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Control of temperature and energy consumption in buildings - A review

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Abstract
Building sector is one of the largest energy consumers in the world and currently it utilizes 40% of the total energy in the European Union. At the beginning of the article, energy crisis related to the buildings is defined with regard to occupant thermal comfort, energy savings and temperature control. Subsequently, a brief presentation of various types of building heating models available for control purposes is given. Afterward, different approaches used for controlling the building thermal comfort and the energy consumption are shown. These strategies are primarily, classical control, advanced control, intelligent control and hybrid control. The proposed survey also provides up-to-date applications of control techniques. The overview hence affords an insight into current control systems used for temperature and energy consumption in buildings. Further, it helps to have a comprehensive understanding about the variety of control techniques in the field of HVAC (Heating, Ventilation and Air conditioning) applications, at the same time delivering information for careful design of suitable controllers.

Keywords: Building heating control; Energy efficiency; Temperature control; Thermal models.

1. Introduction
Buildings are one of the largest energy consumers all over the world. According to the EU Directive on the Energy Performance of Buildings issued in 2010, the building sector in the European Union is continuously expanding and currently uses 40% of total energy consumption in the union [1]. Amongst, residential buildings are the main energy consumer. In 1999, the shares among space heating, water heating and electrical appliances together with lighting were 68%, 14% and 13% respectively [2]. However, during the last 15 years, the space heating energy demand has decreased owing to the national laws, regulations and administrative provisions forced by the governmental bodies [2]. Several policies are mandated by the European Commission because the European Union is dependent on the external oil and gas. In 2000, 50% of the energy supplies were provided by the external countries. Based on the projections it will become increasingly reliant in the future and will reach 70% in 2030 [3]. According to [4], in Norway, household buildings have utilized 34% of the total energy consumption in 2010. Out of that, space heating has consumed two third of the residential building energy and two fifth of commercial building energy [4]. In the early 1990s, Norwegian household energy consumption per square meter was about 210 kWh/m^2, and it has been reduced to 180 kWh/m^2 in 2010, which is a decline in 14% [4]. Recent investigations showed that there is a potential of saving 65 TWh both from residential and industrial buildings in 2020 [5]. Technical potential for savings based on all existing dwelling is 13.4

TWh and possible savings from commercial buildings are 19.5 TWh in 2020 [5]. Norwegian building technical standards, such as TEK10, direct the people for accomplishing these goals.

Even though the buildings constructed before 1970s had enough openings for natural ventilation, later buildings were built with small openings. It helped to overcome the soaring energy cost occurred ought to the oil embargo. This lets low air flow rates into the building. Since people are living inside the buildings for more than half of their life, environmental comfort is important for occupant satisfaction and to obtain a high productivity. There are four main factors that affect the quality of life inside the buildings, and they are: (i) thermal comfort; (ii) visual comfort; (iii) aural comfort; and (iv) indoor air quality [6]. Thermal comfort is measured by Predictive Mean Vote (PMV), which has values from -3 to +3 [7]. Lowest value indicates the coldest condition; the highest value indicates the hottest condition and zero indicates the neutral condition. Comfort conditions are achieved if the PMV belongs to the [-0.5 0.5] range which is desired inside a building [7]. Visual comfort is about having enough luminance level either by solar radiation or lighting. Aural comfort enhances the acoustical environment inside the building which will improve the speech intelligibility and privacy. CO_2 concentration inside a building characterizes the level of indoor air quality (IAQ) [6]. Maintaining IAQ is a major problem with small openings in a building as it reduces the natural ventilation.

If the building is provided with higher amounts of ventilation, more input energy must be supplied to raise the temperature of the incoming air to obtain thermal comfort. When the heating systems are operated continuously throughout the 24 hours of the day, the thermal comfort can be satisfied easily, but it may lead to energy overconsumption as the occupancy is intermittent. Therefore there is a compromise between the air quality and thermal comfort when it comes to energy savings. Further, solar irradiation and lighting helps to increase the indoor air temperature which reduces the external heating requirements. Moreover, the energy consumed to raise the temperature to a different level may be lower compared to preserving the current conditions. Therefore during low outside temperatures, low occupancy levels and at nights temperature can be lowered either by lowering the heater power or by switching it off depending on which is more efficient. Subsequently the temperature can be brought back to the desired level. Hence it is important to manage the three factors ventilation, temperature and lighting simultaneously to obtain a better quality of life while saving energy.

The most often studied building types in the latter discussed research area are residential and office buildings. These buildings range from small rooms to multi-zone buildings with several floors. There are various factors other than the thermal comfort, indoor air quality and lighting that influence the energy consumption in each of these buildings. They are the age of the building, size of the building, envelope construction, weather conditions, efficiency of the equipments and hot water production. Utilization of the best available equipments and components can minimize the impact from these factors, but it will not be an optimal solution. To obtain an optimal energy performance it is necessary to integrate the effects from each and every fact mentioned above. It can be carried out via a precisely selected building control system. A good control system ought to have a lot of benefits such as minimize the energy consumption, reduce the pollution caused by energy usage, improve the comfort, prevent out of hours operation of the equipments, reduce the maintenance cost and limit the excessive wear and tear associated with the building systems. Throughout this article we focus on the control of indoor air temperature for having a better thermal comfort and low energy consumption.

Building heating control systems can be either time controllers (occupancy based controllers) or condition based controllers. Time controlled heating systems response to programmed time frames based on the occupancy of the building. They can be developed either for a 24 hour period with regular daily schedules or for a 7 day period with varying specifications in each day [8]. Further, the time controllers can be either simple on/off type switches or optimal controllers. Optimal time controllers can decide the time needed for reaching the preferred temperature, and they are more efficient compared to the simple on/off time switches [8]. Building heating control by condition means control with respect to temperature, humidity or whatever the control variable. These two control methods may use various strategies such as On/Off control, PID control, predictive control, adaptive control, optimal control and intelligent control or combinations of them [2] to achieve the heating requirements.

