heating network and rooms are heated by waterborne radiators and fan coil units. There are four heat exchangers, one of them dedicated to the AHU heating network (power = 550 kW). All areas in the building have mechanical ventilation, which adjusts airflow based on room temperature and CO_2 concentration. The BEMS is provided by Schneider Electric and allows controlling ventilation, heating, and cooling sub-systems from a centralized console. It enables about 2.000 inspection points, as well as an OPC (OLE for Process Control) module that allows remote setpoint writing.

The main challenge in Sanomatalo is minimizing energy consumption (and costs) while guaranteeing comfort (indoor temperature and CO_2 concentration) during the heating season –usually between September and May, being the period from January to March the coldest one. Indoor temperatures can be retrieved in real-time through the BEMS, whereas CO_2 sensors cannot be remotely accessed –data must be downloaded offline. Heating consumption is monitored every hour by a separated sub-system. District heating prices are fixed for each season, amounting to approximately 50€/MWh in the harsh winter period (Jan-Feb), and 45€/MWh in the remainder of the winter period (Mar-May, Nov-Dec). Electricity price is about 77 and 79€/MWh, respectively. No detailed historical records of sensor measurements were available at the beginning of the project in 2013, but they were acquired in 2015-2017.

For demo purposes, we identified a pilot area of 2,748.60 m^2 encompassing floors 6th to 8th, which include small-size offices, meeting rooms, and open polyvalent spaces. The use of the pilot area is the expected one for an office building, with flexible working hours between 6am–18pm and an overall floor space factor of 26.2 m^2/person. Total electricity consumption in the pilot area in 2017 from January to April was about 60 MWh, while district heating consumption was about 35 MWh in the same area and period. These floors are served by a single not-shared air handling unit (AHU), which is configured by means of a temperature setpoint. This piece of equipment was the main parameter of the energy optimization strategies (see section III.C). In addition, we adjusted the air volume setpoint of three variable air volume (VAV) units serving 8th floor.

B. SIMULATION MODEL AND CALIBRATION

The accuracy of the simulation model is a crucial aspect of MPC approaches to avoid the generation of control instructions under wrong assumptions [58]–[60]. To this aim, control-oriented models must effectively catch all the interactions between HVAC equipment (radiators, heat pumps, etc.) [61]. This is however a difficult and costly process [62].

Grey-box models have showed good performance and cost-benefit ratio [63], [64], even with relatively simple formulations and few input variables [65]. This kind of models rely on the existing corpus of expert knowledge to model thermal behaviour by using differential equations encoding the physical principles of mass, energy and momentum transfer; and they apply statistical models to tune model outputs based on historical and live data.

A canonical grey-box model –namely, the *operational* model– was created at system design time with the IESVE software by IES energy experts with the support of Caverion's building operators. IESVE comprises a series of individual components including climate, geometric modelling, solar shading, energy and carbon, lighting, airflow, thermal mass, value/cost and egress modules that are linked by a single Integrated Data Model (IDM) through a Common User Interface (CUI). By combining these modules, we can model and simulate all aspects of a building's construction, location, geometry, climate, usage, sub-systems and thermal performance.

The simulation model developed for Sanomatalo included: (a) the passive components of the building (façade, claddings, solar irradiation, etc.), created with the ModelIT and the SunCast modules; (b) the active components (anything producing or consuming electricity, especially in relation to the HVAC system), created with the ApacheHVAC, MacroFlo and Vista modules; (c) the expected building conditions (predicted occupancy and weather forecast). Simulation was performed by the ApacheSim module, which dynamically simulates the interaction between all of the active and passive elements over a selected period of time, taking into account the external influences (i.e. weather and occupancy) and the internal thermal behavior. The results of the simulation were viewed in the VistaPro module for analysis of heating and cooling loads, energy consumption, internal temperatures, thermal comfort, etc.

The details of the Sanomatalo model are not public and fall out of the scope of this paper. Nevertheless, this should not be seen as a limitation of our proposal. On the contrary, our approach is agnostic to the underlying simulation model, as far as it allows setting operational profiles as input.

The parameters of the operational model were continuously adjusted to fit live data measurements with the simulation output. Calibration was implemented as a semi-automatic procedure encompassing two iterative steps: (1) measuring the model accuracy by comparing simulation outputs with measured building data; (2) modifying model parameters to reduce model errors. In addition, IES carried out an entropy analysis to detect which parameters have the greatest influence in the model output, and therefore should be firstly modified. Overall, the calibration procedure resulted in a simulation model yielding errors below 5% [66].

C. ENERGY OPTIMIZATION STRATEGIES

Following the Energy IN TIME terminology, control strategies specify the setpoint values allowed for each piece of actionable equipment. Strategies can denote single setpoint restrictions (e.g. setpoint variable range, frequency of change) or cross-parameter restrictions (e.g. two setpoints cannot have specific values at the same time). Besides, strategies can vary depending on the season. Energy optimization strategies are strategies enriched with heuristic information aimed at improving the energy efficiency and maintaining comfort. That is, energy optimization strategies define additional setpoint constraints that can help to reduce energy consumption (e.g. reasonable length of the pre-heating period). Energy optimization strategies can be seen as the instantiation of the Energy Management Control functions proposed in [22] for a particular building.

During the plan generation process, the operational model is cloned and reconfigured according to the forecasted occupancy and weather conditions –namely, the *independent profile variables*. As introduced in Section IV.A, the occupancy was measured as the room occupancy % from the building agenda, and the weather was a set of variables including outdoor air temperature (OAT), solar irradiance, etc.

Therefore, to run a simulation, we specify the operational input profiles –i.e. the equipment setpoint sequences to be tested in the simulation– and the independent profiles –i.e. the occupancy and the weather time series–, in order to get the predicted profiles –i.e. the value sequences for indoor temperatures, CO_2 concentration, and energy consumption.

Energy optimization strategies for the Sanomatalo experiments with the OPG solution encompassed:

(1) The supply temperature of the AHU in the pilot area (*Tsupply*), in the range [17, 23] °C;

(2) The airflow of 3 VAV devices ($VAVairflow_i$) in floor 8th, in the range [50, 200] l/s. The choice of selecting these 3 VAVs was the limited availability of CO_2 sensors at the beginning of the project: only the area affected by these 3 VAVs was monitored.

In pre-OPG operation, *Tsupply* values were manually set by the operators and *VAVairflow* values were automatically set by using presence sensors.

The comfort requirements for the new system in the heating period were the following:

- Indoor air temperature (*IAT*) must be in the range [20.5, 21.5] °C during office hours 6:00–18:00. A flexible margin in [20, 22] °C is considered acceptable. This temperature was represented by 25 output simulation variables, corresponding to 25 sensors spread across the 3 floors directly accessible through the BEMS.
- CO_2 concentration (*Con*) upper limit is 850 ppm during office hours. This concentration was represented by 4 output simulation variables, corresponding to 4 sensors for which there were no live measurements through the BEMS.

The target variables to optimize were the heat and the fan power consumption meters of the pilot area –one of each for the whole pilot area–, which we will call *Heat* and *Fan*. They were represented by two output variables in the simulation model. There were no corresponding physical sensors for these variables, but their values can be directly derived from the BEMS temperature and air flow measurements.

D. EVALUATION METHODOLOGY

Following the International Performance Measurement and Verification Protocol (IPMVP), our evaluation methodology compared energy savings achieved by the OPG with respect to a base case in which it is not used. This process was carried out both in the simulation environment and in the real building:

- Evaluation in the simulation environment: We selected 3 days in the 2016-2017 period, respectively corresponding to a prototypical average (12-Jan-2016), cold (21-Jan-2016), and warm day (30-Jan-2017) of the winter season. The baseline was the real operation of the building for the same days. These data were collected at the beginning of the project. More details of this procedure are described in Section V.A.
- Evaluation in the real building: The OPG was activated in the building during a 30-day period in the late winter season, from April 19th to May 19th 2017. The reason of this choice is that we identified in the simulation environment that the OPG can achieve better results in the transitions between seasons –usually, the heating season in Sanomatalo ends in the second week of May. For the baseline, we built a regression model from historical data which estimates the energy consumption of the HVAC system without the OPG from the weather and the occupancy values, following the recommendations in [67].

