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Autonomic Management Architecture for Multi-HVAC Systems in Smart Buildings

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ABSTRACT This article proposes a self-managing architecture for multi-HVAC systems in buildings, based on the "Autonomous Cycle of Data Analysis Tasks" concept. A multi-HVAC system can be plainly seen as a set of HVAC subsystems, made up of heat pumps, chillers, cooling towers or boilers, among others. Our approach is used for improving the energy consumption, as well as to maintain the indoor comfort, and maximize the equipment performance, by means of identifying and selecting of a possible multi-HVAC system operational mode. The multi-HVAC system operational modes are the different combinations of the HVAC subsystems. The proposed architecture relies on a set of data analysis tasks that exploit the data gathered from the system and the environment to autonomously manage the multi-HVAC system. Some of these tasks analyze the data to obtain the optimal operational mode in a given moment, while others control the active HVAC subsystems. The proposed model is based on standard standard HVAC mathematical models, that are adapted on the fly to the contextual data sensed from the environment. Finally, two case studies, one with heterogeneous and another with homogeneous HVAC equipment, show the generality of the proposed autonomous management architecture for multi-HVAC systems.

INDEX TERMS HVAC system, autonomic computing, data analysis, smart building, multi-objective optimization, multi-chiller, building management systems.

NOMENCLATURE

ANFIS	Adaptive Network based Fuzzy Inference System
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ACODAT	Autonomic Cycle of Data Analysis Tasks
ARIMA	Autoregression Integrated Moving Average
ARMAX	Autoregression Moving Average eXogenous
ARX	Auto Regression eXogenous
BAS	Building Automation System
BCS	Building Control System
BD	Big Data
BEMS	Building Energy Management System
BMS	Building Management System
COP	Coefficient Of Performance
CVaR	Conditional Value at Risk
DAT	Data Analysis Tasks
DL	Deep Learning
DMC	Dynamic Matrix Control
EA	Evolutionary Algorithm
EEV	Electronic Expansion Valve
EER	Energy Efficiency Ratio
ETL	Extraction Transformation and Load process
FBC	Feedback Control
FFW	Feedforward Control
FPGA	Field-programmable Gate Arrays
FAN	Fuzzy Adaptive Network
GA	Genetic Algorithm
GPC	Generalized Model Control
HVAC	Heating, Ventilation and Air-Conditioning
IAQ	Indoor Air Quality
IEC	International Electrotechnical Commission
IoT	Internet of Things
ISO	International Organization for Standardization
JIT	Just in Time

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LQ	Linear Quadratic
LQG	Linear Quadratic Gaussian
MPC	Model (Based) Predictive Control
MOGA	Multi-objective Genetic Algorithm
MPSO	Multi-Objective Particle Swarm Optimization
NZEB	Nearly Zero Energy Buildings
NSGA	Non Dominated Sorting Genetic Algorithm
PID	Proportional, Integral and Derivative modules
PDF	Probability Density Function Approximation
PLC	Programmable Logic Controllers
RC	Resistive Capacitive
SARIMA	Seasonal Autoregressive Integrated Moving Average
SQP	Sequential Quadratic Programming
SPEA	Strength Pareto Evolutionary Algorithm
4SID	Sub-Space State Space Identification
SVM	Support Vector Machines
TCBM	Topological Case Base Modeling

I. INTRODUCTION

The need for saving energy to improve the sustainability of the Planet is increasingly worrying society and requires to put significant research on it. Based on recent studies [1], it is observable that buildings contribute to the 40% of the world energy consumption, being the HVAC systems the most demanding. Nations are also acting to mitigate the impact of an excessive energy consumption, like Europe, where the Community takes directives about the design of NZEB, namely 2010/31/EU and 2012/27/EU [10]. Several strategies address this challenge by retrofitting building architecture and facilities [11], automating control operations control [12], or predicting building behavior with advanced AI and EA techniques [13]–[15]. Working on efficient energy management solutions in buildings, especially for HVAC systems, leads to significant economic, social, and environmental improvements [6], [10].

It is far more sustainable and cost effective to improve the management systems to achieve higher efficiency than replacing HVAC systems with more efficient modern technologies [5], [10]. Recent articles emphasize the use of advanced control algorithms [2]–[4], [6] and the optimization of the HVAC system parameters [8], [18], [19], for improving the energy efficiency in buildings, as an inefficient operation of HVAC systems can result in excessive energy consumption.

Therefore, it is fundamental to improve the efficiency of the existing HVAC systems, in order to decrease energy usage. The HVAC energy demand is directly related to the indoor temperature setpoints, the type of building and the regional climate, among other parameters. Particularly, in this work are analyzed buildings with multi-HVAC systems. In this context, it is required the determination of the optimal functional mode of the multi-HVAC systems for a given situation, in order to improve their energy consumption, equipment performance and thermal comfort.

This research describes a new concept that relies on three fields of study. The first is about the modeling techniques of HVAC systems. The second is about multi-objective optimization for obtaining the optimal configurations of HVAC subsystems for saving energy consumption and cost, maximizing the comfort and the equipment performance. Finally, the last one is about self-management architecture for multi-HVAC systems.

A multi-HVAC system assumes that the system is split it up in several HVAC subsystems, such as chillers, heat pumps or boilers, with their associated mechanisms. Each HVAC subsystem can be turned on or off or regulated, contributing to generate different operational modes for the multi-HVAC system. The optimization identifies possible operational modes and which one best fits the set of objectives. The proposed architecture is based on the Autonomous Cycle of Data Analysis Tasks (ACODAT) [34], [35] paradigm, that defines a set of Data Analysis Tasks (DATs) [35] that autonomously interact providing intelligent supervision for achieving the pursued strategic goals. Some DATs monitor the selected variables (e.g., energy cost, CO2 emissions) and make decisions that deliver to other DATs; other DATs extract knowledge to predict potential system behaviors; others identify relations between variables; there are DATs that search for the optimal multi-HVAC system operational mode, and others supervise the system performance. A particular feature of DATs is that they can extract information from both the system physics formulation or the available historical system data records.

The proposed solution is general for any building, although requires to be customized for each context. This work analyzes buildings with heterogeneous multi-HVAC systems (different heat pumps, chillers, etc.) for testing the versatility of the paradigm ACODAT to deliver the optimal functional mode of the multi-HVAC system for any given situation.

The main contributions of this article are: i) A proposal of a general autonomous architecture based on ACODAT paradigm to manage multi-HVAC systems in buildings, optimizing multiple goals, according to the changing contextual information; ii) An extension of domain-based models with data-driven knowledge models, to predict on the fly multi-HVAC systems context-driven behaviors.

This paper is organized as follows: Section II presents the related works. Section III describes the proposed autonomous management architecture, based on the key aspects of multi-HVAC systems and ACODAT paradigm. Section IV illustrates the generality of this approach, applying it to 2 different case studies. Section V gives the result analysis and compares with other works and, finally, conclusions and further works are described in Section VI.

II. RELATED WORK

Energy consumed in HVAC systems has been widely discussed in the literature. This research extends the scope by addressing different fields while proposing a new paradigm. It starts presenting the progress in modeling HVAC systems, because this is determinant for the proposed architecture. This article outlines some of the recent works on modeling, centered on mathematical models, data-driven models or simulated models. Then, some works introduce strategies for Building Management Systems, being this the appropriate context for the proposed autonomic architecture. Another related area is the implementation of advanced control algorithms and the improvement of the design of HVAC systems to reach the highest possible level of thermal comfort for the occupants, minimizing the energy consumption. This section concludes presenting the ACODAT paradigm and its utilization in different domains. The revision of literature shows that ACODAT-based autonomic management architecture has not been used in HVAC systems yet and that there are not approaches for obtaining an efficient context-based operation of multi-HVAC systems.

