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Autonomic Management of a Building's Multi-HVAC System Start-Up

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ABSTRACT Most studies about the control, automation, optimization and supervision of building HVAC systems concentrate on the steady-state regime, i.e., when the equipment is already working at its setpoints. The originality of the current work consists of proposing the optimization of building multi-HVAC systems from start-up until they reach the setpoint, making the transition to steady state-based strategies smooth. The proposed approach works on the transient regime of multi-HVAC systems optimizing contradictory objectives, such as the desired comfort and energy costs, based on the “Autonomic Cycle of Data Analysis Tasks” concept. In this case, the autonomic cycle is composed of two data analysis tasks: one for determining if the system is going towards the defined operational setpoint, and if that is not the case, another task for reconfiguring the operational mode of the multi-HVAC system to redirect it. The first task uses machine learning techniques to build detection and prediction models, and the second task defines a reconfiguration model using multiobjective evolutionary algorithms. This proposal is proven in a real case study that characterizes a particular multi-HVAC system and its operational setpoints. The performance obtained from the experiments in diverse situations is impressive since there is a high level of conformity for the multi-HVAC system to reach the setpoint and deliver the operation to the steady-state smoothly, avoiding overshooting and other non-desirable transitional effects.

INDEX TERMS Energy management, heating, ventilation and air conditioning systems, autonomic computing, machine learning, multi-objective optimization, smart building.

NOMENCLATURE

| | |
|---------------|---|
| <i>ACO</i> | Ant Colony Optimization |
| <i>ACODAT</i> | Autonomous Cycle of Data Analysis Tasks |
| <i>AFD</i> | Automatic Fault Detection |
| <i>ANN</i> | Artificial Neural Network |
| <i>AI</i> | Artificial Intelligence |
| <i>BEMS</i> | Building Energy Management System |

| | |
|---------------|---|
| <i>BMS</i> | Building Management System |
| <i>CABTSK</i> | Cluster Adaptive Based on Takagi-Sugeno-Kang |
| <i>COP</i> | Coefficient of Performance |
| <i>CM</i> | Control module |
| <i>DAT</i> | Data Analysis Task |
| <i>ESA</i> | Exponential Setpoint Equation-based Semi-Analytical |
| <i>FDD</i> | Fault Detection and Diagnosis |
| <i>FPIPDM</i> | Fuzzy PI-PD Mamdani-type |
| <i>HVAC</i> | Heat, Ventilation and Air Conditioning |

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| | |
|----------------|---|
| <i>IAE</i> | Integral Absolute Error |
| <i>IGPSO</i> | Improved Global Particle Swarm Optimization |
| <i>LAMDA</i> | Learning Algorithm for Multivariable Data Analysis |
| <i>LR</i> | Logistic Regression |
| <i>LWA</i> | Load Weighting Averaging |
| <i>MAPE</i> | Mean Absolute Percentage Error |
| <i>MAPE-K</i> | Monitor, Analyze, Plan and Execute - Knowledge base |
| <i>ML</i> | Machine Learning |
| <i>MLP</i> | Multilayer Perceptron |
| <i>MOPSO</i> | Multi-objective Particle Swarm Algorithm |
| <i>MORL</i> | Multi-objective Reinforced Learning |
| <i>MPC</i> | Model Predictive Control |
| <i>NSGA-II</i> | Non-dominated Sorting Genetic Algorithm Ver. 2 |
| <i>OpM</i> | Operational Mode |
| <i>OM</i> | Optimization Module |
| <i>PD</i> | Proportional Derivative Controller |
| <i>PF</i> | Pareto Front |
| <i>PI</i> | Proportional Integral Controller |
| <i>RF</i> | Random Forest |
| <i>RL</i> | Reinforced Learning |
| <i>SA</i> | Semi-Analytical |
| <i>SM</i> | Supervisory Module |
| <i>SVN</i> | Support Vector Machine |

I. INTRODUCTION

Currently, there is a great need for buildings to become more energy efficient and to be able to maintain interior comfort, reduce the energy cost, and improve their environmental impact. There are a significant number of publications related to optimizing energy consumption, due to its relevance [1], [2], [7]–[9], [13]–[15], [21]–[23], [26]–[28], [33], [34]. Previous research identifies that the highest energy consumption in buildings is due to HVAC systems, followed by that of lighting systems [21], [27]. The management of HVAC systems, sometimes integrated into other building systems, such as a BMS, consists of the supervision and control of the facilities considering several variables read from the sensors, such as the outside temperature, building materials, indoor humidity and temperature, and sends instructions to the controllers to achieve the goals.

In particular, Aguilar *et al.* [2] proposed an AI-based system that defines an autonomic management architecture for multi-HVAC systems in buildings. In this context, autonomic management is a self-management process through which the system itself can readjust its activities to achieve its objectives. In our case, this process is implemented through ACODAT, which defines a set of autonomous cycles of data analysis tasks for the self-management of a system [2], [11], [17]. Thus, the autonomic concept refers to the self-management system of the building multi-HVAC system, which does not require intervention for self-optimization or self-healing, among other tasks.

The multi-HVAC system is configured with operational modes (OpM) that are possible combinations of the capacities of each HVAC subsystem. The proposed approach can improve energy consumption, maintain indoor comfort and maximize the performance of the equipment by identifying and selecting the multi-HVAC OpM. The DATs exploit the data gathered in real-time from the system and the environment to autonomously manage the multi-HVAC system. Some DATs analyze the data to obtain the optimal OpM for a given moment, while others control the HVAC subsystems.

An illustrative example of a DAT to control HVAC systems in buildings is described by Morales *et al.* [20]. The authors propose the application of LAMDA [30] for advanced control in HVAC systems for buildings. LAMDA addresses the control problem using a fuzzy classification approach, without requiring a mathematical model of the plant/system, as other authors have proposed [42], [43]. That study was followed by another proposal of an ACODAT-based supervisory system for building HVAC installations [1]. In this research, DATs incorporate data mining models for extracting knowledge from the system, monitoring and analyzing abnormal situations, and taking automatically corrective actions. The novelty of the proposed supervisory functionality of the HVAC system is the capability to detect subtle deviations over time, such as element degradation or gradual increments of energy consumption under similar working conditions.

Previous works are based on the principle that the controlled variables of HVAC systems are already steadily at their setpoints, with the control systems guiding the operation around them [5], [12], [20], or with optimal configurations of HVAC systems seeking to maintain those setpoints [21], [23], [26], [28], [32]. There are also other articles where the supervision of HVAC platforms is intended to detect malfunctions [1], [8], [9], [14], [15], [31]. However, one fundamental problem that has not yet been considered is how the HVAC system reaches that setpoint at start-up. Many problems arise at the start-up, such as different room cooling load profiles, the demand side equipment competing for the limited supply, or the overspeeding of the secondary water pumps and air fans [38]. Very few articles address these problems, which could lead to 50% savings in pre-cooling or prewarming [40], [41], meaning 5% of the overall consumption [38].

