

Model Predictive Control of a Data-Driven Model of a Medium-Temperature Cold Storage System [†]

Adesola Temitope Bankole ^{*}, Muhammed Bashir Mu'azu , Habeeb Bello-Salau  and Zaharuddeen Haruna

Department of Computer Engineering, Ahmadu Bello University, Zaria 810107, Nigeria; mbmuazu@abu.edu.ng (M.B.M.); bellosalau@abu.edu.ng (H.B.-S.); elzet2007@gmail.com (Z.H.)

^{*} Correspondence: atbankole@abu.edu.ng

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Abstract

At temperatures higher than 5 °C in the cooling chambers of refrigeration systems, bacteria multiply rapidly on fresh fishes, thereby leading to an increased risk of foodborne diseases. Maintaining the storage temperature within the recommended bounds of 0 °C and 5 °C is needed to maintain food safety and quality. This study presents model predictive control of a data-driven medium-temperature cold storage system using subspace system identification techniques. The identified linear model presents a holistic view of the whole system, with each subsystem cohesively linked together. The data-driven model was developed from synthetic data derived from a high-fidelity simulation benchmark model of a supermarket refrigeration system from Aalborg University, Denmark. The benchmark model consists of a medium-temperature closed display case, the suction manifold, and the compressor rack. The data of the expansion valve, suction pressure, compressor capacity, heat transfer rate, and ambient temperature were taken as inputs, while the data of the air and goods temperatures were taken as outputs based on expert knowledge. A linear model predictive controller was designed to control the temperature outputs of the identified linear model, and the outputs were compared with the proportional–integral dead band control used in the benchmark. Simulation results for 24 h showed that the model predictive controller was able to achieve an air temperature and a goods temperature within the recommended temperature range of 0 °C and 5 °C that guarantees safe storage of fresh fishes. These results imply that a reduced-order model of a commercial refrigeration system that is robust, reliable, and stable can be developed and controlled to achieve the goal of food safety, thereby guaranteeing food security and reducing costs.

Keywords: medium-temperature cold storage systems; data-driven modeling; system identification; model predictive control



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1. Introduction

A cold storage system is a kind of commercial facility that uses temperature control to preserve perishable items like meat, vegetables, and fish for a longer period of time [1]. The medium-temperature (MT) cold storage system has been given particular attention in this study. This is because they are extremely vulnerable to disturbances such as external heat loads. Additionally, because the MT system has more compressors, it uses more electricity. Thus, MT systems have greater potential for energy savings than low-temperature systems [2]. This research primarily concentrates on the simulation and

regulation of medium-temperature shelf-type display cases, which are considered to exemplify the worst-case scenario for thermal storage potential. The vapor compression cycle (VCC) is the foundation of the technology utilized in this study. This is due to the fact that the most efficient type of refrigeration cycle is the VCC. This system has the highest average coefficient of performance (COP) and energy input demand [3].

Physics-based modeling [4,5] and data-driven modeling [6–8] are two methods that have been used for mathematical system model creation. Various models of the refrigeration system have been created in the literature using a physics-based modeling method; however, these models have the disadvantage of not precisely predicting food temperatures and not being able to accomplish efficient compressor operations [9–12]. In contrast, the data-driven technique can handle complex, unpredictable, or nonlinear systems, such as refrigeration systems, which can be difficult to represent analytically or numerically [13–15]. Additionally, data-driven systems can quickly adapt to changing conditions, disruptions, or interruptions by learning from fresh data. They can improve the system's performance and reliability while reducing the time and cost of modeling and control design [16]. Consequently, this work used data-driven modeling with subspace system identification.

Refrigeration systems have been controlled using a variety of techniques, including simple feedback control techniques like proportional–integral–derivative control [17], optimal control techniques like Linear Quadratic Gaussian (LQG) [18], and conventional control techniques like on/off control and refrigerant bypass [19]. However, the aforementioned techniques frequently result in product temperature violations, which are harmful to food safety. For this study, model predictive control (MPC) was used because it may serve as an anticipatory controller instead of a remedial controller, which is a preferred choice for controlling cold storage systems [20]. By integrating constraint handling, slow dynamics, and disturbance rejection into the control architecture, it offers several advantages [21].

