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Research Article

Impact of Operating Conditions on Linear ARX Models for Air Source Heat Pumps

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Abstract

Linear black-box models are widely used for control-oriented modelling of air source heat pumps, but their prediction accuracy depends on the operating conditions under which they are identified. This paper analyses the operating-point dependency of low-order linear Auto-Regressive with exogenous input (ARX) models for a variable-speed air-source heat pump. Using simulation data generated from a detailed vapour compression cycle model, separate ARX (2,2,0) models are identified around four compressor speed operating points (30, 60, 90, and 120 Hz) using a consistent excitation and identification framework. Model performance is evaluated on validation datasets with respect to electrical power consumption, thermal capacity, and cooling capacity. The results show that electrical power consumption is predicted with consistently high accuracy across all operating points, with validation FIT values exceeding 95%. Thermal and cooling outputs exhibit stronger operating-point dependency, with reduced accuracy at low compressor speed and validation FIT values above 90% at medium and high speeds when bounded relative excitation is applied. The findings demonstrate that the accuracy of linear ARX models is strongly influenced by operating regime and excitation design rather than by model structure alone, and confirm that compact locally identified linear models remain suitable for control-oriented heat-pump applications.

Keywords: Air Source Heat Pump; ARX Model; Linear System Identification; Operating Point Dependency; Control Oriented Modelling

INTRODUCTION

Air source heat pumps and vapour compression HVAC systems play a central role in building energy consumption and flexibility, making accurate dynamic models essential for energy performance assessment, advanced control, and optimization [1-3]. The literature shows a wide range of modelling approaches, reflecting different trade-offs between physical insight, data requirements, and computational complexity [1, 4]. These approaches are commonly classified as physics-based (white-box), data-driven (black-box), or hybrid (grey-box) models.

Physics based models rely on thermodynamic and heat transfer principles to describe individual components of the vapour compression cycle and generally are the most detailed and correct ones, exposing high fidelity, but they require detailed system information and substantial modelling effort, limiting their applicability in control-oriented contexts [1, 2, 5, 6]. Grey-box models attempt to balance physical interpretability and identification flexibility, but their performance depends strongly on the suitability of the assumed structure across operating conditions [4, 7, 8]. In contrast, linear black-box models, such as ARX-type structures, are widely adopted in control-oriented studies due to their simplicity, low computational burden, and ease of implementation [2, 6, 9, 10]. However, their prediction accuracy may deteriorate when operating conditions differ from those used for identification, limiting validity over wide operating envelopes [2, 11].

The literature further shows that no single black-box structure consistently outperforms others across all HVAC and vapour compression applications [2, 6]. Comparative studies demonstrate that different linear model structures may exhibit significantly different performance depending on the operating conditions and control objectives. For example, Box–Jenkins models have been reported to outperform ARX models in certain variable-speed vapor-compression systems, while ARX remains attractive for its transparency and reduced identification complexity [6].

To address the inherent nonlinearity of HVAC systems, several authors have proposed regime-based or piecewise modelling approaches, such as PieceWise ARX (PWARX) models [3, 6, 12-16]. These approaches explicitly acknowledge that a single linear model may be insufficient to represent system dynamics over a wide range of operating conditions, and instead employ multiple linear sub-models associated with different operating regimes [3]. While such methods can improve global prediction accuracy, they also introduce additional complexity in model selection, switching logic, and implementation.

Despite these advances, many control-oriented studies continue to adopt a single linear model identified around nominal operating conditions, implicitly assuming its validity across the entire operating range [2, 6, 17]. As a result, the impact of operating point variations on the accuracy and robustness of linear black box models is often not quantified explicitly.

In previous work, the authors investigated the use of linear black-box models for modelling the power consumption and thermal performance of an air-source heat pump using a simulation-based dataset derived from a detailed vapour compression cycle model. In that study, an ARX structure was identified and validated under nominal operating conditions, and its prediction accuracy was assessed against both physics-based simulations and simplified steady-state calculation methods. However, the analysis was limited to a global model identified over the full dataset, and the impact of operating point variations on model accuracy was not explicitly investigated. The present work builds upon this previous contribution by focusing specifically on the operating point dependency of ARX models and by quantifying their validity across distinct compressor speed regimes [14].