With this model, we obtained a reliable approximation of the consumption that would have been measured if the system without the OPG had been used during the real test period. More details of this procedure are described in Section V.B.

We also studied comfort in terms of the indoor temperatures (*IAT*) and CO_2 concentration (*Con*) mentioned above, checking that the simulated and measured values were within the acceptable ranges.

IV. PREDICTIVE CONTROL ALGORITHM

A. CONTROL SYSTEM ARCHITECTURE

The Operational Plan Generation module is the core of the control system in Energy IN TIME. It encompasses three main stages:

1) Collection of forecasted building data: The OPG retrieves the weather forecast and the occupancy prediction for the operation period, usually the next day. Within our project, the weather forecast was obtained from the Weather Analytics API,[5] and occupancy predictions were obtained by using an agenda, which identified working days and average room occupancy per hour.
2) Generation, simulation and evaluation of candidate plans: The OPG runs several simulations to reproduce the expected building behavior, in terms of energy consumption and comfort, under different operation plans and according to the forecasted conditions retrieved in the previous stage. The best plan in terms of energy efficiency and comfort satisfaction is selected. We explain in Section IV.B how these candidates to best plan are generated and assessed.
3) Storage and execution of best plan: The best plan is stored in a database and made available to the setpoint writing component, which eventually sends the OP control instructions to the BEMS. This database also stores the context associated to each selected OP, i.e. the forecasted building data used by the OPG algorithm and the simulation results. This information is useful to explain the rationale of an OP to the building managers, who can revise and modify the setpoint values in real time as well.

B. OPERATIONAL PLAN GENERATION

Creation of alternative plans is performed by an iterative algorithm based on a greedy heuristic and extended to balance diversity and local optimization. In this section, we explain the main steps of this stage: (1) identification of situations of interest for energy savings or comfort improvement; (2) generation of candidate plans to address these situations; (3) candidate plans simulation and selection of the best one.

To illustrate the processing in the OPG, we will assume a case with only one *Tsupply*setpoint, in which decrementing the setpoint means reducing the IAT and the energy consumption. We will also center the explanation in type A situations (see below). Nevertheless, the same principle applies to problems involving multiple variables and situations B and C. The explanation can be easily extended to more than one (independent) variable.

The overall functioning of the algorithm is depicted in Fig. 2, and its details are covered in the following subsections.

1) IDENTIFICATION OF SITUATIONS OF INTEREST

In Fig. 3, we show an optimization scenario in which the IAT is controlled by a single *Tsupply* setpoint, as in our building. Given an initial plan for *Tsupply* values, we can simulate it and identify opportunities for energy optimization:

1) 8:00 – 12:00: Heating control results in an IAT above the upper comfort threshold. The previous *Tsupply* setpoints must be reduced to guarantee comfort.
2) 7:00 – 13:00: Heating control results in an IAT within the comfort range, but it may be possible to reduce the previous *Tsupply* setpoints while keeping the temperature above the lower bound of the comfort threshold.

Note that in both situations setpoint decrement may not be possible if it is already at the minimum value allowed by the equipment.

Analogously, we can identify one situation in which more energy is required, since the comfort requirements are not satisfied:

1) 15:00 – 18:00: Heating control results in an IAT below the upper comfort threshold. The *Tsupply* setpoint must be increased

Note that in this case setpoint increment may not be possible if it is already at the maximum value allowed by the equipment.

2) GENERATION OF CANDIDATE PLANS

Let us consider a time instant t, and the corresponding setpoint value at this time s_t. For example, in Fig. 3, let us suppose t = 9:00; hence, $s_t = 23$ for *Tsupply* setpoint. We notate setpoint values at time $t - \Delta t$ as $s_{t-\Delta t}$; e.g. if $\Delta t = 4$, then $s_{t-4} = 20$, considering 1-hour intervals for simplicity's sake.

Let us notate the modification of a setpoint value s as $\hat{s} = s \pm \Delta s$; e.g. decrementing s_t in $\Delta s = 0.5$ give us $\hat{s}_t = 23 - 0.5 = 22.5$. The sets $\{\Delta t\}$ and $\{\Delta s\}$ are discrete and ordered. We define a time horizon $\Delta t^{max} = \max\{\Delta t\}$ to limit the temporal window of the modifications, as well as a maximum setpoint change value $\Delta s^{max} = max\{\Delta s\}$.

The candidate plan generation process starts from the current best plan, which at the beginning can be predefined or roughly estimated from outdoors temperatures. Next, it detects a situation of interest by analyzing the simulation of the current best plan; e.g. in our example, situation A at t = 9:00. For this t, the algorithm will propose a few candidate plans by decrementing previous setpoint values.

[5] http://dev.weatheranalytics.com

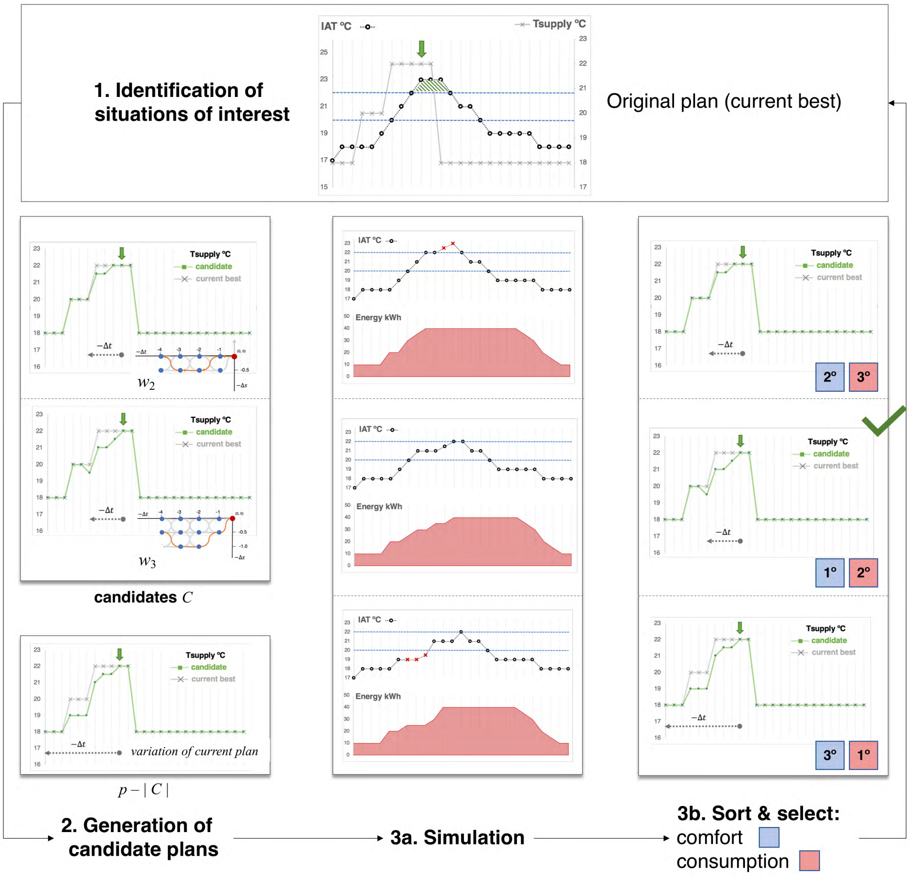


FIGURE 2. Overall functioning of the OPG algorithm, including main stages: (1) identification of situations of interest (Section IV.B.1); (2) generation of candidate plans (Section IV.B.2); (3) plan simulation (IAT outside the comfort range during office hours is marked with ×) and assessment (Section IV.B.3). The second candidate plan is selected, because it has the best comfort ranking.

To model all possible combinations of setpoint modifications in situation A, we define a lattice graph like the one in Fig. 4. Each vertex of this graph represents a setpoint modification at a given previous instant: $\hat{s}_{t-\Delta t} = s_{t-\Delta t} - \Delta s_{t-\Delta t}$. Each directed edge connects a setpoint change with the following setpoint change in reverse time order.

