Monitoring and Prediction in Smart Energy Systems via Multi-timescale Nexting

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Abstract—Reliable prediction of system status is a highly demanded functionality of smart energy systems, which can enable users or human operators to react quickly to potential future system changes. By adopting the multi-timescale nexting method, we develop an architecture of human-in-the-loop energy control system, which is capable of casting short-term predictive information about the specific smart energy system. The developed architecture does either require a system model nor additional acquisition of (sensor) data in the existing system configuration. Our first experiments demonstrate the performance of the proposed control architecture in an electrical heating system simulation. In the second experiment, we verify the effectiveness of our developed structure in simulating a heating system in a thermal model of a building, by employing natural *EnergyPlus* temperature data.

Index Terms—smart energy systems, prediction learning, reinforcement learning, multi-timescale nexting.

I. Introduction

Continuous monitoring of energy systems is crucial for ensuring reliability and security of the systems, such as generator, grid infrastructure, and residential home. 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 (or users) with early warnings or updates of potential issues. Commonly, statistics or system models are employed to detect anomalies in the monitored (sensor) data, cf. [1]–[5].

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 seconds or timesteps. 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. Those living things which have been capable of making accurate predictions about the future are better prepared for suitable actions and perceptions than others. This 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*.

The work in [6] demonstrates a technical implementation of the nexting behavior on a mobile robot. The robot was able to learn how to simultaneously predict all its raw sensor signals at different timescales in real time. In a recent work, 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 [7]. A similar concept of automata learning has been also applied to model, analyze, and detect anomalies in energy consumption of a system, cf. [8].

In this work, we propose an architecture of human-in-theloop energy control system, which is capable of predicting semantically meaningful information about an energy system. It enables human operators to take such predictive knowledge into account to further adjust the goal (or system configuration) to keep the system in an optimal state. Our proposed architecture consists of three interative parts, namely, the physical energy system to be monitored, the operator (or user), and the NEXTMon system. The actual physical system is monitored constantly, and grants access to its system states (sensor readings, statistical data) and controller actions. These data are processed by the NEXTMon system and displayed to the user as additional predictive information. The operator as the human-in-the loop assesses all available data and controls the physical system. This human-in-the-loop architecture is depicted in Figure 3.

Compared to conventional prediction algorithms the NEXTMon system does not require an exact system model and therefore is not limited to specific energy systems. The NEXTMon system combines external information sources (like weather forecasts), sensor measurements, and control actions in order to learn the system behavior. While conventional algorithms often rely on fixed models or regression functions, our approach is able to approximate arbitrary functions (similar to neural networks) and adapt them to changing conditions. Learning a predictive model generally requires a lot of data samples and only predicts one timescale. The proposed nexting algorithm requires only few data samples per update step and simultaneously updates weight vectors for multiple timescales.

In the following, we describe both tile coding (Section II) and the nexting algorithm (Section III) as they are the main components of the NEXTMon system. In Section IV and V we describe an example how the system can be used in a room heating scenario. Finally, we present some experimental results in Section VI and a conclusion in Section VII.

II. STATE REPRESENTATION AS MULTI SENSOR OBSERVATIONS

Reinforcement Learning (RL) [9] is an important machine learning discipline and has been successfully applied to solve model free control problems. A common task of RL is to learn the so-called value function which is designed or constructed to reflect the specific control task, and often defined as the

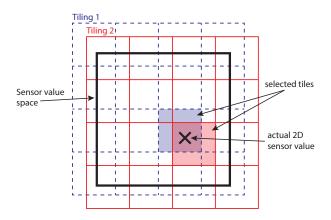


Fig. 1. Tile coding with two tilings for a 2D sensor value state space (adopted from [9])

expected reward. The reward signal often carries incomplete information towards the ultimate goal of the problem. Designing the reward signal differently enables applications of RL in robotics, control, and economics.

A most classic RL method is the so-called temporal difference (TD) learning algorithm. Arguably, the most convenient characteristic of TD methods is via calculating the difference in estimates of the value function between simply two consecutive time steps. Computationally, this requires even less effort than the common stochastic gradient algorithms. This data efficiency is convenient in domains where the current state is acquired with lot of sensors. The algorithm applied in this work is a combination of the basic reinforcement learning framework with a temporal difference update for making short term predictions (c.f. Section III).

Working with RL requires a unique and extensive system representation incorperating all available system information. In small, simulated domains, where RL has proven as an effective learning technique, a good state representation is easily achievable. However, in real world problems where the system state is represented as multiple continuous sensor readings, this could result in a prohibitively large, or infinite, state space.