In this article, the transient regime management is carried out with two DATs: (1) one for determining if the system is moving towards the desired setpoint and, if that is not the case, another (2) for triggering the reconfiguration of the OpM of the system to redirect it accordingly. Thus, this ACODAT-based approach is composed of an SM and an OM. The SM verifies if the operational setpoint is reached at the stipulated time under ideal conditions, and the OM is invoked if the SM determines that the setpoint is not reached in-time. Both modules provide an autonomous functional architecture that self-configures the multi-HVAC system as many times as

necessary until it reaches optimally (time, energy cost, etc.) the operational setpoint.

Thus, the main contribution of this work is to define an approach that leads a multi-HVAC system to quickly reach the setpoint, allowing a smooth handover to steady-state control strategies, which are frequently studied in the literature [1], [2], [20]. This is carried out by watching a system for which (1) the current OpM of the multi-HVAC system is leading the controlled variables towards the setpoint; (2) the cost of energy is bound within the proper range; and (3) there are no anomalous behaviors in the system during the process. This approach is tested with a case study, the multi-HVAC system of the *Teatro Real* (Opera House) of Madrid (Spain), mainly characterized by its energy consumption, operating costs, and comfort (defined as the proximity of the indoor temperature to the setpoint).

This article is organized in the following way: Section 2 presents the related work. Section 3 describes the ACODAT concept and outlines the problem of energetic optimization in smart buildings and Section 4 describes the proposed ACODAT-based approach to transient regime management until the setpoint is achieved. Section 5 starts by describing the case study and presents the experiments in this context. Section 6 compares previous approaches, and finally, Section 7 provides the conclusions and describes future research works.

II. RELATED WORK

Smart building HVACs are normally operated with advanced control methods from BMS [5], [6], [12], [20], [34]. These advanced methods are increasingly making use of AI techniques to predict, detect, etc. behaviors, or adapt the operation to context changes and perturbances. Keeping a comfortable ambient temperature and humidity, and reducing energy consumption are the most typical goals for this control. The operation of an HVAC system causes contradictory effects on these goals, requiring optimization with multiple objectives for its automation [2], [21], [23], [26], [28], [32]. Metaheuristic algorithms are good for this purpose but pose several challenges, such as mathematical models, parameter tuning, and performance assessment [4]. These algorithms can take advantage of the increased computational power, and from recent big data and IoT subfields [10], [21]. The optimization can define the problem with objective functions that are computed with data-driven models, such as neural networks or ML techniques, not requiring the complex formulation of the system physics, but degrading the accuracy slightly.

Particularly, this study considers the supervision and optimization of the building HVAC systems. For the supervision problem, some previous works focused on this aspect. FDD algorithms are classical supervisory systems surveilling abnormal work conditions to discover possible faults in chillers caused by degraded installations or bad human practices [21]. The first FDD generations were based on

rules and statistics [28]. Today's generation uses ML techniques for detection and diagnosis [14], [23]. For example, Wall *et al.* [31] proposed an AFD system to continuously monitor the HVAC system's states with fuzzy algorithms. Classical fault detection and diagnosis approaches are based on supervised learning models, while the prognosis is based on reinforced learning (RL) [18], with different variants, such as the MORL approach, whereas the objective is to learn multiple policies simultaneously for every objective [7].

Kim *et al.* reviewed articles about AFDs for commercial buildings [15], categorizing these methods into three groups and analyzing several of them to understand their strengths and weaknesses. Deshmukh *et al.* present analytical methods embodied in software tools to identify and evaluate some building system faults, which cause large building energy inefficiencies [8]. Additionally, the same authors considered algorithms for faults such as stuck dampers and leaking dampers [9]. These damper fault detection algorithms can be applied to both outdoor and return air dampers. They combine expert-rule-based fault detection models with the first principles of thermodynamics, for fault detection with minimal nonintrusive measurements. The algorithms focus on detecting faults with minimal data in a large monitored academic building. The experiment used the data collected from the BEMS of an academic building in Boston.

In the context of the optimization problem, some previous methods use 'metaheuristics' [4]. Complex, dynamic and nonlinear systems' behavior makes metaheuristics-based algorithms a good choice. The studied cases define a multi-objective optimization problem, in which is required to make decisions for selecting the best nondominated individuals. Multiobjective optimization with evolutionary techniques is interesting to research but has had slow penetration in real building HVAC systems. Hameed *et al.* assessed several optimization methods and pointed out that genetic algorithms perform well in a global search but show poor convergence [12]. Swarm-based algorithms are good for local search but slower than genetic algorithms for global search. However, ACO is faster in search and convergence than simple genetic algorithms. In HVAC system control, the most studied multiobjective optimization techniques are genetic algorithms and MOPSO [23], [26].

Behrooz *et al.* confirmed that genetic algorithms provide optimization for comfort and energy savings because of their good behavior with nonlinear systems but have problems in variable contexts and when subjected to perturbances [5]. Reynolds *et al.* used genetic algorithms for the concurrent optimization of the energy efficiency and the system performance [23]. They obtained good results for nonlinear and discontinuous problems in robustness and efficiency. Satrio *et al.* proposed a framework for assessing and optimizing several building systems, including HVAC systems, with NSGA II, to obtain the best-operating conditions [26]. Fadzli *et al.* showed energy consumption improvements while maintaining comfort by using an IGPSO approach [32].

On the other hand, the literature on the energy optimization of multi-HVAC systems at start-up is scarce. Tang *et al.* [38] showed that there are issues with the HVAC system in the morning start-up, when people are not yet in or are about to enter the building. They realize that the secondary pumps and air delivery fans are overspeeding in an attempt to precool the zones. They implement a control strategy specific for this period and obtained a 35% time reduction, leading to up to 50% energy consumption savings in precooling. This contributes to a 5% overall consumption savings.

Another approach comparable to the multi-HVAC system start-up is the moderation of the peak demand. Haniff *et al.* [37] studied optimal control strategies by scheduling the setpoints to reduce the peak load demand and its cost. With LWA, they obtained a 41% reduction, with an ESA approach 42% and an SA approach 39%. Even with basic techniques improvements in the peak load demand can be achieved, such as Mathews *et al.* [36], who proposed a 30% energy consumption reduction with start-stop times together with air-bypass, reset and setback control. Similarly, Biyik *et al.* [35] considered the HVAC demand, battery power and building thermal comfort, and defined an MPC with a simple mathematical model for the zone transient thermal dynamics to obtain a peak reduction of 50%.