From this graph, the setpoint modifications that form a candidate plan are modeled as the result of a random walk[6] through this graph $w = \langle \hat{s}_t, \hat{s}_{t-1}, \hat{s}_{t-2}, \ldots, s_{t-\Delta t^{max}} \rangle$, with the following properties:

1) The walk starts at (0, 0) node, representing the current setpoint at starting time t (i.e. the current setpoint is not modified)
2) Each step goes from t' to $t' - 1$ for any t' in the sequence (i.e. always moving from right to left in the graph)
3) The length of each path is $|\{\Delta t\}|$ (i.e. each path is a sequence of setpoint changes from t to $t - \Delta t^{max}$)

[6]A random walk is a path consisting of a sequence of random steps on a mathematical space. Formally, it can be defined as a sum of a sequence of independent, identically distributed random variables representing move directions, or as a Markov chain over the subjacent state space [68].

4) The transition probability at each step from $\hat{s}_{t'}$ to $\hat{s}_{t'-1}$ is given by the following function (Eq. 1):

$$p(\hat{s}_{t'} \rightarrow \hat{s}_{t'-1}) = \begin{cases} \delta & \text{if } \Delta s_{t'} = \Delta s_{t'-1} \\ \frac{1-\delta}{|\{\Delta s\}|-1} & \text{otherwise} \end{cases} \quad (1)$$

with the diversification parameter $\delta \in [0, 1]$. This function balances two choices: maintaining the same previous setpoint change (δ) and selecting any setpoint change ($1-\delta$). If $\delta = 0$, the transition probabilities at each step are the same for each allowed direction. If $\delta \gg 0$, the setpoints will tend to decrease in the same amount.

An identical graph is built in situation B. An analogous graph and a corresponding probability function are defined in situation C to represent setpoint increments.

In Fig. 5, we depict two examples of random walks and the resulting setpoint modification sequences w_1, w_2.

To reduce the number of possible alternatives, we can introduce an additional restriction to the walks:

1) Only moves to *closest* nodes in horizontal, vertical and diagonal directions are allowed (i.e. differences between time instants of changes of Δs, if any, are small)

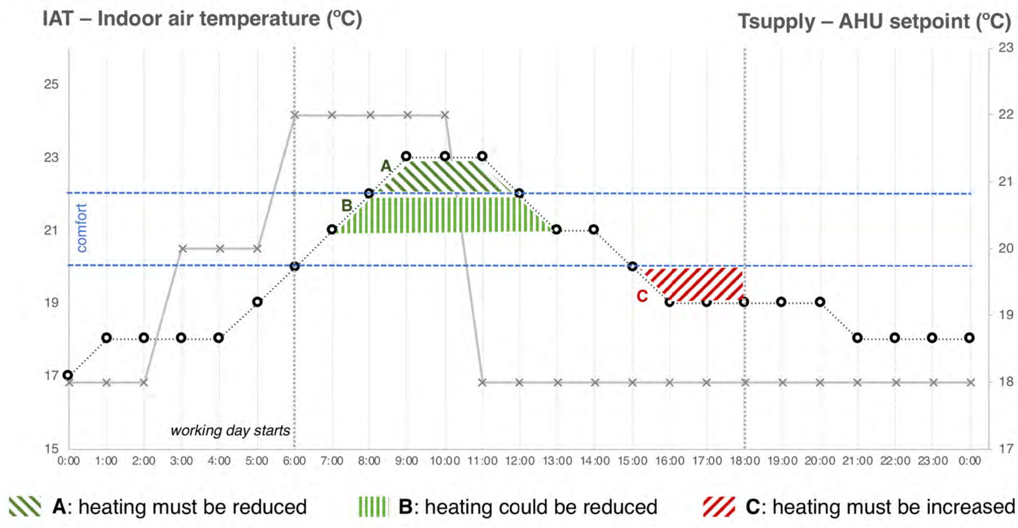


FIGURE 3. Identification of savings opportunities and discomfort in a simulated plan: indoor temperature vs *Tsupply* setpoint values. The comfort range in [20, 22] °C is also shown (dashed line).

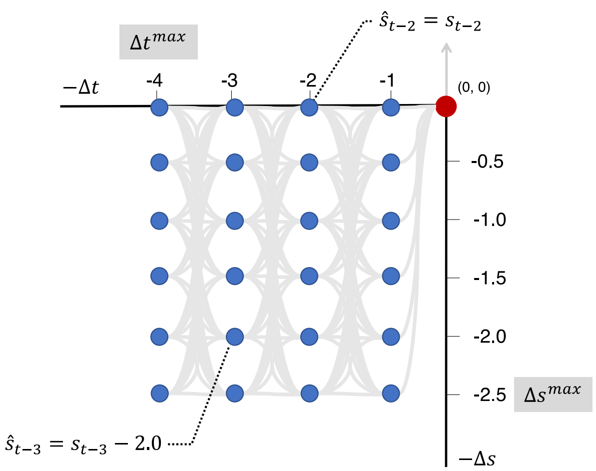


FIGURE 4. Lattice graph representing possible setpoint modifications (situation A, *Tsupply*). Time intervals are set to 1 hour, setpoint modifications are multiples of 0.5 °C.

This assumption considerably reduces the number of possible walks, as shown in Fig. 6. Note that this restriction may prevent the algorithm to explore the complete range of allowed $\{\Delta s\}$ modifications. Moreover, other heuristics could be incorporated to the process by means of additional walk restrictions encoded in the transition probability function; e.g. to limit how many different Δs can be used in the same walk.

Our implementation of the OPG considers two particular situations: pre-conditioning and post-conditioning. Pre-conditioning is performed to achieve comfort at the beginning of the working day, while post-conditioning is performed to save energy by relaxing the comfort requirements at the end of the working day and later. We apply predefined setpoint change strategies for each variable during these intervals, which allow us to reduce the number of required simulations.

3) CANDIDATE PLANS SIMULATION AND SELECTION

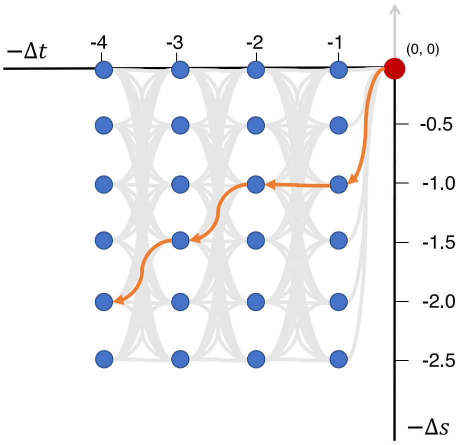
Each $w \in W$ produces a candidate OP, which is built by replacing the appropriate setpoints of the current best plan by $\{\hat{s}_{t-1}, \hat{s}_{t-2}, \ldots, \hat{s}_{t-\Delta t^{max}}\}$. The remaining setpoints outside the $[t - \Delta t^{max}, t - 1]$ interval are not modified. The algorithm only selects a small random subset of candidate OPs $C \subseteq W$ to be simulated. In the best case, all the OPs in C will be simulated in parallel; therefore, the selection of C may depend on the simulator capabilities (see the experimental setup in Section V).

Finally, the algorithm picks the most efficient OP satisfying comfort requirements. Efficiency is calculated as the total energy consumption of the plan, while comfort can be measured in different ways; for example, by using the root-mean-square deviation (RMSD) or the % of time with comfort-related values (e.g. *IAT*, *Con*) inside the comfort range, maybe limited to a period of interest (e.g. office hours). If there is no such plan, the OPG selects the closest one to meet the requirements. To do so, OPs are firstly sorted by comfort satisfaction, and secondly by energy consumption.

