Agent-Based Control of Thermostatic Appliances

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Abstract

Efficiency control of thermostatically controlled appliances has been studied in the literature. Programmable thermostats and computer assisted control systems have been developed. The growing interest in smart grid coincided with the increasing awareness and research in agent-based technologies. This paper discusses an approach for adaptive control of thermostatically controlled appliances. A methodology for utilizing evolutionary agents as control mechanisms as well as a case study of agent-based control of residential water heaters is presented.

1. Introduction

In recent years there has been a heightened public desire to conserve energy consumption. Energy consuming appliances in residential, commercial and industrial settings are good candidates for energy conservation. In particular thermostatically controlled appliances, with on and off cycles have been targeted as sources of conservation.

Efficiency control of thermostatically controlled appliances has been addressed in the literature. Industry has responded with offers of programmable thermostats and computer assisted control systems. This paper offers an agent-based approach for the control of such appliances for significant efficiency gains.

Research on agent-based systems for autonomous control of energy devices has been reported in the literature. Agents have been utilized in areas such as: electrical infrastructure [1], distribution control [2], energy consumption in general [3], and grid load balancing [4]. In fact, the smart grid paradigm views agent-based technologies as the most viable source for control of the energy grid and its components ([5], [6], and [7]).

Agent-based control offers the ability for appliances to learn the patterns of energy consumption and determine an optimal, or near optimal, control schema. Such learning capabilities have not been sufficiently addressed in the literature. The current research relies on human intervention and produces sub-optimal results.

This paper presents an agent-based methodology for learning the usage patterns of energy consuming appliances (ECAs) and generating an optimal control schema from the learned usage patterns. The agents controlling an ECA make use of a genetic algorithm with a novel representational format for determining the optimal control schema. Also presented is a case study utilizing this agent-based methodology for control of a residential electrical water heater.

The remainder of the paper is organized as follows. Section 2 describes the control agents and their genetic algorithm. Section 3 presents the use of the proposed control agents for the control of ECAs. Section 4 illustrates the effectiveness of the proposed methodology through a case study which utilizes the agents to control a residential water heater. Finally, Section 5 offers concluding remarks.

2. Agent Overview

Agents are software programs embedded within an appliance, sensing demand and directing control of the appliance. The genetic algorithm, used by the agents discussed in this paper, evolves a population of individuals towards better solutions through processes of cross-over and mutation [8]. The fittest individual in the population defines the control schema for the agent for a given period of time.

The individuals of the population may use different formats for representing the control schemas. In the case of the proposed agents this representation is a bit string representing the ability for an appliance to run (e.g., 1) or not run (e.g., 0) for a given time.

Standard genetic programs utilize a haploid or single genotype, representation of agents as in (1).

$$ind_i = \{x_1, x_2, ..., x_n\} \text{ for } n \in \Re^2 \text{ and } x \in \{0,1\} \quad (1)$$

where ind_i is the i^{th} individual in the population of the genetic algorithm and x_i is the i^{th} member of the schema. The proposed agents utilize an explicit diploid representation for the genetic algorithm as in (2).

$$ind_i = \begin{cases} x = \{x_1, x_2, ..., x_n\} \\ y = \{y_1, y_2, ..., y_n\} \end{cases} \text{where } x_j, y_j \in \{0,1\} \quad (2)$$

where the vector x represents the dominant genotype and the vector y represents the recessive genotype of the individuals in the population. The recessive genotype is utilized as memory of previously encountered environments.

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Each individual in the genetic algorithm is determined to be "*fit*" based upon a given fitness function. Fitness determines the ability of a given individual to be utilized by the evolutionary processes of crossover and mutation. The more fit individuals have a greater probability of being selected for use by the evolutionary processes. The fitness of the proposed ECA control agents is explained in greater detail in Section 3.

