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Nonlinear Identification of the Suction Manifold of a Supermarket Refrigeration System Using Wavelet Networks †

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Abstract: The dynamics of the suction manifold of a high-fidelity simulation benchmark model of a modified supermarket refrigeration system created in MATLAB 2024a and Simulink 2024a is modeled using a nonlinear system identification technique. The original model consists of a cold storage room, three open display cases, the suction manifold, and the compressor rack. Since open display cases are less energy-efficient, they were removed, while the cold storage room with a door was used for simulation. The suction manifold model has two outputs: the suction pressure and the compressor's power consumption; and it has three inputs: the mass flow of refrigerant, the ambient temperature, and the compressor capacity. A fourteen-day simulation was carried out, and synthetic data were generated from the input and output data of the simulation model. These data were divided into estimation data and validation data. Wavelet networks were then utilized to estimate and validate a nonlinear ARX model. The comparison between the estimation data and the validation data shows a goodness of fit of 87.8% for the suction pressure and 100% for the compressor power, with a simulation focus. The 100% fit for the compressor power occurred because wavelet networks provide excellent identification for nonlinear static systems and the compressor power response was based on static modeling assumption while the suction pressure response was based on dynamic modeling assumption. The data-driven identified model of the suction manifold was stable and robust and could handle strong nonlinearities of the input and output variables when used to replace the Simulink model of the suction manifold subsystem in the simulation benchmark. The simulation results clearly demonstrate how complex refrigeration system subsystems can be replaced with simpler and data-compliant data-driven models.

Keywords: suction manifold; supermarket refrigeration system; nonlinear ARX; wavelet networks

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1. Introduction

Model structure selection and parameter estimation are the two steps in the nonlinear system identification process. Choosing a class of mathematical operators to serve as a model is the first challenge. The estimating algorithm based on process input–output data, a class of models to be found, and an appropriate identification criterion are covered in the following [1]. When the user's inquiries are not satisfactorily answered by linear system identification, nonlinear system identification enters the picture. In some situations, the nonlinear and time-varying nature of the real world makes linear models imprecise or fails to replicate crucial parts of the behavior of the system being tested [2].

System modeling and identification have made extensive use of nonlinear networks' ability to approximate broad continuous functions. When very little a priori knowledge is available, such approximation methods are especially helpful in the black-box identification of nonlinear systems [3]. The identification of broad nonlinear systems based on radial basis networks has also attracted a lot of attention. A new and effective approximation approach that shows promise is the wavelet decomposition [4]. Wavelets have attracted a lot of attention recently in a variety of scientific and technical fields. A helpful foundation for the localized approximations of functions with any level of regularity at various scales and with the required accuracy is provided by wavelet decompositions.

Wavelets can, therefore, be viewed as a new basis for representing functions. Wavelet-based networks, also known as simply wavelet networks, are inspired by both feedforward neural networks and wavelet decompositions. They have been introduced for the identification of nonlinear static systems [5,6], but little attention has been paid to the identification of nonlinear dynamical systems using wavelet networks. Recent advances have also shown the existence of ortho-normal wavelet bases, from which follow the variability of the rates of convergence for approximation by wavelet-based networks.

Over the decades, models for refrigeration systems have been examined [7]. Control system design may become unfeasible due to the fact that analytical modeling for refrigeration processes typically results in a large number of equations with several unknown factors. One suggestion is to construct a discrete nonlinear model from dynamic input and output data using system identification. Four primary subsystems make up a supermarket refrigeration system model: the compressor rack, the condenser, the suction manifold, the expansion valve, and the evaporator of the display cases [8,9]. Afterwards, these separate models are integrated to simulate an entire commercial refrigeration system, facilitating the efficient testing of various system configurations.

The suction manifold has received special attention in this study in order to provide an accurate suction pressure estimate. The suction manifold supplies the refrigerant coming from the display case to the compressor pack. The suction pressure determines the operation of the compressors. Turning on more compressors will decrease the volume of the refrigerant in the suction manifold, which then lowers the suction pressure. The modeling of the suction manifold subsystem is highly essential for energy consumption because it helps the refrigeration system to handle disturbances caused by the environment and loads. The suction manifold subsystem has three inputs: the mass flow of refrigerant, the ambient temperature, and the compressor capacity. Its two outputs are the suction pressure and the compressor's power consumption. The linear estimation for the suction manifold is unsuccessful due to its strong nonlinearity [10].

Consequently, this paper suggests employing wavelet networks to identify the suction manifold of a supermarket refrigeration system in a nonlinear manner. The estimation and validation of a nonlinear autoregressive exogenous input (ARX) model using wavelet networks is performed using the system identification toolbox of MATLAB and the Simulink software. The estimated model is then used to replace the Simulink model of the suction manifold subsystem of a high-fidelity simulation benchmark model of a commercial refrigeration system.