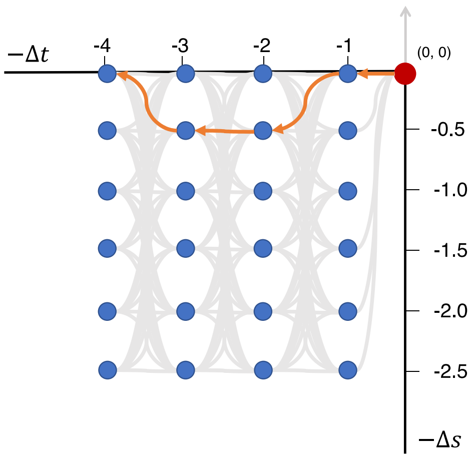
The procedure is restarted to identify the next interesting situation (Section IV.B.1), now using the simulation of the new plan as a reference. The algorithm iterates while there are remaining situations to process or when a maximum number of situations have been processed.

4) TRIGGERING THE OPG ALGORITHM

The OPG algorithm is usually launched before midnight to calculate the setpoints for the next day, allocating enough time to let the process finish before setpoints are due – a few hours in most cases. The algorithm can run again several times during the day, in order to create a new plan for the remainder of the day using updated weather and occupancy predictions and to recover from control deviations and failures.

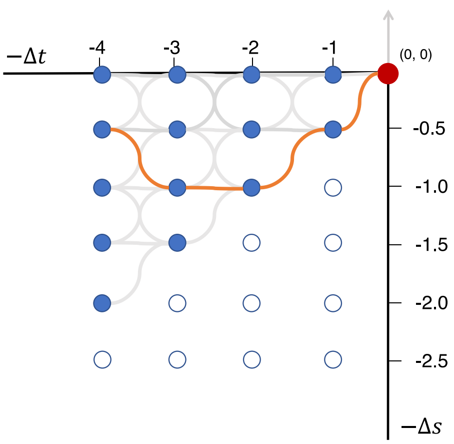


$w_1 =< s_t, s_{t-1} - 1.0,\ s_{t-2} - 1.0, s_{t-3} - 1.5,\ s_{t-4} - 2.0 >$



$w_2 =< s_t, s_{t-1},\ s_{t-2} - 0.5, s_{t-3} - 0.5,\ s_{t-4} >$

FIGURE 5. Samples of setpoint modification sequences obtained by using random walks, restrictions (A)–(D) apply.



$w_3 = \langle s_t, s_{t-1} - 0.5,\ s_{t-2} - 1.0,\ s_{t-3} - 1.0,\ s_{t-4} - 0.5\rangle$

FIGURE 6. Simplified setpoint modification graph and random walk sample, restrictions (A)-(E) apply.

This formulation slightly diverges from the receding horizon control typically implemented in canonical MPC, because the prediction horizon is not shifted. However, note that such a receding horizon could be implemented just by generating control instructions for a whole period (e.g. 24 hours) each time the OPG algorithm is triggered, instead of generating control instructions until the end of the current day.

At the moment, the implemented recalculation process only generates a baseline plan using predefined operation curves when an updated weather forecast significantly differs from the initially used one. Enabling a faster and maybe simplified version of the OPG for quick recovery during the day, triggered by different events –e.g. comfort degradation is detected with live BEMS data–, remains as future work.

C. COMPUTATIONAL PROPERTIES

The OPG algorithm cannot guarantee a global optimum in terms of energy consumption for two reasons: (a) only a limited number of setpoint modifications are explored; (b) the global plan is built from locally pseudo-optimal choices focused on situations of interest A, B, C. Conversely, it yields good solutions in a reasonable time, and allows easy incorporation of heuristics in the setpoint modification process.

Regarding (a), in the general formulation (Fig. 4 and 5), the number of possible setpoint change sequences $|W|$ for each situation and independent variable is bounded by $|W| \leq |\{\Delta s\} + 1|^{|\{\Delta t\}|}$. In the restricted formulation (Fig. 6), the number of possible random walks is bounded by $|W| < 3^{|\{\Delta t\}|}$. The $|W|$ for multiple-dimension random walks grows exponentially [68]. In any case, only $|C| \ll |W|$ candidate OPs will be simulated at each iteration. Therefore, the overall efficiency of the algorithm is bounded by the number of situations of interest processed multiplied by the time required to run each batch of simulations of size $|C|$. Note that the execution time of the OP generation process is insignificant compared to the simulation time.

The parallel cloud version of IESVE allows running a fixed number p of parallel simulations without performance degradation. To increase solution diversity, we can set $|C| < p$, and our implementation will fill the remaining simulation slots with other plans, namely: (a) random variations of the current best OP at any time before t; (b) combinations of previously discarded good OPs; (c) baseline OPs –e.g. for Sanomatalo, OPs based on outdoors temperature. These plans are compared against the plans obtained with the random walks, and can be selected as best current plan for the next iteration in the same conditions.

Regarding (b), under some realistic assumptions, the OPG algorithm finds a good approximation to the optimal solution. Specifically, for *Tsupply* control in Sanomatalo we can assume that external temperatures and internal occupancy values follow a bell-shaped curve. To guarantee comfort in the winter season, the optimal OP would entail increasing the temperature setpoints in the early morning, then decreasing them around noon, and maybe incrementing them again in the afternoon. Moreover, the low external temperatures favor heat losses, which would in turn require supplying hot air frequently. Therefore, it is safe to limit the search to local setpoint increments and decrements.

V. EXPERIMENTS AND RESULTS

The OPG algorithm has been implemented in the Python and R programming languages. For the experiments in this section, it ran on a Supermicro SuperServer 6027R-TRF, configured with 2 processors Intel Xeon E-2600 2.4GHz (2×8 cores), 128 GB RAM, 2×600 GB magnetic storage. The details of the cloud-based version of the IESVE simulator are not disclosed by IES by confidentiality reasons.

Experimentation based only in the simulation environment was performed in advance to test and tune the deployment of the OPG used in the real building. After some preliminary tests and following the building requirements, the OPG parameters were set to the following values:

- Simulation batch size: $p = 50$, resulting in simulation times below 20 minutes
- Ahead period of the OPG: 1 day, no receding horizon
- OPG starting time: $>$ 2 hours before the first setpoint is due
- Maximum setpoint change frequency: 15 minutes
- Simulation output resolution: 15 minutes
- Only minor setpoint changes are allowed in random walks
- $\{\Delta t\}$*Tsupply, VAVairflow* $= \{30, 60, 90, 120\}$ minutes
- $\{\Delta s\}$*Tsupply* $= \{0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0\}$ °C
- $\{\Delta s\}$*VAVairflow* $= \{0, 25, 50\}$ l/s
- $\delta = 0.3$ (random setpoint modifications are preferred)
- Tsupply and VAV setpoints are optimized independently (first *Tsupply* and then *VAVairflow*)
- Comfort satisfaction is measured by using the RSMD from the comfort interval

Additionally, the maximum number of simulation batches was restricted in order to establish an upper limit to the execution time. Since an average simulation batch took 20 minutes (with $p = 50$), we set the maximum number of batches per plan to 6 in order to keep the execution time under 2 hours. This means that 6 A-B-C situations (Figure 3) can be analysed in each run of the OPG. Excluding pre- and post-conditioning, 4 out of 6 were reserved for *Tsupply* changes, and 2 for *VAVairflow* changes. Situations are sorted by relevance at each iteration of the OPG algorithm; e.g. for *Tsupply*, situations A and C are more important than B.

A. SIMULATION ENVIRONMENT

As described in Section II.D, we selected three prototypical days of the winter season: average (Standard), cold (Harsh) and warm (Intermediate). Then, we simulated the behaviour of the pilot area of the building according to the setpoints originally applied (i.e. the base plan) and the setpoints calculated by our algorithm (i.e. the OPG plan), in order to check how they compare in terms of comfort and consumption.

