HVAC Systems of Smart Building

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Early fault detection and diagnosis in heating, ventilation and air conditioning (HVAC) systems may reduce the damage of equipment, improving the reliability and safety of smart buildings, generating social and economic benefits. Data models for fault detection and diagnosis are increasingly used for extracting knowledge in the supervisory tasks. This article proposes an autonomic cycle of data analysis tasks (ACODAT) for the supervision of the building's HVAC systems. Data analysis tasks incorporate data mining models for extracting knowledge from the system monitoring, analyzing abnormal situations and automatically identifying and taking corrective actions. This article shows a case study of a real building's HVAC system, for the supervision with our ACODAT, where the HVAC subsystems have been installed over the years, providing a good example of a heterogeneous facility. The proposed supervisory functionality of the HVAC system is capable of detecting deviations, such as faults or gradual increment of energy consumption in similar working conditions. The case study shows this capability of the supervisory autonomic cycle, usually a key objective for smart buildings.

HVAC system | building management systems | autonomic computing | supervisory system

1. Definition

Early fault detection and diagnosis in heating, ventilation and air conditioning (HVAC) systems may reduce the damage of equipment, improving the reliability and safety of smart buildings, generating social and economic benefits. Data models for fault detection and diagnosis are increasingly used for extracting knowledge in the supervisory tasks. This article proposes an autonomic cycle of data analysis tasks (ACODAT) for the supervision of the building's HVAC systems. Data analysis tasks incorporate data mining models for extracting knowledge from the system monitoring, analyzing abnormal situations and automatically identifying and taking corrective actions.

2. Introduction

Buildings consume above one-third of the total electrical energy supplied to the city. Research on energy efficiency in buildings becomes imperative. Energy consumption can be normally cut down by deploying a BMS (building management system), which monitors and controls the building facilities, such as the elevators, the heating, ventilation and air conditioning (HVAC) or the lighting systems [1]. The BMS processes the logs coming from the connected devices deployed in the building for controlling the equipment, supervising the system or optimizing the energy efficiency. The energy supervisory system is one of the key components of any BMS, comprising a meter module and an efficiency analyzer that captures abnormal situations [1][2][3]. The supervisory function shows what it is worth in case of unforeseen malfunction, such as hardware failures, voltage fluctuations, insufficient fluid pressure or temperature out of range. These events, when not being supervised, turn into expenses due to the required inspections to identify in the building the points where they were originated.

Focusing on the building services, the HVAC system is the most consuming one, as it works with boilers, coolers, air-handling units, cooling towers or water pumps. A smart building requires hence to wisely adjust the HVAC's operational modes to save energy. The automation and optimization have been applied for decades in this field, but there is still room to improve. Previous studies propose an autonomous management architecture that operates on a multi-HVAC model based on the autonomic cycle of data analysis tasks (ACODAT) concept [1], leading to improving the energy efficiency and reducing costs. This management system gathers the data read from the system and environment sensors and regulate the controllers, following the multi-HVAC model predictions. Another article proposes the LAMDA (learning algorithm for multivariant data analysis) robust fuzzy-based control method for HVAC, being susceptible to be incorporated in the management system as an ACODAT [4]. This study keeps this line of research and proves the idea of ACODAT for the supervision of building HVAC systems.

ACODAT paradigm was initially proposed for smart classrooms [5] and lately applied to different fields, such as telecommunications [6], e-learning environments [7][8] or Industry 4.0 [9]. It is based on the autonomic computing paradigm proposed by IBM, also known as MAPE-K (monitors, analyze, plan and execute—knowledge base) [10], which works in autonomic cycles. The first phase, known as the monitoring phase, collects and prepares the data coming from the managed resources. Then, in the analysis phase, complex situations are identified, and future situations assessed for the planning phase, in which the instruction set will be built to approach the system's goals. Finally, the instruction set is executed in the execution phase. ACODAT, similarly to MAPE-K's cycles, allows the development of an autonomous intelligent cycle for achieving the desired behavior, by using sets of data analysis tasks, able to perform both individually and coordinated. In this proposal, the analysis tasks interact with each other assuming specific roles in the cycle [5][7][8], to monitoring the supervised process and analyzing the observations, so that the management system can make effective decisions based on the actual behavior of the HVAC and leads to accomplish the objectives for which it was designed.

