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EVALUATION OF MULTI-AGENT SYSTEM ARCHITECTURE FOR COORDINATION OF PRODUCTION AND DISTRIBUTION OF HEATING SYSTEM USING LEARNING POLICY

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Abstract

In this paper, multi-agent systems for the coordination of a distributed control system for production systems are used to distribute hot water to end users. A heating system comprises production units, a distribution network, and a host of consumer substations. The operation of a heating system usually involves satisfying customers and minimizing production costs. The optimal operation of the district heating system is therefore limited to providing a sufficiently high temperature and pressure to all customers by taking local measurements to achieve this goal without considering other factors such as cost of production and time. The approach studied in this paper is to equip stations with software agents to form a multi-agent system using learning policies. The purpose is to dynamically control the heating system using demand-side management strategies. The simulation tool simulates a heating system to functionally and dynamically support interaction at each time step with the multi-agent system. The tool enables detailed performance analysis of both district heating systems as well as of different strategies of the control system. Results from simulation studies indicate that the approach makes it possible to reduce production costs while maintaining the quality of service. This shows that it is possible to automatically load balance a small district heating network using agent technology.

Key words: District heating system (DHS), multi agent system (MAS) multi-agent control system (MACS)

I INTRODUCTION

This work mainly investigates the applicability of multi-agent systems (MAS) as a distributed control approach for district heating systems (DHS). The consumers, i.e., the heat exchange systems, in current DHS employ purely reactive devices and have typically no communication capabilities. They are only able to make local decisions without taking the global situation in the system into account. In this work, an intelligent multi-agent system is designed using a learning policy that has the advantage of interacting with the environment (the heating system) in order to maximize a reward that is the minimization of production cost for any variation in the consumption level of the substation.

A "distributed control system" usually refers to systems composed of interconnected components like sensors, actuators, and controllers. The availability of small computational units has led to an increasing degree of decentralization within automation systems and a distribution of functionality across geographically dispersed devices. However, resulting from this distribution of devices is an increasing amount of communication and increasing effort for the configuration of individual devices as well as the complete system (Brennan and Norrie 2014). The development of distributed and heterogeneous systems, such as software for automation and control, poses significant challenges for system developers. In general, the functions that can be automated in distributed systems are classified into two categories: monitoring functions and control functions. The properties to consider are comparable to the general properties of complex decentralized systems as described by Rinaldo and Ungar (2014). Furthermore, because automation systems are typically subject to ongoing partial modification, such as the introduction of new hardware, there is a strong requirement for software flexibility and adaptability. They are modeled as reactive systems; hence, they do not have the ability to learn the long-term characteristics of the environment. The most common model for distributed automation and control systems is probably the supervisory control and data acquisition (SCADA) model. The SCADA model is centralized by nature. From a central reading location, a master station monitors a number of remote sites (substations) equipped with remote telemetry units. The remote units measure various conditions and report the data back to the master station, which is carrying out the necessary analysis and control functions. While the SCADA model provides acceptable performance and reliability, experience has shown that this approach can lead to a lack of system fault tolerance, reconfigurability, extensibility, and adaptability (Ferber 2015).

II LITERATURE REVIEW

Researchers in many fields, including computer science, economics, and psychology, have studied the area of coordination, which can be viewed as "managing the interdependencies among activities" (Wernstedt et al. 2019). From the MAS perspective, coordination is a process in which agents engage in order to ensure that a community of individual agents acts in a coherent manner (Bellifemine et al. 2017). A variety of mechanisms have been developed to manage coordination problems. On one side are organizational structures and social laws (Davidsson and Wernstedt, 2018), long-term rules that govern the behavior of a society of agents. On the other end are the black board model (Ferber, 2015) and the one-shot protocols, e.g., contract network (Huhns and Stephens, 2015). In the middle are techniques like partial global planning (Malmström et al. 2011) and various negotiation techniques like market-based (Nwana et al. 2011) and game-theoretic (Paranak 2015). Several researchers have shown that there is no single best organization or coordination mechanism for all environments (Parunak 2016). We will here concentrate on closed MAS, in which the structure of the system can be decided at design time and where agents basically cooperate in order to fulfill a goal on the system level.

The main objective of the research is to investigate the applicability of agent technology for distributed control of DHS. The basic research questions addressed are to design a MAS model for the support of decentralized control in DHS and to design a simulation model for the analysis of real-time control strategies for DHS.

III RESEARCH METHODOLOGY

The learning policy technique was used in this thesis to describe the core subsystems suitable to be modeled as software agents for the district heating system. In this technique, a systems designer moves from having no knowledge of the environmental conditions to increasingly concrete concepts where the interaction with the environment leads to an optimal solution of the environmental variables. Rewards are assigned to the goal value in each state (substation consumption level), and after an exhaustive interaction with the environment, the state with the highest reward is chosen for each substation.