Fig. 7 depicts the simulation results for a Standard day, corresponding to the most common conditions during the winter season. In the top of the figure, we show the setpoints

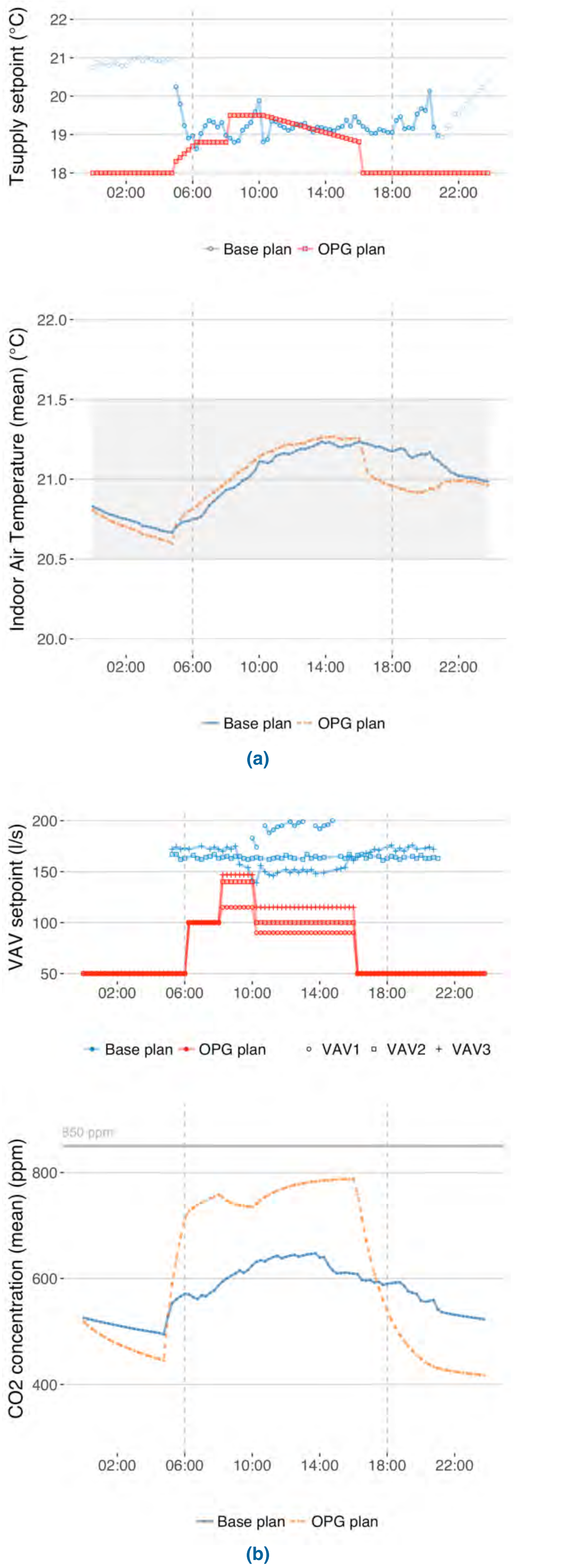


FIGURE 7. **Comparison of baseline and OPG plans in terms of setpoints and comfort values (with comfort thresholds) for a Standard winter day, simulation environment: (a) *Tsupply* operation; (b) *VAVairflow$_i$* operation.**

of the base and the OPG plans for the *Tsupply* and the *VAVairflow$_i$* operation –the main working hours are delimited. In both cases, the largest operation differences correspond to

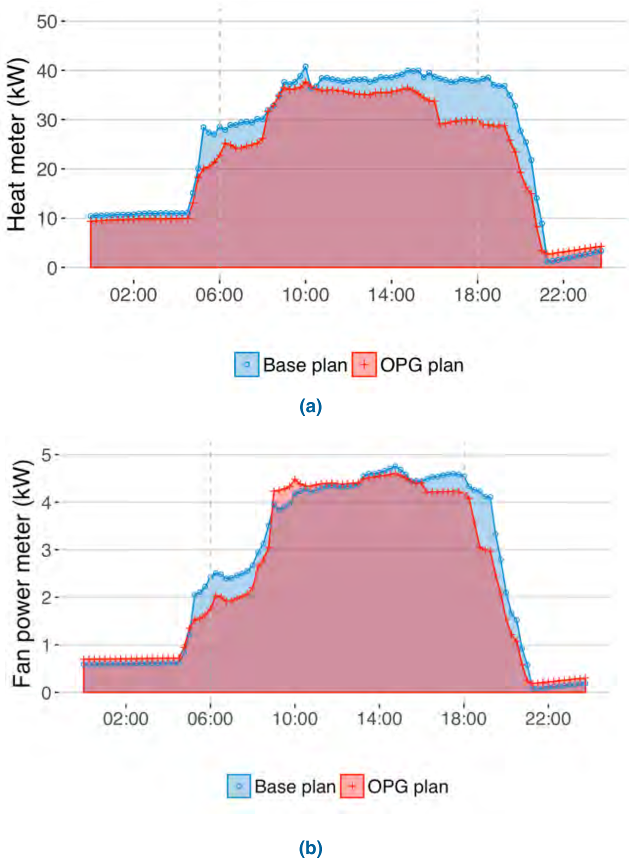


FIGURE 8. Comparison of power (kW) of baseline and OPG plans for a STANDARD winter day, simulated environment: (a) heat meter; (b) VAV fan power meter.

the less crowded periods. Note that the *Tsupply* setpoints of the base plan before 5:00 and after 21:00 are registered but not applied; control is managed by a human-operated switch. In the bottom of the figure, we show the mean comfort values obtained in simulation in terms of *IAT* and *Con*; these values lay within the comfort intervals (also included in the figure).

Fig. 8 shows the power consumption calculated by the simulation model; respectively, the *Heat* and *Fan* power meters values. We can observe that most savings are achieved at the borderline hours, that is, at the beginning and at the end of the working day. This is consistent with the pre-conditioning and post-conditioning provisions made by the OPG algorithm.

TABLE 1. Energy consumption (kWh) for the experiments in the simulation environment.

	STANDARD 12-Jan-2016		HARSH 21-Jan-2016		INTERMEDIATE 30-Jan-2017	
	Heat	Fan	Heat	Fan	Heat	Fan
Base	618.66	62.47	896.64	79.88	207.95	30.99
OPG	539.77	59.23	854.03	74.41	132.98	32.46
Savings (%)	**12.75**	**5.18**	**4.75**	**6.85**	**36.05**	**-4.75**

Table 1 includes the detailed numbers for the three reference days. To obtain the overall energy consumption, we have approximated the integral of the power functions with the area under the curve (AUC). AUC has been computed by: (1) interpolation of data points with a spline; and (2) calculation of the adaptive quadrature of the interpolated function [69].

It can be seen that the OPG reduces the power consumption of the base operation of both the heating and the ventilation subsystems. As expected, in the experiments the highest heating savings are achieved in the warmer intermediate day, when there is still room for adjustments. Broadly speaking, the OPG dynamically adapts the operation to the particular conditions of a specific day without requiring the operator attention, which is convenient in less cold days in the winter season or before transitioning to the spring season. Conversely, the HVAC system is already operating at (almost) full power during the harsh days to achieve comfort, and therefore there is little room for improvement during working hours. A more detailed discussion on these features is included in Section VI. On the other hand, fan power savings have similar values in different working days. The bad results in the intermediate day were the consequence of the misestimation of the occupancy used by the algorithm.

B. ON-SITE TEST AND EVALUATION

The evaluation in the pilot area of the real building was performed from April 19th to May 19th 2017. These days mostly fit into the Intermediate category studied in the previous section, the one which yielded the highest energy savings.

The baseline for daily energy consumption was calculated by a generalized linear regression model (glmnet) [70], a method based on lasso analysis (least absolute shrinkage and selection operator). Other prediction techniques, such as linear regression or autoregression, could have also been explored. Source data for the model was obtained from building sensors (energy, OAT and occupancy) logged in the period February-May 2016.

More specifically, we developed two baseline models for prediction of daily consumption of heating equipment and VAV fans, based on the expected heating demand and occupancy. Expected daily energy demand (*hdd*, in heating degree days) was calculated by using integration with base temperature set to 18 °C and the BEMS OAT [71]. Estimated daily occupancy (*occ*, in %) was the maximum occupancy value of the office agenda. To build the prediction models, we firstly pre-processed the data, discarding outliers and measurement errors.