The following is the outline for this paper: The suction manifold mode and the nonlinear ARX modeling approach is presented in Section 2. Section 3 presents the simulation findings and related remarks. Section 4 finally concludes the paper.

2. Materials and Methods

2.1. Dynamic Model of the Suction Manifold of a Supermarket Refrigeration System

A dynamic equation with a single-state P_{suc} of the suction pressure models the suction manifold. Determining the mass equilibrium along the suction line can be carried out as follows:

$$\frac{dm_{suc}}{dt} = \dot{m}_{suc,in} - \dot{V}_{comp}\rho_{suc} \tag{1}$$

The mass flow rate entering the suction manifold is equal to the mass flow rate exiting the display case evaporator, where m_{suc} is the total mass of refrigerant in the suction line.

$$\dot{m}_{suc,in} = \dot{m}_{ref,out} \tag{2}$$

where $\dot{m}_{ref,out}$ is the mass flow rate of the refrigerant exiting the evaporator and $\dot{m}_{suc,in}$ is the mass flow rate entering the suction line. Rewriting the derivative with respect to pressure, density, and volume produces the following:

$$\frac{dm_{suc}}{dt} = V_{suc}\frac{d\rho_{suc}}{dt} = V_{suc}\frac{d\rho_{suc}}{dP_{suc}}\frac{dP_{suc}}{dt} \tag{3}$$

where the volume and density of the refrigerant in the suction line are denoted by V_{suc} and ρ_{suc}, respectively. Equations (1) and (3) are combined, and $\frac{dP_{suc}}{dt}$ is rearranged to yield the following final dynamic equation for the suction line:

$$\frac{dP_{suc}}{dt} = \frac{\dot{m}_{suc} - \dot{V}_{comp}\rho_{suc}}{V_{suc}\frac{d\rho_{suc}}{dP_{suc}}} \tag{4}$$

The volumetric flow rate induced by compressor work that exits the suction manifold is denoted by $\dot{V}_{comp}$.

The electrical power consumed by the compressor $\dot{W}_{comp}$ is finally approximated by the following:

$$\dot{W}_{comp} = \frac{C_{cap}}{100}\dot{W}_{comp,max} = \frac{\dot{V}_{comp}\rho_{suc}(h_{is} - h_{oe})}{\eta} \tag{5}$$

where the controllable input C_{cap} is the requested capacity in percent (%), $\dot{W}_{comp,max}$ is the power consumption at maximum capacity, h_{oe} and h_{is} are the specific enthalpies in and out of the compressor assuming an isentropic compression, and η is the efficiency from an isentropic process to the actual electrical power consumed. The modified model of supermarket refrigeration system was derived from [11] and is shown in Figure 1.

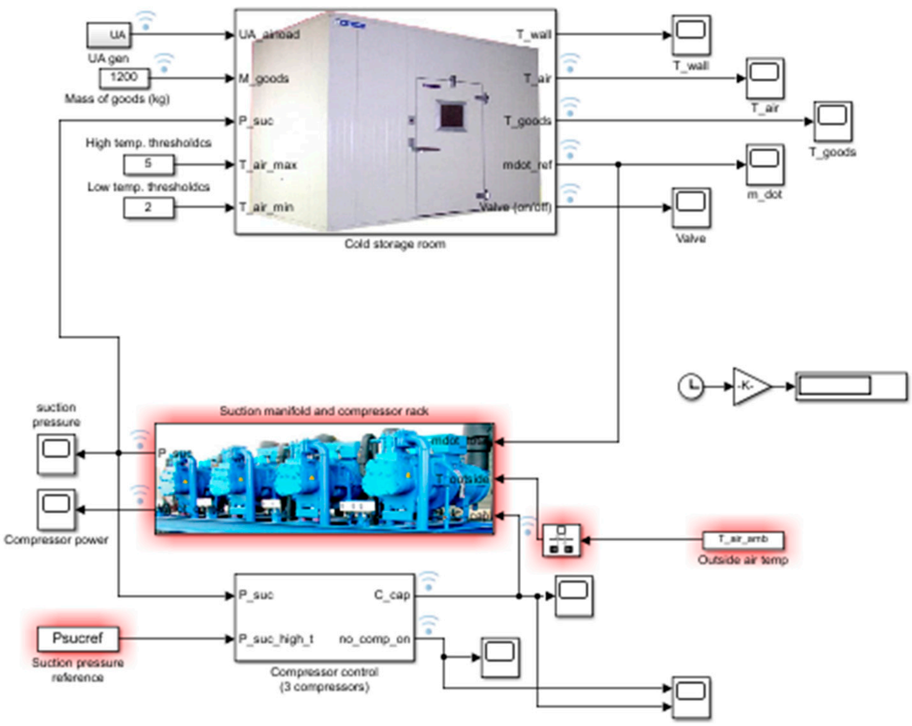

Figure 1. Modified model of a supermarket refrigeration system showing the suction manifold and the compressor rack [11].