1.1 Building heating models

There are three classes of building heating models available for control purposes: (i) mechanistic models (white box models); (ii) black box models; and (iii) grey box models. Mechanistic models are developed based on the physical principles of heat transfer and fluid dynamics. They consist of several equations, which carry numerous coefficients, to represent the building geometry and thermal properties of the building envelope and equipments. A large number of numerical software tools are frequently met for solving such systems of equations [9]. Still, mechanistic models have some deficiencies in the area of control with regard to the calibration of physical parameters. Black box models can be generated for a particular building after measuring the input variables such as temperature, humidity, air flow rates, wind speed and solar irradiation. Examples of black box models are system identification based models, regression models, genetic algorithm, neural network models, fuzzy logic models, neuro-fuzzy models and support vector machine [9-12]. These models do not expect any physical data of the system and also the resulting model coefficients do not have any physical meaning [11]. Black box models may be more reliable compared to physical knowledge based models, but they are valid only for the building where the data is collected. Grey box models are a blend of mechanistic and black box models and hence the information about these systems is partly known [9, 12]. They are most commonly used for parameter estimation and there is only a limited work has been done on them [12].

Simulation programs like Energy Plus, TRNSYS and Fluent provide comprehensive physics based models for buildings. Even though they can be highly accurate, they may have high computational burden specially when applying to on-line control [13]. Black box models can give unrealistic or non-physical results when the inputs are outside the training range. The intended model for building heating control is a simplified, fast enough and in-depth dynamic model which can be integrated with most of the architectural designs. However, to choose the best model for control, model validation is required. Kramer et al. have reviewed contemporary research articles about simplified thermal and hygric building models [10]. They have categorized the simplified models into three collections: (i) neural network models; (ii) linear parametric models; and (iii) lumped capacitance models. Their summing-up concludes that the modeling of sun irradiation and thermal capacitance is not well executed. Besides, it has been hard for them to find good models dealing with both temperature and relative humidity. Another group of researchers has published an article which includes most of the available techniques present in a broad area of building thermal modeling [9]. They have defined physical models, machine learning tools based models and hybrid models as the model classes. In [11], physically based models and data driven models which are predominantly used for control purposes have briefly examined. Zhao and Magoulès [12] follow the same classification produced by [10]. Instead, they use different names: (i) simplified engineering methods; (ii) artificial intelligence methods; and (iii) statistical methods.

1.2 Objective

There are quite a large number of publications dealing with building heating control systems related to thermal comfort and energy saving. In spite of the large amount of research efforts on building heating control strategies, a comprehensive literature review is missing. Still, [2] has briefed the strategies with their advantages and disadvantages. It has classified the indoor building environment control systems into three categories: (i) conventional methods; (ii) computational intelligence systems; and (iii) agent based intelligent control systems. Intelligent control systems are the main focus of their work, and further attention has given to describe the design of agent-based intelligent control systems. Moreover, in [14], available control techniques in HVAC systems are discussed. They have summarized the general details of traditional, advanced and intelligent control techniques.

This article is lined up to give an overview of the existing and most commonly found heating control methods, and appropriate thermal modeling techniques. Section 2 describes theoretical details about control strategies including their advantages, limitations and up-to-date applications. Ultimately, a closure Summary about the building heating control will be presented in section 3.

2. Building control strategies

The primary goal of controlling the building environment (HVAC system) is to maintain the thermal comfort of the occupants and to achieve good energy efficiency. However, in most of the situations, achievement of one of these goals may cause the other goal to be sacrificed to a certain extent. In building control, the usually accepted setpoints for temperature and humidity inside a residential or office building are 22^0C temperature and 45% relative humidity with an operating band of $\pm 2^0$C and ±15% RH [14]. The different strategies used for controlling the building thermal environment within the given ranges are roughly categorized into four classes in this paper. They are: (i) classical control techniques; (ii) advanced control strategies; (iii) intelligent control methods; and (iv) hybrid control methods. However, there exists a certain overlap among the different control technologies.

2.1 Classical control techniques

The two main classical controllers used in building control are two-position control (on/off) and PID control. They have a simple structure and low initial cost, which makes them the most used controllers in HVAC systems in both commercial and residential buildings [14]. Yet, the maintenance cost of the actuator is quite high (because of the intensive oscillations) and the energy efficiency is low for both of these mechanisms that cause high cost [14].

On/off control is one of the oldest techniques that is practiced in buildings for the purpose of energy saving and occupant thermal comfort. It is a simple, fast and inexpensive feedback controller that accepts only binary inputs which is also known as bang-bang control and hysteresis control. This control technique is still being using in domestic and commercial buildings effectively, as the well known thermostat, humidistat and pressure switch [14]. Thermostats are commonly found in home heating systems and domestic refrigerators.

Basic function of a thermostat is to control the heating or cooling equipment according to the target and current conditions. They should not be affected by draughts and heat sources and also advised to fix them in a building halfway up the wall [8]. Thermostat plays a vital role in providing comfort to the people and controlling the most energy intensive systems in dwellings. Furthermore, it can control heating and cooling equipments, humidifiers and dehumidifiers, economizers and ventilation systems [15]. The basic components of a thermostat are: (i) sensor to measure the temperature in the desired environment; (ii) switch/actuator to turn the heating or cooling equipment on and off; (iii) feedback loop to find the offset and decide on/off time; and (iv) user interface to display the current conditions [15]. Thermostat sensor must be accurate, and it should provide a quick response. If the sensor is sluggish, it cannot detect the temperature changes fast enough, which causes the system to consume more energy with less occupant comfort [16]. For example if the thermostat time constant is 1 sec it is fast and if it is 90 sec response is slow [16]. In order to avoid hunting (hunting produces a continuously changing deviation from the normal operating point which is often known as instability, cycling or oscillation), thermostats are introduced with a dead zone of $\pm 1^0$C to $\pm 1.5^0$C. First thermostats were either mechanical or mercury based devices. However they are now replaced with electronic devices, which also have wireless connections instead of wired connections. Nowadays, many new features and functions have emerged to thermostats to facilitate more energy saving [15] such as programmable thermostats [15]. They are simple and trouble free devices [17] and the most advanced thermostats can control even multiple zones and humidity levels [15]. While thermostat is a simple and inexpensive control method, it is often incapable of tracking the setpoint accurately and hence could be inefficient in terms of energy.