Fig. 9 compares the energy consumption in February-May 2016 and the values calculated by the heating and the fan consumption prediction models. The parameters of the regression models are given in Eq. 2 and Eq. 3 respectively, yielding correlation coefficient values of $R^2 = 0.632$ and $R^2 = 0.234$. Note that: (1) the heating baseline model slightly overestimates consumption from mid-April to June, which means that energy savings calculated in the next section are slightly overestimated as well; (2) the fan power model has

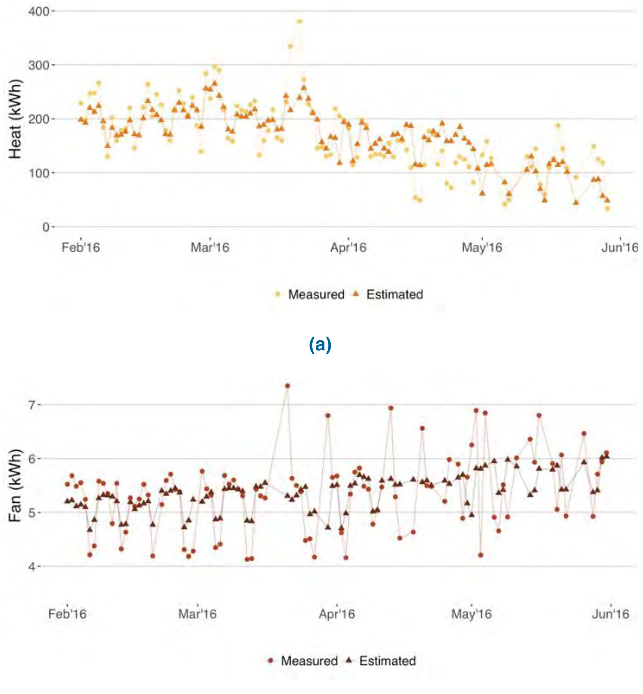


FIGURE 9. **Comparison of daily energy consumption (kWh) estimated by the baseline models vs historical data in Feb-May 2016: (a) heating; (b) VAV fans.**

a low R^2 value, which means that energy savings calculated with this model should be considered with caution.

$$Heat^* (hdd, occ) = -9.122 \times hdd + 0.703 \times occ + 20.71 \quad (2)$$

$$Fan^* (hdd, occ) = -0.038 \times hdd + 0.012 \times occ + 5.015 \quad (3)$$

Fig. 10(a) and 10(b) show the comparison of the values of daily energy consumption in the pilot area obtained from the BEMS (+) with the values estimated by the prediction models (o) for the test period in the real building. Fig. 10(c) shows the energy savings achieved in % of the (estimated) consumption before optimization.

TABLE 2. **Energy savings (kWh) achieved in the on-site test with the OPG control vs estimated by the baseline models.**

	Overall		Workdays		Weekends & Holidays	
	Heat	Fan	Heat	Fan	Heat	Fan
Estimated (daily avg)	156.47	5.47	164.70	5.62	132.79	5.06
OPG (daily avg)	91.12	4.37	101.77	4.78	60.50	3.20
Savings (daily avg %)	**41.76**	**20.12**	**38.21**	**14.91**	**54.44**	**36.73**

As summarized in Table 2, the average savings per day are, respectively, around 40% for the thermal subsystem and around 20% for the electrical subsystem. Weekends and holidays offer opportunities for higher energy savings, since the OPG adjust the operation to the building occupancy better than the manual operation.

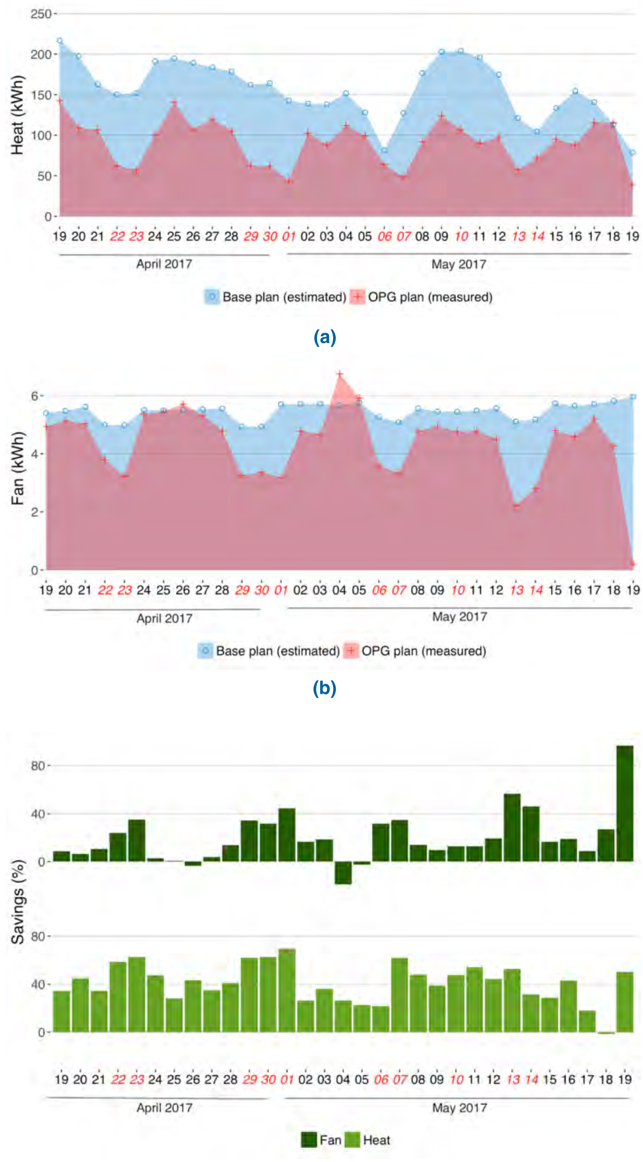
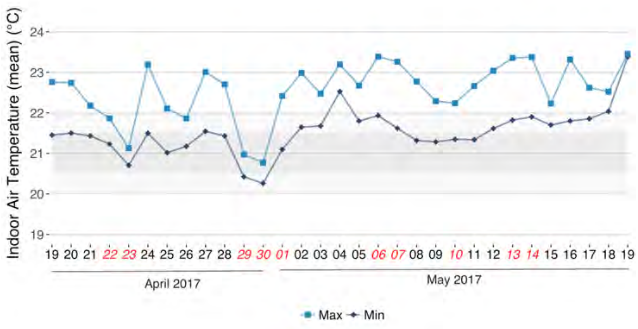
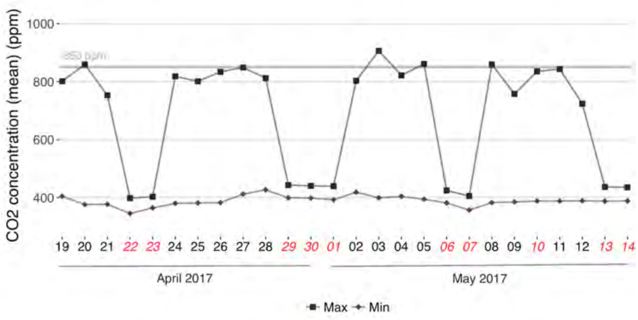


FIGURE 10. **Comparison of daily energy consumption (kWh) during the test period vs estimated by the baseline models: (a) heating; (b) VAV fans; (c) savings. Days in red italic font are weekend or holiday days.**

Savings have been achieved without compromising users' comfort. Figure 11 shows the *IAT* and CO_2 concentration values in the pilot area in the evaluation period. The *IAT* values were calculated as follows: (1) sensor measurements, obtained from the BEMS temperature sensors (25), were resampled and interpolated to match the setpoint change frequency parameter (15 minutes); (2) sensor temperatures were averaged at each timestamp; (3) maximum and minimum values of timestamps within the working hours were



(a)



(b)

FIGURE 11. **Daily comfort values achieved in the on-site test with the OPG control, maximum and minimum sensor average values: (a) indoor air temperature (*IAT*, °C), with comfort interval; (b) CO_2 concentration (*Con*, ppm), with comfort threshold. CO_2 measurements were only available from April 19th to 14th May. Days in italic red font are weekend or holiday days.**

obtained. *Con* values were retrieved from 4 offline sensors; the remainder of the procedure is the same as for *IAT*.