The objective of this paper is not to propose a new modelling structure, nor to compare linear ARX models against alternative black-box or machine learning approaches. Instead, the focus is placed on quantifying the operating point dependency of linear ARX models when applied to an air source heat pump.

Using a simulation-based dataset obtained from a detailed vapour compression cycle model, the compressor operating range is segmented into distinct low, medium, and high speed regions. Separate ARX models are identified for each region, and their prediction performance is evaluated with respect to electrical power consumption, thermal capacity and cooling capacity. By isolating the effect of the operating point while keeping the model structure fixed, this work provides insight into the validity domain of linear ARX models and highlights the conditions under which their use is justified for control and optimization purposes [3, 12].

Unlike many existing studies that identify a single linear model using data spanning a wide operating range, this work demonstrates that the prediction accuracy of low-order ARX models is significantly improved when the identification is performed at specific operating points rather than on global datasets. By systematically comparing locally identified ARX models at fixed compressor speeds with previously reported global identification results, this study shows that operating-point-based identification yields higher accuracy for both electrical and thermal outputs. The novelty of this work lies in quantifying how excitation design and local identification strategies enable compact linear models to outperform a single global model, thereby providing new insight into the practical validity of linear black-box models for heat-pump applications.

SYSTEM DESCRIPTION AND SIMULATION FRAMEWORK

Air source heat pump model

The system considered in this study is a variable-speed air-source heat pump modelled in the MATLAB/Simscape environment [15]. The model represents a conventional vapour compression cycle comprising a variable-speed compressor, condenser, expansion valve, and evaporator. A detailed description of the modelling assumptions, component parameterization, and validation against reference simulations is provided in the authors' previous work and is therefore not repeated here [14]. In the present study, the same simulation framework is reused to investigate the operating-point dependency of linear black-box models.

Operating Conditions and Compressor Frequency Selection

The compressor speed is a primary control variable in variable-speed air-source heat pumps and directly influences both electrical power consumption and thermal capacity. In this work, four compressor frequencies are selected: 30, 60, 90, and 120 Hz. These values represent low, medium, high and close to maximum-load operating conditions and are commonly adopted in modelling and control-oriented studies of vapour compression systems [6, 10].

To enable consistent implementation within the Simscape control interface, the compressor speed command is normalized with respect to the maximum compressor frequency of 130 Hz. Under this normalization, the selected operating points correspond to normalized values of approximately 0.2308, 0.4615, 0.6923, and 0.9231 for 30, 60, 90, and 120 Hz, respectively.

Simulation Protocol, Excitation Design, and Data Preparation

To investigate operating-point dependency, independent simulations are performed for each of the selected compressor frequencies. In each case, the system is operated around a fixed nominal compressor speed defining a local operating regime. A bounded relative staircase excitation is applied to the normalized compressor speed command in order to ensure sufficient dynamic excitation while remaining within the local operating region.

The excitation amplitude is fixed across all operating points and scaled relative to the nominal operating value. Each step in the excitation sequence is held for 3600 s, which is consistent with the dominant thermal time constants observed in the system.

All simulation signals are initially logged at high temporal resolution and subsequently down sampled to a sampling time of 20 s for system identification. This sampling time reflects the slow thermal dynamics of the heat pump while limiting model complexity and improving numerical robustness [2, 4, 9, 14]. The same excitation signal, sampling time, and data preparation procedure are applied consistently across all operating points to ensure a fair comparison of model performance.

Electrical power consumption and thermal output variables are recorded for each simulation run and used as the basis for the subsequent system identification and validation analysis.

