

System Identification Modelling for Humidity Control in a Centralised Water-Cooled Package Unit Air Conditioning System



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ABSTRACT: In humid countries like Malaysia, there is a need to take more cognisance of the control of humidity, as this significantly affects the thermal comfort and health of the occupants. Effective control mechanisms in HVAC systems also assist in regulating energy consumption, as HVAC is the major consumer of energy in the building sector. Intelligent control systems require accurate models that capture the system's dynamics. This study utilises the system identification technique for a multi-circuit centralised water-cooled air-conditioning system in the model development and selection for the control of humidity in the system. Input data of variable speed compressor with a variable speed evaporator blower and output data of indoor humidity of about 3000 samples collected per minute basis were used. Several models, including Box-Jenkins, State Space, Output-Error, Autoregressive with External Input, and Autoregressive-Moving Average with External Input, were estimated and evaluated. The outcome revealed that the Box-Jenkins third-order model gave the overall best fit with a value of 93.56%, the lowest Final Prediction Error with a value of 0.2016, and the lowest Mean Square Error with a value of 0.1978. This result can be used further in the design application of a controller to maintain the desired humidity for the case study

KEYWORDS: Air-conditioning, Dynamic Modelling, Humidity, System Identification, Temperature.

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I. INTRODUCTION

Thermal comfort is the state of mind that expresses satisfaction with the thermal environment and is evaluated subjectively (Frontczak and Wargocki 2011). One of the most important elements affecting the productivity, well-being, and health of building occupants is indoor thermal comfort (Carlucci et al. 2018). This is important since, particularly in industrialized nations, people spend up to 90% of their time indoors. The appropriate control operations in the HVAC system can go a long way in achieving indoor thermal comfort and at the same time saving a reasonable amount of energy (Fasiuddin and Budaiwi 2011). The desired goal of a HVAC system is to ensure indoor thermal comfort with minimum energy consumption. With the continuous increase in energy consumption globally and considering HVAC system taking a large portion of energy utilisation in the building sector, there is a need for proper control of HVAC systems to achieve better thermal comfort and better energy management (Abdullah et al. 2020). Thermal comfort is

important in most indoor spaces because it affects the productivity and thermal satisfaction of the occupants. Poor indoor conditions can lead to lower productivity and rising health cost for the occupants (Abioye et al. 2023a). One of the key parameters affecting thermal comfort is relative humidity. Relative humidity is used as one of the indicators of air quality in a building and the ability to control it, has long been recognized as an important approach to improve indoor ventilation and achieve acceptable indoor air quality. In buildings, proper control of indoor humidity level is imperative because it directly affects the occupants' thermal comfort, indoor air quality and the operational efficiency of building air conditioning systems (Oleolo et al. 2020).

Past studies have shown that using a variable speed compressor with a variable speed evaporator blower has the potential to control indoor humidity and temperature (Ai, Yang, and Chen 2023; Krakow, Lin, and Zeng 1995). In their study, they used a PID signal processor inverter, an electric motor and a transducer in carrying out

experiments. The temperature and humidity were monitored using transducers and the output signals were supplied to the PID signal processor. This then sends a control signal that is a function of the error between the measured value and the set point to the inverter which modulates the frequency of the motor of both the compressor and blower. However, considering the control of these parameters in the air-conditioning system, the majority of existing centralized air conditioning systems currently adopt the conventional on/off control method, which is not effective in the aspect of thermal comfort and energy management (Afram and Janabi-Sharifi 2014a; Perera and Pfeiffer 2014; Behrooz et al. 2017). The indoor humidity in a space served by an on-off controlled system may remain at a high level. When the supply fan runs continuously while its compressor is on-off, the situation can get worse.

Li et al. (2015) presented a neural network model for the control of humidity and temperature. This model was used to design a controller to vary the speed of a compressor and supply air fan of a water-chilled air conditioning system. The neural network model was validated through an experiment. The experimental findings demonstrated the efficacy of the suggested system. It was also shown that the indoor air temperature and humidity can be controlled simultaneously by varying the compressor speed and the supply air fan speed without requiring any other equipment. Jingyun and Ping (2017) applied a variable frequency drive-based predictive model in their work to regulate the indoor air temperature and humidity while the air conditioning system is running.