IAT min values lie within the comfort range during the test period. Actually, it would have been possible to configure the OPG to reduce *Tsupply* even more. However, as explained at the beginning of this section, we prioritized optimizing discomfort situations. *IAT* max values are over the comfort upper threshold by 1 °C. A more detailed analysis of these values identified that discomfort was not sustained and only happened for short time periods (less than 1 hour).

Similarly, CO_2 concentration values are mostly below the comfort threshold, although with some exceptions. After more detailed analysis, we identified that the highest values were measured by a single sensor, which in some cases exceeded 950 ppm. However, the levels calculated by the simulation environment were considerably smaller. This is a clear example of the importance of having all the sensor data available through the BEMS. With the CO_2 sensors offline, our system was not able to recalibrate the simulation model –which would have led to better plans–, nor to detect in real time that some plans were not guaranteeing comfort –which would have triggered a correction action.

VI. DISCUSSION

The results presented in Section V show that the use of MPC in the offices of the Sanomatalo building significantly reduces energy consumption; particularly heating consumption. Automatic control allows for more effective plans since it enables a finer-grained and more frequent scheduling of setpoint changes without the supervision of the building operators. The OPG algorithm and software offer a flexible and configurable framework to generate more efficient operation plans, predicting the building state and adapting energy usage to more realistic demand estimations without compromising users' comfort. As expected, it has proved to be particularly successful in optimizing temperature setpoints, in which a longer control horizon, accounting for the inertia of the equipment, is crucial. The building operators were satisfied by the use of the system during the test period. One highlighted system's feature was the capabilities to validate the plans in advance (and even to modify them) and to provide justifications of the algorithm decisions –by means of graphical depictions of the simulation results, in a similar way to Fig. 11.

As already anticipated by the experiments in the simulation environment (Section V.A), the highest energy savings can be obtained for heating in the mid-season, when it is not necessary to use the heating equipment at full, and particularly, in the warmer days (Table 1, Intermediate). At the same time, the system can react to isolated cold days. The on-site evaluation in the Sanomatalo building, which was carried out at the end of the 2017 heating season, confirmed these assumptions. Energy usage in colder days could be even more optimized by relaxing the comfort temperature restrictions to permit OPs with some minor discomfort for a short period of time. The advantage of our system is that it allows operators to characterize and quantify this discomfort in advance, thus supporting them to make more informed decisions. (Note that this feature was not exploited in the experiments.)

Our system reduced the temperature setpoints given by the normal operation of the building between 0.5 and 2 °C. During the on-site test, this meant savings in heating above 40% (Table 2) while keeping comfort (see Fig. 11(a)). The algorithm adapted well to workdays and weekends, showing slightly better results in the former ones (Fig. 10(c)). A possible explanation for this is that operators have lower availability in weekends and holiday days, and therefore it is not possible for them to create customized plans. The airflow consumption was also reduced in a 20% (Table 2) without compromising the CO_2 concentration comfort (Fig. 11(b)), despite the lack of a proper model calibration and the smaller number of simulations involving VAVs. Nevertheless, due to the lower accuracy of the baseline model, these results are less precise and should be further analyzed; e.g. by using autoregression to build the baseline [72].

In summary, although the Sanomatalo building was already efficiently operated, and considering the limitations of the baseline estimations, the overall savings figures in the intermediate winter are in line with the 30% target of EU energy directive [5] and the 35% savings estimations provided in [7]. The experiments also revealed more opportunities for savings in the future, e.g. by improving the simulation model with online CO_2 data (for calibration) and more detailed occupancy predictions (actual agenda data were not very fine-grained).

TABLE 3. Energy savings (heating, MWh) in the pilot area projected for the whole year.

	STANDARD	HARSH	INTERM.	
Savings (%)	12.75	4.75	36.05	
Monthly consumption (MWh)	7	9	4	
# months per year	3	2	3	TOTAL
Reduction (MWh)	2.6775	0.855	4.326	**7.8585**

In Table 3, we show a rough projection of energy savings in the pilot area for the whole year using: (1) savings calculated in Section V.A (only heating); (2) historical monthly consumption values provided by the building operators; (3) estimated distribution of day types. We assume that the heating system is not used during the summer, and therefore it does not make sense to quantify savings in this period. It can be seen that the overall energy consumption reduction during the whole winter season is around 20%, larger than the consumption of a standard winter month. We can also estimate savings of CO_2 emissions: assuming a carbon factor of 206 $kgCO_2$/MWh for district heating energy in Finland [73], the new system applied in the pilot area can save more than 1.60 Tons of CO_2 per year. These figures could be directly adapted to other estimation of day types (e.g. including savings in the summer) and extended to other sections of the building with similar configuration.

The implementation of the system in other buildings entails: (a) developing a specific simulation model, if not available; (b) parametrizing the OPG algorithm, including the definition of energy optimization strategies; (c) finding appropriate sources for weather and occupancy forecasts; (d) adapting the setpoint writing component, if fully-automatic control is enabled; (e) deploying the computational infrastructure to run these components. As a matter of fact, in the context of the Energy IN TIME project we applied modified versions of the OPG to other scenarios, such as an airport and a hotel – achieving similar results, as briefly described in [66]. Among the tasks required to extend the system to other buildings, developing and tuning the simulation model is the most time-consuming one.

The collaboration with the Sanomatalo building operators revealed some prospective improvements to the system. First, it would be convenient to offer a better interface for configuration of the OPG and interaction with the generated plans, as in [74]. Second, users' comfort should be measured beyond thermal and CO_2 concentration intervals, probably by using PMV, adaptive comfort models and comfort standards [75], [76]. Third, occupancy estimations in our experiments were mostly static, while occupancy monitoring and reconfiguration have shown effective in the past [77], [78]. In this regard, the capabilities and limitations for OP recalculation during the day should also be further explored. Four, a more comprehensive study of energy savings with additional baseline models should be carried out in order to quantify more precisely the return of investing in our solution [79], in particular if only ventilation is addressed. Last but not least, the building setup was relatively simple, with district heating and almost fixed energy costs. It would be interesting to study the applicability and the scalability of the OPG approach to smart grids, including more control variables –some of them affecting the production side– and energy storage equipment; see for example [80], [81].

VII. CONCLUSIONS AND FUTURE WORK

This paper has presented the design and the implementation of an MPC-based control system aimed at reducing energy consumption in non-residential buildings while guaranteeing occupants' comfort. The main difference of our proposal with respect to other approaches is that we use a full-complexity simulation model, which runs in parallel in the cloud. This allows using more accurate models and facilitates communication between computer scientists, building operators and simulation developers, exploiting synergies of their joint work. Comprehensive quantitative and qualitative comparison with MPC approaches using reduced-complexity simulation models would be useful to support decision-making between different alternative approaches.

Experimentation in the Sanomatalo building, located in Helsinki, both in the simulation environment and in the real building, has shown that important energy savings –up to 40% at the end of the winter season– can be achieved, particularly by optimizing the control of the heating equipment. Note that our approach can be adapted to other scenarios, and specifically, to cooling equipment. In our experiments we did not consider the energy costs of running our system, which should be deducted from the HVAC savings [82]. These promising figures can give rise to disruptive models for energy service provision, as we explore in [83].

The OPG algorithm opens several opportunities for further research. The current design relies on a variant of heuristic search, which can be hard to scale up if several variables are to be optimized at the same time. In this regard, other search and optimization techniques could be applied. Specifically, genetic algorithms allow balancing diversification and intensification of solution search by adjusting their parameters. Another possible extension of the OPG would be to incorporate means to define imprecise comfort ranges, thus formalizing the notion of relaxed comfort into the procedure. It would also be interesting to study how to represent energy optimization strategies in a machine-processable language, in such a way that the system could use them for self-configuration. Moreover, self-configuration could be supported by machine learning techniques able to identify successful operation patterns from historical data, and to apply reinforcement learning to reward and reuse particularly efficient OPG plans.