A. HVAC SYSTEMS

Modeling HVAC systems deals with complex structures, including chillers, heat pumps, heating/cooling coils, boilers, air-handling units, thermal storage systems and liquid/air distribution systems. Sensors and actuators allow the regulation of the controllable plant variables, such as the ambient temperature in the occupied zones, the static pressure in the pipes, the chilled flowing water temperature or the air fans speed. At this low level, the HVAC system is difficult to manage, as its physical behavior is dynamic and nonlinear, such as its high thermal-inertia. The generation of an accurate and effective model for these systems is still challenging.

There is a comprehensive work of Afram and Janabi-Sharifi [22], updated by Afroz *et al.* [6], in which the known modeling techniques are evaluated and classified in three kinds: physics-based -also known as white-box, mathematical or forward-; data-driven -or black-box-; and a combination of them, known as hybrid -or grey-box-. Physics-based approaches use governing laws of Physics, such as the flow balance, the heat transference or the energy-mass balance to define a set of mathematical equations that describe the HVAC system. Data-driven approaches collect data from the system and the context under normal or abnormal utilization, identifying the relations between the input and output variables with AI techniques. The grey-box approaches define the basic model with physics-based methods, and adjust their parameters with AI-based algorithms. The physics-based model is normally applied to HVAC system components. This is illustrated with an example. A chiller is one of the main HVAC system components, which removes heat from a fluid in a vapor compression cycle or an absorption cooling cycle and consumes almost half of the total energy. It has four modules: a compressor, an evaporator, a condenser, and an EEV, that is normally modeled separately with the following design assumptions [7]:

- The refrigerant properties of each component are homogeneous.
- The refrigerant mass flow rate goes through the compressor and is considered constant throughout the system.
- The expansion process through the EEV/orifice plate is isenthalpic.
- The temperature of the walls does not vary through the cross-section, or across the ducts.

Supposing that the refrigerant is in a quasi-steady state, using the energy balance equations proposed in [6], the heat transfer rate of the evaporator (Q_e) and the mass flow rate of the refrigerant ($\dot{m}_r$) can be obtained with:

$$\dot{Q}_e = \alpha_{ei} A_{ei} (T_{wo} - T_{we}) \tag{1}$$

$$\dot{m}_r (h_1 - h_6) = \alpha_{eo} A_{eo} (T_{we} - T_e) \tag{2}$$

where, h_1 is the enthalpy of the refrigerant at the evaporator outlet-compressor inlet (kJ/kg), h_6 is the enthalpy of the refrigerant expansion valve exit/evaporator inlet (kJ/kg), A_{ei} is the area of the evaporator inlet (m^2), A_{eo} is the area of the evaporator outlet (m^2). T_{wo} is the return water temperature (°C), T_{we} is the temperature of the evaporator wall (°C), T_e is the temperature of the refrigerant at the evaporator inlet (°C), α_{ei} is the heat transfer coefficient of refrigerant entering the evaporator (W/m^2 K) and α_{eo} is the heat transfer coefficient of the refrigerant leaving the evaporator (W/m^2 K). In a similar way, the heat transfer rate of the condenser (Q_c) and the other parameters of the HVAC system, like the dynamic temperature of the heating/cooling coil, can be obtained applying the energy balance in the air–water heat exchanger [6].

Given the case that the dynamics of the HVAC system could be simulated with their differential equations, the actual behavior would differ from the theoretical construction due to several factors, like the design assumptions made to simplify the equations, or the natural equipment feature degradation.

Besides, when considering an HVAC system, which is already installed in a building, for generating its model formulation, the scarce and unstructured documentation and the hidden acquired habits by the engineers and operators, make the data-driven modeling approach interesting to perfect the mathematical approach. Physics-based systems provide a good generalization capability, but are not accurate, because of the significant number of parameters and assumptions that are defined to work with them and their dynamical characteristics.

Data-driven models collect HVAC system data under different conditions: normal and abnormal situations. A relation is also defined between the input and output variables using Statistics or AI techniques, such as ANNs [16], or, in some cases, with DL techniques [17]. Examples of black-box models are: TCBM, 4SID, PDF, JIT, several ANN architectures, SVM, FAN, Takagi-Sukeno Fuzzy, ANFIS, Linear and Polynomial Time Series regression, ARX, ARMAX, and ARIMA.

Some authors have recently proposed the utilization of BD-based techniques to improve the operations of existing buildings [19]. Several studies addressed the type of buildings differentiating their use, like residential, commercial, office buildings or education facilities [21], limiting the generalization capabilities of these methods. Old buildings with their special requirements [20] have been treated by retrofitting the HVAC systems, but very few have addressed the control system for improving their performance and efficiency, like the case of a museum that requires an environment for the pictures conservation as an unavoidable physical constraint [18]. Other proposals bring useful metaphors for treating the model behavior, like considering an HVAC system as a cyber-physical system [20] because of its "integration of computation and physical processes".

Finally, grey-box models show better generalization capability than data-driven models. The main strength is that are capable to capture any unmodelled effect left out of the equation and adapt to dynamic changes. Some examples in the literature are RC Equivalent Circuit, based on genetic algorithms that discover the resistance and capacitance parameters; Simulated Zone Model RC whose parameters are identified by SQP; or Physics-based ARMAX to predict room temperature.

This research requires to compare the special case of multi-HVAC architectures, mostly treated in literature as homogeneous multi-chiller systems, although not fully comparable to multi-HVAC systems. Literature discusses about the modification of the "thermal load" variable in commercial buildings [7], the optimization of the cooling load sharing of a multi-chiller system using a probability density distribution profile [4], the optimization of multi-chillers with multiphase genetic algorithms [23]. the use of data for evaluating the performance of a multi-chiller system [24], the use of a general algebraic method for modelling multi-chiller systems [25], or a sequencing of multi-chillers [26]. In any case, the term of multi-HVAC used in this article as an alternative to multi-chiller includes the heterogeneous characteristics of the HVAC sub-systems.

B. BUILDING MANAGEMENT SYSTEM

As the complexity of HVAC systems has been growing, a management system is increasingly required. BMS is the generic name, but there are also in the literature other different names that express slightly different approaches. For example, BAS synthesizes the building automation technologies, like ISO/IEC 14543-3 or ISO/IEC-14908. Another example is BEMS that networks the setpoints, device controllers, system logic, timers, trend logs, alarms coming from the different building facilities, or simple controllers, providing a friendly interface to manage them [5]. The three main objectives of BEMS are: a) to provide a healthy and pleasant indoor climate; b) to ensure the safety of users and owners; and c) to ensure cost-effective operations with respect to both energy and personnel. The common functionalities are:

- Energy remote monitoring.
- Optimization and control of energized building facilities.
- Equipment operations according to forecast.
- Energy management information reporting.

The minimal components of a BEMS are: the central station, connected with remote outstations -also called controllers-. The central station has an interface with the remote outstations enabling some control functions on them, depending on the client's requirements (for instance, energy savings, security, etc.). It is yet unclear how much an optimal use of BEMS can reduce energy usage and at what costs. Estimations about the energy savings differ considerably with building uses and other considerations. Some authors estimate energy savings up to 27% with BEMS [8], while others estimate energy savings up to 20% with optimal control of space heating. Others reduce the benefits up to 10% in lighting and ventilation [9].