Compatible with the multi-HVAC system start-up, there are studies related to robustness that do not depend on the accuracy of the predicting models. The transient response is optimized with fuzzy logic applied to the controllers. Aguilar *et al.* [20] used LAMDA, a technique that combines fuzzy logic for decision making and state clustering for context identification for adjusting one PI controller per actuator. They obtained 5% to 6% improvements of the IAE in the transient response with abrupt context perturbances of temperature and humidity with respect to conventional PI controllers. In this regard, another interesting study by Homod *et al.* [39] compares FPIPDM, showing its sensitivity to parameter uncertainty or variations in contrast to the CABTSK, obtaining 37% energy savings compared to a simple on-off strategy.

Considering multi-HVAC system start-up goes beyond the study of its transient response to the steady state. Knowing how thermal inertia behaves with abrupt changes brings new degrees of freedom in energy management. In fact, some buildings keep the HVAC system continuously working to avoid abrupt ambient changes. The application of DATs that learn the behavior of the multi-HVAC system at start-up, as this research proposes, can make it work efficiently out of the peak tariffs, storing thermal energy in advance [2], or can be switched off more frequently, significantly reducing consumption.

According to the analysis of the previous works, none considers at all of the different contributions of this work: (i) multi-HVAC systems; (ii) the initial transitory regime to reach the setpoint at the beginning; (iii) the combination of

autonomously processes of supervision and optimization to manage HVAC systems.

III. MATERIALS AND METHODS

A. AUTONOMIC CYCLES OF DATA ANALYSIS TASKS

Data analytics is used to generate and discover knowledge by examining data. In this regard, data analytics includes collecting, storing, extracting, cleaning, transforming, aggregating and analyzing data. An ACODAT-based architecture implies that all these activities are integrated and automated. This is why the concept of “Autonomic Cycles of Data Analytics Tasks” is developed for each strategic objective of a studied process. Thus, in [3, 11] ACODAT is defined as a set of data analysis tasks whose purpose is to improve the process under study. The tasks of this set interact among themselves, performing different roles: (1) process observers, (2) situation and event analyzers and interpreters, and (3) decision-makers to improve it (see Figure 1).

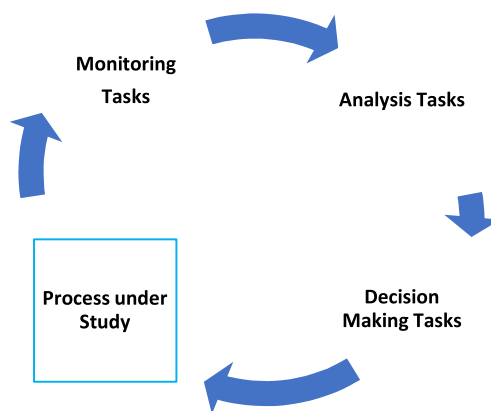


FIGURE 1. Autonomous cycle of data analysis tasks.

It is based on the autonomic computing paradigm proposed by IBM, which monitors, analyzes, plans and executes using a knowledge base (MAPE-K) [29]. The integration of tasks in cycles closes the loop, enabling an autonomic problem-solving. The generic roles of each task in the cycle are as follows [3]:

- **Monitoring Tasks:** They obtain the variables of the process under study. These tasks monitor the process, track its behavior, and extract the data that describe it.
- **System Analysis Tasks:** They interpret what happens in the process. They are used to diagnose, understand, analyze, among other things, what happens. Normally, these tasks are rendered with knowledge models (prediction, description, etc.).
- **Decision-making Tasks:** They define the actions to be carried out to improve the process, considering the objectives defined for the autonomic cycle.

The ACODAT paradigm was initially proposed for smart classrooms [3], [11] and later applied to different fields, such as telecommunications [19] or industry 4.0 [17], [24], [25].

B. MANAGEMENT OF THE HVAC SYSTEM' START-UP

In this study, the transitive regimen is analyzed at the start of the HVAC system to heat or cool the building zones (start-up phase). Other control methods are applicable for keeping comfort at the lowest cost (sustained or steady-state phase). The start-up phase considers supervision and optimization methods. The optimization minimizes the difference between the room temperature (T_r) and the setpoint (T_0), the energy consumption, and the cost of energy, improving the COP of the devices. In addition to these main objectives, the optimization also minimizes the period from when the setpoint is reached until it is required ($t_{event} - t_{end}$) and the room temperature variation rate ($\frac{dT_r}{dt}$ at $t = t_{end}$). The control actuates varying the operational mode of the HVAC subsystems, providing a vector of capacities for each chiller and its associated elements. These instructions are translated into the appropriate signals to open/close, switch on/off, and regulate up/down these elements to reach the setpoint.

The novelty of this approach is that the optimization provides a discrete set of operational modes (OpM) to reach the setpoint at the appropriate time. This means that it is necessary to analyze the different periods until the HVAC system reaches the setpoint (see Figure 2).

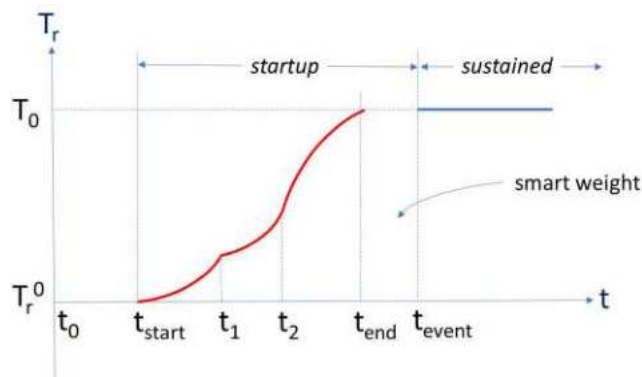


FIGURE 2. Process to reach the setpoint.

At t_0 , the HVAC system must start with the definition of an optimal OpM to reach the setpoint. Once the optimal OpM is determined, the first OpM starts at t_{start} . Then, any change in the behavior during the process to reach the setpoint must be detected (e.g. at t_1 or t_2), and in this case, a new OpM must be defined. One main aspect to consider is to reach the setpoint (t_{end}) at a time the closest to the time required (t_{event}).

Once the system reaches the setpoint a different method takes over the control. The system inertia renders it necessary for the start-up phase to deliver the control at a time the closest to the desired time, t_{event} . That implies two more fitting values:

- $d(t_{End} - t_{Event})/dt$ must be low to damp overshoots and to obtain a steady error in the sustained phase.
- $\Delta t = t_{event} - t_{end}$ must be minimum not to consume unnecessary energy in this period.