Finally, we believe that combining interpretable white/grey-box models, like the one used in this work, and efficient black-box models, learnt from historical data, is one of the most prospective directions for future work. Faster simulation of such hybrid model would allow for the implementation of more sophisticated optimization and planning techniques. Recent approaches to data-driven black-box models have showed good accuracy, but only for short time periods [84]. Learning more general and precise models would require larger datasets, more computational power, and techniques able to exploit them. Recent advances in the Deep Learning area suggest that this is a feasible goal.

NOMENCLATURE

AHU	Air Handling Unit
AUC	Area under the curve
BCVTB	Building Controls Virtual Test Bed
BEMS	Building Energy Management System
C	Set of candidate plans considered in an iteration of the OPG
Con	CO_2 concentration (parts per million, ppm)
δ	diversification parameter
Δt	Time increment / decrement
$\{\Delta t\}$	Set of time increment / decrement values
Δt^{max}	Maximum time increment / decrement
Δs	Setpoint increment / decrement
$\{\Delta s\}$	Set of setpoint increment / decrement values
Δs^{max}	Maximum setpoint value increment / decrement
Fan	Energy consumption due to electrical subsystem (kWh)
Fan$*$	Estimated daily fan energy consumption with the baseline model (kWh)
HDD	Heating Degree Days
hdd	Estimated daily demand measured in HDD (integrated)
Heat	Energy consumption due to thermal subsystem (kWh)
Heat$*$	Estimated daily heating energy consumption with the baseline model (kWh)
HVAC	Heating, Ventilation, and Air Conditioning
IAT	Indoor Air Temperature (°C)
IPMVP	International Performance Measurement and Verification Protocol
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
OAT	Outdoor Air Temperature (°C)
occ	Estimated daily occupancy (maximum) (%)
PMV	Predicted mean value
RSMD	Root mean square deviation
$\mathbf{s_t}$	Setpoint value at time t
$\mathbf{\hat{s}_t}$	Setpoint value at time t modified
t	Time instant
Tsupply	AHU supply temperature setpoint value (°C)
VAV	Variable air volume unit
$\mathbf{VAVairflow_i}$	Airflow setpoint value for VAV number i (liters per second, l/s)
w	Ordered sequence of setpoint changes from t to t $-\Delta t^{max}$
W	Set of all w

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JUAN GÓMEZ-ROMERO received the degree in computer science and the Ph.D. degree in intelligent systems from the Universidad de Granada, in 2004 and 2008, respectively.

He was a Lecturer with the Applied Artificial Intelligence Group, Universidad Carlos III de Madrid, from 2008 to 2013, and a Research Associate in the EU FP7 Project Energy IN TIME with the Universidad de Granada, from 2013 to 2017. He was also a Visiting Researcher with the Data Science Institute, Imperial College London, from 2016 to 2017. He has been a Senior Research Fellow with the Computer Science and Artificial Intelligence Department, Universidad de Granada, since 2016. He has participated in more than 20 projects in security, ambient intelligence, and energy efficiency. His research interests include the use of semantic representation models and machine learning techniques to perform automatic reasoning towards higher-level information fusion.

Dr. Gómez-Romero is the Principal Investigator of the projects BIGFUSE: Semantics for Big Data Fusion and Analysis: Improving Energy Efficiency in Smart Grids and PROFICIENT: Deep Learning for Energy-Efficient Building Control.

CARLOS J. FERNÁNDEZ-BASSO received the degree in computer science and the M.Sc. degree in data science from the Universidad de Granada, in 2014 and 2015, respectively, where he is currently pursuing the Ph.D. degree in computer science and energy efficiency.

He was a Lead Developer in the EU FP7 Project Energy IN TIME in the topics of building simulation and control, data analytics, and machine learning. He also collaborates with the Data Science Institute, Imperial College London, where he has carried out research stays, from 2016 to 2018. He is currently a Research Assistant with the Computer Science and Artificial Intelligence Department, Universidad de Granada.

M. VICTORIA CAMBRONERO received the degree in industrial engineering with a specialization in construction and industrial facilities and the M.Sc. degree in energy technology for sustainable development from the Polytechnic University of Valencia, in 2008 and 2009, respectively.

She was a Project Developer and a Researcher on building management and energy efficiency with the Institute of Energy Engineering, Valencia, before joining Acciona Infrastructures R&D Department, in 2010. Since 2018, she has been a Project Manager with Acciona Ingeniería. She has a wide experience in research and innovation projects and has collaborated and managed several FP7 and H2020 projects in renewable energies, HVAC systems and storage integration, and control strategies for energy efficiency improvement in buildings and districts; e.g., 2DISTRICT, EnergyINTIME, LowUP, Flexynets, FC-DISTRICT, MESSIB, EINSTEIN, CommONEnergy, and COST-EFFECTIVE. She is currently an Industrial Engineer specialized in energy efficiency and building simulation.

Ms. Cambronero holds a Project Management Professional certification granted by the Project Management Institute and a Certified in Measurement and Verification Protocol certification granted by the Association of Energy Engineers and Efficiency Valuation Organization.

MIGUEL MOLINA-SOLANA received the degree in computer science and the Ph.D. degree from the Universidad de Granada, in 2007 and 2012, respectively.

From 2012 to 2015, he was a Research Associate with the Universidad de Granada in the FP7 Project Energy IN TIME. He was a Research Associate on visualization with the Data Science Institute, Imperial College. He is currently a Marie Curie Research Fellow with Imperial College London, U.K. His research interests include applied work in machine learning and knowledge representation in diverse domains such as music, energy management, and business.

Dr. Molina-Solana is the Principal Investigator of the H2020 Project DATASOUND–Understanding Data With Sound.

JESÚS R. CAMPAÑA received the M.Sc. and Ph.D. degrees in computer science from the Universidad de Granada, where he has been a member of the Intelligent Databases and Information Systems Research Group, Department of Computer Science and Artificial Intelligence, since 2005.

From 2013 to 2018, he was a Lecturer with the Universidad de Granada. He has been a member of several research projects related to fuzzy data representation in databases, data mining, text mining, and energy efficiency, including the FP7 Project Energy IN TIME. His research interests include fuzzy databases, XML, knowledge representation, semantic web, data mining, and text mining.

M. DOLORES RUIZ received the degree in mathematics and the European Ph.D. degree in computer science from the Universidad de Granada, in 2005 and 2010, respectively.

She held a non-permanent teaching positions with the Universities of Jaén, Granada, and Cádiz. She has participated in more than ten projects, including the EU FP7 Projects ePOOLICE and Energy IN TIME. She is currently a Research Associate with the Computer Science and Artificial Intelligence Department, Universidad de Granada. Her research interests include data mining, information retrieval, energy efficiency, big data, correlation statistical measures, sentence quantification, and fuzzy sets theory. She has organized several special sessions about Data Mining in international conferences and was part of the organization committee of the FQAS'2013 and SUM'2017 conferences.

Dr. Ruiz belongs to the Approximate Reasoning and Artificial Intelligence Research Group and the Cybersecurity Lab, Universidad de Granada. She has been the Principal Investigator of the project Exception and anomaly detection by means of fuzzy rules using the RL-theory. Application to fraud detection.

MARIA J. MARTIN-BAUTISTA received the degree in computer science and the Ph.D. degree from the Universidad de Granada, in 1996 and 2000, respectively.

She has been a Professor with the Computer Science and Artificial Intelligent Department, Universidad de Granada, since 2018. She was the Principal Investigator in the FP7 European Project Energy IN TIME with the Universidad de Granada, from 2013 to 2017. She has also been a Principal Investigator of several international and national projects and knowledge transfer contracts with private companies. She has published more than 100 papers in international journals and conferences. Her current research interests include intelligent systems, big data, and knowledge representation with applications to energy, security, and health.

Prof. Martin-Bautista is a member of the IEEE Society and the EUSFLAT Society.