A BMS is a computer-based control system that controls and manages building's mechanical, electrical and electromechanical equipment, such as lighting, HVAC systems, fire systems, elevators or security systems. The BMS is capable to improve the energy efficiency, the environmental conditions, or the building operations and manageability [15]. Finally, BCS is another name that focuses on simple control models.

Foreseen evolution directs towards smart buildings with hyper-connected environments, managed with intelligent IoT based BMSs, making use of advanced AI analytics. ACODAT tackles present challenges and its architecture is prepared for managing these new paradigms.

C. HVAC CONTROL SYSTEMS

HVAC control systems make use of conventional and advanced methods. It is interesting to know the evolution as most of them are still in use and object of ongoing research. The first automation was implemented in preprogrammed sequences of instructions in PLCs and FPGAs actuating on the controlled components. Then, PID FBC and FFW modules provide regulation, minimizing the difference between the controlled signal and the setpoint and its timedomain characteristics. PID is still present in 9% of the publications about HVAC control. Self-tuning techniques, like gain scheduling (in 9% of publications), decoupler, statespace representation and transfer functions, have improved the robustness and adaptation capability of HVAC control. Most recent advances in control make use of optimization schemas, like LQ or LQG. Model-based prediction is becoming popular with MPC [3], and its variants, DMC and GPC, today found in 15% of publications. It is also important to note the growing multiagent architectures, so useful for large systems, which are in 14% of publications, and fuzzy logic control systems to optimize the model and control parameters, which are in 13% of the studies.

An interesting case of two-stage energy management strategy for a commercial building, has tried incorporating the uncertainty of electricity prices in a model predictive control (MPC) for the energy management optimization [39]. In this case, they carry out a power balance between the power supply and the load on the building, while the operational costs are minimized. The predicted values for load demand, wind power, and electricity price are forecasted with SARIMA model. In addition, the CVaR value is used to assess the uncertainty in the electricity prices.

D. MULTI-OBJECTIVE OPTIMIZATION IN HVAC SYSTEMS

The HVAC system operations can be managed to get optimal performance. The optimization problem seeks to identify the best system configurations and schedules to save energy, maximize the comfort and reduce the operating costs [3]. Some authors consider thermal comfort as a constraint and others, another objective to maximize, preferring the later in this proposal, adding a degree of freedom to the optimization problem. Some works also consider indoor humidity, subjective IAQ index, retrofit costs, lighting consumption, plug loads, or visual comfort level [27]. Very few authors include the equipment performance in the equations, such as the maximization of the COP for heating, or the EER for cooling, and their seasonal variations in multi-chiller systems [28].

For making practicable this multi-objective optimization process in real-time management, recent literature commonly assesses different EAs. Most popular techniques considered for optimization are based on GAs [3], and its multi-objective variations, such as MOGA, NSGA or SPEA [29]. Other considered techniques are MPSO [30], ANN-based models, Newton-Raphson method or Interior Point method [3]. Some authors also research on non-supervised data mining techniques to discover hidden patterns that could eventually improve the energy efficiency in HVAC systems [31].

E. AUTONOMIC CYCLE OF DATA ANALYSIS

Literature interest focuses on HVAC systems control improvement with optimization techniques, mainly based on predicting models [2], grouping the operating elements in higher layers or orchestrating their control agents to supervise the whole system [15], or just for automating operations [10], but none of them deals with a comprehensive autonomic management architecture for HVAC systems.

ACODAT is a computing paradigm that includes a set of data-driven tasks, DATs to pursue a common goal for the managed process [6]. DATs exploit the data collected from the system to build knowledge models that describe, optimize and predict its behavior. DATs co-operate among them and interact with the system according to their specific roles [35], [36]:

- System inspection: These DATs extract information monitoring the system behavior and its context. This requires systematic ETL processes. DATs generate an image about the current conditions. Data could be predicted or estimated with different contextual information.
- System analysis: These DATs interpret, understand, and diagnose the current state of the system. They build knowledge models with the prepared information from the inspecting DATs considering the system dynamics.
- Decision making: These DATs impact on the system dynamics because their decisions are translated into physical orders for the actuators to activate or regulate the equipment to reach the desired objectives of comfort or deactivate them to save energy.

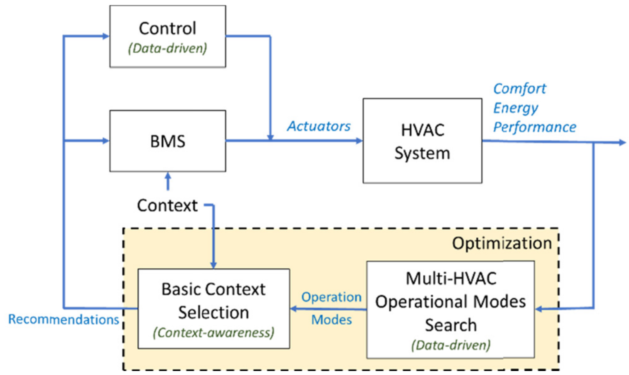

FIGURE 1. Autonomic multi-HVAC management.

ACODAT paradigm requires the following elements to work [36]:

- Multidimensional data model to store the data collected from different sources that characterize the system behavior for the DATs.
- Platform to host the tools for DATs to use data mining, semantic mining or linked data.
- Multi-adaptive and polyvalent mechanisms to respond in real time to new inputs and conditions (e.g., outdoor changes, climate change, new uses, new rules, etc.)

ACODAT-based architectures are prepared to use data mining or semantic mining techniques and allow advanced types of knowledge representations, like ontologies or cognitive maps. Particularly, when data comes in streaming, it is necessary to use ETL combined with data mining mechanisms. When ACODAT reads data from offline sources, like Web repositories, then uses data collection and curation processes with semantic mining and linked data tools.

III. AUTONOMOUS ARCHITECTURE

A. GENERAL MODEL

The first goals of ACODAT paradigm for the management of building's multi-HVAC systems is to identify its optimal operation point, done with the Optimization Module, and adapt the multi-HVAC system to accomplish this optimal operation, done with the BMS and Control modules. This is shown in Figure 1. The first module explores different combinations of HVAC sub-systems and selects the best one for the current conditions. The second module then translates the decision made into specific orders to the Control and BMS Modules. The proposed architecture works perfectly with different AI techniques to solve this problem.

B. DETERMINATION OF MULTI-HVAC OPERATIONAL MODES

1) EXPLORING POSSIBLE MULTI-HVAC OPERATIONAL MODES

The Optimization Module identifies the best operational mode of the multi-HVAC system to minimize the energy consumption and cost, and maximize the ambient comfort and the equipment performance. The problem is defined as a multi-objective optimization. This section sets out the objective cost functions and shows how the knowledge models based on AI exploit the data of the context. These knowledge models will be used in a future ACODAT architecture functionality for supervision, detection and diagnosis of multi-HVAC systems.

a: DEFINITION OF THE MULTIOBJECTIVE OPTIMIZATION PROBLEM

As seen in previous sections, buildings' multi-HVAC system have several combinable HVAC subsystems for heating or cooling generation. The optimization model requires to define those possible operational modes and identify the optimal one that maximizes energy savings with the highest possible indoor comfort, leading to resolve a multi-objective optimization problem with conflict among the objectives. Thus, the proposed approach is to search of non-dominated-Pareto optimal- solutions [18].