IV. MANAGEMENT SYSTEM OF THE MULTI-HVAC SYSTEM' START-UP

A. ACODAT-BASED ARCHITECTURE

The components of the ACODAT-based architecture for the initialization of the multi-HVAC system to reach the established setpoint are as follows (see Figure 3):

- Multi-HVAC System: made of several HVAC subsystems that, working in combination, must achieve the system setpoint, while optimizing the energy cost, energy consumption and comfort. The SM surveils the HVAC subsystems, searching for significant changes in their operations or possible failures. Whenever necessary, their configurations are modified by the OM.
- Supervision Module (SM): monitors the Multi-HVAC system to determine if it is reaching the defined operating point in time. If this is not the case, then it would trigger the OM.
- Optimization Module (OM): modifies the current OpM of the multi-HVAC system to guarantee that the system attains the setpoint in the required time, optimizing the objectives defined in the process (comfort, costs, energy consumption, etc.). The OM is applied when triggered by the SM.
- IoT devices: provide ACODAT-based architecture with the necessary information about the system and the context.

Figure 4 depicts the exchanged variables among the functional modules. Particularly, the SM is used twice: (1) to detect when the initialization process has some problems reaching the setpoints and (2) to evaluate the quality of the OpMs proposed by the OM. Thus, the SM receives the system and context data, and simulates the system to provide fitness for the optimization process. The contextual variables can be physical or virtual. The OM also exchanges data with the multi-HVAC system (particularly, with its control module (CM)) to recommend or fix the optimal OpM. Both the OM and SM consider the problem constraints and make some assumptions about the process, for example, it is possible to simultaneously actuate different HVAC subsystems.

The following subsection describes in detail the supervision and optimization modules of the ACODAT-based architecture.

B. SUPERVISION MODULE

The function of the SM is to determine if the current configuration of the multi-HVAC system is not driving it as expected, i.e., the system cannot reach the setpoints' values in time (t_{event}). To do that, the SM virtually traces a straight line between t_{start} and t_{event} in Figure 2, measures the distance of the controlled variables to the setpoints, and assesses the changes in the environment to determine if everything is going right or not. Since it is only necessary to know if the setpoint is reached at the right time, the SM makes use of a binary classifier (see Table 1).

Thus, this DAT monitors the process on its way to reach the setpoint and detects when something abnormal happens.

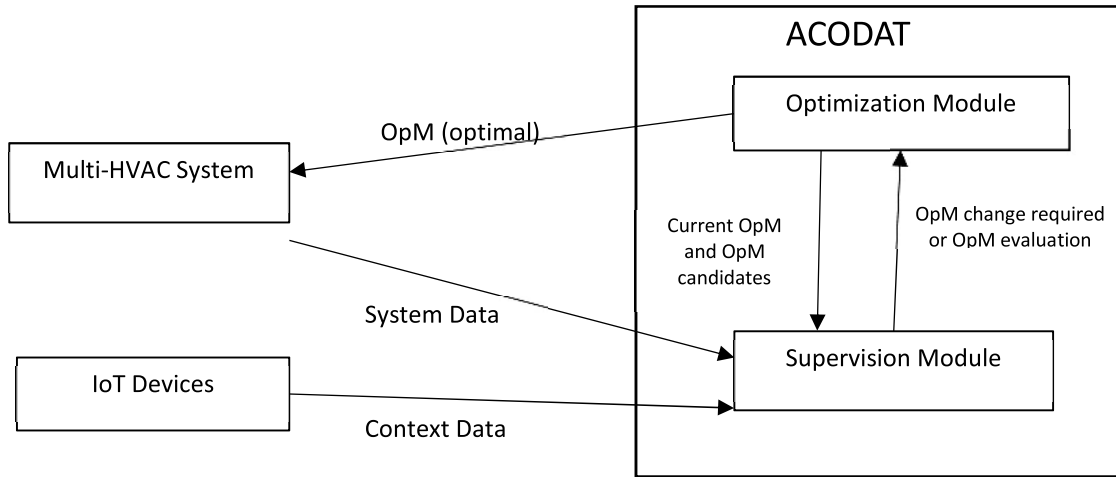


FIGURE 3. ACODAT-based architecture for the management of the multi-HVAC system start-up.

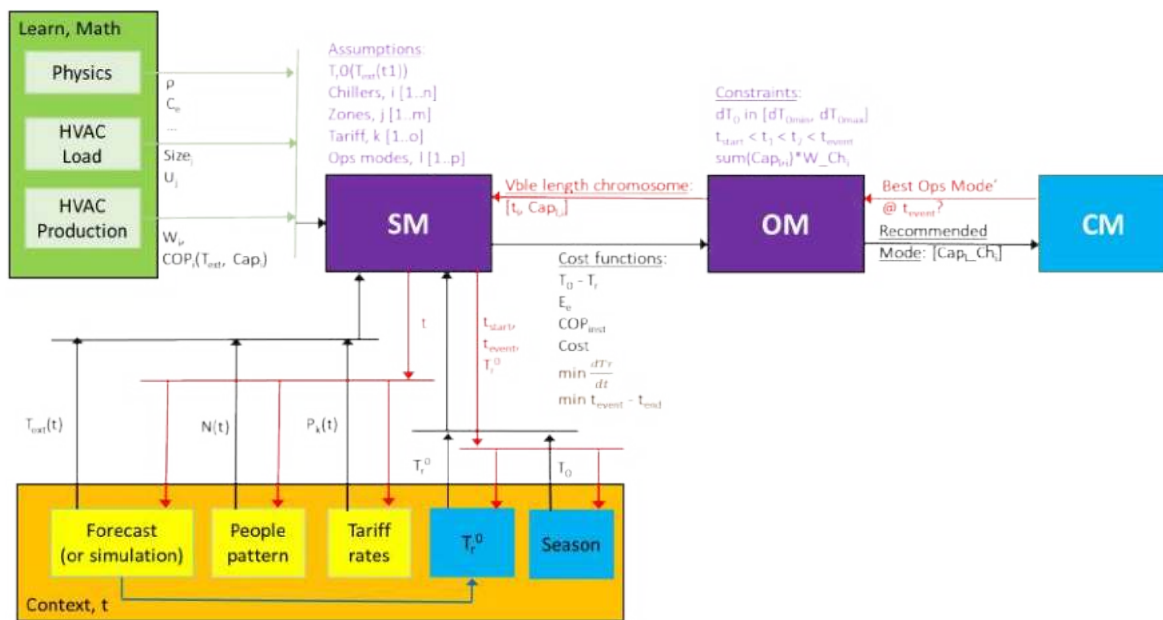


FIGURE 4. Global view of the process to reach the setpoints.