In order to accomplish the goal of food safety and quality, this research proposes using the model predictive control technique on a reduced-order model of a commercial refrigeration system. The system identification toolbox of MATLAB 2024a and Simulink 2024a software is used to estimate and validate a linear state space model utilizing subspace system identification. A modified high-fidelity simulation benchmark model of a supermarket refrigeration system from Aalborg University, Denmark, provided the synthetic data used to create the data-driven model [22]. The compressor rack, the suction manifold, and a closed display case make up the benchmark model. According to expert knowledge, the suction pressure, the expansion valve, heat transfer rate, compressor capacity, and ambient temperature data were used as inputs, and the air and product's temperature data were used as outputs. The ambient temperature was determined using a fourteen-day outside temperature range of 8.9 °C to 32.8 °C, which represents a tropical environment.

This paper's outline is as follows: Section 2 describes the commercial refrigeration system benchmark, the subspace system identification technique, and the model predictive control concept. The simulation results and relevant comments are presented in Section 3. The paper is ultimately concluded in Section 4.

2. Materials and Methods

2.1. System Description

The refrigeration system has a maximum compressor power of 2975 kW, a suction manifold capacity of 4 m³, and suction pressure references of 1.4 bar and 1.1 bar when the store is closed and open, respectively. Since the refrigerant mass flow measurement is not practical, it is ignored. The medium-temperature closed display case model utilized in this study is depicted in Figure 1.



Figure 1. A medium-temperature cold storage system [23].

2.2. Subspace System Identification Procedure

In order to identify a system, input and output data must accurately reflect the key dynamics of the system. The system identification toolbox aids in the creation of models that can as easily replicate the measured data as feasible. The model structure of state-space was selected due to its efficiency in managing systems with numerous inputs and multiple outputs [24]. Using the model order, the model structure may then be set up. The number of states in a state-space representation is correlated with the model order. By reducing the discrepancy between the observed response and the model output, the system identification toolbox program calculates model parameters. A flow diagram of the system identification procedure is presented in Figure 2.

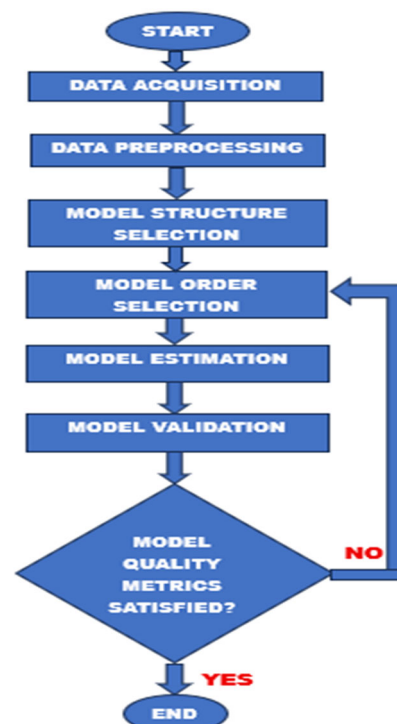


Figure 2. Flow chart for system identification [23].

The following qualities must be included in the best identified linear model:

- a. The model that has the best fit-to-estimation (goodness of fit) percentage
- b. The model that has the lowest final prediction error (FPE)
- c. The model that has the lowest mean square error (MSE) [25].

2.3. Model Predictive Control Concept

The controller in the basic MPC loop employs an internal prediction plant model to estimate the state and compute a series of control actions that minimize a cost function over a specified horizon after receiving the plant's observed outputs and disturbances. Generally speaking, decreasing the cost function entails lowering the error between a reference trajectory and future plant outputs. The model predictive control design workflow that shows the process of designing a linear model predictive controller using MPC toolbox in MATLAB is given in Figure 3.