A good control algorithm, which ensures thermal comfort, is dependent on accurate dynamic modelling and accurate optimisation techniques (Afroz et al. 2018). This shows that a model is necessary to enable intelligent control, and the system model depends on internal changes. Researchers can model the thermal behaviour of buildings using a variety of methods. System modelling is categorised into Physics-Based model, Grey box/Hybrid model and Black box/Data-Driven model (Afram and Janabi-Sharifi 2014b; Mckoy et al. 2023). The Physics-Based model is also known as a first-principle model or a white box model. They are based on comprehensive knowledge of the mechanism and the system's physical concepts (Synnøve Jönsson 2015). Physical modelling entails a thorough analysis of all the parameters that impact the thermal system. Physical modelling is challenging due to the complexity of thermal systems and the numerous parameters involved (Abioye et al. 2023b; Kim et al. 2022). In grey box modelling, the knowledge of the physical concept and data from the process operations is required to develop the model. The models are based on physics as a model structure in which the model parameters are calculated from the process data. This type of modelling approach is applicable to existing systems and the system parameters are estimated by making use of the measured input and output data. Black box models are often the choice for HVAC systems due to the complex nature of

thermodynamic relationships (Barone et al. 2023; Oleolo et al. 2022; Scotton 2012). The black-box modelling strategy employs "data mining" techniques to draw conclusions about correlations between all collected data. As a result, black-box system identification modelling can create models at minimal development costs. With these models, understanding the internal workings of the system is not necessary. Yiu and Wang (2007) investigated the identification of a black box model for HVAC systems. An approximation was made for a multi-input multi-output ARMAX model, and compared with a single-input single-output ARMAX model. This study aims to utilise system identification techniques for a multi-circuit centralized water-cooled air-conditioning system for the model development and selection for the control of humidity in the system. Several models, including Box-Jenkins, State Space, Output-Error, Autoregressive with External Input, and Autoregressive-Moving Average with External Input, were estimated and evaluated.

II. MATERIALS AND METHODS

A. System Description

In this study, a water-cooled packaged unit (WCPU) air conditioning system was utilized. Water-cooled package air conditioning (AC) systems are widely used in commercial and industrial settings due to their superior efficiency, compact design, and quieter operation compared to air-cooled systems. These systems rely on water as the primary medium for heat rejection, making them ideal for applications requiring precise temperature and humidity control, such as data centres, hospitals, and laboratories. However, maintaining optimal humidity levels in such systems presents a challenge due to dynamic thermal loads and varying environmental conditions. The water-cooled packaged unit consists of two refrigeration circuits in parallel. Each circuit consists of a direct expansion evaporator coil with expansion valve, water-cooled condenser and a scroll type compressor. The two refrigeration circuits were designed to provide partial capacity in case of failure of any of the compressors. Each refrigeration circuit is a vapour compression cycle where the refrigerant enters the compressor as a vapour and is compressed to the pressure of the condenser. Cooled air is supplied to the indoor space via the blowers and ducting. It is located in Block F54 of Universiti Teknologi Malaysia, Johor Bahru, and it comprises a two-circuit refrigeration unit. Each unit consists of an expansion valve, a compressor, an evaporator and a condenser. The air distribution section comprises of the supply fan that sends cool air to the indoor space through a ducting network. The indoor space serves the purpose of office operation, with an average of 40 occupants.

B. Data collection

The data collection process involved placing data loggers at different strategic locations indoor, the air handling unit (AHU) room and outdoor. The WCPU is operated daily

between 8:00 am and 4:00 pm from Sunday to Thursday. Figure 1 shows the WCPU at the ground floor of the Block



Figure 1 WCPU at Block F54

The data was categorised into input and output data, which is an essential stage in the model construction process. The parameters recorded were indoor air temperature, indoor air humidity, compressor and supply fan power consumption. The instruments used for data collection were clamp-on power analyser for compressor and supply fan measurement, an EasyLog wifi temperature and humidity data logger for indoor and outdoor temperature and humidity measurement, and supply air velocity transducer to measure the rate of flow of the supply air through the duct network. The data was taken on a per-minute basis for a month. The data was then analysed using the MATLAB system identification toolbox. The system

F54 building, while Figure 2 shows the power panel that controls the WCPU.