Some examples that this DAT could detect are if with the current configuration the process stops its approach at the setpoint, surpasses the setpoint, or slows down in excess. In these cases, it triggers the OM to compute a new optimal OpM of the multi-HVAC system for the current situation.

The detection function is a binary classifier implemented with ML, which takes the Δ (incremental or decremental) values of the variables depicted in Figure 2 to determine the changes in the evolution to the setpoint (Δsp) over time (Δt). Thus, with these values, it can determine if the virtual line is being followed or changes are very slow (below the line) or very fast (above the line). In this way, this task uses the Δ values to determine if the current rate of changes is adequate or not, within the current context, to reach the setpoint at the right time. The binary classification model is

capable of determining whether the evolution of the process is correct. The quality of the binary classification model is determined by the classical metrics of accuracy and precision.

The SM makes use of a second DAT that implements a predictive model, which determines if the given configuration of the multi-HVAC system (OpM) reaches the setpoint (see Table 2). This DAT is the fitness function of the optimization and is called by the OM to evaluate the costs of each individual.

C. OPTIMIZATION MODULE

The function of the OM is to solve a multiobjective optimization problem that obtains the appropriate OpM of the multi-HVAC system to reach the setpoint before an event begins (see Table 3). The problem is defined by objective

TABLE 1. Description of the detection DAT.

| Task 1 | Supervision |
|--|--|
| Description: | Identification of an abnormal situation during the initialization process of the multi-HVAC system |
| Data source: | Information of the process to reach the setpoint (Figure 2) |
| Data analytics type: | Classification |
| Possible data analytics techniques: | Random forest, linear regression, etc. |

functions that compute comfort, energy consumption, cost, and COP. The optimization works on a decision space made of individuals (chromosomes, particles, etc.) that define the OpM of the multi-HVAC system. The optimization objectives are then evaluated to identify the nondominated solutions, i.e., which are solutions where none of these objectives can be improved without degrading the others. The nondominated solutions define the Pareto front (PF). Without any additional subjective preferences, all the nondominated solutions are considered equally good.

For the implementation of the OM, two population-based multiobjective optimization algorithms have been considered, NSGA II and MOPSO, because they have obtained good results in HVAC scientific literature [23], [26]. MOPSO is one of the most popular swarm intelligence-based algorithms today for multiobjective optimization. NSGA II is also a genetic algorithm that can solve nonconvex and rough multiobjective optimization problems. Although recent studies prove that NSGA II yields better coverage of the PF than MOPSO in similar applications, this research chooses MOPSO for delivering faster results. The cost functions are computed by calling the predictive model seen in the previous module (Table 2). Table 3 describes the Optimization DAT.

TABLE 2. Description of the prediction DAT.

| Task 2 | Evaluation |
|--|--|
| Description: | Determination of the quality of a configuration of the multi-HVAC system |
| Data source: | Information from the optimization module (see Figure 3) |
| Data analytics type: | Prediction |
| Possible data analytics techniques: | Random forest, artificial neural network, etc. |

V. RESULTS

The proposed ACODAT-based architecture for HVAC system start-up is proven with real data from the BMS controlling the multi-HVAC system of the *Teatro Real* (Opera House) of Madrid (Spain).

A. EXPERIMENT BACKGROUND

The Opera House in Madrid, Spain, has a sitting capacity of 1746 for performances, mostly opera, and a total floor area

TABLE 3. Description of the Optimization DAT.

| Task 3 | Optimization |
|--|---|
| Description: | Determination of the new configuration of the multi-HVAC system |
| Data source: | Information about the multi-HVAC system and context |
| Data analytics type: | Optimization |
| Possible data analytics techniques: | Evolutionary approaches |

of 65,000m² (700,000ft²). The building allocates 11 multiveneue lounges, 4 rehearsal rooms, 7 multipurpose studios, staff offices surrounding the main performing room on several floors and technical areas with warehouses in the basements. The building is used from September to July, requiring heating power in the winter and cooling power in the summer. The multi-HVAC system is composed of several HVAC subsystems: (1) two water–air heat pumps of 195 kW for heating and cooling and (2) two water–water coolers of 350 kW connected to two cooling towers on the roof for extra cooling supply. The multi-HVAC system is supervised and operated with a BMS that gathers the temperatures and other variables from sensors in equipment and premises, and actuates on the controllers regulating the water, air flow rates or fluid temperature.

The BMS records 169 historical variables every 15 min in one table, including the outdoor temperature, zone temperatures, power supply from transformers, thermal energy from HVAC subsystems and their COPs. Another table has 45 additional temperatures from other building rooms sampled every hour. There are some other tables with different variables only sampled during the performances, from 69 sensors every 10 min.

Previous works used the ACODAT concept for the management and supervision of the multi-HVAC system of this building [2]. Figure 5 shows how ACODAT is instantiated in the multi-HVAC system, and the DATs run embedded into its BMS. Particularly, Figure 5 shows the BMS, which has a supervision system based on ACODAT for the supervision of the building multi-HVAC systems as proposed by Aguilar *et al.* [1]. Additionally, there are two other components for the management of the multi-HVAC system: (i) a controller for each HVAC subsystem that regulates its behavior using control loops, as proposed by Morales *et al.* [20], which is implemented like a fuzzy-based control method, and (2) the optimizer that determines the ideal configuration of the multi-HVAC system in a given moment to improve the energy efficiency and costs [2].

This study continues the abovementioned research, proving an ACODAT to manage the initial start-up process to reach the setpoint (see Figure 2). The data models are trained with the following values, corresponding to each HVAC subsystem:

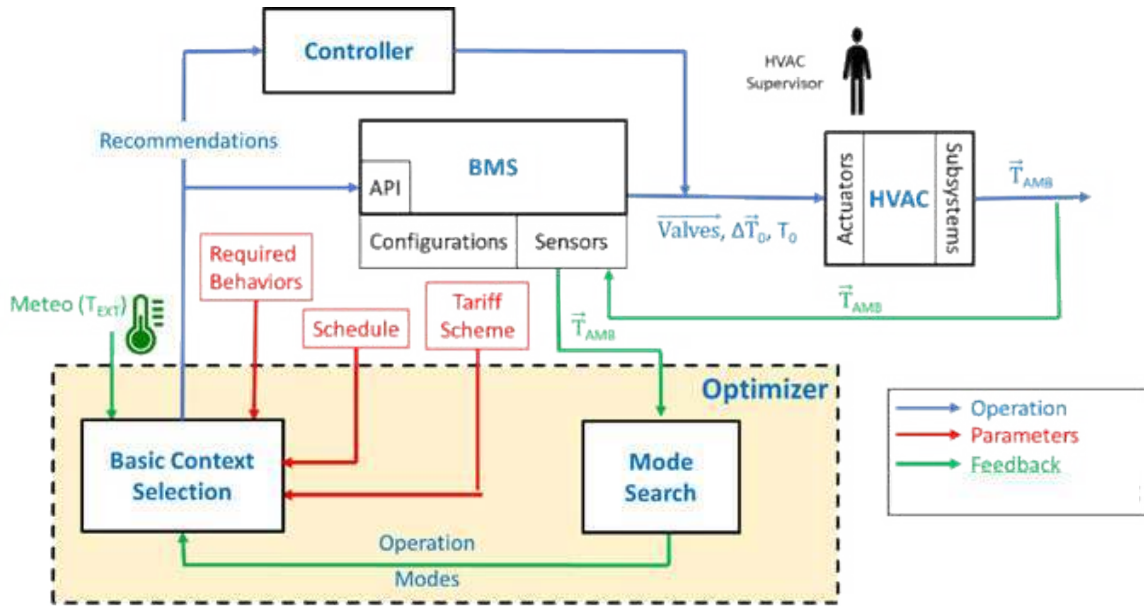


FIGURE 5. ACODAT-based first integration [2].

- Fluid specific heat capacity in subsystem j : $c_{fluid}(j)$;
- Refrigerant fluid density in subsystem j : $\rho_{fluid}(j)$;
- Maximum electrical power consumed in subsystem j : $P_{max}(j)$;
- Maximum temperature provided with subsystem j : $T_{max}(j)$;
- Thermal capacity of subsystem j : $CAP(j)$.

These values are typically available in the manufacturer’s technical specifications under standard working conditions. The specific data of the Opera House chillers are shown in Table 4.

TABLE 4. Extracted cooling characteristics from the manufacturer’s user manuals.

| Parameter | Value |
|-------------------------------|--------------|
| $c_{water}(\text{Chiler})$ | 4.186 J/g °C |
| $\rho_{water}(\text{Cooler})$ | 1 kg/L |
| CAP(Cooler) | 350 kW |

In the experiment, the proposed ACODAT uses the historical data in the BMS database and the contextual information as the setpoint and the desired time to attain it.

B. ACODAT INSTANTIATION

The ACODAT modules were instantiated with the following techniques:

- For start-up process deviation detection: logistic regression (LR), random forest (RF) and support vector machine (SVM).
- For behavioral prediction: artificial neural network (ANN), specifically, the multilayer perceptron (MLP).

- For operational mode optimization: multiobjective particle swarm optimization (MOPSO) and nondominated sorting genetic algorithm version 2 (NSGA-II)

Supervision Module

The SM is made of two DATs for detection and prediction. The detection DAT implements a binary classifier, for which the experiment proves three ML techniques: LR, RF and SVM. The dataset comes from the real data on the system and the context. The general quality of the classification models is shown in Table 5. LR performs better than the other two models in tracking the start-up process of the multi-HVAC, closely followed by RF. The metrics of the model quality are accuracy and precision.

TABLE 5. Quality of classification models.

| Classifier ML Technique | Precision | Accuracy |
|-------------------------|-----------|----------|
| Logistic regression | 0.93 | 0.95 |
| Random forest | 0.91 | 0.91 |
| SVM | 0.83 | 0.86 |

The other DAT of the SM is implemented with the MLP model. The inputs are (1) the current OpM applied to the multi-HVAC system, (2) indoor and (3) outside temperatures, and (4) interval, Δt . The outputs are: (1) the energy consumption, (2) indoor temperature evolution, and (3) energy produced. The optimization objectives are obtained from the model’s outputs: the consumed energy comes directly from one of the outputs; the comfort comes from the difference between the setpoint and the final indoor temperature; and the COP is obtained as the ratio of the produced [thermal] energy in the chillers to the energy that they consume.

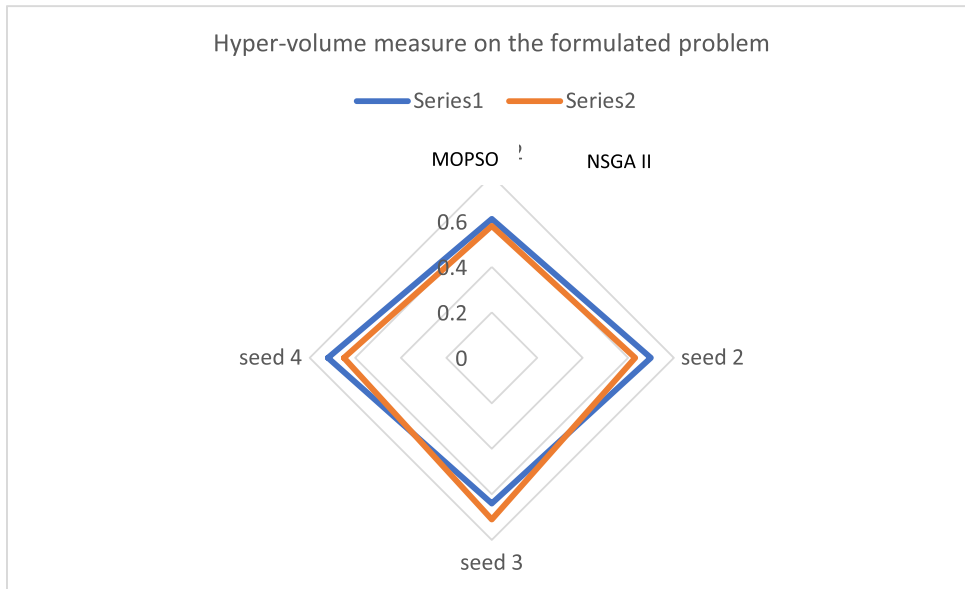


FIGURE 6. Hypervolume measure of the formulated problem.

The MLP must predict the behavior of the system with these inputs, requested by the optimization algorithm (for its individuals). The quality metrics to evaluate the model are the mean absolute percentage error (MAPE) and the coefficient of determination (R^2), which are also used as the minimization criteria in the learning stage of the MLP [16]. The training with the dataset reaches the best configuration with $MAPE = 4.5\%$ and $R^2 = 0.92$. The obtained values of MAPE less than 5%, denote the high accuracy for prediction. A value close to 1.00 of R^2 indicates a good fitting and therefore a highly reliable model. These results of the MLP are good enough in our context, which allows us not to think about using other predictive techniques.

