Machine learning-based modeling and controller tuning of a heat pump

Mohammad Khosravi\(^1\), Nicolas Schmid\(^1\), Annika Eichler\(^1\), Philipp Heer\(^2\), Roy S. Smith\(^1\)

\(^1\) Automatic Control Laboratory, ETH Zürich, Physikstrasse 3, 8092 Zurich, Switzerland
\(^2\) Urban Energy Systems Laboratory, Empa, 8600 Dübendorf, Zurich, Switzerland

E-mail: kholravm@control.ee.ethz.ch, nicolas.schmid@msn.com, echlean@control.ee.ethz.ch, philipp.heer@empa.ch, rsmith@control.ee.ethz.ch

Abstract. In this paper, we consider the problem of controller tuning for an operating unit in a building energy system. The illustrative example used here is a real heat pump located in the NEST building at Empa, Dubendorf, Zurich, with its outflow temperature controlled by a PI-controller. The plant is in use and accordingly, intervening in its normal operation is not allowed. Moreover, the model of plant is not available or it can be changed due to aging or possible modification. Accordingly, it is desired to utilize a tuning method which is model-free, operates online, does not intervene with the normal operation of the plant and use only the available historical measurement data. Additionally, it is required to guarantee the safety of the plant during the tuning procedure. In this regard, we formulate the controller tuning problem as a black-box optimization and adopt a safe Bayesian optimization approach for controller parameters tuning. In order to assess numerically the performances of the scheme, first we model the plant as a nonlinear ARX model in form of a feedforward neural network. Subsequently, we train the neural network using the available historical measurement data. Finally, the obtained model is used as an oracle in the controller tuning procedure in order to numerically verify the effectivity of the proposed approach.

1. Introduction
The building sector consumes nearly 40% of the global energy in the industrial countries [4]. This has motivated researchers to optimize energy systems in buildings, and accordingly, specifically designed advanced control schemes have been introduced in the recent years [5, 7]. The energy systems in buildings are essentially large-scale systems with various units controlled via hierarchical control schemes where units of lower levels are connected to a central higher level controller and operated under its supervision. Normally, advanced control strategies such as model predictive control (MPC) schemes are employed in the higher levels while less complicated control schemes such as P, PI and PID controller are utilized in the lower levels. In order to obtain the desired performance of operation, it is required to optimize all levels of a control system. In this paper, we focus on the performance optimization in the lower level where the corresponding implemented control scheme is a PI or a PID controller. These types of controllers are widely used in industry and various methods are introduced for their tuning [8]. Meanwhile, many of these procedures are either time consuming or require specific experiments, models and system identification, or modifying the plant. Moreover, these tuning approaches may not be feasible in...
many situations due to the financial costs, preferences of user of the plant, or operational safety and risk. Accordingly, it is desired to utilize a completely automated and data-driven tuning method, which can be utilized safely. Additionally, the tuning method should be suitable for systems which are in use without intervening in their normal mode of operation and are not limited to particular performance metrics, specific types of dynamics, systems and applications. Here, our main motivation is deriving such a tuning method for the operating units in building energy systems.

The controller-tuning problem can be formulated as a maximization problem where the controller parameters are the corresponding optimization variables, the objective function is an appropriately designed metric indicating the performance of the system, and the constraints are metrics indicating predefined safety levels. In general, the dependency of performance and safety metrics to the controller parameters is in a black-box oracle form. Therefore, one can adopt a safe Bayesian optimization algorithms for solving this problem [6]. In order to numerically verify this approach, we use the available measurement data for learning the model of the system and then, the obtained model is used as an oracle in the proposed controller tuning procedure. Due to the well-known universal approximation property of neural networks [2], the trained model here is a nonlinear AutoRegressive eXogenous (ARX) model in form of a feedforward neural network. Here, we follow similar lines of [3] where the plant model is based on first principles. Accordingly, this work is the complementary approach to [3] for the proposed tuning method.