Figure 2 WCPU control unit

identification procedure consists of data selection, estimation and validation. The toolbox estimates model parameters by minimising the error between the predicted and measured outputs. The dataset was pre-processed and split into two parts of 50% for model estimation and 50% for model validation.

The data was then pre-processed to remove the outliers before being finally processed in the system identification toolbox. Figures 3 and 4 shows the installation of the instruments used for data collection both in the indoor space and the Air Handling Unit. Table 1 lists the instruments and measurement parameters



Figure 3 Power Transducer



Figure 4 Humidity data logger

Table 1 Instrument and Measurement Parameters

No	Parameter	Instrument	Accuracy
1	Power to supply fan (kW)	Clamp-on Power Analyzer	±0.5% of full scale
2	Supply Air flow rate	Air flow meter	±2.0% of reading
3	Indoor Humidity	EasyLog wifi Humidity Data Logger	±2% RH of reading
4	Outdoor Humidity	EasyLog wifi Humidity Data Logger	±2% RH of reading
5	Indoor Temperature	EasyLog wifi Temperature Data Logger	±2% RH of reading
6	Outdoor Temperature	EasyLog wifi Temperature Data Logger	±2% RH of reading

C. Data Processing and modelling

The installation of effective control mechanisms for HVAC systems is important, and the significance of selecting an accurate dynamic model as a first step towards achieving efficiency in the control strategy cannot be overemphasised. The complexity in the system's characteristics that the HVAC control system must deal with, makes the design of the control system more difficult. These characteristics include the system's nonlinearity, time-varying disturbances, set points, and time-varying system dynamics (Abioye et al. 2023b; Oleolo et al. 2021, 2022). System identification is an essential technique for creating various model structures that closely approximate the measured data. Every control algorithm that effectively results in good system performance requires a good model that fully captures the dynamics of the system (Afram and Janabi-Sharifi 2014a; Harish and Kumar 2016). The modelling approach in this study is data-driven, and it was carried out using the MATLAB System Identification Toolbox. System identification involves constructing of mathematical models of a dynamic system based on a set of samples of data. System identification can be used in a wide variety of applications. It gives solutions to analysing raw data and creating the best model to fit the plant system. It is widely used in various fields including mechanical engineering, biology, chemistry, meteorology, economics and model-based control design. It involves the process of acquiring and pre-processing data, as well as identifying and selecting mathematical models based on the raw data. Royer et al. (2014) in their studies stipulated that system identification is a versatile toolbox for modelling HVAC systems. Mustafaraj, Chen, and Lowry (2010) applied system identification using a linear parametric model to design a dynamic model for a HVAC system based on different weather conditions. Some of the models that were utilized are ARX, ARMAX, Box-Jenkins, and Output-Error. The nonlinearity of the HVAC systems makes it complex and challenging in using system identification to convert to linear models for the application of controller design. The system identification toolbox software estimates model parameters by minimizing the error between the predicted and the measured output (Samuel et al. 2018).

System identification was applied to derive the mathematical models which linearises and reduces model complexity. The air conditioning system in Block F54, Universiti Teknologi Malaysia, was monitored from the cloud, and data was collected during its operational hours. The data was then analysed after measuring the input and output parameters. The analysis yielded a substantial collection of models in various orders and structures. The steps involved in achieving a good model that can adequately represent the system are outlined in figure 5. After setting up the experiment and collecting the input and output data, the data processing involved dividing the

whole data equally, 50% for the estimation and 50% for validation.