2.2. Nonlinear ARX Model

An output function and model regressors make up a nonlinear ARX model. For every model output, the output functions include one or more mapping objects. A linear function and a nonlinear function that act on the model regressors to produce the model output and a fixed offset for that output can be included in each mapping object. The construction of a single-output nonlinear ARX model in a simulation scenario is shown in this block diagram (Figure 2).

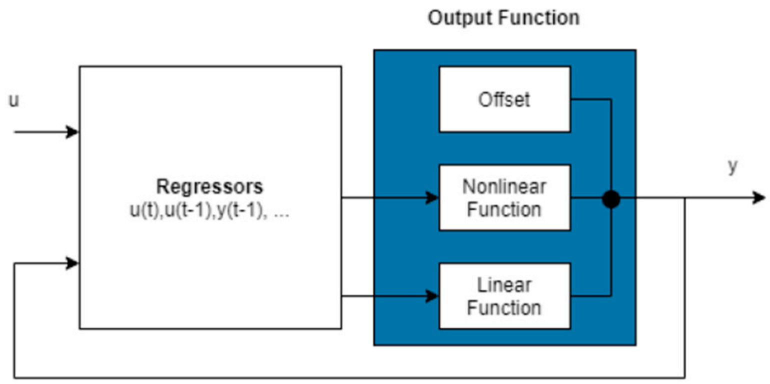

Figure 2. Block diagram of a single-output nonlinear ARX model [12].

The system identification app in MATLAB computes the nonlinear ARX model output y in two stages:

(i) Using historical output data, current and past input values, and past input values, it calculates regressor values. Regressors are simply delayed inputs and outputs, like u(t−1) and y(t−3). We refer to these regressors as linear regressors. Custom, periodic, and polynomial regressors are among the additional regressors that can be made. Any of the regressors can be assigned as an input to either the nonlinear function block or the output function's linear function block, or both.

(ii) An output function block is used to translate the regressors to the model output. Multiple mapping objects, each having parallel blocks for linear, nonlinear, and offset functions, may be included in the output function block. Consider, for instance, the following equation:

$$F(x) = L^T(x-r) + g(Q(x-r)) + d \tag{6}$$

where x is a vector of the regressors, and r is the mean of x. $F(x) = L^T(x-r) + y_0$ is the output of the linear block. The output of the nonlinear function block is represented by $g(Q(x-r)) + y_0$. The calculations are made well-conditioned by the projection matrix Q. The combined outputs of the nonlinear and linear blocks have a scalar offset d added. The exact form of $F(x)$ depends on your choice of output function. You can select from the available mapping objects, such as tree-partition networks, wavelet networks, and multilayer neural networks. You can also exclude either the linear or the nonlinear function block from the output function. When estimating a nonlinear ARX model, the software computes the model parameter values, such as L, r, d, Q, and other parameters specifying g.

Typically, model orders are selected by trial and error until a model that produces an accurate fit to the data is obtained. The best nonlinear model for data is estimated based on the various model structure choices that are explored. The best model is the simplest model that accurately describes the dynamics [12].

3. Results and Discussions

The suction manifold model has two outputs: the suction pressure and the compressor's power consumption; and it has three inputs: the mass flow of refrigerant, the ambient temperature, and the compressor capacity. A fourteen-day simulation was carried out, and synthetic data were generated from the input and output data of the simulation model. The data for the first 7 days with 120,960 samples sampled at 5 s were used for estimation while the data for the last 7 days with 120,961 samples sampled at 5 s were used for validation.

Wavelet networks were then utilized to estimate and validate a nonlinear ARX model. The number of wavelets selected for the two outputs is 2 and 20. The prediction error method (PEM) was employed for estimation, Akaike's final prediction error (FPE) for the developed model was 1.277×10^{-16}, and the mean-square error (MSE) for the model was 0.0005913 with simulation focus.

From Figures 3 and 4, it can be observed that the model outputs for the estimated model of the suction manifold closely represent the dynamics of the suction pressure and the compressor power when compared with the validation data. The goodness of fit of the measured and the simulated output of the suction pressure gave 87.8%, while the measured and the simulated output of the compressor power gave 100%. This implies that the highly nonlinear suction manifold subsystem of a supermarket refrigeration system can be replaced by a data-driven nonlinear model with great accuracy.