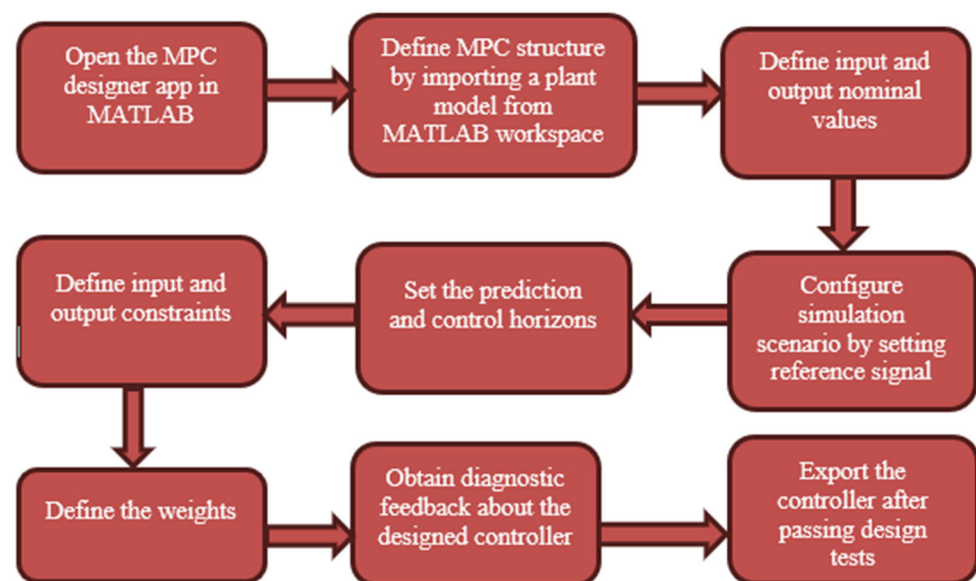


Figure 3. MPC design workflow [23].

3. Results and Discussions

The modified benchmark model was used to generate synthetic data in a fourteen-day simulation. The input and output data were imported into the MATLAB system identification application after being transformed into *iddata* object. Detrending was used to eliminate offsets from the data, and state-space model structure was selected for model estimation. The first seven days' worth of data (120,960 samples collected at 5 s) were utilized for estimation, while the final seven days' worth of data (120,961 samples sampled at 5 s) were utilized for validation. Model estimate was carried out for various model orders, simulation focus was set to ensure stability, and N4SID was chosen as the subspace identification approach to be applied. The optimal linear time invariant model was selected after model validation. For the simulation, a computer system with an HP Intel Core i7, 8 GB RAM, and 3.00 GHz was utilized. The best identified linear model has the maximum goodness of fit of 98.66% and 90.42% for both outputs. It also has the lowest FPE of 4.11×10^{-15} and MSE of 0.0005660, respectively, indicating a reliable and robust model.

The goods temperature response using proportional–integral (PI) with dead band control and model predictive controller for 86,400 seconds (24 h) is displayed in Figures 4 and 5. The goods temperature of the data-driven model utilizing model predictive controller climbed initially and stabilized at 2.7 °C, whereas the benchmark model using PI with dead

band had the greatest temperature of 3.08 °C. This suggests that despite varying external temperatures, the designed data-driven MPC system can ensure food safety and quality for the preservation of fresh fish.

