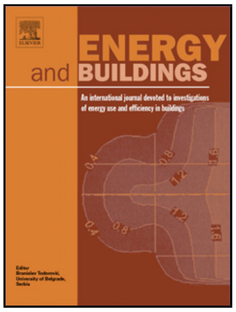

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Model-Free Control of Thermostatically Controlled Loads Connected to a District Heating Network

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Abstract

Optimal control of thermostatically controlled loads connected to a district heating network is considered a sequential decision-making problem under uncertainty. The practicality of a direct model-based approach is compromised by two challenges, namely scalability due to the large dimensionality of the problem and the system identification required to identify an accurate model. To help in mitigating these problems, this paper leverages on recent developments in reinforcement learning in combination with a market-based multi-agent system to obtain a scalable solution that obtains a significant performance improvement in a practical learning time. In a first step, all relevant (and practically available) state information is collected from which a limited set of features is extracted, resulting in a low-dimensional representation of the system state. In a second step, a control action for the entire cluster is extracted from a policy determined offline. In a third and final step, this control action is dispatched over the different thermostatically controlled loads using a market-based multi-agent system. This process is repeated following a receding horizon approach. The control approach is applied to a scenario comprising 100 thermostatically controlled loads connected to a radial district heating network supplied by a central combined heat and power plant. Both for an energy arbitrage and a peak shaving objective, the control approach requires 60 days to obtain a performance within 65% of a theoretical lower bound on the cost.

Keywords: District heating, combined heat and power, reinforcement learning, thermostatically controlled loads.

1. Introduction

A District Heating Network (DHN) offers the opportunity to provide the collective heat demand of a cluster of geographically concentrated buildings through a set of central heat sources. This allows the use of centralized production techniques with an efficiency exceeding that of distributed production. Combined Heat and Power plants (CHPs) are a prominent example, as 80-90% of the primary energy is converted to heat and electricity [1, 2, 3]. But also heat from a geothermal source [4] or excess heat resulting from an industrial process can be used as primary heat source. The heat from the sources is transported through a network of pipes using water as a medium. At each building, heat is extracted in a local substation, resulting in water at a lower temperature, being transported back to the different heat sources. A typical operational model at the production side is to modulate the power of the heat sources to keep the supply temperature close to a design setting. This basically results in the thermal supply following the thermal demand. Heat storage however, can provide demand flexibility enabling flexibility at the production side through demand response approaches. This flexibility allows operational opportunities for cost reduction, examples being peak shaving/valley filling [5] and energy arbitrage by selling the electricity production of the CHP on the wholesale market [1, 2, 6]. Well referenced embodiments of local heat storage are Thermostatically Controlled Loads (TCLs) [7] such as a hot water storage tank [8] where the heat is stored directly in the water, but also the building envelope [1, 7, 9, 10] can be used to store heat.

From an operational point of view, controlling a cluster of TCLs connected to a DHN can be considered as a sequential decision-making problem under uncertainty. One well studied control paradigm for operational management of a DHN is that of Model Predictive Control (MPC) [11**?**]. When projected on the setting of TCLs connected to a DHN, this requires defining control actions for the central sources as well as for all individual TCLs. Developing a practical implementation requires one to tackle the problem of *scalability*, as the state dimensionality and number of control variables quickly result in an intractable optimization problem. This is complicated further by non-linear system dynamics. A second important challenge is that of *system identification* [13] as identifying an accurate model of both the DHN and all TCLs requires significant amounts of not readily available data and expert knowledge.

This work contributes in mitigating operational control challenges for TCLs connected to a DHN by working on these two problems.

Scalability: To obtain scalability, a heuristic dispatch approach as described in [14], is applied to the setting of TLCs connected to a DHN. Instead of calculating an individual con-

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