3. Data, Model, Applications and Influences

3.1. Related Work

BMS is considered as an assistant tool requiring a human behind and never has been the advantage of getting some of their functions running autonomously. In any case, several considerations related to this topic have been treated independently, such as its automation, control optimization, FDD, process supervisory management or its energy efficiency improvements with predicting models. The multiple dimensions of the proposed problem, such as its nonlinear responses, dynamic nature, wide and unpredictable range of perturbations and, sometimes, the fear of the building owners and the operators to new experimental technologies, make it complex. The next subsections describe the main elements of this proposal.

3.1.1. Smart Buildings

The ‘smart building’—or ‘intelligent building’—concept has been primarily associated with the bare automation of the systems providing any service to building’s users. It extended certain characteristics of the ‘smart home’, where the technology automated several processes with schedule and remote control [11]. In general, the most consuming systems were the first ones to be automatized (controlled and supervised), as a whole, with building automation systems (BAS). The BAS, also known as BMS, stresses its management behavior to plan midterm and long-term strategies for the improvement of the performance of the systems. The introduction of ICT (information and communications technologies) allowed this significant advance. The advances in telecommunications enabled the use of the existing data networks for the interconnection of the elements, and even, the systems. The state of the equipment, the controlled variables and the context information, could be gathered to make better decisions about the comfort and energy savings. But it is yet a hard task to get the perfect optimization of all systems. However, the automated supervision brings benefits, such as the maintenance cost reduction and the robustness against unpredictable perturbations [12].

On the other hand, the industry around the smart cities is increasingly providing solutions in areas like energy, water, mobility, buildings or government in the short term. Energy is probably the most concerning matter because of its economic impact and social concerns. Buildings consume over 40% of the electrical energy in the most populated cities of the West [13]. The HVAC system is the building service that consumes more with 32.7% of the power supply on average, while lighting requires 17.1% of the supply and the computers and appliances the 13.6% [14]. When buildings are public, such as offices, malls or museums, the HVAC consumption is even higher, reaching 40.3% on average of the total supply.

To address this problem, researches have been seeking to optimize the consumption of the building’ services, like HVAC, lighting or elevators, applying control policies, automation and optimization. If the energy efficiency is critical, other objectives, such as improving the security & access control or people-centered policies, are gradually getting importance in smart building’s considerations. Technology evolution makes systems become ‘smarter’. Energy efficiency has been achieved with good practices in the daily operations, with social responsibility, government’s enforcement regulation or by financial departments’ cost-effectiveness pressure. Now, a smart building is broadening the response to these challenges with AI, the Cloud, Big Data, IoT or hardware parallelization, to improve the mobility, ubiquity, accuracy and interoperability.

The study of Navigant Research pointing at a cognitive management concept, identified in 2016 the following trends in the smart building’s market [15]. Utility companies, such as electricity, water, telephone or gas suppliers, have started significant investments in BMS aiming to hopefully experience a noticeable development in management. Another trend is that the energy cloud will redefine buildings as energy assets. Climate policies will be oriented towards improving the energy efficiency. Buildings will optimize the experience of the occupants and their health conditions. New operational practices will drive to more savings and generate new financial opportunities. Finally, cybersecurity will become in this new context a key differentiator. However, some of these trends are difficult to implement and expensive, not giving back clear returns (e.g., the energy cloud) [16].

3.1.2. HVAC Systems

HVAC systems are complex structures, made up of coolers, heat pumps, heating or cooling coils, boilers, air-handling units, fans, pumps, thermal storage systems and liquid or air distribution systems. Deployed sensors and actuators allow the regulation of the controllable variables, such as indoor temperature, humidity, fluid pressure flowing throughout the pipes, chilled or heated water temperature or air fans speed. The system is difficult to model due to its dynamic and nonlinear nature [1].

The simplest way for controlling HVAC has been by sequencing ON–OFF orders, but these are far to meet the multi-objective building requirements [17]. Continuous regulation is widely performed with classic and inexpensive proportional integral derivative (PID) controllers. Nonlinearities, like partial loads, requiring self-tuning techniques, such as relay-autotuning, open-loop step tests and more recently fuzzy logic, Ziegler–Nichols or Cohen–Coon methods [4]. HVAC also requires multiple input and multiple output variables (MIMO) handling, like splitting the mechanism into several SISO subsystems—or just the PID. This in any case remains difficult to stabilize [4]. Complexity arises in applying multi-objective optimization requiring advanced control methods. Advanced control works with models that fall into three categories: ‘white box’, ‘black box and ‘gray box’ [17].