One technique to overcome this difficulty is the tile coding technique [9], which achieves a good balance between accuracy of representation, computational costs, and complexity. Tile coding is widely adopted and used in different disciplines of RL. In tile coding, the sensor value space is partitioned into tiles (c.f. Figure 1). The complete partition covering the whole sensor value space is called a tiling. For one sensor value space there can exist several overlapping tilings. The algorithm determines for each sensor value the corresponding position within all tilings. The overall resolution of tile coding is determined by granularity and generalisation parameters. Granularity is set by the number of overlapping tilings and the generalization parameters describe the shape of each tile. Dividing a sensor value space into 4×4 tiles and using two different tiles like in the example of Figure 1 results in a coarse generalisation between sensor values, that are within 0.25 of each others for both dimensions. A second tiling with an offset to the first one refines this generalisation. This results in an overall resolution for this example of 0.25/2 or 0.125.

The resulting feature vector representing the actual sensor state is then calculated as follows. Tile coding determines the actual activated tile for each sensor value and each tiling. All tiles on each tiling are sequentially-numbered, thus for each activated tile the corresponding index can be determined. With all activated tiles or indexes a binary feature vector is created. A binary column vector with a length equal to the number of all available tiles is used to represent the state of activated tiles. Each entry of the feature vector ϕ_t for each activated tile is set to one, all other entries are set to zero.

Joint Tile Coding

In Figure 1 an example of joint tile coding is shown. Generally tile coding can be used for each sensor reading and each state value independently. Each value is coded separately and the calculated feature vectors can be concatenated afterwards. Thus tile coding can be considered as a mapping from state information to feature representation and hence formulated as

$$\phi_t = f(\mathbf{x}_t, a_t),\tag{1}$$

where x_t corresponds to all available sensor data, a_t to the actions the controller has performed at time step t, and $f(\cdot)$ the non-linear mapping performed by tile coding. In this work we use bold face notation for vectors and matrices.

In most real world applications there are different types of sensors and variables representing the actual state. An efficient way to achieve a state representation using tile coding resulting in more distinct feature vector in such domains is joint tile coding. Joint tile coding works better than independent tile coding provided that there is limited interaction between the different state dimensions. So for different types of sensors and state values joint tile coding groups are created and there values are coded jointly.

Compared to other feature selection techniques such as radial basis functions, Kanerva coding, etc. tile coding delivers an intuitive way for representing the state features without requiring complex feature engineering.

III. MULTI-TIMESCALE PREDICTIONS USING NEXTING

The common goal of RL is to learn the value function that computes the long-term expected reward. In the multi-timescale nexting setting, the raw sensor signals take on this role of reward within the learning algorithm, they are called *pseudo rewards*.

For each raw sensor signal several predictions with different timescales will be made at each discrete time step t. We indicate variables by the index i to point out that the quantity corresponds to a prediction with the specific timescale i.

The sensor reading at time t, i.e. the pseudo reward at time t concerning the ith prediction, is denoted by $R_t^i \in \mathbb{R}$. The overall discounted sum of the respective future pseudo

rewards R_t^i , denoted by the *return* G_t^i , is defined to be the ideal prediction $V_t^i \in \mathbb{R}$:

$$V_t^i := \sum_{k=0}^{\infty} (\gamma^i)^k R_{t+k+1}^i = G_t^i , \qquad (2)$$

where $\gamma^i \in [0,1)$ is the *discount rate* for the *i*th prediction. Here, G^i_t is the ideal value for the *i*th prediction at time step t – the so-called *ideal prediction*. It is worth noticing that this ideal prediction is simply an approximation of the real sensor signal to be predicted. In order to reflect the correct timescale of the prediction, it is crucial to choose an appropriate discount rate. Specifically, the discount rate γ^i for a timescale of τ^i time steps can be determined by

$$\gamma^i = 1 - \frac{1}{\tau^i} \,. \tag{3}$$

Multi-timescale nexting uses linear function approximation to compute each prediction. If $\phi_t \in \mathbb{R}^N$ denotes the *feature vector* with N features characterizing the state of the system at time step t, all predictions V_t^i can be generated with the scalar products of the feature vector ϕ_t and the appropriate weight vector $\boldsymbol{\theta}_t^i \in \mathbb{R}^N$ denoted as

$$V_t^i \approx \boldsymbol{\phi}_t^{\top} \boldsymbol{\theta}_t^i = \sum_{i=1}^N \boldsymbol{\phi}_{t,j} \, \boldsymbol{\theta}_{t,j}^i \; . \tag{4}$$

Here ϕ_t^{\top} is the transpose of the feature vector ϕ_t while $\phi_{t,j}$ and $\theta_{t,j}^i$ denotes the *j*th component of each vector. The feature vector ϕ_t is calculated using tile coding (see Section II).