The use of the explicit diploid representation allows agents to "*memorize*" optimal schemas for previously encountered environments. Upon a detected change in the current environment (e.g., a significant decrease in best fitness of the agent) the agent's genetic algorithm queries the recessive genotypes of the population to discover previous solutions that are similar to the newly encountered environment and which may speed the convergence of the algorithm in the new environment. This use of the recessive genotype allows for the genetic algorithm to continue functioning despite the fitness function, and thus the environment, changing. This explicit diploid representation is a novel approach to give genetic algorithms memory within the agent.

The recessive genotypes are populated at the time of fitness change detection. If a significant decrease in fitness is detected, the algorithm stores the current best solution in one or all of the recessive genotypes. Upon the first change detection each of the recessives in the population are populated with the same best solution. Thereafter a similarity metric such as (3) is used to determine the recessive genotype most similar to the current best solution. That recessive genotype is then replaced with the current best solution.

$$similarity_i = \sum_{j=0}^{N} \begin{cases} 1 \text{ } if \text{ } ind_{ij} = best_j \\ 0 \quad otherwise \end{cases} \qquad (3)$$

In addition to using the recessive genotypes at change detection to assist the genetic algorithm in rapid convergence to a good solution for the new environment, the explicit diploid genetic algorithm utilizes the recessive genotypes for a form of hypermutation. This hypermutation allows the dominant genotype to be replaced by its recessive counterpart in a given individual. This is performed randomly based upon some small percentage set as a parameter to the algorithm. This replacement of the dominant by the recessive has shown to assist the algorithm in anticipating changes in the environment [9].

The use of the explicit diploid genetic algorithm within the control agents is presented in the next section.

3. Use of agents for control of ECAs

The agents proposed to control ECAs utilize the explicit diploid genetic algorithms of Section 2. This section describes the control schema that is generated and how this schema is utilized for control of the ECAs.

During normal appliance operation the agents record the consumption of energy by the appliance. In the case of thermostatically controlled appliances the true demand usage patterns are learned through data mining techniques which remove the cycling of the appliance. The agents utilize this usage pattern record, in part, to measure the fitness of each control schema in the population of the agent's genetic algorithm.

In addition to learning the usage patterns of an ECA the proposed agents may also receive input from a smart meter concerning variable pricing. Often utilities charge different prices for peak and off-peak electricity. This rate history is also utilized by the genetic program of the agents to determine the fitness of the individual control schemas within the population.

The fitness of each individual schema in the population of the agent's genetic program is determined through measuring its control schema against the true usage pattern and the rate history. Control schemas are considered fit if they allow for energy consumption at the times indicated by the mined true usage patterns and minimize energy cost as determined by the rate history. The fittest schema in the population is utilized by the agent as its primary schema for a given time.

The primary schema is used by the agent to determine if the ECA should be allowed to operate at a given time. The schema utilized by the proposed agents indicates times in which the appliance should be allowed to operate (e.g., a 1 in the schema) or not be allowed to operate (e.g., a 0 in the schema). The schema is therefore a bit string representing 10 minute increments for an entire week starting at midnight on a given day.

Consumer buy-in of such control would be limited if the agent-based control system did not allow for energy consumption upon their schedule. To account for this, the agents utilize sensors to detect a demand on the ECA. In the case of water heaters this demand would be in the form of flow out of the water heater's reservoir tank. While allowing for unforeseen usage of energy by the consumer of the appliance, the agents continue to learn usage patterns. These new patterns change the environment causing the current pattern to be stored in the recessive genotypes of the explicit diploid genetic algorithm of the agents.

Other factors are also considered by the agents when determining the ability of an ECA to operate at a given time. In the case of a water heater, tank temperature decreasing to 65% of the normal set point would allow the appliance to run regardless of the control schema. Additional factors may include information from a smart meter which may cause the appliance to not operate due to emergency situations such as brown outs or black outs.