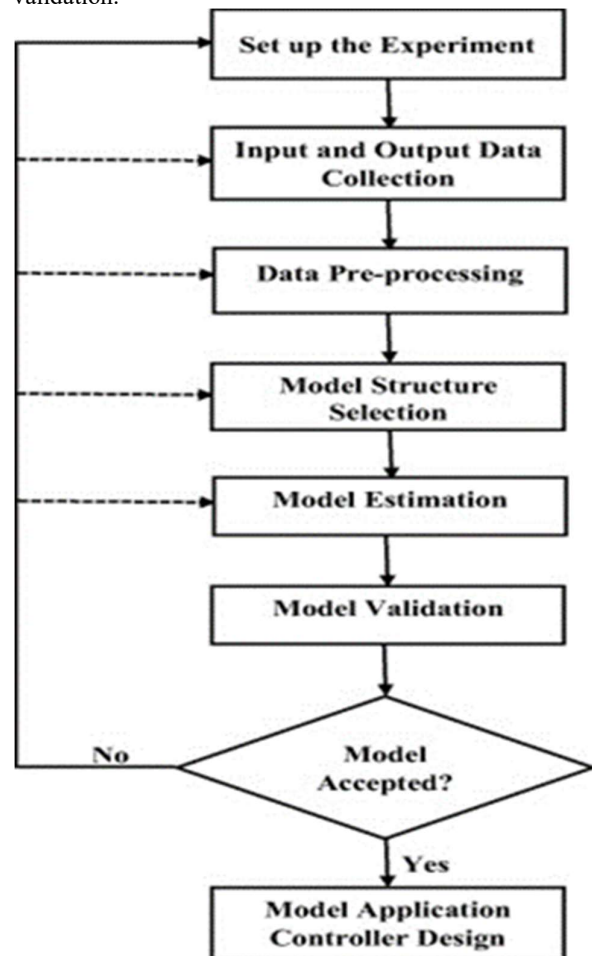


Figure 5 Dynamic modelling flow chart

In general, several parametric model structures can be used in the modelling process. Some examples of the models include the ARX, ARMAX, Box-Jenkins, and Output-Error models (Ljung 2002; Akpenpuun et al., 2023). The plant model is built using the input and output signals of a real plant that needs to be identified. Evaluation metrics such as the Final Prediction Error (FPE), best fit, and mean square error were used as criteria to determine the best model. The general model structure is represented by Equation (1) (Synnøve Jönsson 2015).

$$A(q)y(t) = \frac{B(q)}{F(q)}u(t) + \frac{C(q)}{D(q)}e(t) \quad (1)$$

where

$u(t)$ is the input, $y(t)$ the output, $e(t)$ the error, and $A(q)$, $B(q)$, $C(q)$, $D(q)$ and $F(q)$ are polynomials in the shift-operator, q^{-1}

1) Autoregressive with external input (ARX) model

The ARX model is the simplest among all the model structures. ARX is autoregressive with exogenous terms, and its structure is as shown in equation 2. The disturbance term in the ARX model is white noise and appears directly in the difference equation. The ARX model is an effective estimation technique, particularly for higher-order models. The estimation by the ARX model would be impacted if the system disturbance were not white noise because disturbances are a natural feature of system dynamics. The ARMAX model, which has the same qualities as the ARX model but incorporates the moving average (MA) portion, was created to address this problem by including the disturbance as a moving average of white noise. The ARX model structure is represented by Equations (2) and (3).

$$A(q)y(t) = B(q)U(t) + e(t) \quad (2)$$

$$y(t) + a_1y(t-1) + \dots + a_ny(t-na) = b_1u(t-nk) + \dots + b_nu(t-nb-nk+1) + e(t) \quad (3)$$

where

na = number of poles

nb = number of zeroes plus 1

$(t-1) \dots (t-na)$ = past outputs that the current output is based on

$(t-nk) \dots (t-nk-nb+1)$ = past and delayed inputs that have an impact on the current output

2) Autoregressive moving average with external input (ARMAX) model

The flexibility in disturbance modelling and noise handling are two of the key qualities and benefits of an ARMAX model over an ARX model. (Florakis, Fassois, and Hemez 1998) reported that residual analysis, where the ARMAX structure can produce residuals closer to white noise, suggests that a more thorough ARMAX structure is a better option than the ARX structure. He compared an ARMAX structure to an ARX structure and listed its primary features and benefits. Among them are the ability to deal with noise, having low computing complexity, high precision, assured algorithmic and model stability, and precise model parameter estimates. Additionally, ARMAX is significantly less researched in the literature than ARX and is more difficult. It also has low computational complexity while providing great precision, model stability, and parameter estimation. The ARMAX model equation is stated in Equations (4) and (5).

$$A(q)y(t) = B(q)U(t-nk) + C(q)e(t) \quad (4)$$

$$y(t) + a_1y(t-1) + \dots + a_ny(t-na) = b_1u(t-nk) + \dots + b_nu(t-nb-nk+1) + c_1e(t-1) + \dots + c_ne(t-n_c) + e(t) \quad (5)$$