White box models are built with direct mathematical formulations, modeling the mass balance, heat transfer, thermal momentum or flow rates with differential equations. The system analysis and generalization are simple but require deep knowledge in physics field. These models can be used only in simple systems, like SISO and steady-state systems, because otherwise could incur in heavy computational costs or low accuracy due to simplifications.

Black box or empirical models work with data and need to be built in a preliminary phase, by relating the recorded outputs to the inputs via statistic or ML methods. These data models are being implemented for real-time control, plant modeling, controller design, system performance improvement, calibration and parameterization. Once the model is learned, they are very fast, consume low computational resources, and can be used for simulating any layer components, since heat pumps up to complete subsystems, like multi-HVAC [1]. As a drawback, they have less capability of generalization, remaining constrained to the experience learned from the actual data.

Gray or hybrid models balance the black and white box drawbacks, improving simultaneously the accuracy and generalization capabilities. They normally use optimization like least squares, gradient descent or genetic algorithm (GA) to discover the ideal system parameters. fuzzy logic (FL) optimization shows also satisfactory performance, using simple mathematics—without formulating the physics inside- ruling robustly the systems even when they were nonlinear and complex. fuzzy adaptive network (FAN), Takagi–Sugeno fuzzy model (TS) and adaptive neuro-fuzzy inference system (ANFIS) controllers improve the accuracy of the prediction with a fast execution. However, when higher accuracy is needed, they require more grading, increasing exponentially the number of rules, and therefore, performing slower. When contextual information, such as the year season or scheduled activities are incorporated into the system’s knowledge, they are translated into fuzzy rules that shorten the training stage.

Other models are used to fit the system to desired trajectories based on evolutionary algorithms or statistics or linear or polynomial regressions, like nonlinear ARX (autoregressive with exogenous inputs), ARMAX (autoregressive-moving average with exogenous variables) and ARIMA (autoregressive integrated moving average) models. ANNs (artificial neural networks) also contribute through the application of NNARX (neural network autoregressive with exogenous inputs), FFBP (feed forward back propagation) and RBF (radial basis function). frequency–domain, state–space, geometric, case-based reasoning, stochastic and instantaneous methods are also applied.

3.1.3. BMS

The BMS is a computer-based control system that supervises and manages the building's service, actuating in the networked electromechanical equipment. It was originally intended for monitoring the systems and improve the energy savings with the automation of control and is also known as BAS (building automation system). Nowadays, BMS usually stores data that can be analyzed for making longer-term decisions supporting the optimization of multiple objectives, such as healthier environments, pleasant indoor climate or cost reduction. The architecture has evolved from closed and standalone to an open and networked paradigm with more efficient remote procedures, providing intelligence and analytics, becoming in a cloud-based and multi-sourced architecture [14].

However, it is unclear in the state-of-the-art that the current technology can simultaneously optimize the multiple required objectives. The estimations about energy savings differ considerably depending on where solutions are applied, i.e., production, load or user's behavior; the type of building; or the number of pursued objectives. For example, some authors claim that energy can be saved up to 27% working on the BMS [18]. Others estimate that they can save up to 20% of the energy applying control optimization in space heating and others that can be reduced up to 10% in lighting and ventilation [19].

Focusing on the technological challenges for the research applied to BMS, the following ones are identified [20]:

- The integration and usability of heterogeneous networks, technologies and applications into one single platform;
- The maintenance and support of smart, self-adaptive, autonomous applications and objects.
- The on-demand and flexible service provision;
- The size of the foreseen infrastructure with an estimation of 500 billion devices connected to the Internet by 2020, 50 billion of them via mobile wireless [21];
- The machine-machine communication and multi-agent orchestration.

3.1.4. Self-Management

HVAC management literature has treated about supervision of control and optimization processes with predicting models, networked elements in higher hierarchical layers or orchestrated in multi-agent architectures. However, the potential of an autonomic management entity has not been fully studied and proved yet. Plain operational decisions still require manual procedures. The autonomic learning capability of the management system will probably lead to improve the system control accuracy and robustness. The ACODAT-based management for HVAC will likely improve the multi-objective based on changing fuzzy policies [1]. The original idea published by IBM in 2001 [22] was that the software was sufficiently intelligent for caring of itself, similar to what the autonomic nervous system does, getting self-configuration, self-optimization, self-protection and self-healing. The data analysis tasks comprised in an autonomous cycle work together for shared common goals in the managed process, exploiting the data collected from the system to build knowledge models that describe, optimize and predict its behavior. They co-operate among them and interact with the system according to their specific roles.