4. Residential Water Heater Case Study

In this section, the explicit diploid agents are applied to control and optimization of an electric residential water heater. Such heaters are ideally suited for a case study of agent-based control as they represent a significant amount of energy consumption (25% of all household consumption according to the Department of Energy [10]). A significant portion of this consumption is exhibited by the cycling of the water heating system to maintain water temperature even when a demand for heated water does not exist.

Residential water heaters typically contain a reservoir (tank) of water which is maintained at a specific set point temperature. This reservoir is known to lose heat at a constant rate. Modern water heaters are often insulated to decrease this heat loss. Taking into account the standard heat loss and the insulation of the tank, the heat loss of residential tank water heaters is expressed in (4).

$$H = \frac{9.59A(T_{hot} - T_{cold})}{R} \tag{4}$$

where: H is the heat loss [J], A is the surface area of the water heater as given in Eq. (5) [m^2], T_{Hot} is the water temperature in the tank [^{o}C], T_{Cold} is the air temperature of the room containing the heater [^{o}C] and R is the R-value of the insulation [K/W]

$$A = 2(\pi r)^2 + 2(\pi r h) \tag{5}$$

where: r is the radius of the water heater tank [m], and h is the height of the water heater tank [m].

Thus, without demand on the water heater a loss is occurring and the unit must cycle to maintain its temperature. When the hot water is used (a demand is made), the water heater temperature drops even more due to the cold water added to the tank to make up for the hot water used as the demand. For the purposes of this case study, demand decreases the temperature of the water within the tank instantaneously according to (6).

$$tnk_{temp} = \frac{\delta_{in}\tau_{in} + \delta_{cur}\tau_{cur}}{tnk_{size}} \tag{6}$$

where: δ_{in} is the amount of water being replaced in the water heater[l], τ_{in} is the temperature of the water coming into the water heater, [^{o}C], δ_{cur} is the amount of water of water currently in the water heater, [l], and τ_{cur} is the temperature of the water currently in the water heater, [^{o}C].

This case study utilizes a simulated electric water heater with a reservoir. The water heater being simulated has a reservoir that is 1.4732 m tall with a radius of 0.3556 m. The insulation factor of the insulation surrounding the tank is set at 90.85 K/W and the room temperature is given as 20^{o} C. The temperature of the water in the tank (to be maintained) is set at 57.22^{o} C.

The given simulation utilizes external files to define demand of the consumer on the appliance. This file indicates the hour at which an event should occur and the number of gallons that should be utilized by the simulated consumer for the event. The simulation then randomizes the demand by randomly choosing a time within the given hour for the event to occur as well as randomly choosing a percentage (70%-100%) of the predefined usage to simulate. During a run of the simulation the external files are changed to simulate changes in usage patterns such as company arriving for an extended stay.

In addition to the demand file, the simulation utilizes flexible pricing. For this simulation, electrical energy costs are set at \$0.15 per kwh for peak usage (8am – 6pm) and \$0.08 per kwh for off-peak usage.

Fig. 1 illustrates the normal operation of a water heater. The vertical axis represents the amount of heat loss while the horizontal axis represents time.

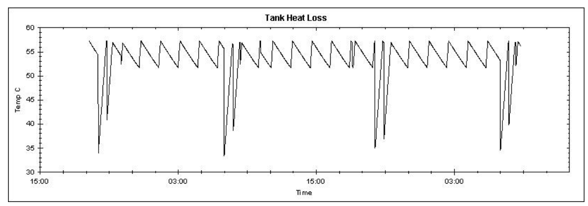

Figure 1. Simulated Water Heater Tank Loss Under Normal Operation for 24 hours

To maintain the proper temperature in the water heater tank, energy must be consumed to account for the heat loss. This energy is used to return the temperature of the water within the tank to the original set point, provided by the end user. Fig. 2 presents the energy consumption required to maintain the tank's water temperature for the example illustrated in Fig. 1.