The main decision variable is the $\mathrm{HVAC_{mode}}$, that defines the optimal combination of multi-HVAC subsystems to be used in a given time, t. The multi-objective optimization problem is formulated as follows:

$$Min_{HVAC_{mode},t}(P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t),\ Cost_e(\mathrm{HVAC_{mode}},t),COP_{global}(\mathrm{HVAC_{mode}},t),\ \mathrm{Comfort}(\mathrm{HVAC_{mode}},t)) \tag{3}$$

where, the cost functions to be optimized are:

- $P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t)$ is the total power required by the current mode of the multi-HVAC system, defined as [7]:

$$P_{\mathrm{consumed}}(\mathrm{HVAC_{mode}},t) = \sum P_{\mathrm{chiller}}(j,t) + P_{\mathrm{CT}}(j) + P_{\mathrm{cwp}}(j) + P_{\mathrm{wpp}}(j),\quad \forall j \in HVAC_{mode} \tag{4}$$

where, $P_{\mathrm{chiller}}(\mathrm{j,t})$ is the power required by j$^{\mathrm{th}}$ chiller, $P_{\mathrm{CT}}(j)$ is the power required by j$^{\mathrm{th}}$ cooling tower, $P_{\mathrm{cwp}}(j)$ is the power required by j$^{\mathrm{th}}$ cooling water pump, and $P_{\mathrm{wpp}}(j)$ is the power required by j$^{\mathrm{th}}$ primary circuit chilled water pump. Typical fluids in HVAC subsystems are water and gas, condensing water or air [32]. The variables of Equation (4) are specific for water and when the fluid is air, the variables P_{cwp} and P_{CT} are not applicable - equals 0 in this model-. $P_{\mathrm{CT}}(j)$ is obtained from the cooling tower manufacturer's technical specifications, while $P_{\mathrm{cwp}}(j)$ and $P_{\mathrm{wpp}}(j)$ are defined in the design of the HVAC system. $P_{\mathrm{chiller}}(\mathrm{j,t})$ is:

$$P_{\mathrm{chiller}}(\mathrm{j,t}) = CC(j,t)/COP_{maker}(j)$$

$$\mathrm{CC(j,t)} = \begin{cases} Q_{fluid}(j,t) * Heat_{fluid}(\mathrm{j}) * \rho_{fluid}(\mathrm{j}) \\ \quad * \Delta T_{HVAC}(j,t), & \text{if } < \mathrm{CAP(j)} \\ CAP(j), & \text{otherwise} \end{cases}$$

$COP_{maker}(\mathrm{j})$ is the coefficient of performance of the j$^{\mathrm{th}}$ chiller, CAP(j) is the capacity of the j$^{\mathrm{th}}$ chiller, both obtained from the manufacturer's technical specifications, $Q_{fluid}(j,t)$ is the flow rate of the j$^{\mathrm{th}}$ chiller, $Heat_{fluid}(j)$ is the specific heat capacity of the fluid in the j$^{\mathrm{th}}$ HVAC subsystem, $\rho_{fluid}(\mathrm{j})$ is the density of the fluid in the j$^{\mathrm{th}}$ HVAC subsystem, $\Delta T_{HVAC}(j,t)$ is the difference between the input and the output temperatures of the j$^{\mathrm{th}}$ HVAC subsystem.

- $\mathrm{Cost_e(HVAC_{mode},t)}$ is the cost of the energy, and it is obtained with:

$$Cost_e(\mathrm{HVAC_{mode}},\mathrm{t}) = P_{consumed}(\mathrm{HVAC_{mode}},\mathrm{t}) * TE_i,\quad for\ t \in i \tag{5}$$

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

- $\mathrm{Comfort(HVAC_{mode},t)}$ is the comfort perceived in the different building zones (offices, halls, etc.) and grows as the difference between the setpoints and the current room temperatures in each zone ($\overrightarrow{\Delta T}_{comfort}(zones,t)$) gets smaller. The optimization problem seeks to minimize this difference. The equation transforms comfort to demanded power ($P_{demanded}(\mathrm{t})$) in t to the HVAC system to reach the thermal comfort in each zone:

$$P_{demanded}(t) = Heat_{air} * \rho_{air} * \sum_{z=1}^{Z} \times (Q_{air}(\mathrm{z,t}) * \Delta T_{comfort}(z,t) \tag{6.a}$$

where Z is the number of zones in the building. The minimization of $\mathrm{P_{demanded}(t)}$ implies the maximization of $\mathrm{Comfort(HVAC_{mode},t)}$, hence allowing to replace the later with $\mathrm{P_{demanded}(t)}$ in Eq. (3).

Comfort ($\mathrm{HVAC_{mode}}$, t) can also be redefined considering that the multi HVAC system has a maximum power $P_{max}(\mathrm{HVAC_{mode}}) = \sum_{j\in HVAC_{mode}} \mathrm{CAP}(j)$, delimiting the maximum temperature change ($T_{max}(\mathrm{HVAC_{mode}})$, which can be obtained from the manufacturers' specifications. This idea allows to determining $\Delta T_{off}(\mathrm{HVAC_{mode}})$ as the difference between the global temperature setpoint and the maximum temperature that the current $\mathrm{HVAC_{mode}}$ can supply. Some authors call the global setpoint as *social setpoint,* and has different ways to be obtained [37]. The demanded thermal power to the current $\mathrm{HVAC_{mode}}$ ($P_{thermic}(\mathrm{HVAC_{mode}},t)$) for the thermal comfort is:

$$P_{thermic}(\mathrm{HVAC_{mode}},t) = (\Delta T_{comfort}(\mathrm{HVAC_{mode}},t) * \times \sum_{j\in HVAC_{mode}} \mathrm{CAP}(j))/\Delta T_{\mathrm{off}}(\mathrm{HVAC_{mode}}) \tag{6.b}$$

where ($\Delta T_{comfort}$ (HVAC$_{mode}$, t) is the global temperature desired in the building (social setpoint) at time t. In this case, the minimization of P$_{thermic}$(HVAC$_{mode}$, t) implies the minimization of $\Delta T_{comfort}$, hence the maximization of Comfort(HVAC$_{mode}$, t), so that it can be replaced by P$_{thermic}$(HVAC$_{mode}$, t) in Eq. (3).

- COP_{global} (HVACmode, t) is the current coefficient of performance of the multi-HVAC system for the selected operational mode, which is the ratio between the supplied thermal power ($P_{demanded}(t)$) or $P_{thermic}$ (HVAC$_{mode}$, t)), and the electrical power that the multi-HVAC system consumes (P_{consumed} (HVAC$_{mode}$, t):

$$COP_{global}(\text{HVAC}_{\text{mode}}, \text{t}) = \frac{P_{demanded}\ (\text{t})}{P_{\text{consumed}}\ (\text{HVAC}_{\text{mode}}, t)} \tag{7.a}$$

or

$$COP_{global}\ (\text{HVAC}_{\text{mode}}, \text{t}) = \frac{P_{thermic}\ (\text{HVAC}_{\text{mode}}, t)}{P_{\text{consumed}}\ (\text{HVAC}_{\text{mode}}, t)} \tag{7.b}$$

With this set of equations (4, 5, 6, and 7) the multi-objective optimization problem is defined generating a Pareto front, i.e. a set of optimal solutions, for each possible HVAC$_{mode}$.

b: DATA-DRIVEN APPROACHES IN THE DEFINITION OF THE OPTIMIZATION PROBLEM

The previous objective functions are defined according to specific mathematical models. In this section, the mathematical expressions are complemented using data-driven models that identify the actual conditions from the data captured from the multi-HVAC system.

