HIERARCHICAL FUZZY RULE-BASED CONTROL OF RENEWABLE ENERGY BUILDING SYSTEMS

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ABSTRACT

Proper control of low energy buildings, which is more difficult than in conventional buildings due to their complexity and sensitivity to operating conditions, is essential for better performance. In this paper, a three-level hierarchical fuzzy rule-based supervisory control scheme is described that is capable of optimising the operation of a renewable energy building system. For the first level rules, a fuzzy decision tree is used to choose the appropriate set of rules according to weather and occupancy information; the second level fuzzy rules generate an optimal energy profile; and the third level fuzzy rules determine the mode of operation of the equipment and select the control variables so as to achieve the optimal energy profile in the most efficient way. The controller is developed using a computer simulation of a typical building using a renewable energy system. The optimization is partitioned into long-term energy profile optimization and hourly subsystem optimization. Fuzzy rules are learned from data generated by the above optimization. A hierarchical structure is used to reduce the number of rules, trim redundant information and reduce the computing time required for the optimization. The energy consumption and the thermal comfort when using the proposed control scheme is compared with those when using expert rule based control.

INTRODUCTION

The greatest energy consumption in buildings occurs during their operation rather than during their construction. Optimized control is vital for the performance of low energy buildings. There are some major differences between renewable energy systems and conventional systems: the existence of local energy generators; the intensive interaction with the natural environment; the different building insulation standards, the relationship between the renewable systems and the conventional back up systems. These factors introduce new problems that make the proper control both complicated and challenging.

Some work has already been reported by several researchers. Predictive control is widely adopted to optimize building behaviour to save energy and improve comfort. The future load and environment are input into a building simulation model, an optimization algorithm is used to find optimum set points[1,2,3,4]. At the equipment level, the mode of operation is chosen so as to achieve short-term set points or sub goals[5,6]. Genetic algorithms, neural networks, dynamic programming and fuzzy logic are popular methods to solve the complex nonlinear problem of building energy system optimization [7]. Although some promising results have been presented, the high computational demands of on-line optimization limit the practical application of most of the proposed methods.

In this paper, a method of partitioning the high dimensional problem into sub problems is introduced to reduce the optimization time. A novel hierarchical fuzzy supervisory controller is generated from results of off-line optimization and the performance of this controller is compared with the performance of a controller based on expert rules.

SIMULATION OF A LOW ENERGY BUILDING SYSTEM

A typical low energy building system located in central England [5] is used to investigate the design of the hierarchical control scheme. The building includes three different zones: an exhibition room (217.9m^2), a dinning area (74.0m^2) and a class room (178.6m^2).

The heating system is composed of two subsystems, a water circuit and an air circuit. In the water circuit, all the equipments (a boiler, a solar water collector, a VPV heated coil, an AHU heating coil) are all connected to a stratified hot-water storage tank. In the air circuit, the system is composed of a VPV unit, a heat recovery heat exchanger, an AHU, three heated zones, air supply fans and air dampers. The system can run in different modes according to the positions of the dampers. The inlet air can be preheated by the VPV unit, warmed by heat recovery, and heated by the AHU or a combination of them. The VPV unit can work in four modes: cool the PV cell, preheat the inlet airflow, store the thermal energy from the VPV unit into the hot-water water tank or turn off. Details of how the system works and the modes of the operation of the VPV unit are given elsewhere[5,8].