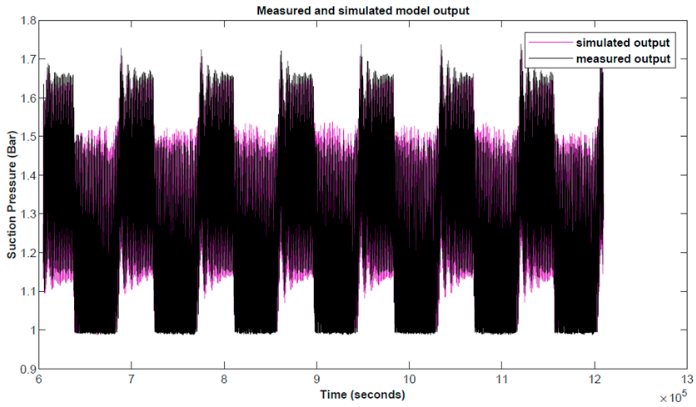

Figure 3. Model validation for suction pressure.

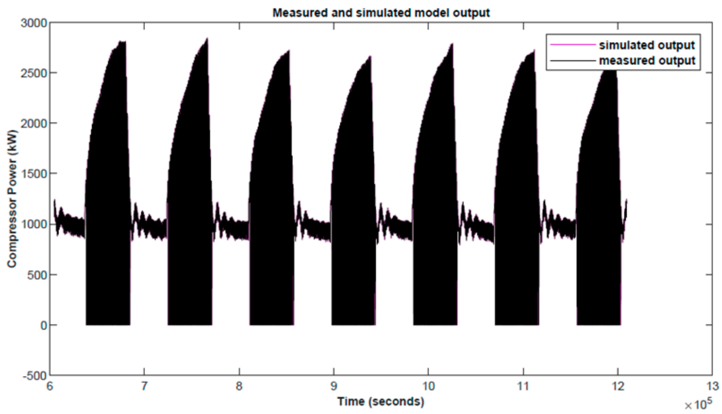

Figure 4. Model validation for compressor power.

From Figures 5 and 6, when the estimated model was compared to the original suction manifold model, it can be observed that the identified model closely represents the nonlinear system dynamics. This implies that the nonlinear identified model can perfectly predict the compressor power and also predict the suction pressure to a great extent. Therefore, it can be deduced that the nonlinear identification of nonlinear systems such as supermarket refrigeration system subsystems like the suction manifold using wavelet networks is suitable for deriving low-cost and reliable data-driven models.

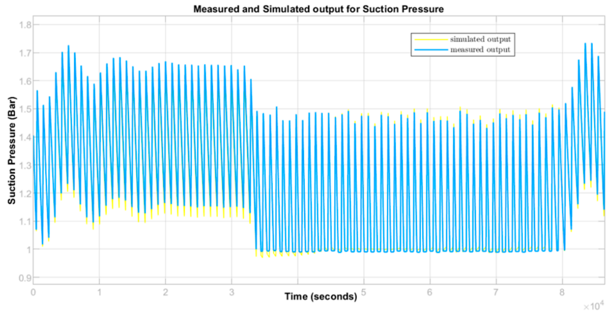

Figure 5. Model outputs for suction pressure.

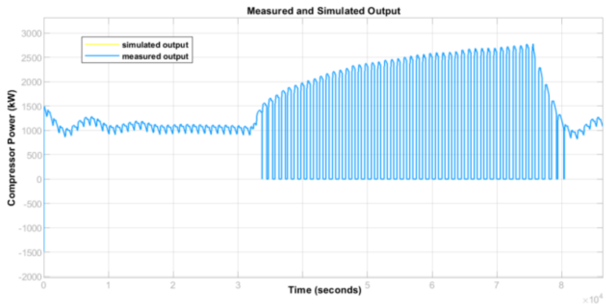

Figure 6. Model outputs for compressor power.

4. Conclusions

A nonlinear system identification of the suction manifold of a supermarket refrigeration system is presented using wavelet networks from the system identification toolbox of MATLAB and the Simulink software. The wavelet networks were able to estimate a model that accurately captures the dynamics of the suction manifold subsystem, with a goodness of fit of 87.8% for the suction pressure and 100% for the compressor power, using simulation focus. The 100% fit occurred for the compressor power because it has been established in the literature that wavelet networks provide excellent identification for nonlinear static systems and the compressor power response was based on static modeling assumption while the suction pressure response was based on dynamic modeling assumption. This shows that nonlinear ARX model estimation using wavelet networks is capable of being used to derive stable and robust systems that can effectively handle the strong nonlinearities of the input and output variables like the suction manifold. The developed model will help to achieve low-cost and reliable solutions for refrigeration systems in predicting suction pressure and accurate estimates of compressor power in the presence of changing ambient loads. Learning-based strategies for nonlinear systems modeling will be the main topic of future research.

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