Unlike in other learning policy environments where the model of the environment is not explicitly designed, the abstract concepts to be used during analysis to conceptualize the system in this research will be modelled using the MATLAB toolbox. In order to further evaluate the applicability of MAS for control of the DHS, a high-granularity simulation tool was needed where every part of the DHS was modeled at a detailed level, e.g., the water flow and temperature propagation in every part of the distribution network needed to be modeled. All of these control structures can be simulated using MATLAB's Simulink tool. This thesis also includes a theoretical analysis based on a literature study regarding the properties of agent-based and classical optimization techniques to evaluate the advantages and disadvantages of distributed agent-based approaches compared to classical mathematical optimization techniques. Finally, to generalize the domain of DHS, we develop a formal characterization of the logistics network and describe DHS in terms of this general framework.

3.1 The Multi-agent system Model for Distributive Heating System

Q-learning is a reinforcement learning method in which an agent interacts with the environment in order to maximize a cumulative reward. The agent learns through continuous interaction with the environment by going through the state spaces. In a dynamic sequential decision-making process, the *state* $S_t \in \mathcal{S}$ refers to a specific condition of the environment at discrete time steps t=0,1,…. The states in this research are the different substations. By interacting and responding to the environment, the agent chooses a deterministic or stochastic *action* $A_t \in$ (selecting from a pool of consumption levels) that tries to maximize future returns (maximal supplies heat energy to substations at all times) and receives an instant *reward* $R_{t+1} \in \mathcal{R}$ as the agent transfers to the new state S_{t+1}. The reward is usually represented by a quantitative measurement.

The generalization of the Markov decision process to the multi-agent distributive heating system is the stochastic game.

A stochastic game is a tuple $(X, U_1, \ldots, U_n, f, \rho_1, \ldots, \rho_n)$ where n is the number of agents, (substations) X is the finite set of environment states, (i.e. different substations) U_i, i= 1, . . . , n are the finite sets of actions available to the agents, (different consumption level of the substation), yielding the joint action set $U = U_1 \times \cdot \cdot \cdot \times U_n$, $f : X \times U \times X \rightarrow [0,1]$ is the state transition probability function, and Ui: $X \times U \times X \rightarrow$R, i= 1, . . . ,n are the reward functions of the agents.

It is assumed here that the reward functions are bounded. In the multi-agent case, the state transitions are the result of the joint action of all the agents, $u_k = u_{1,k}^T, \ldots \ldots . u, u_{i,} k \in U_i$ (where T denotes vector transpose). The policies $hi : X \times Ui \rightarrow [0,1]$ form together the joint policy h. Because the rewards $r_{i,k+1}$ of the agents depend on the joint action, their returns depend on the joint policy.

The Q-function of each agent depends on the joint action and on the joint policy, this is depicted Q_i^h: X x U R, with Q_i^h(x,u) = E { $\sum_{k=0}^{\infty} \gamma^k r_{i,k} + 1 | x_0$ = x, u_0 = u,h} 1

In fully cooperative stochastic games, the reward functions are the same for all the agents: It follows that the returns are also the same, and all the agents have the same goal: to maximize the common return. If $n = 2$ and the two agents have opposing goals, and the stochastic game is fully competitive. Mixed games are stochastic games that are neither fully cooperative nor fully competitive. This research deals with competitive stochastic game because the goals of the distributed system and the substations are opposing. The distributed system wants to minimize energy use in supplying hot water to the substations while the substations want to maximize the consumption needs of the customers.

Multi-agent control system

When it comes to a multi-agent control system (MACS) in a district heating system, each agent implements autonomous actions in order to optimally run the substation models in a dynamic system. In most of the studies, the hierarchical central local agent structure is embedded in the district heating system models to balance energy consumption and the consumer's comfort. A multi-object particle swarm optimization (PSO) technique is utilized for optimizing intelligent management. For instance, in a district heating system, the central agent communicates with the substation (consumer) agent to decide the optimal power distribution to each substation by considering their comfort demand. A substation agent, on the other hand, communicates with consumers and decides energy demand. The local agents take care of temperature control, water flow in pipes, expansions in pipes due to heat, and air quality control. The objective function aims at maximizing total thermal comfort and minimizing energy consumption. Similar central local systems utilize FL controllers for maximizing thermal comfort.

IV Result Analysis

The result depicted in Figure 1 show that the substation is set to have a constant demand for radiators. The radiator temperature at the substation is set to 48 °C (approximately 25 kW), and the system is first allowed to reach a steady state for five minutes. After five minutes, the substation initiates a domestic hot water tapping of 0.02 kg/s for duration of five minutes. The system is then given ten minutes to stabilize.