Same as on/off control, PID control is also a feedback control mechanism, which does not use knowledge/model of the interested system. It determines the error, which is the difference between the measured process variable and the desired setpoint, and adjusts the control signal according to that value. There are three separate control techniques used in the PID control algorithm: (i) proportional term relates to the present offset; (ii) integral term depends on the accumulation of past errors; and (iii) derivative term predicts the future offsets based on the current rate of change of the process. A control signal is delivered based on a weighted sum of these three actions. The distinct effect of these three terms causes the most important stimulus for the survival of the PID control mechanism, and it also committed to the evolution of modern control approaches [14]. It could be beneficial for certain applications to apply only one or two actions out of the three by setting the other parameters to zero. P control and PI control are two mostly used control algorithms. Thermal process dynamics in a building is usually a slow responding process. Therefore, proportional control can be engaged in building temperature control with a good stability and a reasonable small offset. Also, it is good in building humidity control. Derivative term also contributes to combat the sudden load changes encountered in the system [14]. Still, small amounts of measurement and process noise can cause large variations in the output due to the derivative term present in the PID control.

Even though there are a number of advantages in using PID control such as simplicity of implementation [14], it may not be the most suitable controller for building control due to several reasons [18]. It requires three parameters to be trained for each building zone after the installation. This is quite a time consuming task and re-tuning after the commissioning may be inconvenient. They are unable to handle random disturbances, and therefore large deviations from the setpoint can occur. In buildings, thermal interaction between the zones leads to multi-variable behavior. However, standard PID controller assumes a single-input single-output (SISO) system during the analysis which may cause unacceptable deviations. Since these controllers operate at low energy efficiencies they may not be suitable in the long run [18].

Shein et al. [19] have used a PID controller to control the room temperature using 2 actuators; (i) air conditioner; and (ii) window opening. Kulkarni and Hong have introduced a proportional control system for a residential building heating system, and they have compared it with the two position and PI control schemes with respect to energy consumption and thermal comfort perspectives [20]. They concluded that both two position control and proportional control are pretty similar in the energy consumption perspective, but PI control has benefits over thermal comfort too. Finally, they have stated that proportional control has advantages over on/off control relative to equipment life owing to much smoother control signal.

2.2 Advanced control techniques

Classical control strategies can be applied to building control with certain limitations. They are easy to tune for (SISO) systems but, it is not easy or even impossible to tune them for multiple-input, multiple-output (MIMO) systems. Even though, PID control is one of the best control strategies, it cannot reflect the very important outside temperature effects unless feed forward control is integrated. Moreover, it may not be the best solution for non-linear systems like HVAC systems. Large time delays and higher order dynamics are still hard to control using PID controllers. These requirements can be satisfied with advanced control techniques. These techniques usually use a dynamic model of the system for control purposes, and show non-linear characteristics [2]. As HVAC systems are non-linear, these techniques are extensively used in building control [14]. This paper outlines the advanced control techniques in three different aspects: (i) predictive control; (ii) adaptive control; and (iii) optimal control.

2.2.1Model predictive control (MPC)

Application of predictive control for building automation systems can provide increased energy savings, and they are more cost effective than non-predictive control applications. Several benefits, other than the energy savings, can be attained by using the predictive control framework in building automation. Some of benefits are robustness to disturbances and changes, multivariable control, improvement of the steady state response, future disturbances prediction, future control actions prediction and many more [21, 22]. There are many applications where predictive control is applied to a variety of building HVAC systems. They can be applied to both single zone and multi zone (a zone is generally a completely enclosed or partly open division of a building) buildings including residential, office and public buildings [22]. However, the decision of implementing the predictive control for a particular building depends on the return time of investments [23].

MPC was formulated in 1970s, and at present, it is extensively used in process control applications. It generally provides superior performance in terms of lower energy consumption, better transient response, robustness to disturbances and consistent performance under fluctuating conditions [22]. MPC can also cope with slow moving processes with time delays, and with a large number of manipulated and controlled variables [24]. This multivariable control technique is based on a prediction model which utilizes past information and the future inputs to predict the future output. While controlling the process, using the system model, MPC generates a control vector that minimizes a certain cost function over the prediction horizon in the presence of disturbances and constraints. Model identification is the bottleneck of the whole MPC application procedure, and there are not any stringent requirements on the model structure. It is possible to use any kind of model out of the three types: black box, grey box and white box [23].

Physics based models used in MPC are generally analogous to electrical RC networks. They are dynamic first order models produced using lumped thermal capacitance and resistance of the building. However, finding the first principle model could be time consuming for complex building structures. Data driven models (grey or black box models) fit linear and non-linear mathematical functions to the measured data of the building HVAC system. They can be developed using artificial neural networks, fuzzy logic, support vector machine, first and second order time delay models, statistical models (AR (Autoregressive), ARX (Autoregressive exogenous), ARMA (Autoregressive moving average), ARMAX (Autoregressive moving average exogenous), BJ (Box Jenkins), OE (Output Error)) and combinations of them. Prívara has explained subspace identification methods (4SID), prediction error methods (PEM), MPC relevant identification (MRI), deterministic semi-physical modeling (DSPM) and probabilistic semi physical modeling (PSPM), which are popular statistical methods used in the predictive model formation [23]. MRI, DSPM and PSPM are grey box models while 4SID is a black box model. Accuracy of these data driven models depend on the quality of the measured data. Hence the measurements must have high accuracy, low noise and appropriate sampling frequency depending on the process dynamics [22]. However, in general, precision of the data driven models is high compared to physics based models. Even though, the comprehensive models formulated using programs such as Energy Plus, Fluent and TRNSYS are highly accurate; they are not usually used for controller development [22]. High quality models are very accurate, but quite complex and not good in computational tractability with the loss of physical insight. Use of low quality models may result in less energy saving potential. The best is to use a model with least possible complexity, which is developed on simple physics or simple mathematical formulations, to achieve reasonable accuracy and computational simplicity.

A family house consisting of two rooms and an attic is controlled using MPC in [25]. A linear state space model developed with resistor capacitor network is used as the predictive model to control heating and cooling with a prediction horizon of 24 hours. Kim and Brown have also developed a reduced order state space model with 10 states for controlling a single zone of a building [13]. Reduced order models (ROM) provide less model complexity and less computational requirements while preserving the prediction accuracy. They have successfully used the ROMs in MPC and compared the results with a TRNSYS model.