3) Output Error (OE) Model

The only two active polynomials in the output-error (OE) models are B and F. OE models are a unique combination of polynomial models. White noise is incorporated into OE models as an additive output disturbance in addition to traditional transfer functions that connect measured inputs to outputs. Time- and frequency-domain data can be used to estimate OE models. In situations where the output is only disturbed by white measurement noise, the output Error model is always considered (Zhong et al. 2017). The OE model is represented in Equation (6).

$$y(t) = \frac{B(q)}{F(q)}u(t) + (e)t \quad (6)$$

4) Box Jenkins (BJ) Model

Using inputs from a specific time series, the Box-Jenkins Model is a mathematical formula for predicting data ranges. A variety of time series data types can be analysed using the Box-Jenkins Model to make forecasts. To determine results, the system compares data from different points. Using moving averages, seasonal differencing, and auto-regression as part of the technique, the model can foresee patterns and identify them. Complete independent parametrisation using a rationale polynomial function is what is provided by Box-Jenkins models. Equation (7) below represents the BJ structure

$$y(t) = \frac{B(q)}{F(q)}u(t) + \frac{C(q)}{D(q)}e(t) \quad (7)$$

5) State-space model structures

State space representing dynamics of the Nth order system as a differential equation of the first order in an N-vector state variable is used to describe a system by a set of first-order differential equations. This kind of model may be used to analyse the system's dynamic features across a wide variety of environments that are critical for the design of the control system (Afroz et al. 2018). Work on state space models in HVAC systems is scarce. By creating the building simulation using the MATLAB simulation code, (Kulkarni and Hong 2004) provided a state-space modelling technique for the building system, specifying the dynamic properties. It was used to examine the system's important dynamic components. To facilitate computer calculations, the study provided the link between the model's input and output variables using a matrix structure. The model structure has the drawback of failing to accurately represent some aspects of the system's physical characteristics (Mustafaraj et al. 2010). The discretisation of the state space model is represented by Equations (8) and (9). As a stand-in for the number of independent components in the system, n, the number of state variables is used. The overall system energy, as well as the time

derivatives of the state variables, both have an impact on how quickly the system's energy changes. The system state variables, t , can also be used to derive the values of all other system variables at any given time, t .

Continuous-time

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t)\end{aligned}\quad (8)$$

Discrete-time:

$$\begin{aligned}x(t+T) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t)\end{aligned}\quad (9)$$

Model structure selection, estimation, and validation were conducted after the data preparation and analysis. All the models were put to the test and compared to one another in various orders. Based on the model validation criteria, the best model is chosen. The validation criteria are Final Prediction Error (FPE), Mean Square Error (MSE), and Best Fit (BF).

The mean square error and the best fit percentage are represented in equation 10 and 11. The final Prediction Error is represented by Equation (12).

$$BF = \left(1 - \frac{\text{norm}(y - \hat{y})}{\text{norm}(y - \bar{y})} \right) \times 100 \quad (10)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (11)$$

where

y = measured output

\hat{y} = simulated output

\bar{y} = measured mean

$$FPE = \det \left(\frac{1}{N} E^T E \right) \left(\frac{1 + \frac{np}{N}}{1 - \frac{np}{N}} \right)$$

(12)

where

N = Number of values in the estimation data set

E = Matrix of prediction errors

np = Total number of estimated parameters

IV. RESULTS AND DISCUSSION

In this section, the results show the Best Fit, Mean Square Error, and Final Prediction Error for the humidity models. Table 2 shows the results for the first-order humidity models. The ARX model has the highest best fit, with the lowest final prediction error (FPE) and mean square error (MSE).

Table 2 Results for first-order humidity model structures

Model Structure	BF (%)	FPE	MSE
State Space	90.47	0.4359	0.4331
ARX	93.14	0.2284	0.2241
ARMAX	91.74	0.3296	0.3255
Box-Jenkins	91.78	0.3281	0.3219
Nlarx	91.36	0.3601	0.3555

Figure 6 shows the performance of all the humidity models for the measured and predicted output in the first-order. Based on the comparison of different model structures using performance metrics such as BF, FPE, and MSE, the ARX model clearly outperforms the others by achieving the highest BF of 93.14%, which indicates the closest match between the model output and the actual system behavior, along with the lowest FPE (0.2284) and MSE (0.2241), reflecting its superior predictive accuracy and minimal error, thereby making it the most reliable and effective choice for accurately capturing the dynamics of the system among all the evaluated first order modeling approaches, including State Space, ARMAX, Box-Jenkins, and Nonlinear ARX (Nlarx), which showed comparatively lower fit and higher prediction errors