- Data model for Equation (4). Historical records have the P_{consumed} (HVAC$_{mode}$, t) simultaneously with other variables, which it could depend on. To incorporate these possible relations, the equation is redefined as

$$P_{\text{consumed}}\ (\text{HVAC}_{\text{mode}}, t) = V1\ (j) \tag{8}$$

where, $V1$ (j) is a *predictive model* based on the historical data of the jth HVAC subsystem. It is of significant interest to note that this hybrid approach, not only refine the results of the pure mathematical model, but also allows the inspection of the performance degradation throughout the lifecycle of the jth HVAC subsystem, impossible to obtain otherwise (see equation (4)).

- Data model for Equation (5). This equation can be improved in different ways. In some countries, the pricing period could be contracted in real time auctions. In this case, the historical price evolution and the climatic conditions could be used to predict the optimal tariff rate periods to hire energy, modifying Equation (5):

$$\begin{aligned} &Cost_e\ (\text{HVAC}_{\text{mode}}, \text{Hire}_{\text{mode}}, t) \\ &= P_{Max,i} * TP_i\ (\text{Hire}_{\text{mode}}) \\ &\quad + P_{consumed}\ (\text{HVAC}_{\text{mode}}, t) * TE_i(\text{Hire}_{\text{mode}}), \quad \textit{for } t \in \boldsymbol{i} \end{aligned} \tag{9}$$

where, Hire$_{mode}$ indicates if tariff rates are fixed or auctioned, and $TP_i(auction)$ and TE_i(auction) are predictive models based on historical data from the auctions and climatic conditions. This model optimizes the energy contractual cost and can be automated the auction process.

The other possible extension of the mathematical model is to obtain the optimal moments to activate the HVAC subsystems according to the tariff period i, which will be studied in next works.

- Data model for Equations (7.a) and (7.b). Global COP, COP_{global} (HVAC$_{mode}$, t), is also registered or easily obtained from historical records coming associated with variables, which it could depend on. This allows building a model of this variable using these variables to predict future COP values. The expression can be redefined as:

$$COP_{global}(\text{HVAC}_{\text{mode}}, \text{t}) = \text{V2(j)} \tag{10}$$

where $V2$ (j) is a *predictive model* based on the historical data from each HVAC subsystem. COP_{global}(HVAC$_{mode}$, t) can be redefined as an unknown function F(j) between the variables defined in Eq. 7.a or 7.b. In this case, it is necessary to define this function F(j), which is an *identification model* based on the historical data of COP_{global}(HVAC$_{mode}$, t), and these variables. Again, this model is also capable to capture the performance degradation of the jth HVAC subsystem according to the current behavior of these variables, which is not done with just the mathematical definition.

The enhancement of the mathematical optimization problem with these data-driven models improves predicting capabilities, in order to bring new functionality and capabilities, such as the analyses of the subsystem's degradation or the automation of power tariff contracting.

2) SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO IMPLEMENT

The previous phase identified a set of solutions for each operational mode -individuals on Pareto front- obtained with any of the possible multi-objective optimization techniques. Now, the optimization problem must consider multiple Pareto fronts to select the optimal operational mode. An individual in a Pareto front represents an optimal solution for a given operational mode, where some of the objective functions are weighted to get optimal nondominated solutions. For example, one of the solutions could only minimize the COP_{global}(HVAC$_{mode}$, t). Several solutions are therefore possible for this problem. One particular Pareto Front could be obtained from the intersection of the different Pareto Fronts of the different operational modes, considered together to build a single Pareto Front from them that can be seen as a convex hull. This case is solved using classical multi-objective optimization techniques. Another solution analyzes the behavior of each Pareto Front of each HVAC mode with respect to the high level optimization requirements and then select one of them. This section explores these alternatives.

a: DETERMINATION OF ONE GENERAL PARETO FRONT

In Equation (3), the multi-objective problem is defined for only one Pareto Front, analyzing different HVAC modes that could be used in the current multi-HVAC system, where each HVAC mode represents the combination of HVAC subsystems used in Equations (4), (5), (6.a) or (6.b), and (7.a) or (7.b). Thus, Equation (3) is general, evaluates the HVAC modes and uses a general Pareto Front to analyze them.

b: ANALYSIS OF EACH PARETO FRONT

This section proposes an intelligent decision system based on the results of the previous phase and some other relevant information to select the HVAC mode. The general structure of the intelligent decision system is:

$$\text{If(decision\_condition) then (individual}_i\text{)}$$

where *decision_condition* is a set of weights that defines the importance of each objective function, and $individual_i$ is the selected solution from the proposed Pareto Front with the multi-objective optimization technique. Each weight is set in real-time according to the relevance of each objective function for the current context and are defined as fuzzy variables as follows:

- *W1(P)* defines the importance of the minimization of P_{consumed}. It is a fuzzy variable that depends on the current values of $\Delta T^f_{HVAC}(\text{j, t})'s$ of the j^{th} chiller in the current HVAC mode. With this information, *W1(* P) is defined as:

$$\text{If } \Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j, t}) \text{ then W1(P)}, \quad \forall j \in HVAC_{mode}$$

where $\Delta T^f_{HVAC}(j,t)$ is a fuzzy variable with values {high, average, low}, and so does *W1(P).*

- $W2(Cos_{te})$ defines the importance of the minimization of *Cost* e, and it is a fuzzy variable that depends on the current values of TE^f_i and $\Delta T^f_{HVAC}(\text{j, t})'s$. With this information, $W2(Cost_e)$ is defined as

$$\text{If } TE^f_i \text{ and } (\Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j, t})) \text{ then } W2(Cost_e)$$

where $W2(Cost_e)$ can be {high, average, low} and TE^f_i values are{coming in, in, going out}.

- *W3(COP)* defines the relevance for maximizing the *COP*. It is a fuzzy variable that depends on the current values of $\text{P}^f_{demanded}(t)$ or $\text{P}^f_{thermic}(\text{HVAC}_{\text{mode}},t)$ and $\Delta T^f_{HVAC}(\text{j, t})'s$. With this information, *W3(COP)* is defined as

$$\text{If } (\text{P}^f_{demanded}(t) \text{ or } \text{P}^f_{thermic}(\text{HVAC}_{\text{mode}},t))) \text{ and } \Delta T^f_{HVAC}(1,\text{t}) \text{ and } \ldots \Delta T^f_{HVAC}(\text{j, t})) \text{ then } W3(COP)$$

where $\text{P}^f_{demanded}(t)$ or $\text{P}^f_{thermic}(\text{HVAC}_{\text{mode}},t))$ are fuzzy variables with the values {high, average, low}; and *W3(COP)* with {high, average, low}.

