Learning based Model Predictive Control of a High-Altitude Simulation Chamber

Arsema Derbie[1], Maurice Kettner [1] and Eyassu Woldesenbet [2]
[1] IEEM-Institute of Energy Efficient Mobility, Karlsruhe University of Applied Sciences
arsema.derbie2@h-ka.de, maurice.kettner@h-ka.de
[2] Addis Ababa institute of Technology
dreyassu@gmail.com

Abstract. The limitation of conventional methods to explicitly model and monitor physical systems emanates from system complication, uncertainties, and so forth. Artificial intelligence approaches, Artificial Neural Networks in particular, resolve this difficulty by efficiently capturing the pattern of physical systems and exploring key relationships of determinant parameters effectively. The development of an artificial neural network model to catch the interrelation of the input and output variables was successful. Time series data collected using a variety of combinations of control variables were used to train a sequential model which predicted the chamber temperature from the inputs of control variables. From such a black box model, developing a model predictive controller that predicts upcoming events and sets control actions accordingly was developed. Optimization is a major essence of Model Predictive Control as each suggested step by the controller must be optimized to the required control law. Such optimization is better realized in mathematically modeled systems. But, for non-linear and non-convex relationships as in neural networks, this is cumbersome. This difficulty is addressed by the use of input convex neural networks which relate model outputs with the inputs in a convex relationship. Optimization is relatively simpler when convexity is granted. Finally, a 3 layers input convex neural network that represent the system specifications was developed and optimized control steps were generated using COBYLA (Constrained Optimization by Linear Approximation) solver.

Keywords: Input convex layers, Model Predictive control, convexity

1. Introduction

In Bruchsal Germany, there exists an environment chamber that simulates global temperature and altitude conditions to test the performance of hand-held power tool engines to date [1]. The pressure control, that provides the altitude feature, is monitored and controlled by Raspberry operated actuator manipulating the throttle that controls the amount of conditioned air that flows to the chamber. The matter, air and refrigerant, together with the data flow to and out of the chamber is shown in Fig. 1.

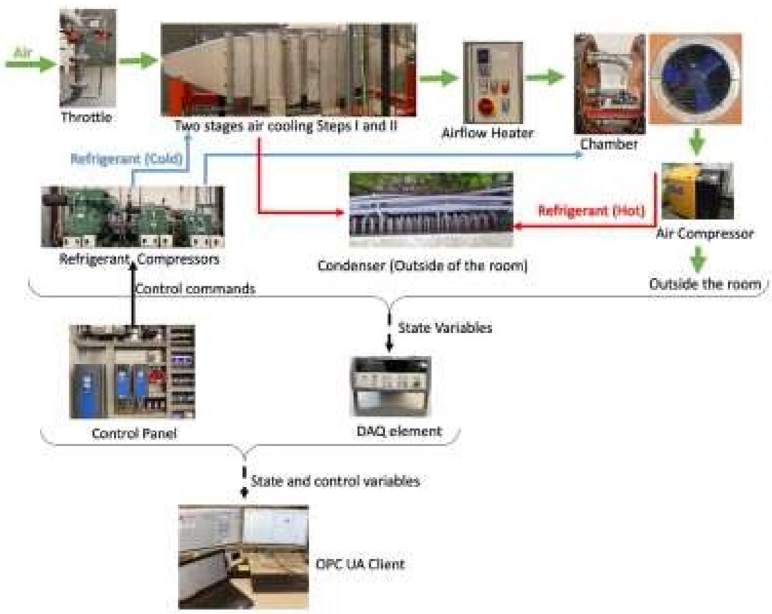

Fig. 1. Matter and data flow to and out of the chamber

The system monitory and control were enhanced by a digitalization solution which allowed the field devices (low level components) to be connected to high level supervision station making the setup a Cyber Physical System (CPS)[2].

For such a digitized system of non-linearly related multiple inputs and multiple outputs with time delays, the classic control mechanisms are limited since they disregard the knowledge of the process, possess constant parameters and solely rely on the measurements from sensors [3]. MPC provides optimal, predictive, and adaptive control with a simple structure and dynamic performance [4]. It's maximum potential of commands in order to impose temperature bounds makes it highly recommended for thermal (conditioning) control applications like heating, ventilation and air conditioning (HVAC) units and environment chambers [4].