ARX MODEL STRUCTURE AND IDENTIFICATION PROCEDURE

Linear Black-Box Modelling Framework

In this study, the dynamic behaviour of the air source heat pump is represented using a linear Auto-Regressive with eXogenous input (ARX) model structure. Linear black box models of this type are widely investigated due to their low computational complexity, ease of identification, and suitability for control oriented analysis [2, 6, 9, 14, 16]. Although such models do not explicitly represent the underlying thermodynamic processes, they can provide accurate dynamic approximations within limited operating regions when properly identified.

$$\mathrm{y(k)} + \sum_{\mathrm{i=1}}^{\mathrm{n_a}} \mathrm{a_i y(k-i)} = \sum_{\mathrm{j=1}}^{\mathrm{n_b}} \mathrm{b_j u(k-n_k-j+1)} + \mathrm{e(k)} \tag{1}$$

$$\mathrm{A(q^{-1})y(k)} = \mathrm{B(q^{-1})u(k-n_k)} + \mathrm{e(k)} \tag{2}$$

In Equation (1), $y(k)$ denotes a generic system output at discrete time k, $u(k)$ represents a generic input signal, n_a and n_b are the model orders associated with the output and input regressors, respectively, n_k represents the input delay, and $e(k)$ is a zero-mean disturbance term capturing unmodeled dynamics and noise. Equation (1) is written in scalar form and is used to describe each output channel individually. Equation (2) represents the compact polynomial-matrix formulation of the ARX model for the multi-input, multi-output

(MIMO) case. This formulation is commonly adopted in control-oriented modelling due to its simplicity and linear parameter structure [2, 6, 9, 14, 16].

In the context of HVAC systems, ARX models are commonly adopted to describe the relationship between control inputs and measured outputs, such as electrical power consumption or thermal capacity, while accounting for the influence of boundary conditions and disturbances [2, 6, 10, 14]. Their simplicity makes them attractive for predictive control, observer design, and real time optimization applications [4, 12].

Model Inputs and Outputs

In this study, the air-source heat pump is modelled as a multi-input, multi-output (MIMO) discrete time system. The manipulated input of the system is the normalized compressor speed command, while indoor and outdoor air temperatures are included as measured exogenous inputs. This modelling approach is widely adopted in HVAC and vapour compression applications, where system performance depends not only on actuator commands but also on environmental conditions [1, 2, 6, 10].

The input vector is defined as, Equation (3):

$$\mathrm{u(k)} = \begin{bmatrix} u_c(k) \\ T_{out}(k) \\ T_{in}(k) \end{bmatrix} \tag{3}$$

where $u_c(k)$ is the normalized compressor speed command, and $T_{out}(k)$, $T_{in}(k)$ are the outdoor and indoor air temperatures, respectively. The output vector is defined as, Equation (4):

$$\mathrm{y(k)} = \begin{bmatrix} P_{el}(k) \\ Q_{cool}(k) \\ Q_{th}(k) \end{bmatrix} \tag{4}$$

where $P_{el}(k)$ is the electrical power consumption, $Q_{cool}(k)$ is the cooling capacity, and $Q_{th}(k)$ is the delivered thermal (heating) capacity. Similar multi variable modelling formulations are widely used in HVAC and vapour compression applications because system performance depends not only on compressor actuation but also on boundary conditions such as indoor/outdoor temperatures [1, 2, 6, 10, 14].

For identification purposes, separate ARX models are estimated for each output channel using the same input vector and model structure. This allows the different dynamic characteristics of electrical and thermal variables to be captured while preserving a consistent modelling framework across operating points [2, 9, 11, 16].

ARX Model Structure and Order Selection

The ARX model structure is characterized by the model orders n_a and n_b, which define the number of past output and input samples included in the model, respectively, as well as the input delay n_k. In control-oriented HVAC modelling, low order linear models are typically preferred to limit model complexity and improve numerical robustness, particularly when slow thermal dynamics are present [2, 4, 12].

In this work, the same ARX structure is adopted for all operating points and output variables. Fixing the model structure across operating regimes ensures that differences in model performance can be attributed to operating-point effects rather than to changes in model order or identification settings. This choice is consistent with previous studies that emphasize fair comparison when analysing model validity across different conditions [2, 6, 9].