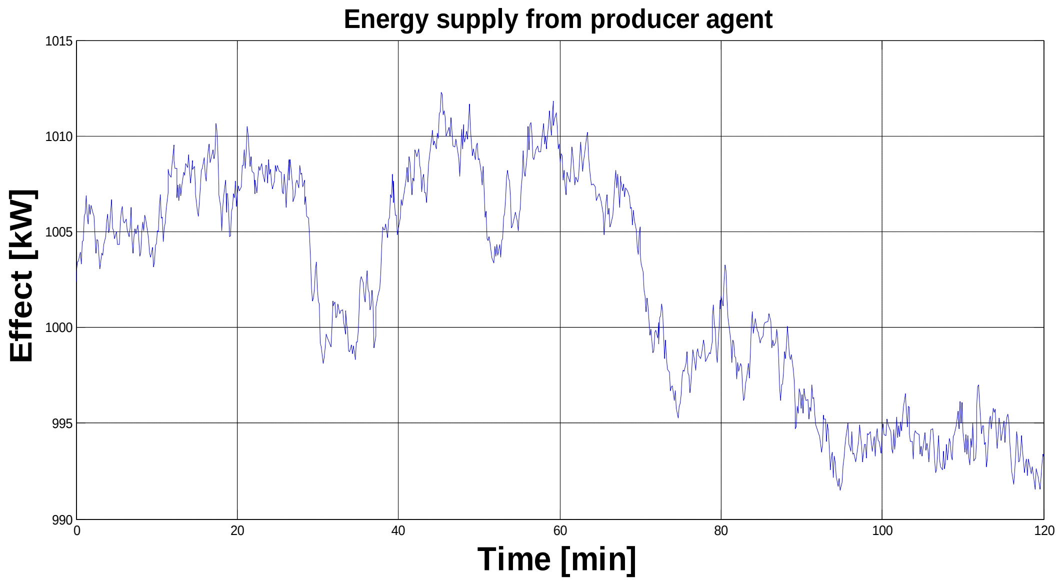

Figure 1: Household heating and domestic hot water tapping from Q-learning model

From figure 1 it can be seen that the Q-learning is able to stabilize the injection of additional heat by adjusting its output production accordingly within the ten minutes interval.

Result and Analysis for different Control Strategies Employed

The control strategies used in the experiment are described in table 1.

Table 1 Control strategies

Q-learning restriction	Consumer agents individually enforce restriction based on the up to date consumption level of the end users
Local restrictions	The consumer agents enforce reductions individually, when the consumptions attains a particular limit. This may require assistance from other consumer agent
Distributed / Hierarchy restrictions	The consumer agents enforce restrictions individually, when the consumptions attains a particular limit

Figure 4.2 shows the total energy consumption for the four different control strategies.

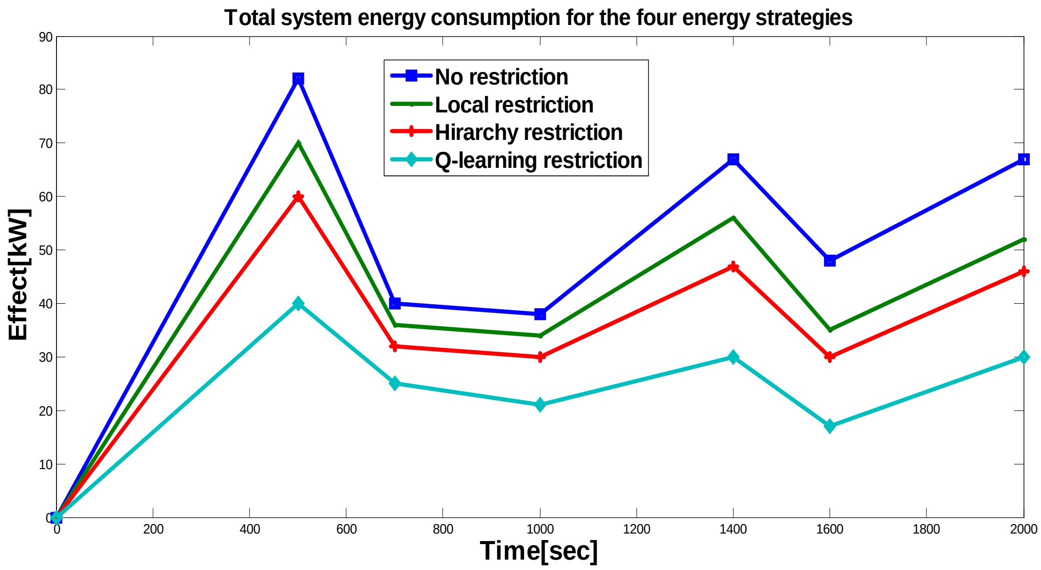

Figure 2: Total system energy consumption for the four control strategies.

The desired global consumption is 50 kW, It can be seen that the strategy of using local restrictions clearly reduces the consumption peaks by 6% and that the strategies to use hierarchical as well as distributed multi-agent-based approaches reduce the peaks by 13%. However, the Q-learning-based approaches take slightly longer (6 seconds) to reach a stable level after reductions. It should also be noted that, despite continuous tapping for five minutes, the strategy with local restrictions fails to reach the limit level of 50 kW. In Figure 4.2, shown the primary flow of the energy consumption indicates that it is important to keep the flow down for reasons of both production and potential flow limitations in the network.

V CONCLUSION

This study highlights the use of learning policy in the design of a multi-agent system for district heating management. A multi-agent system comprises a number of agents that act cooperatively for the attainment of a set goal. To the best of my knowledge, the learning policy technique has never been applied to the monitoring and control of district heating systems. It will provide a novel combination and integration of existing technologies, which will open up new possibilities.

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