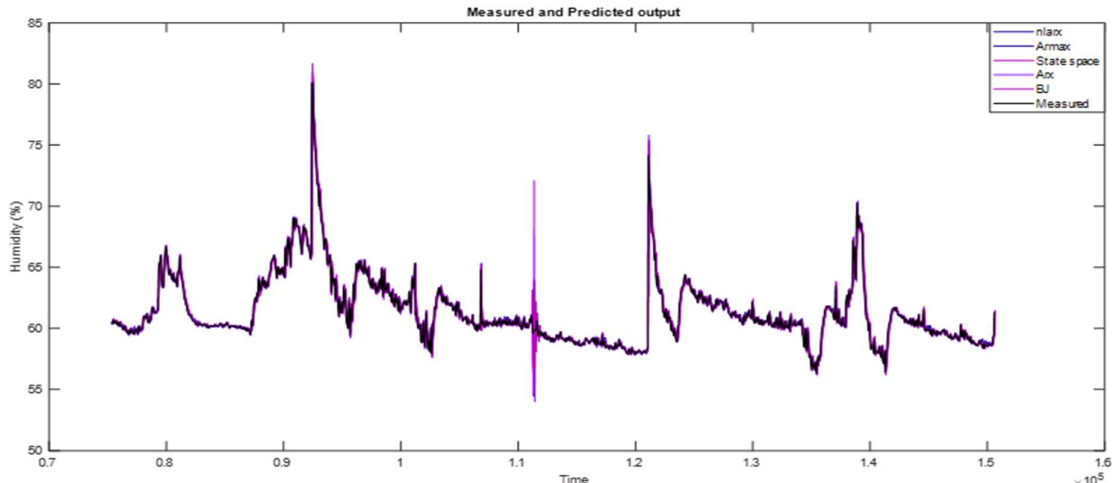


Figure 6 Humidity first-order model performance

Table 3 shows the results for second-order humidity models. The ARX model also has the highest best fit, with the lowest final prediction error and mean square error.

Table 3. Results for second-order humidity model structures

Model Structure	BF (%)	FPE	MSE
State Space	90.70	0.4171	0.4119
ARX	93.01	0.2370	0.2326
ARMAX	91.43	0.3542	0.3497
Box-Jenkins	90.74	0.4167	0.4088
Nlarx	91.31	0.3607	0.3551

Figure 7 shows the performance of all the humidity models for the measured and predicted output in the second order. Upon evaluating the performance of these model structure, in the second order, the ARX model once again emerges as the most effective, achieving the highest BF of 93.01%, which signifies the closest alignment between the model's output and the actual system response, while also recording the lowest FPE (0.2370) and MSE (0.2326) among all models, indicating superior predictive accuracy and minimal deviation from actual values; in contrast, other models such as State Space and Box-Jenkins, despite having comparable BF scores around 90.7%, demonstrate significantly higher FPE and MSE values, suggesting relatively less accurate performance, whereas ARMAX and Nlarx offer slightly better results than State Space and Box-Jenkins but still fall short of ARX in all performance measures, thereby reinforcing ARX as the most robust and reliable model structure for representing the system dynamics in this identification task.