Optimization Module

The optimization objectives are based on those outlined by Aguilar et al. [2]. The main decision variable is the OpM ($HVAC_{mode}$ in that article) that defines the optimal combination of the capacities of the multi-HVAC subsystems at a given time, t . The multiobjective optimization problem is formulated as follows [2]:

$$\begin{aligned} &Min_{OpM,t}(P_{consumed}(OpM, t), \\ &Cost_e(OpM, t), \\ &COP_{global}(OpM, t), \\ &Comfort(OpM, t)) \end{aligned} \quad (1)$$

where, the cost functions are:

- $P_{consumed}(OpM, t)$: the consumed energy according to the predictive model.
- $Cost_e(OpM, t)$: the cost of the energy, defined as

$$Cost_e(OpMt) = P_{consumed}(OpM, t) * TE_i \text{ for } t \in i \quad (2)$$

where, TE_i is the tariff rate in Period i applied to the consumed energy at time t .

- $Comfort(OpM, t)$: obtained by adding the variation of the indoor temperature to its initial value and subtracting the setpoint (or target temperature).
- $COP_{global}(OpM, t)$: obtained by the division of the produced [thermal] energy by the consumed energy.

With these values, the multiobjective optimization problem is defined to generate a set of optimal solutions, or PF, for each possible OpM. To implement the optimization, the experiment uses a genetic algorithm, NSGA-II, and a swarm-based algorithm, MOPSO. Both implementations are executed under similar parameters: population (swarm_size) = 500, max_iterations = 25.

The quality of the evolutionary strategies is analyzed with the hypervolume (HV) metric applied to the obtained PFs. The HV metric measures the volume of the dominated portion of the objective space. It is of exceptional interest, as it provides a highly desirable feature called strict Pareto compliance. This feature means that, whenever one approximation set completely dominates another approximation set, the HV of the former is higher than the HV of the latter. The results are depicted in Figure 6.

The results of both are very similar, making NSGA-II and MOPSO overlap, with slightly better behavior by NSGA-II, corroborating previous related studies [23], [26]. Even though the results for the decision variables and objective variables are very similar, the selection is based on the execution time, selecting MOPSO because it computes faster.

The Pareto results show some interesting and important relationships between the considered variables. It is observable that $P_{consumed}$ is proportional to $Cost_e$, but is inversely related to $Comfort$. It can also be noted that COP degradation generates a larger $P_{consumed}$ (see Figure 6).

C. CASE STUDY PERFORMANCE

This section evaluates the performance of the proposed ACODAT architecture under different scenarios, where the contextual information varies, or the real-time data stream from the multi-HVAC system changes, simulating standard failures or unexpected situations. The objective of the test is to analyze the ability to detect these exceptions and reconfigure the multi-HVAC system to achieve the process’s goal. The following situations have been proved:

1. An abrupt stop of the start-up process (induced deliberately) could be a failure in one of the HVAC subsystems.
2. An abrupt acceleration of the start-up process (induced deliberately).
3. An excessive energy consumption.

The following restrictions of the OpM have been selected to improve the discussion of the analysis:

- a. All HVAC subsystems are available.
- b. Only water–air heat pumps are used.
- c. Only water–water coolers are used.

In the previous section, we saw that the different techniques used by the tasks of the autonomous cycle generally provide quite good results that are very similar.

These experiments implement the SM with the LR and MLP techniques, and the OM with the MOPSO algorithm. The experiments test the detection ability of the SM, and analyze the PF of the OM. As none of these Pareto-optimal solutions can be considered better than the others in the absence of additional information, it is necessary to decide according to our context, which, in this case, is prioritizing the comfort (i.e., selecting the solution closer to the setpoint).

The experiments trialed 30 iterations of the different OpMs. The obtained results are shown in Table 6, where the $Cost_e$ is no longer considered because of its direct relation with $P_{consumed}$. The values of the vector (individual) in the third column are $P_{consumed}$, in kW, COP and Comfort in °C.

TABLE 6. Results of the simulations.

| Simulated Conditions | % of correct degradation detections | Individual selected from the Pareto Front ($P_{consumed}$ COP Comfort) |
|----------------------|-------------------------------------|---|
| 1 and a | 93% | (33, 6, 0.5) |
| 1 and b | 94% | (34, 2, 0.09) |
| 1 and c | 95% | (37.2, 4.1, 0.23) |
| 2 and a | 96% | (32.3, 3.6, 0.11) |
| 2 and b | 91% | (41.1, 2.4, 0.02) |
| 2 and c | 90% | (41.9, 4.2, 0.6) |
| 3 and a | 81% | (62.3, 2.2, 0.08) |
| 3 and b | 78% | (61.1, 4.2, 0.4) |
| 3 and c | 82% | (61.8, 3.9, 0.06) |

In the cases when the energy consumption rises excessively, the SM cannot detect this condition as well, as in the other cases. The reason is that the SM has not learned specifically this scenario and works with general assumptions.

It is also noticeable that the best-selected individual depends on the situation. For example, an abrupt stop using only the heat pumps (case 1 and b) obtains an OpM that delivers $P_{consumed} = 34$ kW, $COP = 2$ and $Comfort = 0.09^\circ\text{C}$. The case of excessive power consumption with only coolers (case 3 and b) obtains an OpM that delivers $P_{consumed} = 61.1$ kW, $COP = 4.2$ and $Comfort = 0.4^\circ\text{C}$.

In general, the proposed ACODAT architecture for the multi-HVAC system start-up process reacts significantly well, depending on the situations (see options 1 and 2), proposing optimized OpMs with detection values greater than 90%. Case 3, which detects the excess energy, is different because such consumed energy amounts have not been used to train the classification model, causing a problem in its generalization. In fact, the SM detects the problem when acceleration or deceleration takes place in the start-up process. However, the use of incremental learning approaches helps to improve the quality of SM by the possibility of learning new situations online.

VI. DISCUSSION

This section compares this research with other similar approaches. The following criteria are listed for comparison with other articles:

- a. The article is based on the autonomous paradigm for HVAC systems
- b. The article considers the start-up or transient response of the system dynamics
- c. The article considers the integration of several ML techniques
- d. The article is easily adaptable and extensible
- e. The article considers a supervision process with detection, diagnosis, etc.
- f. The article considers an optimization process of multi-HVAC systems

Table 7 shows the classification of the articles matching these criteria.