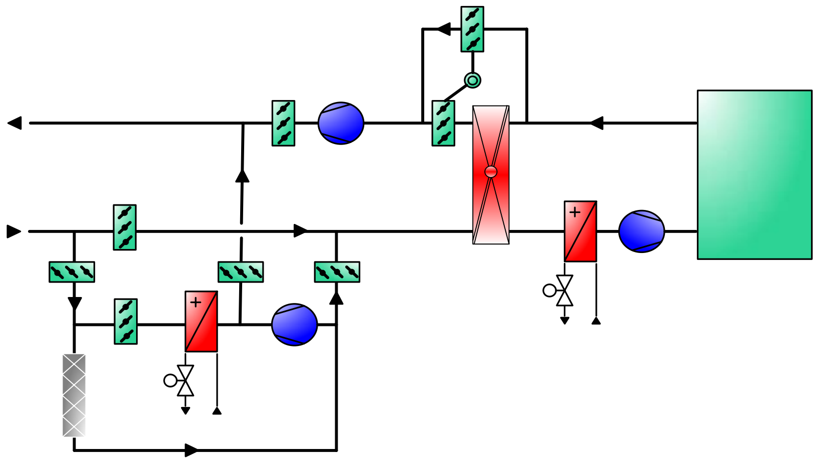


Figure 1 Air sub system

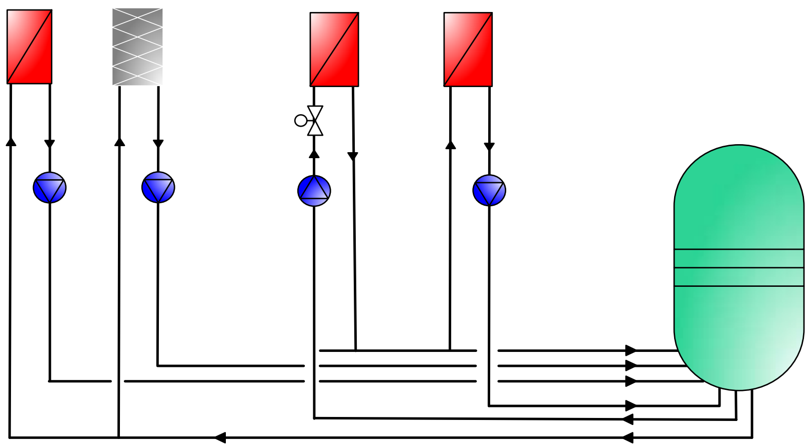


Figure 2 Water sub system

The system is simulated in a MATLAB/SIMULINK® environment. A simplified first order room model is adopted. A commercial HVAC toolbox [9] is used to model the equipment and outdoor environment. This simulation of the building and the equipment is used to develop the optimal controller and to validate the hierarchical fuzzy rules.

HIERARCHICAL FUZZY RULE BASED SUPERVISORY CONTROL

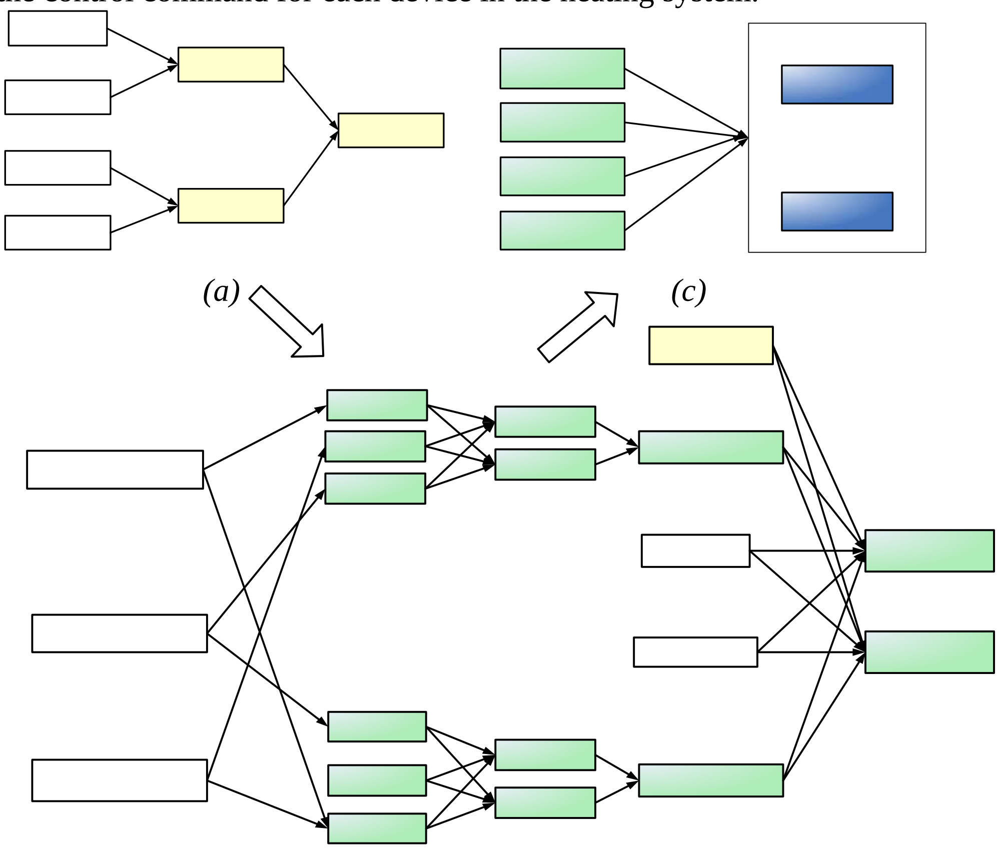
A hierarchical fuzzy rule based control strategy is proposed for the optimum control of the heating system. Fuzzy rule based controllers are widely used on systems with high uncertainties and can be interpreted linguistically. It is also easier to adapt them online than to identify the system model online. The rules are of the following forms:

Rule Level 1: ***If** A1 is LOW **&** B1 is HIGH **&** C1 is MEDIUM **Then** D2 is 3.4*

Rule Level 2: ***If** D2 is LOW **&** E2 is HIGH **Then** F3 is 5.6*

Rule Level 3: ***IF** F3 is LOW **&** G3 is HIGH **Then** H4 is 1*

Fuzzy rules are generated from optimization results calculated for values of the inputs at the centres of the fuzzy sets. Even if it is assumed that each of the fuzzy input variables is described by only 3 fuzzy sets, the total number of rules would be very large (3^{78}). It would therefore take many years to generate the rules and they would be very difficult to understand. A hierarchical approach is adopted to reduce the number of fuzzy rules. The control strategy is split into 3 levels. At the first level, the date, time, schedule and prediction of the future outdoor temperatures are used to decide which of the rules at the second level and third level will be used. At the second level, predictions of the future solar radiation, outdoor temperature and internal load are used to find the optimal tank and building temperatures. At the third level, the room and tank temperature set points are used, together with a measurement of the current solar radiation and an estimate of the excess energy that is currently available, to determine the control command for each device in the heating system.



(a) *(c)*

(b)

Figure 3: Hierarchical fuzzy rules (a. sub rule selection; b. set points rules; b. action rules)

Even with this three level hierarchy, the total number of rules is still very high (3^{74}). The following changes are made to reduce the number of rules further.

1) The optimization is based on the average values of future operation conditions

As can be seen in Figure 3, predictions of the future outdoor temperature, solar radiation and internal load are used to determine the long term energy profile. However, because the future is uncertain, it is unnecessary to calculate these values to such a level of details. The average values of the data are used instead, which reduces significantly the input variables but maintains the key information. The number of rules is then reduced to 6723.

2) Intermediate variables

The total number of rules can be reduced further by introducing hierarchical rules inside level 2. The details are given in Figure 3.b. The intermediate variables, which maintain physical and linguistic meaning, are chosen so that the reasoning process is similar to that used by an expert. The total number of rules is then reduced to about 350.

HIERARCHICAL OFF-LINE OPTIMIZATION OF THE SYSTEM

The fuzzy rules are identified from data obtained from off-line optimization of the simulated system. The task of the optimization is to operate the equipments so as to achieve maximum comfort with minimum energy consumption. The behaviour of the system is dynamic, complex and nonlinear. The search space of the off-line optimization is large (see Figures 1) as there are 10 independent binary variables (P1~P5, D1, D4, D5, Fan1, Fan2) and 3 independent analogue variables (the positions of the AHU valve; preheat VPV dampers; heat recovery bypass-face dampers). A future sequence of the control variables must be considered to guarantee a long-term optimum [5]. The length of the time horizon is dependent on the time constant of the building. Here it is chosen to be 24 hours. Therefore, the optimization search space is more than 2^{312} (the value when all of the control signals are assumed to be binary). Besides, the simulation problem is stiff because some equipment has very small time constant compared to the building. The size of the search space, the nonlinearity of the system and the stiffness of the simulation result in an optimization problem that exceeds the current capability of most computers. A method of simplifying the problem is therefore needed.