MPC predicts future system behavior based on a system model considering it in the optimization that determines the optimal trajectory of manipulated variables [5]. A typical MPC consists mainly of a system model and a controller design which comprises an objective function and a control law.

This paper reports the results of a learning-based Model predictive control by first stating about the data acquisition process. Then, it discusses the system modeling and Control design before concluding.

2. Data Acquisition

System variables are basically divided into three depending on their role from the entire relationship: state variables, control variables and parameters. Table 1 summarizes the variables of the system accordingly.

Table 1. Variable types

State variables	**Control Variables**	**Parameters**
Step-I T, Step-II T, Heater T, Fan speed, Mass flow, Chamber T, Motor T	Step-I T_{set}, Step-II T_{set}, Heater T_{set}, Fan $speed_{set}$, Chamber cooler T_{set}	Room Temperature, Humidity, Season

Parametric variables do not affect state variables directly as control variables do. But, their influence on the system is significant. For the parameters of the chamber, there are two datasets depending on the relatively long seasons of the year, summer and winter, which dictate the room temperature and humidity. Both the winter and the summer datasets are collected with varying pressure and temperature values with different starting points to make the data of a high volume and variety. The data was recorded every 2 seconds with suffices to the velocity requirements for such a slow system. Hence, the three basic features of big data acquisition: volume, variety and velocity are fulfilled [6].

Multiple recordings were taken within the upper bounds and lower bounds of attainable temperature and pressure values [1]. 11 temperature points ranging between 30 ℃ and -20 ℃ with a step of 5 ℃ and four pressure values of 990 mbar, 900 mbar, 800 mbar and 700 mbar for the two datasets with a total file size of more than 300MB having millions of data points were collected.

3. System Modeling

One of the basic features of MPC include making optimized decisions depending on the system dynamics. The accuracy and effectiveness of an MPC are highly dependent on the identified model. Modeling and identification are the most difficult and time-consuming parts of automation processes. The basic conditions that each model intended for MPC usage should satisfy are reasonable simplicity, well estimated system dynamics and steady-state properties as well as satisfactory prediction properties [7].

System modeling techniques can be broadly classified into three: physical modeling (or white box, mathematical, forward), data-driven (or black box/empirical/inverse), and gray box (or hybrid). System models can be dynamic or static (steady) depending on the variability of parameters with time. Depending on the linearity of the system, the models can be linear or nonlinear. Most physics-based models fall under inductive types of system models while data- based models are mostly deductive. Other classifications include explicit and implicit, discrete or continuous, deterministic or probabilistic/stochastic models [8].

To represent the environment chamber, a data-based approach was selected. The concept of this approach is to fit a transfer function model to the input/output real model data to yield coefficient polynomials that can be factored to provide resonance frequencies and characterization of damping coefficients without knowledge of the internal working [9]. The strengths of such system identification technique are lower engineering cost because it follows a data-in-data-out approach; less domain knowledge because it is based on the mapping of input and output data, and greater adaptability because the model will evolve itself with new data. Some of its drawbacks include high demand for data quality: missing, wrong, or biased data lead to low quality models [10].

For most thermal systems that are dynamic, nonlinear, and very high order due to physical properties such as high thermal inertia, real lag time, uncertain disturbance factors, etc. black-box models provide better accuracy without a comprehensive knowledge of the operations [9]. Deep neural networks have proven to be successful in many identification tasks, however, from a model-based control perspective, these networks are difficult to work with because they are typically nonlinear and nonconvex. To bridge the gap between model accuracy and control tractability faced by neural networks, networks that are convex concerning their inputs are con- structed explicitly [11].

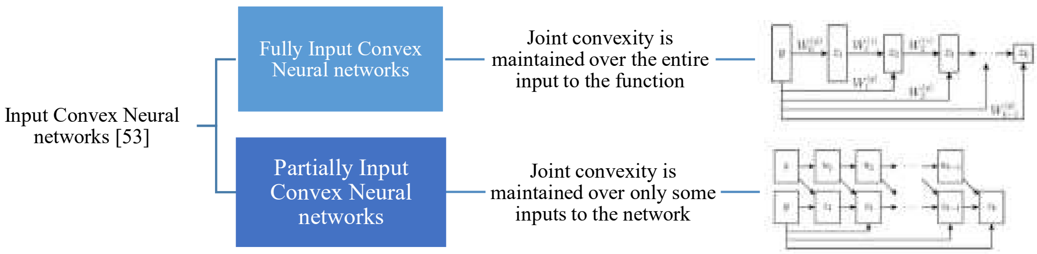

Fig. 2. Classification of Input Convex Neural networks

From the numerous variables in the environment chamber, a three-layered partially input convex neural network where only the control variables are convex to the output was constructed. Their development is highly dependent on the selection of convex and non-decreasing activation functions and non-negative weights. The proof of convexity in these networks is given by the fact that non-negative sums of convex functions are also convex and that the composition of a convex and non-decreasing function is also convex [12]. The system representation capacity is compensated as can be seen in Fig. 3.