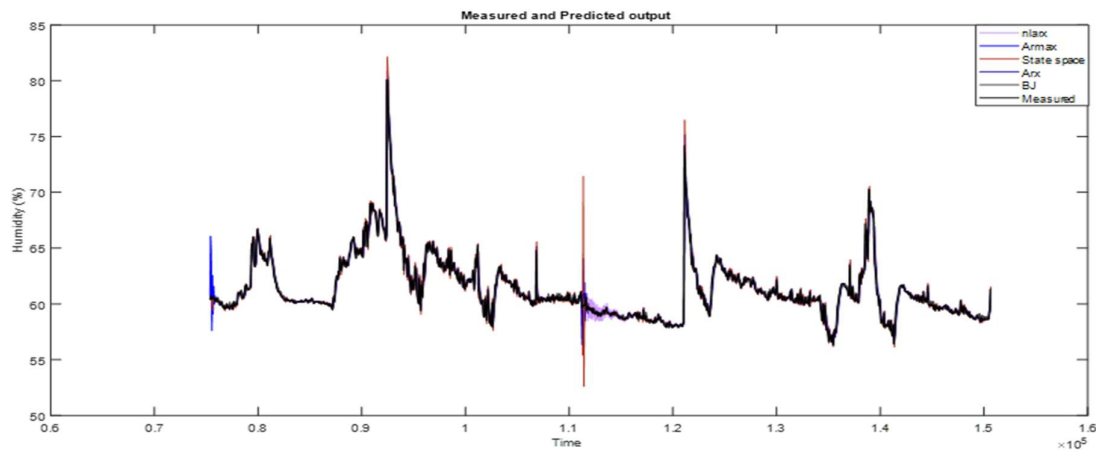


Figure 7 Humidity second-order model performance

The above results indicate that for the first and second order humidity models, the ARX model outperforms other compared models in terms of accuracy, predictive capability, and overall performance. Specifically, the highest best fit means the model explains the observed data more effectively, achieving a superior best-of-fit measure, which reflects its ability to capture the underlying trends and variations. Additionally, the lowest final prediction error (FPE) suggests that the ARX model generalizes well to unseen data, striking an optimal balance between complexity and simplicity to avoid overfitting. Meanwhile, the lowest mean square error (MSE) confirms that the model's predictions are the closest to the actual values, minimizing the average squared deviations between predicted and observed data points. Together, these metrics demonstrate that the ARX model is a better, more reliable choice out of the first and second order models for forecasting or system identification in the given context, as it not only fits the training data exceptionally well but also ensures robust performance when applied to new, unseen data. This makes it the preferred model when

both accuracy and predictive stability are critical. The third-order model results is shown in Table 4 below.

Table 4 Results for third-order humidity model structures

Model Structure	BF (%)	FPE	MSE
State Space	91.58	0.3447	0.3382
ARX	92.76	0.2546	0.2498
ARMAX	91.37	0.3598	0.3552
Box Jenkins	93.56	0.2016	0.1978
Nlarx	91.35	0.3605	0.3549

Figure 8 shows the best fit for all the humidity models for the measured and the predicted output in the third order. the Box-Jenkins model demonstrates the overall best performance, achieving the highest BF of 93.56%, which indicates the most accurate replication of the system's output behavior, and also attaining the lowest FPE (0.2016)

and MSE (0.1978) values, suggesting excellent predictive precision and minimal residual error; while the ARX model follows closely behind with a high BF of 92.76% and moderately low FPE and MSE (0.2546 and 0.2498, respectively), the other models—State Space, ARMAX, and Nlarx—show slightly lower fit percentages (ranging

between 91.35% and 91.58%) and higher error values, indicating comparatively reduced modeling accuracy and efficiency, thus reinforcing Box-Jenkins as the most suitable and reliable model structure for capturing the system's dynamics with the highest fidelity among those evaluated.