HVAC systems are non-linear complex systems with delays, and, therefore, it is usually difficult to model them using first principles and apply them in MPC. Back propagation neural networks (NN) with few layers can approximate these non-linear systems with high recognition. A back propagation neural network to establish a prediction model for a HVAC system is used in [26]. They have used four inputs (room temperature and chilled water inlet valve opening at time t and $t-1$) to develop a prediction model and used MPC and feedback correction to control the air handling unit. It has been concluded that the used control mechanism can efficiently control the room temperature. Both feed forward neural network prediction model and an ARX model for a single zone building block have been developed by [27], and they have concluded that non-linear NN models with Levenberg Marquardt algorithm gives accurate temperature prediction than linear ARX models. Fuzzy logic techniques can also be applied to building predictive control applications. Fuzzy predictive control scheme has been practiced to control the temperature in an air-conditioning (AC) system in [28]. The controller is based on a Takagi Sugeno fuzzy model, and it performs well in controlling the non-linear dynamic AC unit with less computation. Support vector regression (SVR) has universal approximation ability, and it can be used to model non-linear HVAC systems [29]. It minimizes the prediction error and model complexity simultaneously. Xi et al. used SVR to build a non-linear dynamic model for a HVAC system. Consequently, they developed a non-linear MPC based on SVR model, to control the temperature and relative humidity in a thermal chamber successfully [29]. Lixing et al. also used SVR to predict the cooling load of a building HVAC system [30].

Subspace identification methods with Kalman filter prediction are demonstrated for a two floor residential building by [31]. The building was equipped with a large wireless sensor network to measure the temperatures, humidities and solar radiation. Two statistical approaches, ARMAX and subspace identification methods, to predictively control a ceiling radiant heating system are used in [32]. Collection of data from a large multi-zone office building to build a predictive control model is not straightforward. To overcome this issue, [33] has developed an implicit model of the office building in Energy Plus software. Then they have generated good quality data for predictive model, after exciting the implicit model with specially proposed signals. Later, predictive control of the building is implemented with system identification methods. ARMAX models are also a type of black box linear parametric models preferred in building predictive control. One such a model is presented in [34], which can be used to control the room temperature in office buildings. Furthermore, [35] justified the application of black box linear ARX, ARMAX, BJ and OE models for prediction of room temperature and relative humidity of an office room in a commercial building. For more details about statistical prediction models, interested readers can refer to [36, 37].

2.2.2 Adaptive control

Adaptive control is a specific type of non-linear control system applicable to processes with changing dynamics in normal operating conditions subjected to stochastic disturbances. They control the processes in a closed loop and the information about the system characteristics are obtained online while the system is operating. When the parameters of the plant dynamic model are unknown and/or vary in time the adaptive control system still can obtain or sustain the desired level of control system performance [38]. Conventional control systems use feedback to reject the effect of disturbances upon the controlled variables. Further, they do not determine the control system performance. Instead, adaptive control system measures a particular performance index of the control system using the inputs, the states, the outputs and the known disturbances [38]. After analyzing the measured performance index with the reference PI's, adaptation mechanism modifies the parameters of the adjustable controller in order to maintain the performance index of the control system. Hence the adaptive control system can be interpreted as a feedback system where the controlled variable is the performance index [38]. The primary feedback handles the process signal variations and secondary feedback handles the process parameter changes making the control adaptive. The basic configuration of an adaptive control system is presented in Figure 1.

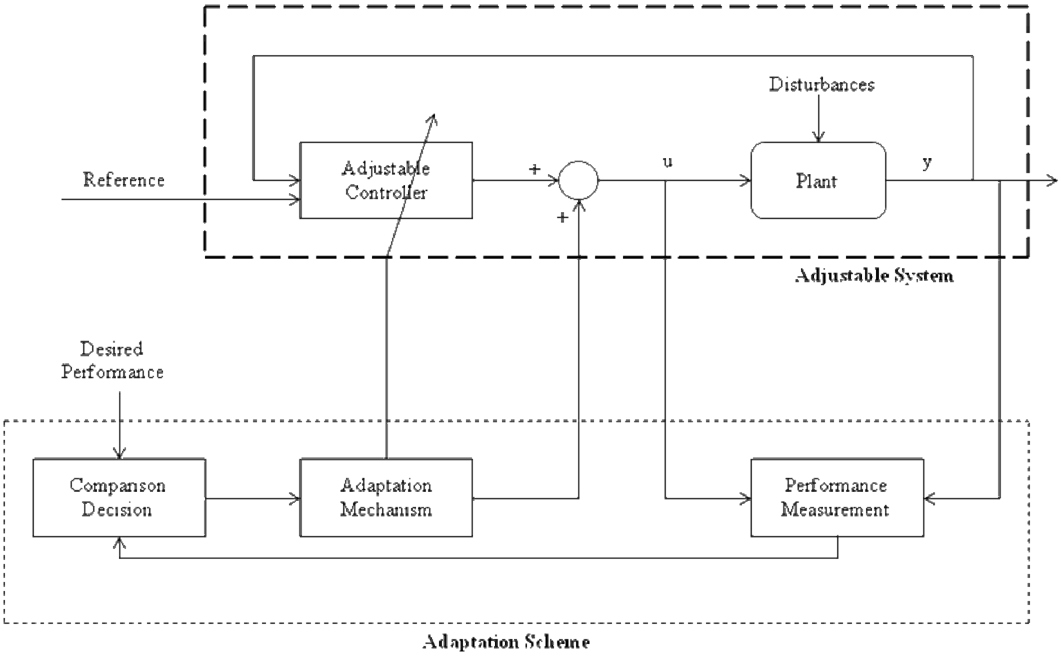

Figure 1. Basic configuration of adaptive control system [38]

Most adaptive control systems can be split into two main groups as feedback adaptive control and feed forward adaptive control. Feedback adaptive controllers are further classified into several categories [39]. Feed forward adaptive control is also said to be open loop adaptive control. This technique considers that there exists a rigid relationship between some measurable variables characterizing the environment, and the parameters of the system model. System performance modifications resulting from the controller parameter changes are not measured and fed back to a comparison-decision block in order to check the efficiency of the parameter adaption [38, 39]. Hence, there is a possibility of system failure if the relationship between the environmental measurements and system model parameters change [38]. However, this type of adaptive control systems react fast to the process changes which is an advantage [39]. There are also some limitations of open loop adaptive control. Negligence of all effects related to unmeasured signals/disturbances, unpredictable changes of the system behavior and the parameter storage requirements to accommodate many operating conditions are some of them [39]. Gain scheduling, a feed forward adaptive control scheme, was used for the first time in 1950s to control aircrafts and they are widely used in variety of situations though they are not fully adaptive [38].
Wen et al. [40] present the use of feed forward adaptive control for a four room building and they have devised a model of the building relating lumped thermal capacitors and resistors. Neural networks can also be used to generate a model for adaptive control that has been illustrated in [41]. Extensive work has been done related to the application of adaptive control in building HVAC systems and they can be observed in [18, 42-46].