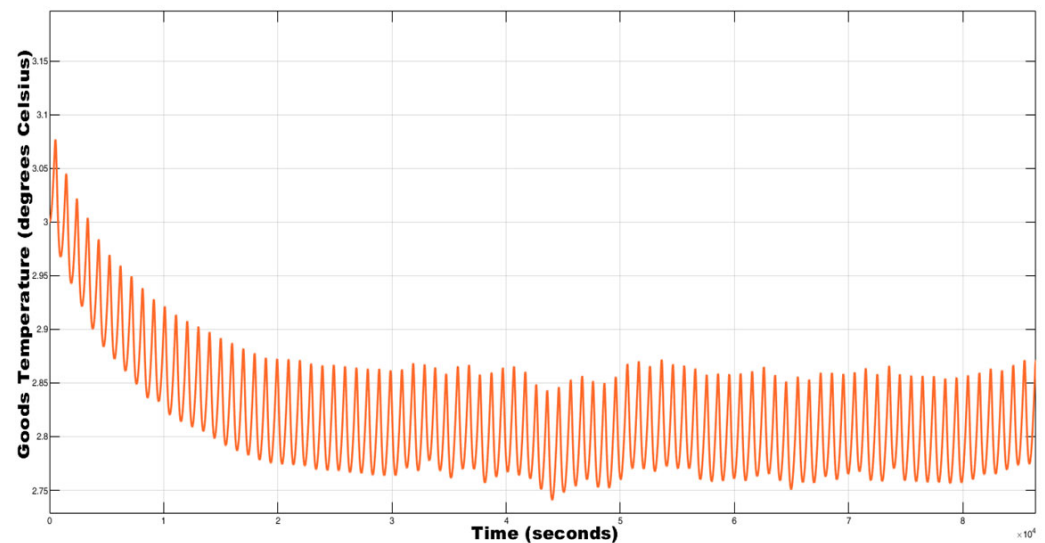


Figure 4. Goods temperature response of the benchmark model.

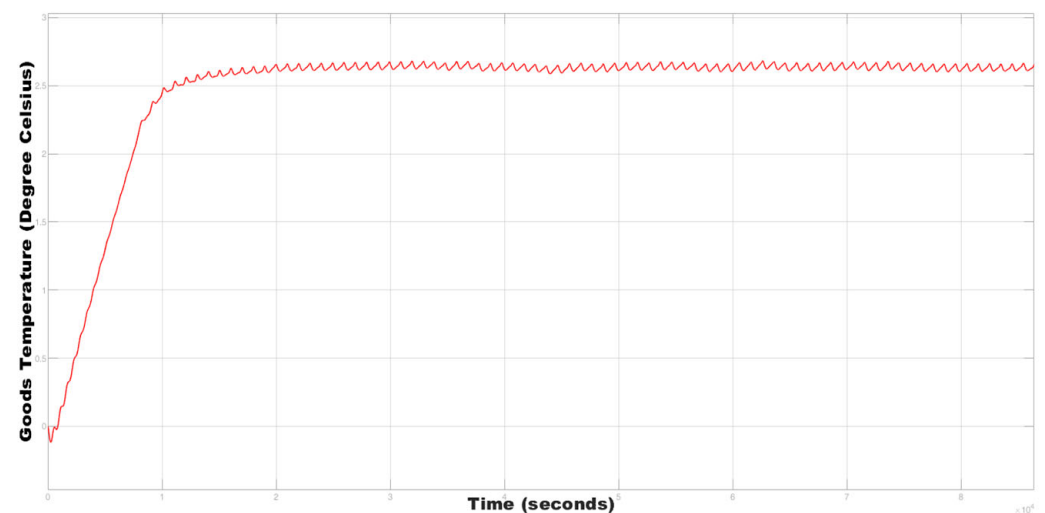


Figure 5. Goods temperature response of the data-driven MPC system.

It is evident from Figures 6 and 7 that PI with dead band control has 117 compressor switches, whereas the MPC has 119. In comparison to the nonlinear benchmark model, the reduced order linear model can be stated to perform satisfactorily with very low variation in compressor switching frequency. This means the effect of wear and tear on the compressor's components using MPC is moderate and can be easily handled through proactive maintenance. The data-driven MPC model's capacity to better regulate the goods temperature more steadily, in spite of outside temperature fluctuations, justifies its disturbance handling capability. This will in turn further increase the shelf lives of fresh fishes and guarantee high return on investment. Consequently, it can be concluded that the subspace identification technique is appropriate for building complicated systems, such as supermarket refrigeration systems, in order to produce dependable, low-cost data-driven models that are appropriate for control, while the model predictive control technique offers excellent system response with disturbance rejection abilities for identified linear systems.