- *W4(Comfort)* defines the importance for maximizing the comfort. It is a fuzzy variable that depends on the current restrictions of $\overrightarrow{\Delta T}^f_{comfort}(zones,t)$, which can be {high, not}. This information defines W4(Comfort):

$$\text{If } \overrightarrow{\Delta T}^f_{comfort}(zones,t) \text{ then } W4(Comfort)$$

where $\overrightarrow{\Delta T}^f_{comfort}(zones,t)$ is a set of fuzzy variables with values {very strict, strict, normal, not strict}; and *W4(Comfort)* can be {high, average, low}. *W4(Comfort)* can also be calculated considering $\Delta T_{comfort}(\text{HVAC}_{\text{mode}},t)$ as a fuzzy variable defining the *social setpoint* of the building at time *t* [37].

C. TRANSLATION OF SELECTED OPERATIONAL MODE TO THE MULTI-HVAC SYSTEM

This module translates the operational mode obtained in the previous module to a set of control signals to operate the multi-HVAC system. Chillers generally work with discrete ON/OFF or PID controllers. They could perform at their level improvements for energy efficiency, as shown in the previous section. Particularly, RC model is quite popular method for modeling thermal dynamics based on MPC. The first order RC modeling HVAC dynamics is formulated as:

$$C_i \dot{T}_{i,t} = \frac{T_{o,t} - T_{i,t}}{R_i} + \sum_{j \in N(i)} \frac{T_{j,t} - T_{i,t}}{R_{ij}} + P_{i,t}$$

where N(i) are neighboring zones of zone i, C_i and T_i are the thermal capacitance and room temperature of zone i, T_o is the outside dry bulb temperature, $P_{i,t}$ is the energy consumption at time t, and R_i and R_{ij} are the thermal resistance for zone i against the outside and the neighboring zone j. Once calculated C_i, R_i, R_{ij} for every zone, there is a 1st order system that models the thermal dynamics.

At time t, the building's running profile is $\text{X}_\text{t} := [\text{X}^{\text{uc}}_{,\text{t}}; \text{X}^{\text{c}}_{,\text{t}}; \text{X}^{\text{phy}}_{,\text{t}}]^\text{T}$, where T is the rolling horizon; $\text{X}^{\text{uc}}_{,\text{t}}$ denotes a collection of uncontrollable measurements, such as zone temperature, lighting schedule, in-room appliances schedule or room occupancies; $\text{X}^{\text{c}}_{,\text{t}}$ denotes a collection of controllable measurements, such as zone temperature setpoints or appliances working schedule; $\text{X}^{\text{phy}}_{,\text{t}}$ denotes the set of physical measurements or forecast values, such as dry bulb temperature, humidity and radiation level. Since $\text{T}_\text{i} \in \text{X}^{\text{uc}}$ and $\text{T}_\text{o} \in \text{X}^{\text{phy}}$, equation (10) can be reformulated by summing the P_i for all zones to get the overall building thermal dynamics:

$$P_\text{t} = f_{RC}(X_{t-T}; \ldots; X_t) \tag{11}$$

Equation (12) is further used in the optimal control problem:

$$minimize_{X^c_t \ldots X^c_{t+T}} \sum_{\tau=0}^{T} P^2_{t+\tau} \tag{12}$$

where T denotes the rolling horizon of the predictive model. $\text{X}^{\text{uc}}_{,\text{t}}$ and $\text{X}^{\text{c}}_{,\text{t}}$ have constraints.

This research considers an intelligent controller based on AI techniques that automatically makes changes according to weather parameters, and will be developed in future works. The data driven control method replaces the traditional MPC controller, building the dynamic model as it takes data from the multi-HVAC system.

IV. CASE STUDIES

A. HETHEROGENEOUS MULTI-HVAC SYSTEM IN OLD BUILDINGS

1) BACKGROUND

This case study is the HVAC system in Madrid Opera, known as Teatro Real, in Madrid City, Spain. The floor size is 65,000m^2 (700,000ft^2), the theatre occupancy is 1,746 seats. The stage area is 1,430m^2 (15,400ft^2) operated with an advanced rigging system that fully changes scene resources. The building has 11 lounges for events, 4 rehearsal rooms, 7 studios, a surrounding office area, warehouses and technical areas.

Madrid climate is predominantly dry with cold winters, with day average 0°C (32°F) in January, and hot summers with temperatures above 35°C (95°F).

The building is used from September to July and recently opens for specific events in August, requiring heating and cooling. The multi-HVAC system has two water-air heat pumps with 195kW of nominal thermal power each for heating and cooling, and two water-water chillers with 350kW each for extra cooling. Each HVAC machine could be seen as a HVAC subsystem. The multi-HVAC system is supervised and operated with a BMS that collects the temperatures from sensors located all over the zones and writes the instructions on the actuators regulating the water or air flow rates and fluid temperature. The BMS supervises 1,824 digital and analog variables.

The diversity of uses of the theater, rehearsal rooms and lounges in different seasons and hours of the day make the HVAC operation complex and require routines established beforehand for the field operators. They receive an order sheet with the schedule, setpoints and the HVAC subsystems to activate for the events. The engineering department takes the schedule of activities, labor hours and weather forecast to prepare the order sheet, which is a set of basic start/stop instructions that, once they are grouped in the different subsystems, can be mapped into an operational mode of the multi-HVAC system.

Figure 2 depicts the existing working scenario in which the field operator executes the instructions of the order sheet. BMS are generally versatile and can be programmed according to the timetable or optimization policies, however, in practice, this is so complicated that only a little functionality is used.

The BMS saves records with 169 variables, like outdoor temperature, room temperatures, electrical supplied power, thermal energy generated by each subsystem and their current COP, sampling every 15 minutes, in a persistent database. The BMS also stores 45 additional temperatures read from different zones of the building, sampled every hour in another

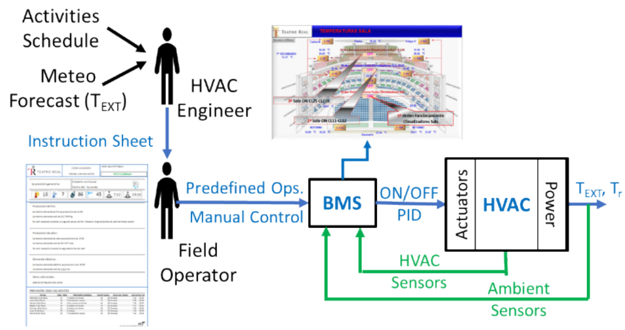

FIGURE 2. Existing multi-HAVC system operation.

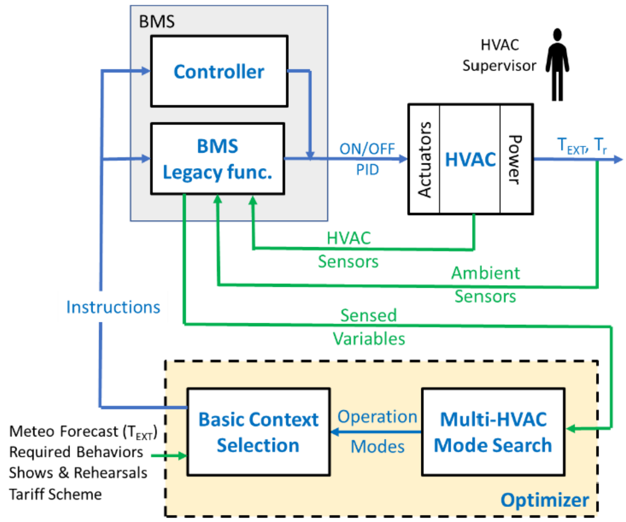

FIGURE 3. Instantiation of ACODAT in opera building.

table of the database. Another table keeps other variables read from subsystem components only during the theater shows and rehearsals from another 69 sensors every 10 minutes.