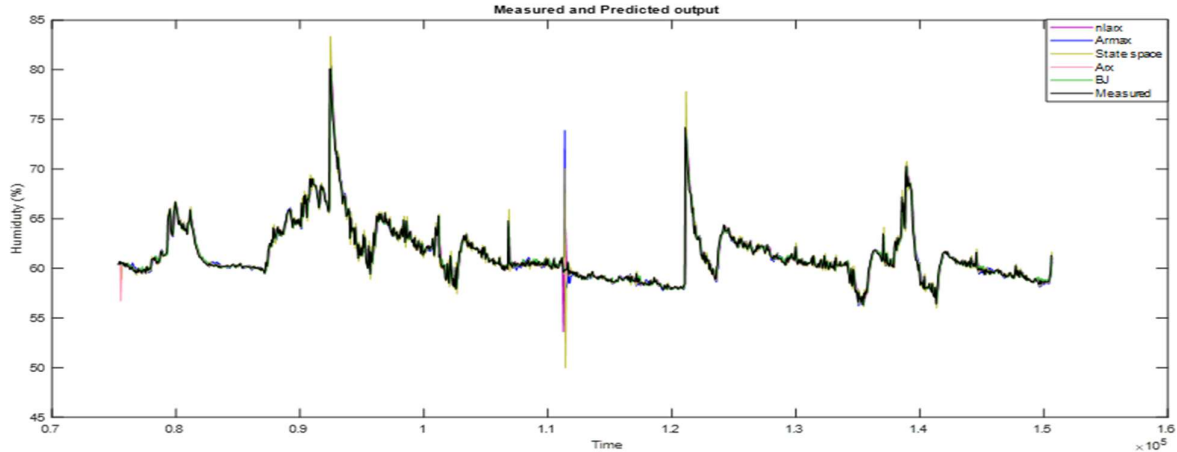


Figure 8 Humidity third-order model performance

All the results above for the first, second and third order models has been summarized in table 5 showing the results for all the models. Considering the overall results from the system identification analysis, it was found that the Box-Jenkins third-order model gave the overall best fit with a value of 93.56%, the lowest Final Prediction Error with a value of 0.2016, and the lowest Mean Square Error with a

value of 0.1978 as shown in Table 5. This means that the box-Jenkins third-order model represents the dynamics of the system the most. It provides a comprehensive assessment of the model's superior performance across three critical statistical metrics, demonstrating its effectiveness in capturing the underlying system dynamics while maintaining robust predictive capabilities.

Table 5 Results for the five model structures

Model Structure	Order	BF (%)	FPE	MSE
State Space	1 st	90.47	0.4359	0.4331
	2 nd	90.70	0.4171	0.4119
	3 rd	91.58	0.3447	0.3382
ARX	1 st	93.14	0.2284	0.2241
	2 nd	93.01	0.2370	0.2326
	3 rd	92.76	0.2546	0.2498
ARMAX	1 st	91.74	0.3296	0.3255
	2 nd	91.43	0.3542	0.3497
	3 rd	91.37	0.3598	0.3552
Box Jenkins	1 st	91.78	0.3281	0.3219
	2 nd	90.74	0.4167	0.4088
	3 rd	93.56	0.2016	0.1978
NLAX	1 st	91.36	0.3601	0.3555
	2 nd	91.31	0.3607	0.3551
	3 rd	91.35	0.3605	0.3549

The best fit value of 93.56% indicates that the model explains a remarkably high proportion of the variance in the observed data, suggesting it accurately represents the system's behavior with only minimal unexplained variability, likely attributable to noise or minor unmodeled effects. This high best-of-fit underscores the model's ability to replicate the observed patterns with high fidelity.

Furthermore, the lowest Final Prediction Error (FPE) of 0.2016 highlights the model's exceptional generalization performance, meaning it is not only well-suited to the training data but also reliably predicts future or unseen data points. The FPE metric inherently penalizes excessive model complexity, so this low value confirms that the third-order Box-Jenkins formulation achieves an optimal balance between simplicity and explanatory power, avoiding the pitfalls of overfitting while still capturing essential system dynamics. This makes the model particularly valuable for real-world applications where predictive accuracy on new data is paramount.

Complementing these findings, the lowest Mean Square Error (MSE) of 0.1978 reinforces the model's precision by quantifying the average squared deviation between its predictions and the actual observations. The minimal MSE indicates that the model's forecasts are consistently close to the true values, further validating its reliability and accuracy. Together, these metrics, high best fit, low FPE, and low MSE paint a compelling picture of the Box-Jenkins third-order model as the standout choice among the evaluated options. Its ability to deliver precise, generalizable, and well-fitted results makes it ideally suited for applications requiring robust system identification, such as industrial process control, economic forecasting, or any scenario where dependable predictive modelling is critical. The results also suggest that the model's structure is well-matched to the system's characteristics, though the residual unexplained variance (6.44%) might warrant further investigation to determine if additional refinements or external factors could enhance performance even further.

V. CONCLUSION

Selecting an accurate model is a fundamental part of developing a control strategy. This study has simulated different orders for the linear and non-linear parametric models. The best-fitting model with the lowest mean square error and final prediction error is chosen as the model for designing a controller. In this study, it was found that the Box-Jenkins third-order model is the best model to describe the system dynamics for the case study in this research work. This result can be used further in the design of a controller to maintain the desired humidity for the case study. The results of this study will be useful in the area of building automation systems, thermal comfort in indoor spaces and energy management for buildings.

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