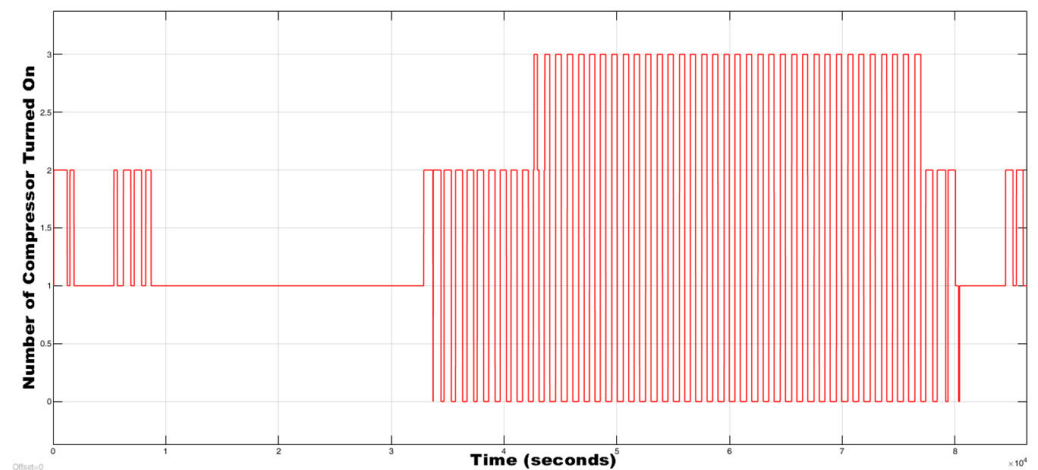


Figure 6. Compressor switches using PI with dead band (benchmark model).

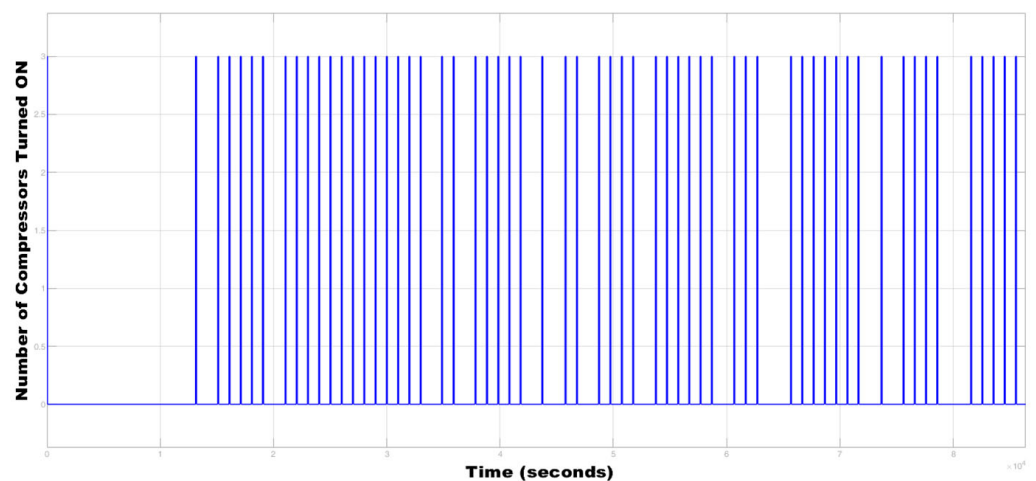


Figure 7. Compressor switches using data-driven MPC.

4. Conclusions

Using the system identification toolbox and the model predictive control toolbox of MATLAB and Simulink software, a data-driven model of a commercial cold storage system subspace system identification is demonstrated. Simulation focus was enforced in the system identification app to ensure stability and N4SID was utilized to construct a model that accurately captures the dynamics of the system. With a goodness of fit of 98.66% and 90.42% for both outputs, an FPE of 4.11×10^{-15} and MSE of 0.0005660, the identified linear model gave excellent metrics of performance. Using the model predictive control toolbox, a linear model predictive controller was created, and the prediction and control horizons were adjusted by trial and error. By keeping the temperature at 2.7 °C, which is within acceptable parameters and ensures food safety and quality, the data-driven MPC system functioned well while still achieving an acceptable duty cycle of compressors in the compressor rack despite being a reduced-order system. Future research will focus on learning-based techniques for modeling and controlling nonlinear systems.

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