2) INTRODUCTION OF ACODAT IN EXISTING HVAC INSTALLATION

Figure 3 shows the instantiation of ACODAT in the Opera HVAC. In this case, the different components of the optimization module are incorporated into the multi-HVAC system, except the Control Module that resides in the BMS. The selection of the multi-HVAC operational mode is essential and uses the strategies and equations defined in Section III.B. The Optimization Module can use the historical data stored in the BMS for data models.

a: EXPLORATION OF POSSIBLE MULTI-HVAC OPERATIONAL MODES

The first activity is to define the existing HVAC subsystems in the Opera building to identify then the possible operational modes of the multi-HVAC system. This requires the definition of the next variables for each HVAC subsystem:

TABLE 1. Some characteristics of the chillers obtained from manuals.

$Heat_{Water}(j)$	4.186 J/g°C
$\rho_{Water}(j)$	1 Kg/l
CAP(Chiller)	350 KW

TABLE 2. Tariff periods (TE) of the power.

Tariff price	Period 1	Period 2	Period 3		Period 4	Period 5	Period 6
€/KW	39,1394 27	19,5866 54	14,3341 78		14,3341 78	14,3341 78	6,5401 77

TABLE 3. Utilization of the TEs during the year.

Rate Periods																								
Months	Hours																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
JANUARY				P6					P2			P1				P2				P1			P2	
FEBRUARY				P6					P2			P1				P2				P1			P2	
MARCH				P6								P4							P3				P4	
APRIL				P6												P5								
MAY				P6												P5								
JUNE (1-15)				P6					P4			P3								P4				
JUNE (15-30)				P6						P2					P1						P2			
JULY				P6						P2					P1						P2			
AUGUST												P6												
SEPTEMBER				P6					P4			P3								P4				
OCTOBER				P6												P5								
NOVEMBER				P6								P4							P3				P4	
DECEMBER				P6					P2			P1				P2				P1			P2	

- Specific heat capacity of the fluid in Subsystem j, $Heat_{fluid}$ (j)
- Density of the cooling fluid in Subsystem j, ρ_{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 normally available in manufacturers' specifications. ACODAT also requires tariff rates in period i, TE_i, to calculate the energy cost. The tariff scheme varies throughout the year (see Tables 2 and 3).

The Opera HVAC system has two similar heat pumps and two similar water-water chillers. Some of the characteristics of the chillers are given in Table 1.

The model also requires the zone's size -lounges, rehearsal rooms, studios, offices, theater- to specify the demanded thermal power.

Data driven models use the historical data in the BMS database (see Section IV.A.1) to predict behaviors and identify deviations of the different components of the multi-HVAC system. The management is not only reduced to immediate operations, but also allows mid- and long-term functionality, such as monitoring the performance degradation of the equipment, which will be developed in next works.

b: SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO BE LAUNCHED

In this case study, the selection of the operational mode also depends on contextual variables, like weather forecasts, events schedule, which naturally suppose different weights for the cost objectives. A fuzzy intelligent decision system, as proposed in Section III.B, will select the convenient mode for each situation.

The event scheduling portraits information about the date, hour, duration of the required temperature setpoints for each zone. With this table and weather forecasts, fuzzy variables that weight the importance of each objective cost are defined:

- *W1(P)* is defined with the values of variables P_{consumed} and $\Delta T^f_{HVAC}(\text{j, t})'s$.
- *W2*(Cos_{te}) is defined with the values of variables TEi and $\Delta T^f_{HVAC}(\text{j, t})'s$.
- *W3(COP)* is defined with the values of variables $\text{P}^f_{demanded}(t)$ or $\text{P}^f_{thermic}\,(\text{HVAC}_{\text{mode}}, t)$ and $\Delta T^f_{HVAC}\,(\text{j, t})'\,s$.
- *W4(Comfort)* is defined with the importance of the restrictions ($\overrightarrow{\Delta T}^f_{comfort}\,(zones, t)$).

Thus, this system is context-aware, capable to change the weights based on contextual information (events, working hours…) and sensed variables, to evaluate different states of the system. The Fuzzy Intelligent Decision Module can autonomously select the optimal multi-HVAC mode for each state. The system selects one non-dominated individual, according to the real scenario and changes the system behavior accordingly.

c: TRANSLATING THE SELECTED OPERATIONAL MODE FOR THE MULTI-HVAC SYSTEM

At the end of the process, the output of the fuzzy intelligent decision module directly feeds the BMS at the right time, with the necessary instructions to activate the optimal multi-HVAC mode, closing the control loop with the low-level instructions to operate each multi-HVAC subsystem. This requires that the recommended optimal multi-HVAC mode obtained in the Fuzzy Intelligent Decision Module to be translated in a set of values necessary for the BMS to accomplish the mode by activating, deactivating or regulating the addressed elements of the multi-HVAC system.

B. HOMOGENOUS MULTI-HVAC SYSTEM IN A NEW BUILDING

1) BACKGROUND

This second case study introduces ACODAT for San Pedro Hospital HVAC at Logroñ o City, Spain. The HVAC system is composed of 4 chillers, three with 3.5MW of thermal power and another with 1MW and 5.8 EER and, again, ACODAT determines the optimal operational mode. Figure 4 depicts the HVAC system functional diagram.

The Logroñ o's climate is warm and temperate, with significant precipitations. Temperatures are higher on average in July, 21°C (70°F), and lower in January with temperatures averaging 5°C (41°F).

Hospital zones include patients' rooms with 630 hospital beds, 12 examination rooms, 30 operating rooms, 18 recovery posts, 21 monitoring boxes, 16 emergency boxes, 4 resuscitation beds, radiology and scanning areas, kitchen, café, pharmacy, assembly hall with 200 seats, chapel room, administrative offices. The total floor size is 126,057m^2 (1,356.866ft^2).

2) INTRODUCTION OF ACODAT IN EXISTING HVAC INSTALLATION

The ACODAT can be also used to determine the multi-HVAC operational mode to be deployed, as it was explained in Section III. In addition, the data driven approaches allow exploiting the prediction models previously defined for this system, to make the optimization model more robust.

a: EXPLORATION OF THE POSSIBLE MULTI-HVAC OPERATIONAL MODES

Again, the first activity is to define the different HVAC subsystems in the Hospital, considering the similarities of three of the chillers. Thus, it is necessary the definition of the different variables as of Section III in this context. Particularly, the next variables must be defined for each HVAC subsystem: $Heat_{fluid}$ (j), ρ_{fluid} (j), T_{max} (j) and $CAP(j)$. It is necessary to define the foreseen hospital zones, such as operating rooms, patient rooms, etc. The Hospital tariff scheme has a single rate.

On the other hand, data driven models built for predicting energy consumption of the Multi-HVAC system can be used, with the data driven approach defined in Section III, to solve the optimization problem. Equal to the first case study, these models can be used for determining the degradation of the equipment.

b: SELECTION OF THE MULTI-HVAC OPERATIONAL MODE TO BE LAUNCHED

The hospital has only one type of HVAC subsystem, water-water chillers, 3 of them with the same capacity. The objective reduces to determine the number of chillers to use. Thus, it is necessary a general Pareto Front, resolvable with classical multi-objective optimization techniques, using the equations defined in Section III.B.2.