2.2.3 Optimal control
In optimal control, control signals are derived to satisfy some physical constraints and at the same time to extremize a chosen performance criterion. Optimal control and its ramifications have found applications in many different disciplines, including aerospace, process control, robotics, bioengineering, economics, finance, and management science, and it continues to be an active research area within control theory

[47]. According to [47], formulation of optimal control problems requires: (i) mathematical model of the system to be controlled; (ii) specification of the performance index; (iii) specification of all boundary conditions on states, and constraints to be satisfied by states and controls; and finally (iv) a statement of what variables are free.

Rather using conventional control methodologies, building control has concentrated on much advanced control techniques. There is an increased interest in applying optimal control for buildings lately to improve the comfort and to minimize the energy consumption. This twofold objective can be accomplished by minimizing a cost function encountered in the optimal control aspect. The Indicated control strategy could rely either on white box, grey box or black box models [48].

Optimal control strategies using mathematical models for building heating control are developed in [49-52]. Grey box models can be used for optimal control that has been illustrated by [53]. They have used measured data from one floor elementary school building to identify a grey box model and later the model has been used to test two optimal control strategies based on setpoint temperature. According to [53], grey box models are well adapted to perform optimization because they run quickly and are liable to constraints.

2.3 Intelligent/Soft control

It is a challenging task to identify a suitable mathematical model for HVAC systems as they are complex, non-linear and MIMO systems. Further, they are exposed to lots of disturbances, contingencies and time delays. Human sensation of thermal comfort is a vague and subjective matter and taking it into account is therefore difficult [54]. In intelligent control, no model is needed for controller configuration and is solely based on the human perception of the thermal comfort. Consequently, it avoids the issues associated with physical model development for distinct building structures. Therefore, intelligent controllers are promising control techniques for HVAC systems [14]. Artificial Intelligence (AI) was started to use in advanced building control in 1930s [55]. However, these techniques were started to use extensively in 1990s [2].

Intelligent control techniques can directly be used in HVAC control and they can also be employed to improve the existing traditional controllers, as well. These intelligent techniques are presented under three fundamental subcategories: (i) fuzzy logic (FL) based controllers; (ii) artificial neural network (ANN) based controllers; and (iii) neuro-fuzzy based controllers. The two last methods are adaptive techniques engaging iterative self tuning process during system operation. Moon et al. have described the three AI based thermal control techniques used for building control [56]. Performance of each control method is tested in a typical two story residential building in USA. They have concluded that adaptive AI based control methods are potentially good in maintaining indoor air temperature more comfortably than conventional methods. However, they have not seen significant energy saving effect over the three techniques.

2.3.1 FL based intelligent control

Fuzzy logic comprised of three basic processes: (i) fuzzification; (ii) fuzzy inference; and (iii) defuzzification. Fuzzification is the process of mapping crisp numbers in the input data matrix into fuzzy sets. Membership functions (such as triangular, trapezoidal, gaussian distribution, bell functions and sigmoidal functions) play the main role throughout this process by mapping each input value to a degree of membership between 0 and 1. Fuzzy inference system maps a fuzzy set into a different fuzzy set using fuzzy rules and logical operations. Fuzzy rules are usually denoted as IF-THEN statements and they can be derived by professionals or be automatically generated from the available numerical data using soft computing techniques and evolutionary algorithms. There are two principal types of fuzzy inference systems: Mamdani fuzzy inference and Sugeno fuzzy inference. Mamdani type is generally accepted and extensively used while Sugeno type is particularly good for dynamic non-linear systems. The aggregate linguistic output value produced from the former processes is the input for the defuzzification process. The target is to have a single crisp value as the output from the final process. Fuzzy logic can explain the thermal comfort linguistically and, therefore, can describe the thermal comfort levels rather than temperature or humidity levels which result in improved thermal comfort. There are several control methods originated based on fuzzy logic control and they are briefly described hereafter.

Fuzzy P controller is a technique where the FL is used in closed loop control. Inputs to the controller are obtained from process measurements and the fuzzy logic system output is used to control the process. In fact, this is a pure FL system which is indicated as fuzzy P controller [2, 55].

PID-like fuzzy controllers are categorized into two main classes. The first type is a typical FLC (Fuzzy Logic Controller), realized as a set of heuristic control rules [2, 55]. This type is usually referred to as PI-like or PD-like fuzzy controllers. Second type consists of a conventional PID controller in conjunction with a set of fuzzy rules and fuzzy reasoning mechanism to tune the PID gains online. This system is, however, model dependent [2].

Application of fuzzy logic control to buildings is effective as this technique is well-suited for non-linear system control [57]. They are capable of uniformly approximating any non-linear function to any degree of accuracy and also provide rapid operation. If the fuzzy rules are designed to be more robust, fuzzy controllers can improve the disturbance response by reducing the overshoot/undershoot present in the controlling variable [57]. Fraisse et al. applied this technique to control discontinuously occupied buildings [57]. Many other researchers have been working on the application of only fuzzy logic to control the thermal comfort of buildings [58-62].

The use of fuzzy-PID, fuzzy-PD and adaptive fuzzy-PD for controlling thermal-visual comfort and indoor air quality is described in [63]. One of their main aims was to reduce the energy consumption and lowest values are obtained with the adaptive fuzzy-PD controller. Moreover, [64] presents the development of a PID-Fuzzy controller for indoor temperature control consent to energy resources management in buildings.

2.3.2 ANN based intelligent control

ANNs are inspired by the human brain, nervous system and its learning process. They consist of a set of interconnected neurons in different layers (input, hidden and output layers) of the network. Output of the network is computed using the inputs, network weights and transfer functions. ANN models have adaptability via a self tuning process and they are increasingly used in advanced thermal control of buildings. Amongst diverse AI methods, ANN method has some advantages over the others: (i) ANNs handle a large number of input variables (fuzzy and neuro-fuzzy methods can use only a limited number of inputs as the increased number of membership functions and fuzzy inference rules make the system more complex to solve); (ii) ANN can handle a large number of input data [65]. With these benefits, application of ANN for predicting the energy consumption of building services claimed to be more reliable. An overview of different neural network architectures in building's energy prediction is presented by [66] with appropriate examples, for a detailed understanding of the concept.