Because the equipment can reach steady state much faster than the building, by choosing the time step properly, the devices will have reached steady state at every step and the dynamics of building can be represented adequately. On this time scale, the only linkage between the present and future is the energy stored in the building and the hot-water storage tank. One hour is generally used as the time step by researchers for long term energy analysis in buildings. For short term device simulation, a 10 seconds time step can meet most requirements. The problem can be partitioned into maximizing the long term performance by choosing sub goals and achieving the sub goals by optimising the equipment control variables. The energy stored in building and tank can be used as sub goals because they are the only linkage of the current and the future in the hourly analysis. By this approach, the searching space of the problem can be reduced to 2^{24}.

To optimize the long-term energy profile, a simplification of the Dynamic Programming (DP) method is. At every hour, different set points of tank temperature and building temperature are used to define the current status, and the possible actions are the transitions from the current set points to the next set points. The search is accelerated by checking when the cost of a sub root is bigger than a threshold value, in which case the region associated with this sub root will not be searched. This boundary check technique reduces the searching space by about 50%. For the short term optimization of the equipment, traditional optimization methods are not useful because of the mixed-integer nature and nonlinearity of the problem. Exhaustive search is used in this case. A genetic algorithm can be used to accelerate the searching process for more complex problems. Using this divide and conqueror approach, all the fuzzy rules can be generated in 48 hours on a Pentium® 3.4GHz PC.

PERFORMANCE ANALYSIS

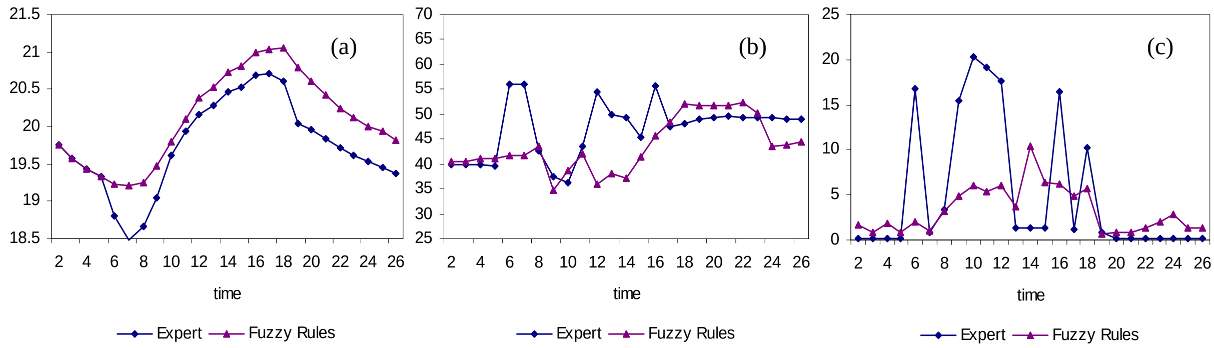


Figure 4 Comparison of the performance of the expert and fuzzy rule-based control schemes (a) room temperature (b) tank temperature (c) energy consumption