There seems not to be any fully similar works, at least not specifically focused on the start-up process of an HVAC system. They are more general, dealing with the supervision of HVAC systems. The paper of Aguilar et al. [1] proposed an ACODAT for the supervision of building HVAC systems. DATs incorporate data mining models for extracting knowledge from system monitoring, analyzing abnormal situations, and automatically identifying and taking corrective actions. Deshmukh et al. [8], [9] presented analytical methods embodied within software tools to identify and evaluate selected building system faults that cause large building energy inefficiencies. They considered damper fault detection algorithms, which can be applied to both outdoor air and return air dampers. The technical contributions of this work include expert rules that adapt to the HVAC equipment scale and operation, and methods for sorting fault signals according to user-defined interests such as the annual cost of energy inefficiencies. They combined expert rule-based

TABLE 7. Comparison with other works.

| Reference | Criteria | | | | | |
|-----------|----------|-----|-----|-----|-----|-----|
| | (a) | (b) | (c) | (d) | (e) | (f) |
| [1] | | | x | x | x | |
| [8, 9] | | | | x | x | |
| [14] | | | x | x | x | |
| [18] | x | | | x | | |
| [21] | | | | x | | x |
| [26] | | | x | x | | x |
| [28] | | | | x | x | |
| [31] | | | | x | | |
| [35] | | x | | | | x |
| [36] | | x | | x | | x |
| [37] | | x | | | | x |
| [38] | | x | | | | x |
| [39] | | x | | | | x |
| This work | x | x | x | x | x | x |

fault detection with first principles thermodynamic modeling that leads to quicker fault detection with minimal nonintrusive measurements. Kiluk presented a method for the evaluation of diagnostic information gathered in district heating efficiency supervision based on exploring the evolution of the information system and analyzing its dynamic features [14]. He proposes a process of data mining and knowledge discovery applied to the data acquired from district heating substations' energy meters to provide the automated discovery of diagnostic information necessary for the efficient supervision of district heating-supplied buildings. The work of Mason and Grijalva [18] provided a comprehensive review of the literature relating to the application of reinforcement learning to develop autonomous building energy management systems. Energy savings of greater than 20% are reported in the literature for building energy management problems when implementing reinforcement learning. Minoli *et al.* [21] reviewed some of the technical opportunities and challenges faced by the IoT in the smart building arena. They analyzed the cost-effective IoT applications for smart buildings, with requirements in terms of comfort, usability, security, and energy management. In particular, they studied the power over Ethernet, as part of an IoT-based solution, for an in-building connectivity of a large number of devices. The work of Satrio and Saito [26] developed artificial neural networks that take weather, occupancy and indoor temperature as inputs, which were used as the fitness function by a genetic algorithm to minimize energy consumption. The optimization strategy can be deployed in two modes, day-ahead optimization or model predictive control which reoptimizes every hour. Additionally, when a time-of-use tariff is introduced, the optimization is altered to minimize cost rather than energy

consumption. Tamani *et al.* proposed a supervision and control approach for buildings using semantic technologies [28]. They defined a data model that describes the main physical and conceptual building elements (e.g., incidents and performance metrics), their characteristics and interrelationships. Wall [31] described a dynamic, machine learning-based technique for detecting faults in commercial air handling units. He analyzes automated fault detection and diagnostics tools to good maintenance practices in building energy systems, using machine learning techniques instead of rules-based techniques.

Our approach is the only one that proposes an ACODAT for the start-up of a multi-HVAC system, which integrates several ML approaches for the different aspects to be considered during this process: supervision and optimization. The main finding of this work is that it integrates different tasks to achieve a better performance of the system during its initialization. The ACODAT concept naturally manages these aspects, simplifying the development of robust solutions. We have studied its behavior in different scenarios, and the results show that the system is quite flexible since it can incorporate more DATs to conduct a deeper study of the supervision problem or improve some of the tasks. For example, the supervision task can be improved since it can be considered a more complex determination of the ideal behavior to reach the setpoint (here a straight line was assumed) that considers energy costs, and time bands of those costs. That would allow considering when to start the process, if it is better to get to the setpoint earlier and stay there, etc. Another relevant aspect is that our ACODAT does not depend on the techniques used to implement the tasks, so for each context, the most appropriate could be identified, and even introduce advances in the area of machine learning, such as incremental learning or transfer learning, to improve the results

VII. CONCLUSION

This study proposes a new functionality of the recently proposed autonomic ACODAT-based management architecture for building multi-HVAC systems. One DAT detects deviations of the multi-HVAC system variables to reach the setpoints in the desired time at the start-up stage, and another triggers the mechanisms to keep the trajectory towards the goal, if adjustments are required. DATs are flexible and may be implemented with several ML techniques that work together to share common goals. The multi-HVAC system start-up is a new approach that could bring significant benefits in energy efficiency and cost savings, as obtained in similar research on peak demand moderation, transient time controllers, or setting a basic scheduling in the morning before the users get in. ACODAT self-optimization makes the DATs steadily retrained with new context data read during the operations, improving their adaptation capability and accuracy.

The ACODAT start-up functionality has been proven with real data obtained from the BMS of the multi-HVAC system

of *Teatro Real* of Madrid (Spain). The multi-HVAC system of this building is heterogeneous, making the scenario more appropriate than others for trial and generalizing the results, which shows the ability of this scheme to detect abnormal situations during the start-up phase and self-reconfigure under several scenarios. The detection success rate is high, which is essential for triggering the reconfiguration of the multi-HVAC system. The experiment yielded good values of $P_{consumed}$ and COP for the nondominated solutions of the PF prioritized according to *Comfort*.

Our transient regime management approach is defined by two tasks: one is to verify if the operational setpoint is reached at the stipulated time, and the other is invoked if the setpoint is not reached in-time to reconfigure the system, to redirect it accordingly. These tasks have been implemented using supervised learning methods and an optimization technique. However, it is possible to use other approaches or combine them with other approaches. Next studies must analyze these improvements, for example, the utilization of fuzzy approaches to consider different configuration actions or to detect the operational setpoint.

Future work will extend this ACODAT-based start-up process to other types of buildings, such as public buildings, commercial malls, museums. In addition, other future works will incorporate meta-learning approaches to autonomously update the knowledge models of the cycles. Additionally, these DATs will be extended with more information about the context. For example, the energy costs according to the band of time of the day or week can change. These data can be used to build more complex detection schemes, considering the interval of time where the energy costs are lower. In this way, this information can be used, for instance, to preheat or pre-cool the room during cheaper periods (e.g., the time band with the lowest energy cost), and then adopt another strategy for maintaining the values close to the setpoint. A final work will study the integration of this scheme with existing BMS standards aiming to optimize and effectively control HVAC systems, which is an essential requirement for smart buildings.

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DISCLAIMER

The content of this article does not reflect the official opinion of the European Union. Responsibility for the information and views expressed herein lies entirely with the authors.

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