ANN based controllers are very useful in optimizing the energy demand of buildings, especially having high thermal masses [67]. There are vast number of applications covering the neural network control of buildings such as: [65, 67-70]. Moreover, as building HVAC systems are dynamic and non-linear, it is also very usual to use dynamic neural network based controllers. A dynamic neural network based on the idea of a non-linear autoregressive with external input (NARX) to model and control a HVAC system is used in [71].

2.3.3 Neuro-Fuzzy based intelligent control

Fuzzy logic has a challenge in producing optimal fuzzy rules and determining membership functions for better control. In order to overcome this problem and to develop an optimum rule base, a new method coupling both FL and ANN has introduced. Here, the neural network technology is used in fuzzy technology and one such neuro-fuzzy approach is the adaptive neuro fuzzy inference system (ANFIS).

Marvuglia et al. present a demonstration of a combined neuro-fuzzy model for indoor temperature regulation [72]. An autoregressive neural network with external inputs has been used to produce indoor temperature forecasts using the outside temperature, relative humidity, wind speed and past forecasts as inputs. Considerable work has been done in the field of building control using ANFIS [73].

2.4 Hybrid control

Hybrid controllers are formulated by the fusion of soft control techniques (FL and ANN) and classical or advanced control techniques [22]. Some examples of this control strategy are discussed in the previous sections such as fuzzy-PID control, adaptive neuro control and neuro-fuzzy control. Here, the soft control techniques are used at higher levels and the other control technique is used at lower levels of the control structure [22]. Hybrid controllers are beneficial as the combination can solve problems that may not be solved by the individual controller. However, the design of the soft control part obliges user experience and an immense quantity of data for training, whereas the classical or advanced controller is laborious to tune (especially for HVAC systems), which are some constraints of the controller.

Various techniques have been used to improve the performance of PID controllers, and fuzzy-PID control scheme is one of them. A self tuning fuzzy PI controller for the supply air pressure control loop for a HVAC system has been developed in [74]. It performs better under normal operating conditions, and when there exists large parameter variations. Adaptive PI control is also a new technique that can be used to tune PI controllers in HVAC systems [75]. It has faster response, smaller overshoot, higher accuracy, stronger robustness and better stability. Paris et al. have presented the application of three heating control schemes (PID, PID-MPC and PID-FUZZY) for indoor temperature control in multi-energy buildings [76]. They found out that the PID-MPC scheme is versatile over the others as it permits better management of different energy sources. Application of ANN models in thermal control of residential buildings with adaptive and predictive logics is presented in [77]. They take air temperature, humidity and PMV as control variables. These systems are observed to be more comfortable than typical thermostat systems, and have potential of enhancing thermal comfort of residential buildings. Besides, a performance analysis of the ANN based predictive and adaptive models for disturbances in and around residential buildings is given by [78].

3. Summary

Variety of control methodologies as employed in the control of building temperature and energy usage were reviewed in the present study. At the beginning of the paper, energy crisis owing to buildings in all over the world is described. Next, different building control strategies, classical; advanced and intelligent techniques, were presented. Classical control methods are still the first choice in building control today, while advanced and intelligent methods are gaining increased attention. The types of control systems and their advantages and limitations are listed and summarized in Table 1.

Table 1. Advantages and limitations of building heating control strategies

Control strategy	Advantages	Limitations
On/Off control	Low initial cost, Simple structure, Fast response, Feedback type	Accepts only binary inputs, often incapable of tracking the setpoint accurately and hence could be inefficient, Not versatile and effective in the long run
PID control	Feedback type, Derivative term combat with sudden load changes in the system	Little measurement and process noise can cause large variations in the output due to derivative term, Energy inefficient, Tuning is time consuming
MPC	Increased energy savings, Cost effective, Robustness to disturbances, Control of multiple variables, Steady state response improvement, Future disturbance prediction, Prediction of future control actions, Better transient response, Handle slow moving processes with time delays	Need to identify a suitable model of the system, Installation could be expensive
Adaptive control	Increased energy savings, Good stability, Parameters can be changed quickly in response to changes in process dynamics, Easy to apply, React fast	Need to identify a suitable model of the system, The design required for implementation is enormous
Optimal control	Increased energy savings, Rapid response, Multi-variable control	Need to identify a suitable model of the system
Fuzzy control	Non-linear control method and can be applied to HVAC systems effectively, High accuracy, Rapid operation	Can use only a limited number of input variables, Development of optimal number of fuzzy rules and determination of the membership function parameters are not straightforward
ANN control	Handle large number of input variables and data, Reliable predictions	Require large number of data for quality predictions
Neuro-Fuzzy control	Combination can develop optimal fuzzy rules and determine membership function parameters	Can use only a limited number of input variables
Hybrid control	Combination of soft control and classical/advanced control can solve problems that may not be solved by an individual controller	Soft control requires large quantity of data for training, It is difficult to tune the classical/advanced controller

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As a whole, the use of classical controllers is because of their low initial cost and simplicity of implementation. However, they admit high maintenance cost and higher energy consumption. Further, they cannot be used in MIMO systems efficiently. Advanced control methodologies could be an alternative approach in building control. These techniques require a good quality dynamic model of the building and they exhibit non-linear characteristics. As HVAC systems are non-linear and time delayed processes, advanced control methods can handle them more smoothly than conventional methods. In intelligent control, no mathematical model is needed and it is solely based on the human perception of the thermal comfort. Hence, it can provide improved thermal comfort to the occupants. Further, these controllers can be used to upgrade the existing traditional controllers.

References

[1] EBPD, On the energy performance of buildings. Official Journal of the European Union, Directive 2010/31/EU of the European Parliament and of the council, 2010: p. 13-34.

[2] Dounis, A.I. and C. Caraiscos, Advanced control systems engineering for energy and comfort management in a building environment-A review. Renewable and Sustainable Energy Reviews, 2009. 13(6-7): p. 1246-1261.

[3] European-Commission, Towards a European strategy for the security of energy supply, green paper., 2000.