ACODAT is decision-making oriented [5][7][8], and its tasks work together to achieve the objective of the supervised process. The tasks have different roles in the autonomous cycle, such as observing the process, analyzing and interpreting the events and making decisions to reach the objective for which the cycle was designed. This cycled solution allows solving complex problems in real time. The detailed description of the roles of each task is as follows:

- Monitoring: Tasks in charge of observing the supervised system. They capture data and information about the behavior of the system. In addition, they are responsible for the preparation of the data for the next steps (preprocessing, selecting the relevant features, etc.).

- Analysis: Tasks in charge of interpreting, understanding and diagnosing what is happening in the monitored system. These tasks use building knowledge models of observed dynamics and behaviors, to understand what is happening in the system.

- Decision-making: Tasks in charge of defining and implementing the necessary actions based on the previous analysis, in order to improve the performance, detect failures, among other things, in the supervised system. These tasks impact the dynamics of the system to improve it. The effects of these tasks are again evaluated in the monitoring and analysis steps, restarting a new iteration of the cycle.

An ACODAT has a multidimensional data model that works with the data collected from different sources, to characterize the behavior of the context and transform it into knowledge. Particularly, it can work with multiple data models, like ontologies, cognitive maps, etc. It runs on a single platform that integrates the necessary tools required for the tasks to process the information. Some of these tools are of data mining, semantic mining or linked data.

Thus, the tasks specifically required for the HVAC management perform system and context monitoring, data analysis, state diagnosis and decision-making, transformed into physical signals for the actuators.

3.1.5. Supervision System

The supervision system interacts with the controller. The latter regulates the machines and/or processes and the former watches the activity to detect abnormal situations [2][3][23]. FDD is one of these supervision systems indicating abnormal conditions necessary to discover. Faults in coolers are usually caused by degraded installations or bad human practices. coolers' performance degradation is hardly detected and causes 42% of the service calls and 26% of repairing expenses [23].

Classifying fault severity level has three steps: the detection of the fault, its isolation and its identification. First-generation FDDs were based on rules and statistics and provided simplistic knowledge with a limited set of expected faults, and thus the support of field experts was unavoidable [3]. Today's generation uses ML techniques and stands out for detection and diagnosis [24][25]. An AFD (automatic fault detection) system continuously monitors the HVAC system' states with fuzzy algorithms [26]. Recent AI models allow dynamic fault detection thresholds minimizing the number of false positives and reducing the number of missed faults, with agglomerative clustering that starts with one cluster per data point and groups them into likelihood-based clusters. Some studies associate these models with the Bayesian's DBNs (dynamic Bayesian networks) and Markov's HMM (hidden Markov model) techniques.

The fault prognosis (early diagnosis) by detecting equipment degradations allows keeping the optimum performance throughout the facility's life cycle. Classical fault detection and diagnosis is based on supervised learning models, while the prognosis is based on RL [27]. The most common reinforced learning (RL) is implemented with MDP (Markov decision process) or its variant, POMDP (partially observable Markov decision process), necessary when the context state is not fully known. RL can be applied to a multi-agent problem, such as MARL (multi-agent reinforcement learning) or deals with the optimal coordination between cooperative or competitive agents with decentralized POMDP. When the problem applies to different tasks, TL (transfer learning) transfers knowledge once the problem is solved to support solving the next one. MTL (multi-task learning) is also based on this principle, but tasks are variants of the same problem. Another important approach is the MORL (multi-objective reinforced learning), whereas the objective is to learn multiple policies simultaneously for every objective [28][29].

Kim et al. review studies about the automated FDD (AFD) since 2004 for commercial buildings [30]. They categorize AFD's methods in three groups and analyze several to understand their strengths and weaknesses. Deshmukh et al. present analytical methods embodied in useful software tools to identify and evaluate some building system faults, which cause large building energy inefficiencies [31]. They define the target faults, such as the imbalanced airflows within several large air-handling units. The experiments show that embracing uncertainty with an HVAC's fault detection system is paramount to a good fault inference. Deshmukh, continuing his study, considers algorithms for faults like stuck dampers and leaking dampers [32]. These damper's 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 non-intrusive 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 (building energy management system) of an academic building in Boston.

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