Monitoring Smart Energy Systems using Multi-timescale Nexting

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With increasing number of externally controllable energy components within smart grids, the complexity of monitoring and controlling each individual component is a challenging task. Continuous monitoring of energy systems is crucial for ensuring reliability and security of the systems, such as generator, grid infrastructure, and residential homes. There has been a significant effort in developing failure detection techniques and outlier detection algorithms. These methods are expected to deliver reliable estimations or predictions of the system status, so as to assist human operators with early warnings or updates of potential issues. They all depend on clear visual presentation of the monitoring data and the experience of the human operator. In case of distributed energy generation systems obtaining this experience is often complex and needs long training periods. Therefore, predictions about future system states are an useful additional information source.

Besides anomaly detection systems, which employ statistics or system models to detect abnormal system states, there are also predictive control systems. Most predictive control systems use one timescale to predict the future behaviour of the considered system. This means the predictions about what is to be happening in the future is restricted to a fixed number of time stepss. On the other side, human beings as well as other animals seem to use experiences from earlier situations to anticipate what is about to happen next and adjust their actions accordingly. Such ability makes it easier for them to take advantage of upcoming opportunities as well as to evade future danger. The process of continuously anticipating the immediate future in a local and personal sense is called nexting. Nexting uses temporal-difference methods to learn multiple long-term predictions in real-time (cf. [1]). The proposed nexting algorithm updates the predictions in each time step solely based on the previous predictions and the newly observed information (sensor readings). A system model is not necessary and with one update multiple time-scales can be efficiently calculated in parallel.

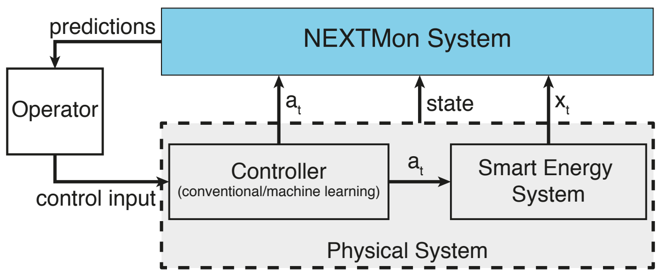

Fig. 1. System Architecture

Recently, such predictions of raw sensor signals are used in a laser welding robot to improve the quality of the weld seam by adjusting the process parameters adaptively [2]. In this work we have implemented those multiple time-scales predictions in a human-in-the-loop control system in a smart home scenario where a simulated heating system is operated by a simple threshold based controller. The indoor temperature is monitored and together with predicted values presented to an operator. The nexting algorithm uses all available information to calculate its prediction: the actual indoor and outdoor temperature and the heater state. In Figure 1 we have depicted the NEXTMon architecture with the physical system representing the energy system to be monitored, the operator controlling the physical system using actual system state information and predictions. With the prediction the operator is able to react proactively to changing system states. Figure 2 shows a timespan of 25 hours of our simulation results where the dashed vertical lines show the possible proactive actions the operator could have triggered to ensure that the temperature stays within the optimal region.

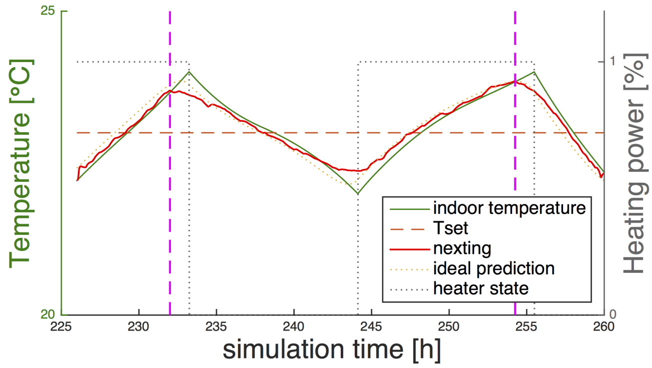

Fig. 2. Simulation Results

Besides this simple heater simulation example, the NEXTMon architecture can be used in systems where raw sensor values are available but no exact system model exists. For example, the prediction of generated wind power using the observed wind speeds and weather forecasts of different locations might be possible. Taken together, the nexting algorithm is straightforward to implement and can be used in energy systems where the exact system model is hard to derive.

[1] J. Modayil, A. White, and R. S. Sutton, "Multi-timescale nexting in a reinforcement learning robot," Adaptive Behavior, vol. 22, no. 2, pp. 146–160, April 2014.

[2] J. Günther, P. M. Pilarski, G. Helfrich, H. Shen, and K. Diepold, "Intelligent laser welding through representation, prediction, and control learning: An architecture with deep neural networks and reinforcement learning," Mechatronics, 2015.