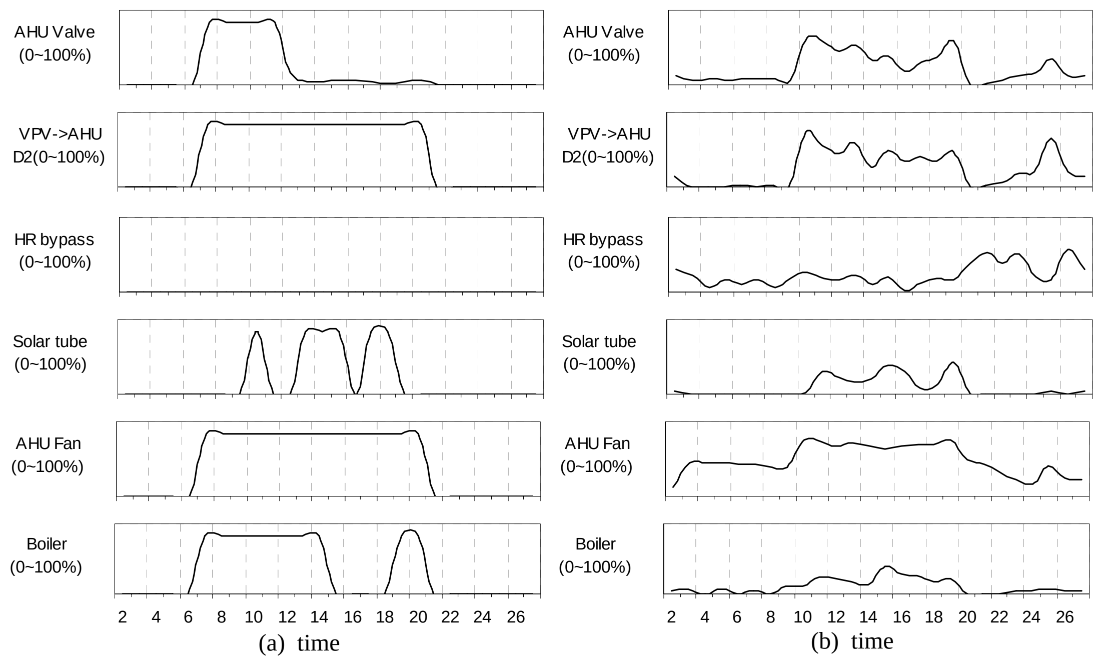


Figure 5 Behaviour of the equipment (a) expert rules (b) fuzzy rules

The performance of the hierarchical fuzzy rules is compared with the performance of the expert rules for a typical winter day in Figure 4. The expert rules, which are acquired from the designers of the real system [5], are used as a bench mark for comparing the energy consumption and the thermal comfort. Here it is assumed that the initial tank temperature is 40°C and the initial room temperature is 20°C. The simulation starts at 2:00 am.

The hierarchical fuzzy rules maintain a higher room temperature than the expert rules which leads to better thermal comfort performance and avoids discomfort at the beginning of the morning. With the expert rules, the low building temperature observed during this period is caused by the use of a simple time schedule to control the ventilation flow rate. The indoor temperature cannot be maintained because both the outdoor temperature and the tank water temperature are low in the morning. The hierarchical fuzzy rule-based controller identifies this problem, preheats the building and limits the flow rate for the morning ventilation. The fuzzy rule based controller uses less energy and provides better comfort conditions. The total energy usage and the percentage of the time the building temperature is in the comfort region are given in Table 1.

	Method name	Energy(kWh)	Comfort (*)	Description
1	Expert rules	128	91%	* = the percentage of the time the building temperature is in the comfort region
3	Fuzzy rules	82	100%	

Table 1 expert rules vs. fuzzy rules

CONCLUSIONS AND FUTURE WORK

A hierarchical fuzzy control approach is introduced in this paper. This novel approach reduces the fuzzy rule numbers but still maintains the linguistic meaning of fuzzy variables. The optimization of the low energy building system control problem is partitioned into two sub problems: long term optimization of energy profile and short term optimization of the equipment operation. The performance of the hierarchical fuzzy rule based controller is compared to that of an expert rule based controller. The results show that the hierarchical controller has better thermal comfort performance while using less energy.

Future work will consider using fuzzy decision trees to analyze the sensitivity of the fuzzy rules to different antecedents and develop an automatic method of searching for the intermediate variables, rather than relying on expert knowledge. Online adaptation of hierarchical fuzzy rules is also to be investigated because offline optimisation using an inaccurate simulation of a real system will inevitably generate suboptimal rules.

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