2. Problem Formulation

In large-scale systems with various sub-systems, the control scheme is designed in a hierarchical form. In these schemes, a higher level (HL) controller performs the overall supervisory control task of the sub-systems based on advanced control methods such as MPC. Meanwhile, each of the sub-systems is controlled locally by a lower level (LL) controller with simple structures like a PI-controller. The LL controllers are designed and characterized by determining a specific vector of few parameters, denoted here by $\theta$ (see Figure 1). The overall performance of the controlled system not only depends on the design of HL controller, but also it depends on the LL controllers and subsequently, the design of vector of parameters $\theta$. Accordingly, for obtaining the desired performance, it is required to design $\theta$ optimally. In this regard, one may define the performance of system as a function of $\theta$, denoted by $f : \Theta \rightarrow \mathbb{R}$, where $\Theta$ is the parameter region, a compact convex subset of $\mathbb{R}^{n_\theta}$ describing the candidate parameters. During the design of controller parameters, it is crucial to guarantee the safety of the underlying system. Accordingly, one may define a function $g : \Theta \rightarrow \mathbb{R}$ as a metric for safety, i.e. being $g(\theta)$ non-negative is an indication that $\theta$ is a safe choice for vector of parameters. Based on the introduced functions, one may formulate the optimal controller parameter design as

$$\theta^* := \arg\min_{\theta \in \Theta, \, g(\theta) \geq 0} f(\theta).$$  (1)
In general, the dependency of performance and safety functions to $\theta$ can be in an oracle form rather than in a given algebraic or simple mathematical closed form. In other words, for a given $\theta$, the value of $f(\theta)$ and $g(\theta)$ can be obtained only via performing experiments and subsequent measurement data. Since, this can be significantly time consuming and costly, and meanwhile, the size of vector $\theta$ is considerably small, Bayesian optimization methods can be suitable for solving problem (1). The optimization method should maximize the performance and meanwhile respect the safety of plant during the tuning procedure. Accordingly, we are required to employ safe Bayesian optimization approaches like SafeOpt [1], which is the one we have used here. Since the underlying sub-systems are usually expensive facilities, it is desired to verify this approach at the numerical level before validating on real plants. In this regard, we consider a real heat pump located in NEST building (Figure 1), derive a realistic simulation model for it based on the available measurement data, and then verify the proposed approach on the simulated model.

3. Nonlinear ARX Modeling of the Heat Pump
The heat pump has a nonlinear nature and accordingly, we model its dynamics as a nonlinear ARX. Additionally, we use nonlinear regression for modeling other parts in the loop. Before providing the details of the modeling, we first explain the operation scheme of the heat pump.

3.1. Heat Pump Structure and Operation Scheme
The heat pump is connected to two external flow circuits called the secondary circuits. One of the secondary circuits corresponds to the heating side of the heat pump (shown in red in Figure 2), and the other one corresponds to the cooling side (shown in orange in Figure 2). The heat pump itself has an internal flow circuit, called primary circuit where a refrigerant is circulating. As shown in Figure 2, the primary circuit consists of two compressors, a controlled expansion valve, a valve controlling the flow rate of the refrigerant and three internal heat exchangers, labeled as evaporator, condenser and super-heater. The evaporator transfers the heat content of the glycol to the refrigerant. Similarly, the condenser transfers the heat content of the refrigerant to the water. The super-heater improves the heating cycle by using the remaining heat content of refrigerant after it passes through the condenser and also controlling the heat transfer process via the internal compressors and valves. At the condenser side, there exists a return flow pipe, which returns the heated water to mix it with the incoming water before entering the heat pump. This mixing is controlled via a mixing valve. As shown in Figure 2, in order to guarantee the return flow, a pump is placed after the outlet. This pump maintains a pressure to provide a flow to the mixing valve. The temperature set point of the mixing valve is controlled via a PI-controller. The controller should be tuned so that the output temperature at the condenser tracks a given temperature reference. At the cooling side of the heat pump, a similar structure regulates the output temperature at the evaporator. The heat pump is driven in cyclic operation,
switching between operation mode and non-operation mode. The decision on switching between these modes is done by a higher level supervisory controller and depends on the demand.