For learning these weight vectors, the *linear gradient-descent* $TD(\lambda)$ algorithm is used. The update rule for learning the weight vectors $\boldsymbol{\theta}_t^i$ at each time step t is

$$\boldsymbol{\theta}_{t+1}^i = \boldsymbol{\theta}_t^i + \alpha \, \delta_t^i \, \mathbf{z}_t^i \,, \tag{5}$$

where $\alpha>0$ is a step-size parameter (which influences the rate of learning) and

$$\delta_t^i = R_{t+1}^i + \gamma^i \boldsymbol{\phi}_{t+1}^\top \boldsymbol{\theta}_t^i - \boldsymbol{\phi}_t^\top \boldsymbol{\theta}_t^i$$
 (6)

is the *TD error* for the *i*th prediction at time step *t*. Furthermore, $\mathbf{z}_t^i \in \mathbb{R}^n$ denotes the vector of *accumulating eligibility traces*. Eligibility traces serve as extra memory variables which are linked to each state characterized by the feature vector $\boldsymbol{\phi}_t$. The initial value of the eligibility trace vector \mathbf{z}_t^i is $\mathbf{0}$. Afterwards, the eligibility trace is updated in each step t by

$$\mathbf{z}_t^i = \gamma^i \,\lambda \,\mathbf{z}_{t-1}^i + \boldsymbol{\phi}_t \,\,, \tag{7}$$

where $\lambda \in [0,1]$ is called the trace-decay parameter. By Equation (7), the eligibility trace of all currently present features is incremented by 1, whereas all other features, i.e. all features which are currently nonpresent, are decayed by $\gamma^i \lambda$.

In this way, the learned weight vector represents an implicit knowledge about the underlying process. It is constantly updated with each new observation and adapts to changing conditions and stores them in the corresponding weights. Therefore, the interplay between number of features and the way they are extracted are the most crucial part of the nexting

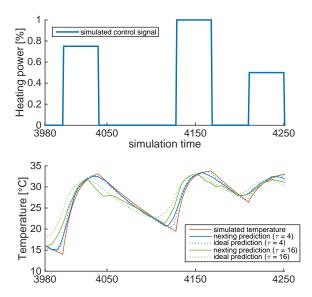


Fig. 2. Example of a prediction produced by the nexting algorithm.

algorithm. Tile coding is an appropriate technique to calculate such unique feature vectors with sufficient entropy.

IV. MULTI-TIMESCALE NEXTING FOR MONITORING APPLICATIONS

As described in the previous section, the nexting algorithm uses all available state information ϕ_t and a weight vector θ_t^i for calculating a prediction V_t^i . In Figure 2 we depicted a result of the nexting algorithm. In this example we simulated the characteristic of heating an insulated water tank. The heater is turned on with different power levels (50%, 75%, and 100%), the temperature (red line) of the water tank increases during heating and it cools down after switching the heater of. Firstly, we calculated the ideal prediction G_t^i for $\gamma^1 = 0.75$ and $\gamma^2 = 0.9375$ corresponding to a prediction time of $\tau^1 = 4$ and $\tau^2 = 16$ time steps ahead respectively (dotted lines). Then we used the nexting algorithm for calculating an online prediction of the temperature signal. In tile coding, only the control and the temperature signals were used to calculate the actual feature vector. At each time step the feature vector is expanded with a history of four preceding feature vectors to add more information. Therefore, each update step only requires the information of the actual and four preceding states. After an initial learning phase (in this example after about 3000 time steps) the corresponding weight vectors for each prediction V_t^i are sufficiently approximated. Multiplying the actual feature vector ϕ_t with each weight vector $\boldsymbol{\theta}_t^i$ results in multiple predictions as plotted in blue (for 4 time steps ahead) and green (for 16 time steps ahead) in Figure 2.