3) TRANSLATING THE SELECTED OPERATIONAL MODE FOR THE MULTI-HVAC SYSTEM

The multi-objective optimization technique identifies the operating mode of the multi-HVAC system. This information provides the control commands to execute the optimal multi-HVAC mode in the Hospital. The previous module determines the optimal multi-HVAC mode in the current context, which is then translated in the setpoints and control signals that govern the control system and equipment.

V. DISCUSSION AND COMPARISON WITH PREVIOUS WORKS

This section presents a comparison of the proposed approach with previous works, based on the next questions (see Table 4):

A. Do the articles propose an autonomic process of management for HVAC systems?
B. What is the scope of the proposal when considering other tasks beyond control and optimization (supervision, maintenance, etc.)?
C. Is it possible to exploit data from HVAC systems to build knowledge models (classification, state recognition, prediction)?
D. Is it possible to expand the study to different contexts (smart buildings, malls, museums)

TABLE 4. Comparison with other works.

Works vs. Criteria	A	B	C	D
[5], [11], [13], [14]			x	
[17], [20], [25], [26]			x	
[27], [29]				x
[3], [10]		x		
[4]	x			
[18]			x	x
[15]		x	x	
This proposal	x	x	x	x

The selected references have the closest topics to the proposed HVAC concept, including multi-objective optimization, control systems, energy optimization, multi-chiller systems, BMS and data-driven predicting models.

This research and [4] are the only ones that propose an autonomic management for HVAC systems. In this proposal, the analytical tasks can be shared with other autonomic cycles with different goals, such as the HVAC system supervisor or the self-configurator for mitigating faults and degradations throughout the lifecycle. Most works are very context specific and, therefore, not generalizable as the proposed solution.

This approach can use any possible AI method during the instantiation of the paradigm and is adaptable to multi-HVAC or single-HVAC systems, either centralized or distributed. It also defines self-improving scenarios, steadily monitors the equipment performance degradation, provides correction measures to reconfigure the operations autonomously or reports recommendations to the system administrator. This is based on an ongoing learning from the gathered data that minimizes the impact of initial bad operations habits, and provides a wider view of tactic and strategic functionalities, reducing the cost of operations. In conclusion, ACODAT management does not only control, but also forecasts, plans, organizes or commands. This approach does no need to invest in retrofitting the existing HVAC installations, changing facilities or redesigning the building.

The proposed approach is also the only work that combines a mathematical formulation of the optimization problem with data-driven models of prediction, which can be used to solve performance degradation problems, get better tariffs, etc. while the architecture searches for the best multi-HVAC configuration.

Finally, this work includes the maximization of the COP for heating or the EER for cooling, which have been rarely considered for multi-chillers in the literature [28]. This information about these coefficients, not only improves the optimization, but also detects the degradation of the

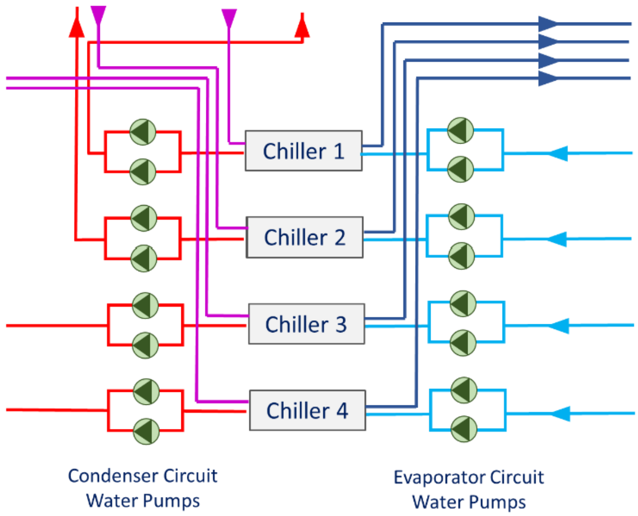

FIGURE 4. HVAC system of the Granada hospital.

HVAC system components throughout the time, becoming an original contribution of this article.

In general, ACODAT paradigm improves the energy consumption, the indoor comfort and the equipment performance. It allows the determination and selection of the optimal operational mode of the multi-HVAC system, i.e. the optimal combination of HVAC subsystems for a given context. It is the only work that considers multi-HVAC systems and proposes the full management of the closed loop (optimization and control phases). There are many approaches for controlling HVAC systems for improving energy efficiency depending on the building uses -commercial, residential-, such as the predominant nonlinear adaptive controls or MPC [2]. Others just focus on comfort control in the energy optimization strategy [5], assuming normal occupancy conditions [3], or applying deep learning to predict complex user behaviors [17].

At this moment, as far as we know, there is not any other architecture in the literature of self-management for multi-HVAC systems in a building, preventing from comparing the outcomes of the proposed model with previous models. It is observable that previous works are: 1) normally HVAC system centered [2], [6], [13]; 2) Some of them are focused on delimited problems, like control or optimization problems in HVAC systems [3], [10], [13], [14], [18], [27], not considering their integration in an autonomic architecture; 3) with datasets of specific HVAC systems, and normally not for buildings with multi-HVAC systems [4], [25]. Thus, the proposed autonomic management architecture for multi-HVAC systems is a novelty that integrates autonomous tasks that not only solve the brought up problems so far, but also improves itself and is ready for effectively incorporate new functionality at any level to improve its efficiency. Section IV details how to use this architecture in different building types with heterogeneous or homogeneous multi-HVAC systems, showing with 2 case studies the versatility of the proposed approach.

VI. CONCLUSION

This paper proposes an autonomous management architecture for multi-HVAC systems for buildings, based on the ACODAT concept. This architecture determines the optimal operational mode of the multi-HVAC systems, this is the set of HVAC subsystems to be activated, deactivated or regulated in a given context, in real time.

Specifically, ACODAT allows self-optimizing multi-HVAC systems. The optimization problem has multiple objectives to explore each feasible multi-HVAC operational mode (combination of HVAC subsystems), to maintain the comfort and improve the energy efficiency in a given context. The architecture is then complemented with data-driven models for prediction, to inspect performance degradation or to work with better tariff rates when the architecture searches for the possible multi-HVAC modes. This brings up another interesting problem: the selection of the best individual from the set of Pareto Fronts obtained for each possible operational mode. This work proposes two alternatives to solve this problem, either the utilization of fuzzy decision systems to select the best individual from the Pareto Fronts weighting fuzzy variables according to current contextual policies, or the utilization of a global Pareto Front as a consequence of joining the different sets of Pareto Fronts.

ACODAT uses/develops different models of knowledge, such as predictive, identification or optimization models. These data-based knowledge models can be also used in other contexts, for example, with supervisory tasks, or inspecting tasks that determine the performance degradation of multi-HVAC system components. ACODAT can be extended furthermore to incorporate more goals, even for improving itself like self-healing or self-security.

Next works will focus on the development of data-driven knowledge models (predictive and identification models) and the implementation of multi-HVAC system optimization strategies, particularly, the fuzzy decision system to select the best individual from the set of Pareto Fronts. Other case studies will also be considered to test the scalability and versatility of the architecture. It is also in consideration to evaluate how it works in distributed multi-HVAC system, where maybe some ideas about multiagent systems orchestration could be used [33], [38]. The modularity of ACODAT will also make possible to adapt and test it in IoT, smart building, big data scenarios. Finally, this research foresees future study on the necessary inclusion of indoor humidity and the subjective IAQ index, the retrofit costs, lighting consumption, or the visual comfort.

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