3.2. NARX Modeling Using Feedforward Neural Network

For modeling the system, we mainly focus on the heating side. In this regard, we model the mixing valve and the condenser as shown in Figure 3. Let $T_i$ and $T_o$ denote the temperature of water before and after passing through the condenser, respectively. Also, let $T_c$ be the average temperature of the refrigerant in the condenser and $T_d$ be the temperature of the water entering the plant. Denote the flow rate of water in the returning pipe and the flow rate of water entering the plant by $F_r$ and $F_d$, respectively. Set the sampling time $T_s = 10s$ and consider the sampled signals. Accordingly, for the $k$th time step, define $w(k) = [T_d(k), F_r(k), F_d(k)]^T$ and $v(k) = [T_o(k), T_i(k), T_c(k)]^T$. According to the physical intuition, one can say that $v(k)$ is determined based on the history of itself and $w(k)$ via the physical dynamics of plant (heat pump, return flow pipe and the valve). Therefore, one can suggest a dynamics of the following NARX form:

$$v(k) = F(w(k-1), \ldots, w(k-d), v(k-1), \ldots, v(k-d)), \quad (2)$$

where $F$ is the non-linear latent function to be determined from the measurement data and $d$ is the number of time lags. According to the measurement data, the return pipe induces a time lag of almost 5 samples and therefore, we set $d = 5$.

The well known universal approximation theorem [2] says that continuous functions with compact domain in Euclidean spaces can be approximated arbitrarily close by feedforward neural networks with finite number of neurons and a single hidden layer. Accordingly, we approximate the nonlinear function in NARX model (2) using a feedforward neural network with a single hidden layer (Figure 3). In order to learn the dynamics and meanwhile avoid over-fitting, we set the size of hidden layer equal to $d = 5$. The activation function used here is the sigmoid function, i.e. $\sigma(x) = 2(1+e^{-x})^{-1} - 1$. Accordingly, the nonlinear function $F: \mathbb{R}^{6d} \to \mathbb{R}^{3}$ is in the form of

$$F(x) = \Phi^{-1}(W_o \sigma(W_h \Phi(x) + b_h) + b_o), \quad (3)$$

where $\Phi$ is an affine map for normalizing the data, $W_h, b_h$ and $W_o, b_o$ are the pairs of weight matrix and bias vector for the hidden layer and the output layer, respectively. Using the measurement data, prediction error minimization and the Levenberg-Marquardt algorithm, one can estimate $W_h, b_h, W_o$ and $b_o$. Figure 4 shows the prediction results of the derived NARX model for a validation operation cycle.

3.3. Modeling the Valve and Flow Rates

Define $u(k) \in [0, 1]$ as the set point of the valve which determines how much the valve is open at time step $k$. When the valve is completely closed, i.e., $u = 0$, the return flow is zero. If the
valve is completely open, i.e., $u = 1$, the return flow significantly affects and suppresses the flow $F_d$. Therefore, the flows $F_r$ and $F_d$ depend on the set point of the valve $u$. More precisely, it is assumed that there exist functions $f_d, f_r : [0, 1] \rightarrow \mathbb{R}$ such that, at any time instant $k$, we have that

$$F_d(k) = f_d(u(k)) + \delta F_d(k), \quad F_r(k) = f_r(u(k)) + \delta F_r(k),$$

where $\delta F_d(k)$ and $\delta F_r(k)$ denote the disturbances. We model functions $f_d$ and $f_r$ as polynomials. Using the measurement data and square error minimization, we estimate the coefficients of the polynomials. To avoid overfitting and meanwhile obtaining a reasonable fit to the data, the order of polynomials is set to 3. The results of the nonlinear regressions is shown in Figure 4.

4. Numerical Results of PI-controller Tuning Using Bayesian Optimization

Setting the output $y$ as $T_o$, the input $u$ as the set point of the mixing-valve, the PI-controller with P-term and I-term respectively as $k_p$ and $k_i$, we can form a closed loop system. One can see that the output of system, $y$, depends on the vector of parameters of controller which is defined as $\theta := [k_p, k_i]^T$. Here, it is desired to have a reasonable response, i.e., it should not have large overshoot and settling error. Also, since $T_o$ is the temperatures of water after the condenser, safety can be modeled as avoiding high temperature in the response of system. Accordingly, we define the performance function, $f$, and the safety metric, $g$, as

$$f(\theta) = -\alpha \max \{\max_{1 \leq k \leq N}(y(k)) - r, 0\} - \frac{1-\alpha}{N+1} \sum_{k=1}^N |y(k) - r|, \quad g(\theta) = y_{\max} - \max_{1 \leq k \leq N} y(k),$$