Keeping this simple example in mind, the *NEXTMon* system uses the nexting algorithm as a model free prediction technique for calculating predictions as additional information for an experienced operator. It is obvious that nexting cannot deliver

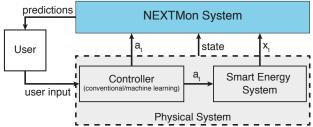


Fig. 3. A human-in-the-loop smart energy system.

perfect predictions about future system states and therefore a direct control using the prediction data could be risky. Therefore, we propose a system which can be used as an extension to existing monitoring techniques delivering short term predictions for a complex energy system. The nexting algorithm does not require either a complete system model nor special sensors. Furthermore, it can calculate predictions for several timescales without a drastically increase of computational power due to the limited information needed for updating the weight vectors and information stored in memory. Also the feature extraction using tile coding does not require strong expert knowledge since it uses just scaled versions of all available sensor signals and event signals. Only setting up different joint coding groups requires some experience in high dimensional systems.

Installing the nexting algorithm on an existing system does not require any changes on the system itself. It only needs access to all available data and control signals (see Figure 3). After an initial learning phase, which depends on the number of unique system states, the nexting algorithm is not only able to predict each sensor state which was previously observed, but extrapolate this acquired knowledge about the system to new, unseen situations. Such a capability can be explained by the generalization capability of tile coding. Namely, states that are previously not recorded are mapped closely to already experienced ones and therefore sharing information about them.

Furthermore, we can use the generated predictions together with a redundant controller to calculate a control strategy using the predicted data. Those predicted control actions can be used to highlight upcoming actions which will be undertaken by the system currently monitored through the NEXTMon architecture. Those highlighted actions are potentially useful for a human operator to decide if a monitored system needs attention in the near future. In the following experiment we demonstrate a thermal house model which is heated to a desired temperature while the outdoor temperature varies according to natural temperature data of a weather station.

V. EXPERIMENTAL SETTINGS

In our experiment we use a thermal house model to simulate temperature variations within a building. We focused on implementing primary effects of heat loss and heat production within a building. The differential equation for the indoor

temperature is described by

$$\frac{dT_{in}}{dt} = -\alpha(T_{in} - T_{out}) + \beta P_t, \tag{8}$$

where T_{in} is the indoor and T_{out} the outdoor temperature. The factors $\alpha = \frac{1}{C}(a_{windows} \cdot u_{windows} + a_{walls} \cdot u_{walls})$ and $\beta = \frac{\eta}{C}$ describe the characteristics of the house model. We use a simple one-room model where the window area is given by $a_{windows} = 2m^3$ with a corresponding thermal transmittance $u_{windows} = 50 \frac{W}{m^2 K}$ (U-values). The area of all walls is $a_{walls} = 10m^3$ with a thermal transmittance of $u_{walls} = 1 \frac{W}{m^2 K}$. Total heat capacity is approximated by $C = C_{air} + C_{furniture} + C_{walls}$, where we assume that the room has a volume of $30m^3$ and 200kg of furniture thus $C_{air} = 39000 \frac{J}{K}$, $C_{furniture} = 840000 \frac{J}{K}$, and the effect of the walls contribute with $C_{walls} = 9 \cdot 10^6 \frac{J}{K}$. The heater has a total power P = 2000W and an efficiency factor of $\eta = 0.8$. It is assumed that the heating power P together with the β raises the room temperature according to the power consumed (convection and other thermal heat radiation is neglected). The outdoor temperature T_{out} is simulated using 20 days of hourly recorded temperature measurements [10] starting in April of a weather station in Berlin. The model was simulated for one minute time steps resulting in N = 28800 data points.

There are certainly more sophisticated controllers like PID controllers for controlling the heater according to a set point. For simplicity and better readability of the selected actions, we decided to use an on-off controller with a hysteresis of one degree Celsius. Therefore, the heater is fully turned on if the temperature falls one degree below the set point and is turned off again if the temperature has raised to $T_{set} + 1^{\circ}C$.

VI. SIMULATION RESULTS

In Figure 4 the simulation output and the prediction results for a prediction time horizon of 50 minutes ($\gamma=0.98$) are depicted. The temperature set point T_{set} was set to $23^{\circ}C$. If the heater was turned on the black dotted signal is set to 1 corresponding to full power ($P_t=2000W$) and reset to 0 after turning it off. The outdoor temperature is plotted in blue, the simulated indoor temperature is depicted in red overlayed by the nexting prediction (green). Due to the binary feature representation used for the nexting algorithm the predictions are affected with short peaks and can be filtered (moving average) afterwards to get clearer prediction results.