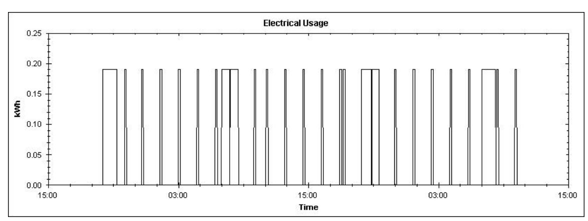

Figure 2. Energy Consumption for the Case Given in Fig. 1.

The agent-based control proposed in this paper learns the usage patterns of the appliance as shown in Fig. 1. This learning takes place by recording the energy consumption of the water heater. The data in this record is then clustered (e.g., k-means algorithm) to determine the true demand as opposed to cyclical consumption. The agents maintain a history of the true demand and utilize this history as part of the fitness function for the genetic algorithm which determines the optimal control schema to reduce consumption.

Fig. 3. presents the energy usage of the simulated water heater for a seven day period. This is compared to Fig. 4. which illustrates the agent controlled consumption for the same time frame. Again, the vertical axis represents usage while the horizontal axis represents time.

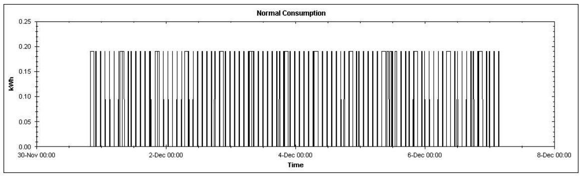

Figure 3. Normal energy usage for a 7 day period

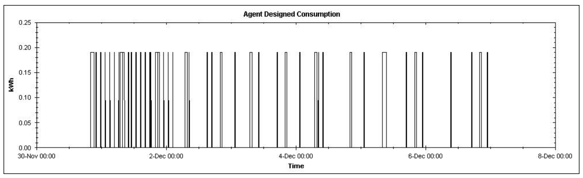

Figure 4. Agent-based controlled usage for the same 7 day period as given in Fig. 3.

As can be seen in Fig. 4, the agent-base control learns the actual demand pattern of the consumers upon the water heater and develops an optimal control schema based upon that pattern as well as the flexible pricing rate history.

Clearly, the proposed agent-based control system is more efficient than standard thermostatic control of the simulated water heater. In fact, it has been shown (through this simulation) that the proposed agent-based control generates a savings of over 55% of the normal operation, in just 14 days, and reduces the cost of energy through minimizing rate costs. This is shown in Fig. 5 where the topmost increasing line indicates the normal usage, the bottom line shows the usage of the agent-based operations and the middle line indicates the savings percentage of the agent-based control over normal usage.

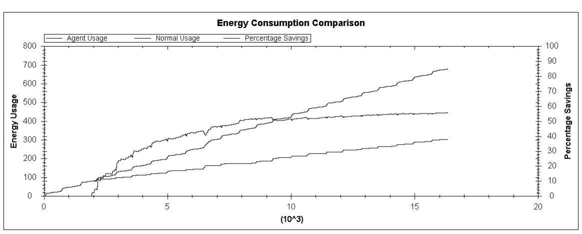

Figure 5. Savings of the agent-based control over the normal operation of the simulated water heater.

This case study has illustrated that agent-based control of thermostatically controlled ECA produces an optimal control schema which significantly reduces energy consumption of a residential water heater. This case study is easily extended to all thermostatically controlled ECA.

5. Conclusion

In this paper the application of an agent-based approach in control of energy consuming appliances was discussed. A novel explicit diploid representation was proposed to enhance the genetic algorithm with a memory of previously encountered environments. This novel explicit diploid agent control system was applied to optimize energy usage of a simulated residential water heating system. This novel control methodology produced a 55% savings over normal operations of the simulated residential water heater in just 14 days of operation. Given that residential water heating accounts for 25% of all energy consumed in households, this results in a household energy reduction of 13.75%, which is significant.

Future research in this area will include the ability for the agent-based technologies to communicate with one another via ontologies to form an emergent whole building control system. Additionally, the agent-based technologies should communicate with the external world with similar ontologies to receive data not discussed within this paper.

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