where $N$ is the length of measurement data of experiment, $r$ is the value of reference, $\alpha \in [0, 1]$ is the trade-off factor between the the overshoot and the tracking error, and $y_{\max}$ is the maximum tolerated output value. Here, we set $r = 65 \degree C$, $y_{\max} = 80 \degree C$, $\alpha = 0.5$, and $N = 720$ which equals to 2 hours. In order to solve the black-box optimization problem (1) with the performance and safety functions given in (5) and $\Theta := [0.02] \times [0.02]$, one can use SafeOpt [1] algorithm. This approach generates iteratively a sequence of vectors of parameters which safely explores the space of parameters and meanwhile searches for the optimal solution. The resulting sequence is shown in Figure 5. The algorithm starts with an initial safe and possibly not optimal set of parameters (green dots) and then, iteratively samples from the parameter space. As it is shown, the final best sample, derived after 35 iterations (red solid dot), is close to the optimal parameters (blue square). For comparison, the response of the system is shown for different choices of parameters, including initial one, optimal parameters, and the result of algorithm. One can see that the response of system with the resulting parameters tracks the reference without significant overshoot and tracking error.
Figure 5: The sequence of parameters generated by SafeOpt algorithm and also, the contour plots corresponding to the performance function (left) and the safety function (middle) are shown. The dashed black curve shows the boundary of the safe-unsafe region. Initially, the algorithms start with safe samples (green dots) and then iteratively take samples from the parameter region (black dots). As it is shown, the final best sample (red solid dot) is close to the optimal parameters (blue square). The response of system is shown in the right for different choices of parameters, including initial one, optimal parameters, and the result of introduced approach after 35 iterations.

5. Conclusion
In this paper, the problem of controller tuning for an operating unit in a building energy system is considered. The problem is formulated in form of a black-box optimization. A safe Bayesian optimization (SafeOpt) is adopted for obtaining the solution. In order to assess numerically the performances of the scheme, first the plant is modeled as a nonlinear ARX model in form of a feedforward neural network. Subsequently, the historical measurement data is used for training the neural network. Following that, the obtained model is used as an oracle in the controller tuning procedure and the effectivity of the proposed approach is verified. More precisely, the proposed approach finds the optimal parameters in few number of iterations.

Acknowledgments
This research project is part of the Swiss Competence Center for Energy Research SCCER FEEB&D of the Swiss Innovation Agency Innosuisse.

References
[1] F. Berkenkamp, A. Krause, and A. P. Schoellig, “Bayesian optimization with safety constraints: safe and automatic parameter tuning in robotics,” arXiv preprint arXiv:1602.04450, 2016.
[2] G. Cybenko, “Approximations by superpositions of a sigmoidal function,” Mathematics of Control, Signals and Systems, vol. 2, pp. 183–192, 1989.
[3] M. Khosravi, A. Eichler, N. Schmid, P. Heer, and R. S. Smith, “Controller tuning by Bayesian optimization: An application to a heat pump,” European Control Conference, 2019.
[4] J. Laustsen, “Energy efficiency requirements in building codes, energy efficiency policies for new buildings,” International Energy Agency (IEA), vol. 2, no. 8, pp. 477–488, 2008.
[5] F. Oldewurtel, A. Parisio, C. N. Jones, D. Gyalistras, M. Gwerder, V. Stauch, B. Lehmann, and M. Morari, “Use of model predictive control and weather forecasts for energy efficient building climate control,” Energy and Buildings, vol. 45, pp. 15–27, 2012.
[6] B. Shahriari, K. Swersky, Z. Wang, R. P. Adams, and N. De Freitas, “Taking the human out of the loop: A review of bayesian optimization,” Proceedings of the IEEE, vol. 104, no. 1, pp. 148–175, 2015.
[7] D. Sturzenegger, D. Gyalistras, M. Morari, and R. S. Smith, “Model predictive climate control of a Swiss office building: Implementation, results, and cost–benefit analysis,” IEEE Transactions on Control Systems Technology, vol. 24, no. 1, pp. 1–12, 2015.
[8] R. Vilanova and A. Visioli, PID control in the third millennium. Springer, 2012.