Two main results are visible in Figure 4: In the beginning, the algorithm needs some amount of samples to learn the weight vector in order to produce usable results. After that initial phase it is able to predict the indoor temperature signal also in the case, where the natural outdoor temperature changes. It is important to notice that the type of controller is unknown to the NEXTmon system. The length of the initial learning phase depends on the number of unique states to be observed (the learning curve of the nexting algorithm is currently an active research topic). In Figure 5 we zoom in the period between t=225h up to t=260h in order to better visualize the resulting predictions. There are three different

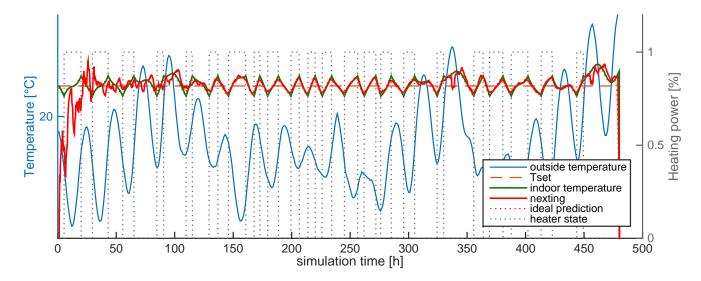


Fig. 4. Comparison of simulated indoor temperature (red) data against the values predicted by the nexting algorithm (green) including the effects of varying outdoor temperatures (blue) and a threshold controlled heater (black). The system needs about 100 hours of learning data to achieve good prediction results.

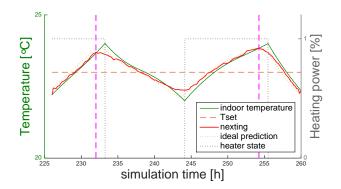


Fig. 5. Simulation result of a human-in-the-loop control system with predicted switching points.

kinds of predictions. The ideal prediction (dotted line) offline calculated using Equation 2, the predicted indoor temperature (red line), and the predicted actions outputted by a local maxima detection algorithm. The ideal prediction corresponds to the best prediction possible under the assumption that the full signal is known. This ideal prediction could be achieved theoretically by the nexting algorithm with an infinitely long feature vector (highest precision of tile coding) and after an infinitely long learning phase. In practice, the nexting prediction does not achieve this optimum but approximates it very well and is most of the time precursory to the signal to be predicted. Applying a local maxima detection algorithm to the predicted indoor temperature signals enables to detect the switching off events (c.f. Figure 5, vertical dashed lines). This approach could be compared to the heuristic a human operator would apply during monitoring the raw predictions. Currently obtaining reasonable general numerical results of the NEXTmon system is difficult. Calculating the root mean squared error (RMSE) according to the ideal prediction or

the source signal would be possible. But we have seen that in different domains the RMSE is not a useful qualitative characteristic. Also the number of successful predicted events does not deliver a good qualitative figure. Its accuracy is highly depended on the local maxima detection algorithm which depends again on the problem. Beyond that, our idea is the development of a human-in-the-loop monitoring system enriched with predicted raw sensor signals. Only for predictive control systems the absolute prediction accuracy would matter, but this was not the intended goal.

VII. CONCLUSIONS

Monitoring complex energy systems often require fast reactions. However, a complete system model or the external factors (like weather) cannot be modeled accurately for a prediction or simulation algorithm. Therefore, we designed the NEXTMon architecture, a model free prediction algorithm for raw sensor signals delivering predictive information while keeping the human-in-the-loop. In our experiments, we verified that this framework is able to supply sufficient information to detect upcoming actions enabling a human operator to reason about future system states. This could avoid faulty decisions in complex environments and extends the time an operator has to focus her attention to a monitored system before an upcoming action is executed.

It is also obvious that the nexting algorithm can produce inaccurate results and does not always deliver optimal predictions that lie in a certain error threshold. This drawback is compensated by the applicability of the algorithm in all systems where raw sensor signals are available and used for monitoring purposes. The NEXTMon system does not require significant changes to the energy system and can use additional external signals and measurements (weather forecasts, schedules) to learn an inherent and flexible model

for the predictions. Furthermore, compared to other prediction algorithms the nexting algorithm is data efficient and needs less historic data at each update step than comparable algorithms.

Current advances in integrating the NEXTMon architecture into a distributed wind power generation system together with weather forecasts show promising results. In the future, we plan to integrate the architecture in more complex domains and in productive scenarios. For this, additional formal analysis and verification of the predictions are needed. Also an ergonomic user interface for the online usage has to be developed. With the NEXTMon architecture we have proposed a framework for integrating short-term predictions into a human-in-the-loop monitoring and control scenario enabling proactive decisions of an human operator.

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