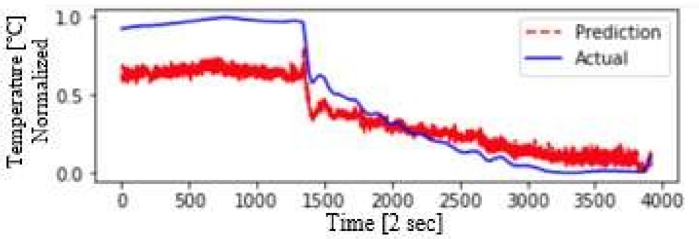

Fig.3. PICNN representation of Chamber Temperature at 700mbar (Temperature [°C] Vs Time [sec]-Normalized)

4. Control Design

Defining an optimization problem is an important task in the controller design step of an MPC. This problem is again constrained by the system representation equation and the boundary conditions of the input and output, together with state and control variables. System representation equations of many thermal systems (discrete-time linear time-invariant system that evolves in time) are given in equation 1.

$$X_{t+1} = AX_t + BU_t \qquad \text{Eqn 1a}$$

$$y_t = CX_t + BU_t \qquad \text{Eqn 1b}$$

where x, y and u are input state variables, output state variables and control actions while A, B, C and D are System Matrices.

A general optimization problem can be stated as shown in equation 2.

$$\min_{n} \sum_{t=0}^{\infty} y_t^T Q_{x_t} + u_k^T R u_k \qquad \text{Eqn 2a}$$

Subject to:

$$X_{t+1} = AX_t + BU_t \qquad \text{Eqn 2b}$$

$$y_t = CX_t + BU_t \qquad \text{Eqn 2c}$$

$$y_{min} \leq y_t \leq y_{max} \qquad \text{Eqn 2d}$$

$$x_{min} \leq x_t \leq x_{max} \qquad \text{Eqn 2e}$$

$$u_{min} \leq u_t \leq u_{max} \qquad \text{Eqn 2f}$$

The system model predicts chamber temperature and the respective motor temperature which makes these variables output variables (y). The customized optimization problem is given in equation 3.

$$\min \sum \left(\sqrt{(\mathrm{T_{set}} - \mathrm{T_{chamber}})^2} + \sqrt{(\mathrm{T_{set}} - \mathrm{T_{motor}})^2}\right) \qquad \text{Eqn 3}$$

This optimization was carried out by COBYLA (Constrained Optimization by Linear Approximation) solver. The output of the controller hence becomes a series of optimized control actions when a certain temperature in the chamber is desired to be achieved. An example of the changes in the chamber temperature with respective changes in the control actions is shown in Fig. 4.

