Abstract

Building energy consumption accounts for a large proportion of global energy consumption. Utilizing energy storage and implementing corresponding control schemes in building energy management systems increase demand-side flexibility. This idea is promising in terms of improving the capability to meet fluctuating $CO2$-factors and energy prices. However, the tradeoff between demand, energy conservation, and economic interest is challenging and requires an appropriate control strategy. Traditional methods based on engineering best practices have difficulties in finding the optimal performance and cannot be easily applied to dynamic conditions, while model predictive control schemes are costly as they require extensive modeling efforts. A further challenge lies in the accuracy of the constructed physical models, which is problematic in many cases. The documentation of the plant, on which the engineer depends in the modeling process, is also problematic. White box modeling is time consuming and prone to error. This thesis presents a selection of machine learning algorithms to address the abovementioned challenges. First, a data-driven modeling approach is applied to model a cooling energy system supplying an adaptive cooling network in Berlin, Germany. The cooling network consists of various business and research facilities. Machine learning algorithms are used to build sub-models, which are aggregated and used as training environment for a reinforcement learning approach. The selected deep Q-learning algorithm and proximal policy optimization are applied to control two chillers and an ice storage to achieve a balance between meeting the cooling energy demands and other economic and ecological constraints.