[4] Bergesen, B., et al., Energy consumption 2012 - household energy consumption, 2013, Norwegian Water Resources and Energy Directorate.

[5] Valmot, O.R., Enormt potensial for energisparing, in Teknisk Ukeblad2013. p. 30-31.

[6] Krzaczek, M. and J. Tejchman, Indoor Air Quality and Thermal Comfort in Naturally Ventilated Low-Energy Residential Houses, in Air Quality - Monitoring and Modeling, S. Kumar and R. Kumar, Editors. 2012, InTech.

[7] Fanger, P.O., Thermal comfort: Analysis and applications in environmental engineering. 1970: Danish Technical Press.

[8] Carbon-Trust, Building controls - Realising savings through the use of controls, 2007: UK.

[9] Foucquier, A., et al., State of the art in building modelling and energy performances prediction: A review. Renewable and Sustainable Energy Reviews, 2013. 23(0): p. 272-288.

[10] Kramer, R., J. van Schijndel, and H. Schellen, Simplified thermal and hygric building models: A literature review. Frontiers of Architectural Research, 2012. 1(4): p. 318-325.

[11] Spindler, H.C. and L.K. Norford, Naturally ventilated and mixed-mode buildings-Part I: Thermal modeling. Building and Environment, 2009. 44(4): p. 736-749.

[12] Zhao, H.-x. and F. Magoulès, A review on the prediction of building energy consumption. Renewable and Sustainable Energy Reviews, 2012. 16(6): p. 3586-3592.

[13] Kim, D. and J.E. Brown. Reduced-order building modeling for application to model-based predictive control. in 5th national conference of IBPSA. 2012. USA.

[14] Mirinejad, H., et al., Control Techniques in Heating, Ventilating and Air Conditioning (HVAC) Systems 1. Journal of computer science, 2008. 4(9): p. 777-783.

[15] Peffer, T., et al., How people use thermostats in homes: A review. Building and Environment, 2011. 46(12): p. 2529-2541.

[16] Wen, J. and T.F. Smith. Review of thermostat time constant on temperature control and energy consumption. in Sensors for Industry. 2001.

[17] Maheshwari, G.P., et al., Programmable thermostat for energy saving. Energy and Buildings, 2001. 33(7): p. 667-672.

[18] Virk, G.S., J.M. Cheung, and D.L. Loveday. Development of adaptive control techniques for BEMs. in International Conference on CONTROL '91. 1991.

[19] Shein, W.W., Y. Tan, and A.O. Lim. PID controller for temperature control with multiple actuators in cyber-physical home system. in 15th International conference on network based information systems. 2012.

[20] Kulkarni, M.R. and F. Hong, Energy optimal control of a residential space-conditioning system based on sensible heat transfer modeling. Building and Environment, 2004. 39(1): p. 31-38.

[21] Gwerder, M. and J. Todtli. Predictive control for integrated room automation. in 8th REHVA World congress for building technologies. 2005.

[22] Afram, A. and F. Janabi-Sharifi, Theory and applications of HVAC control systems – A review of model predictive control (MPC). Building and Environment, 2014. 72(0): p. 343-355.

[23] Prívara, S., et al., Model predictive control of a building heating system: The first experience. Energy and Buildings, 2011. 43(2–3): p. 564-572.
[24] Bao-Cang, D., Modern predictive control. 2010, Boca Raton, Fla.: CRC Press. xv, 276 s. : ill.
[25] Vasak, M., A. Starcic, and A. Martincevic. Model predictive control of heating and cooling in a family house. in MIPRO. 2011.
[26] Li, S., S. Ren, and X. Wang. HVAC room temperature prediction control based on neural network model. in 5th Conference on Measuring Technology and Mechatronics Automation. 2013.
[27] Thomas, B. and M. Soleimani-Mohseni, Neural network models for predictive climate control in intelligent buildings., 2005, CABA.
[28] Sousa, J.M., R. Babuška, and H.B. Verbruggen, Fuzzy predictive control applied to an air-conditioning system. Control Engineering Practice, 1997. 5(10): p. 1395-1406.
[29] Xi, X.-C., A.-N. Poo, and S.-K. Chou, Support vector regression model predictive control on a HVAC plant. Control Engineering Practice, 2007. 15(8): p. 897-908.
[30] Lixing, D., et al. Support vector regression and ant colony optimization for HVAC cooling load prediction. in International Symposium on Computer, Communication, Control and Automation. 2010.
[31] Toffoli, E., et al. Thermodynamic identification of buildings using wireless sensor networks. in IFAC World Congress. 2008.
[32] Ferkl, L. and J. Siroky, Ceiling radiant cooling: Comparison of armax and subspace identication modelling methods. Building and Environment, 2010. 45: p. 205-212.
[33] Privara, S., et al. Modeling and identification of a large multi-zone office building. in Control Applications (CCA), 2011 IEEE International Conference on. 2011.
[34] Wu, S. and J.-Q. Sun, A physics-based linear parametric model of room temperature in office buildings. Building and Environment, 2012. 50(0): p. 1-9.
[35] Mustafaraj, G., J. Chen, and G. Lowry, Development of room temperature and relative humidity linear parametric models for an open office using BMS data. Energy and Buildings, 2010. 42(3): p. 348-356.
[36] Prívara, S., et al., Building modeling as a crucial part for building predictive control. Energy and Buildings, 2013. 56(0): p. 8-22.
[37] Prívara, S., et al., Building modeling: Selection of the most appropriate model for predictive control. Energy and Buildings, 2012. 55(0): p. 341-350.
[38] Landau, L., et al., Adaptive control. 2011, London: Springer.
[39] Isermann, R., K.H. Lachmann, and D. Matko, Adaptive Control Systems. 1992: Prentice Hall.
[40] Wen, J.T., et al. Building temperature control with adaptive feedforward. in Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on. 2013.
[41] Torres, J.L. and M.L. Martin. Adaptive control of thermal comfort using neural networks. in Argentine Symposium on Computing Technology. 2008.
[42] Chaudhry, S.I. and M. Das. Adaptive control of indoor temperature in a building using a desirable reference temperature profile. in Circuits and Systems (MWSCAS), 2013 IEEE 56th International Midwest Symposium on. 2013.
[43] Chaudhry, S.I. and M. Das. Adaptive control of indoor temperature in a building. in Electro/Information Technology (EIT), 2012 IEEE International Conference on. 2012.
[44] Hongli, L., et al. A novel adaptive energy-effcient controller for the HVAC systems. in Control and Decision Conference (CCDC). 2012.
[45] Leephakpreeda, T., Implementation of adaptive indoor comfort temperature control via embedded system for air-conditioning unit. Journal of Mechanical Science and Technology, 2012. 26(1): p. 259-268.
[46] Zaheer-Uddin, M., Optimal, sub-optimal and adaptive control methods for the design of temperature controllers for intelligent buildings. Building and Environment, 1993. 28(3): p. 311-322.
[47] Becerra, V.M., Optimal control, in Scholarpedia2008.
[48] Wang, S. and Z. Ma, Supervisory and Optimal Control of Building HVAC Systems: A Review. HVAC&R Research, 2008. 14(1): p. 3-32.
[49] Burns, J.A. and E.M. Cliff. On optimal thermal control of an idealized room including hard limits on zone-temperature and a max-control cost term. in Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on. 2013.