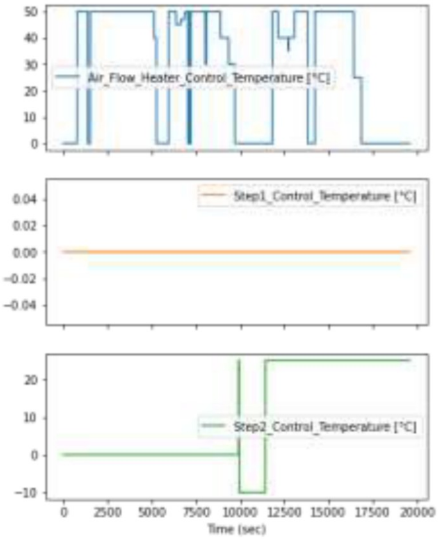

Fig. 4a. Control actions of Air heater, Step-I and step-II coolers at 700mbar

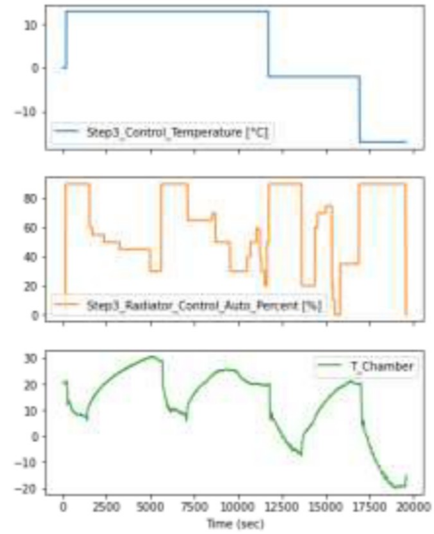

Fig. 4b. Changes in the chamber temperature according to the control variables at 700mbar with control actions of chamber cooler and fan

5. Conclusion

The high-altitude simulation chamber with unpredictable ways to reach desired chamber and motor temperature values was represented with neural networks to find the optimum control actions of its thermal components. The biggest challenge of optimization on non-linear and non-convex models was addressed by the implementation of partially input convex neural networks. MPC parameters that correspond to the slow thermal process were defined and the optimum control actions were generated by a linearization solver. Hence, the chamber can be conditioned with the most efficient control steps in terms of time and resource.

References

1. A. Martel, F. Scholl, and D. Weierter, "Development of a Climate and Altitude Simulation Test Bench for Handheld Power Tools," 2018, doi: 10.4271/2018-32-0033.
2. A. Derbie, P. Nenninger, C. Hadamek, and M. Renner, "Digitalization of a Climate and Altitude Simulation Test Bench for Handheld Power Tools to Automate Its Thermal Management System," *SAE Technical Paper*, 2022, doi: 10.4271/2022.
3. M. Tesfay, F. Alsaleem, P. Arunasalam, and A. Rao, "Adaptive-model predictive control of electronic expansion valves with adjustable setpoint for evaporator superheat minimization," *Build Environ*, vol. 133, no. December 2017, pp. 151–160, 2018, doi: 10.1016/j.buildenv.2018.02.015.
4. P. Hameed, N. Bin, M. Nor, P. Nallagownden, I. Elamvazuthi, and T. Ibrahim, "A review on optimized control systems for building energy and comfort management of smart sustainable buildings," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 409–429, 2014, doi: 10.1016/j.rser.2014.03.027.

5. M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: an engineering perspective," *International Journal of Advanced Manufacturing Technology*, vol. 117, no. 5–6. Springer Science and Business Media Deutschland GmbH, pp. 1327–1349, Nov. 01, 2021. doi: 10.1007/s00170-021-07682-3.
6. H. Singh, "Big data, industry 4.0 and cyber-physical systems integration: A smart industry context," *Mater Today Proc*, 2020, doi: 10.1016/j.matpr.2020.07.170.
7. S. Prívara, J. Cigler, Z. Váňa, F. Oldewurtel, C. Sagerschnig, and E. Žáčeková, "Building modeling as a crucial part for building predictive control," *Energy Build*, vol. 56, pp. 8–22, Jan. 2013, doi: 10.1016/j.enbuild.2012.10.024.
8. Z. Afroz, G. M. Shafiullah, T. Urmee, and G. Higgins, "Modeling techniques used in building HVAC control systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 83. Elsevier Ltd, pp. 64–84, Mar. 01, 2018. doi: 10.1016/j.rser.2017.10.044.
9. R. Z. Homod, "Review on the HVAC System Modeling Types and the Shortcomings of Their Application," *Journal of Energy*, vol. 2013, no. May, pp. 1–10, 2013, doi: 10.1155/2013/768632.
10. Y. Li, Z. O'Neill, L. Zhang, J. Chen, P. Im, and J. DeGraw, "Grey-box modeling and application for building energy simulations - A critical review," *Renewable and Sustainable Energy Reviews*, vol. 146. Elsevier Ltd, Aug. 01, 2021. doi: 10.1016/j.rser.2021.111174.
11. Y. Chen, Y. Shi, and B. Zhang, "Optimal control via neural networks: A convex approach," *7th International Conference on Learning Representations, ICLR 2019*, pp. 1–25, 2019.
12. F. Bünning, A. Schalbetter, A. Aboudonia, M. H. de Badyn, P. Heer, and J. Lygeros, "Input Convex Neural Networks for Building MPC," pp. 1–11, 2020, [Online]. Available: http://arxiv.org/abs/2011.13227