[50] Kummert, M. and P. Andre. Building and HVAC optimal control simulation. application to an office building. in 3rd Symposium on Heating, Ventilation and Air Conditioning (ISHVAC 99) conference. 1999.

[51] Yahiaoui, A., et al. Model based optimal control for integrated building systems. in 6th Int. Postgraduate Research Conf. in the Built and Human Environment. 2006.

[52] Rui, Y. and W. Lingfeng. Optimal control strategy for HVAC system in building energy management. in Transmission and Distribution Conference and Exposition (T&D), 2012 IEEE PES. 2012.

[53] Berthou, T., et al. Optimal control for building heating: An elementary school case study. in Conference of International Building Performance Simulation Association. 2013. Chambéry, France.

[54] Mirinejad, H., K.C. Welch, and L. Spicer. A review of intelligent control techniques in HVAC systems. in Energytech, 2012 IEEE. 2012.

[55] Song, Y., S. Wu, and Y.Y. Yan, Control strategies for indoor environment quality and energy efficiency—a review. Int. J. Low-Carbon Tech., 2013.

[56] Moon, J.W., et al., Comparative study of artificial intelligence-based building thermal control methods – Application of fuzzy, adaptive neuro-fuzzy inference system, and artificial neural network. Applied Thermal Engineering, 2011. 31(14–15): p. 2422-2429.

[57] Fraisse, G., J. Virgone, and J.J. Roux, Thermal control of a discontinuously occupied building using a classical and a fuzzy logic approach. Energy and Buildings, 1997. 26(3): p. 303-316.

[58] Shahnawaz Ahmed, S., et al., Fuzzy logic based energy saving technique for a central air conditioning system. Energy, 2007. 32(7): p. 1222-1234.

[59] Eftekhari, M.M. and L.D. Marjanovic, Application of fuzzy control in naturally ventilated buildings for summer conditions. Energy and Buildings, 2003. 35(7): p. 645-655.

[60] Gouda, M.M., S. Danaher, and C.P. Underwood, Thermal comfort based fuzzy logic controller. Building services engineering research and technology, 2001. 22(4): p. 237-253.

[61] Homod, R.Z., et al., Gradient auto-tuned Takagi–Sugeno Fuzzy Forward control of a HVAC system using predicted mean vote index. Energy and Buildings, 2012. 49(0): p. 254-267.

[62] Kristl, Ž., et al., Fuzzy control system for thermal and visual comfort in building. Renewable Energy, 2008. 33(4): p. 694-702.

[63] Kolokotsa, D., et al., Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal–visual comfort and indoor air quality satisfaction. Energy and Buildings, 2001. 33(6): p. 531-543.

[64] Paris, B., et al., Hybrid PID-fuzzy control scheme for managing energy resources in buildings. Applied Soft Computing, 2011. 11(8): p. 5068-5080.

[65] Moon, J.W., S.-H. Yoon, and S. Kim, Development of an artificial neural network model based thermal control logic for double skin envelopes in winter. Building and Environment, 2013. 61(0): p. 149-159.

[66] Kumar, R., R.K. Aggarwal, and J.D. Sharma, Energy analysis of a building using artificial neural network: A review. Energy and Buildings, 2013. 65(0): p. 352-358.

[67] Argiriou, A.A., I. Bellas-Velidis, and C.A. Balaras, Development of a neural network heating controller for solar buildings. Neural Networks, 2000. 13(7): p. 811-820.

[68] Liang, J. and R. Du, Design of intelligent comfort control system with human learning and minimum power control strategies. Energy Conversion and Management, 2008. 49(4): p. 517-528.

[69] Moon, J.W., et al., Determining optimum control of double skin envelope for indoor thermal environment based on artificial neural network. Energy and Buildings, 2014. 69(0): p. 175-183.

[70] Castilla, M., et al., Neural network and polynomial approximated thermal comfort models for HVAC systems. Building and Environment, 2013. 59(0): p. 107-115.

[71] Kusiak, A. and G. Xu, Modeling and optimization of HVAC systems using a dynamic neural network. Energy, 2012. 42(1): p. 241-250.

[72] Marvuglia, A., A. Messineo, and G. Nicolosi, Coupling a neural network temperature predictor and a fuzzy logic controller to perform thermal comfort regulation in an office building. Building and Environment, 2014. 72(0): p. 287-299.

[73] Soyguder, S. and H. Alli, An expert system for the humidity and temperature control in HVAC systems using ANFIS and optimization with Fuzzy Modeling Approach. Energy and Buildings, 2009. 41(8): p. 814-822.

[74] Pal, A.K. and R. Mudi, Self-tuning fuzzy PI controller and its application to HVAC systems. International journal of computational cognition, 2008. 6.
[75] Bai, J. and X. Zhang, A new adaptive PI controller and its application in HVAC systems. Energy Conversion and Management, 2007. 48(4): p. 1043-1054.
[76] Paris, B., et al., Heating control schemes for energy management in buildings. Energy and Buildings, 2010. 42(10): p. 1908-1917.
[77] Moon, J.W. and J.-J. Kim, ANN-based thermal control models for residential buildings. Building and Environment, 2010. 45(7): p. 1612-1625.
[78] Moon, J.W., Performance of ANN-based predictive and adaptive thermal-control methods for disturbances in and around residential buildings. Building and Environment, 2012. 48(0): p. 15-26.

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