The model orders are selected based on a preliminary analysis of the system dynamics, taking into account the dominant settling times observed in the simulations and the chosen sampling time of 20 seconds. Low order models are sufficient to capture the dominant dynamics of interest while avoiding overfitting and excessive parameterization. Similar order-selection strategies are commonly adopted in black box identification studies of HVAC and refrigeration systems [2, 6, 10].

Identification Procedure and Dataset Preparation

The ARX model parameters are identified using standard least-squares estimation techniques applied to the simulation datasets described in Chapter 2. Prior to identification, the recorded input and output signals are mean-centered to remove steady-state offsets, which is a common preprocessing step in linear system identification [9, 12].

For each compressor operating point, the dataset corresponding to the multi-step excitation sequence is used for parameter estimation. The identification is performed independently for each operating point, resulting in a set of locally valid ARX models. This operating point-based identification approach is aligned with regime dependent modelling concepts reported in the literature, where local linear models are used to approximate nonlinear system behaviour around specific operating conditions [3, 12, 13, 16].

To ensure consistency and comparability, the same identification procedure, sampling time, and data preprocessing step are applied to all datasets. No additional tuning or adaptation is performed for individual operating points. This allows the effect of the compressor operating regime on ARX model accuracy to be isolated and analysed in a systematic manner.

$$\hat{\theta} = argmin_{\theta} \sum_{k=1}^{N} (y(k) - \hat{y}\,(k|\theta))^2 \tag{5}$$

In Equation (5) θ is the vector of ARX parameters and $\hat{y}(k|\theta)$ denotes the model-predicted output. Least-squares estimation is widely used in black-box identification due to its computational efficiency and robustness for linear-in-parameter models [2], [9], [12], [16].

Model Validation Approach

The performance of the identified ARX models is evaluated using standard time domain validation metrics. For each operating point, the identified model is validated against simulation data obtained under the same excitation conditions. Prediction accuracy is assessed by comparing predicted and simulated outputs, with particular attention paid to transient response characteristics following step changes in compressor speed.

Model validation focuses on the ability of the ARX models to reproduce the dominant dynamics of electrical power consumption, thermal power and cooling power within each operating regime. This validation approach is consistent with control-oriented modelling practices, where accurate prediction of transient behaviour is often more critical than exact steady-state matching [4, 6, 12].

By applying the same validation procedure across all operating points, the relative performance of the ARX models can be compared directly. This enables a clear assessment of how model accuracy varies with compressor speed and provides insight into the operating point dependency of linear black box models for air-source heat pump applications.

$$NRMSE = 1 - \frac{\left(\frac{1}{N}\sum_{k=1}^{N}\left(y(k)-\hat{y}\,(k|\theta)\right)^{2}\right)^{\frac{1}{2}}}{\sigma_y} \tag{6}$$

In Equation (6) σ_y denotes the standard deviation of the measured output. The NRMSE metric provides a normalized measure of prediction accuracy and is commonly used in validation of black-box models [2, 6, 9, 16].

Model Order Selection

The selection of the ARX model order is guided by both previous work and the specific objectives of the present study. In the authors earlier conference contribution, ARX model orders were primarily selected based on information theoretic criteria, such as the normalized Akaike Information Criterion (nAIC), leading to the choice of an ARX (3,3,0) structure as a suitable compromise between model fit and complexity [14]. In contrast, a subsequent journal study by the authors investigated multiple ARX structures using prediction-based performance metrics and showed that a lower order ARX (2,2,0) model achieved superior prediction accuracy on control relevant outputs while exhibiting improved robustness and reduced complexity [17].

In the present work, the primary objective is not global model selection but the comparative analysis of ARX model performance across different compressor operating points. For this purpose, a fixed and compact model structure is required to ensure fair comparison and to limit overfitting effects when transferring the identification procedure across operating regimes. Based on the findings reported in [17], the ARX (2,2,0) structure is therefore adopted as the baseline model in this study. This choice reflects a deliberate emphasis on prediction accuracy and generalization capability rather than solely on information theoretic optimality, and is consistent with control oriented modelling practices where low order linear models are often preferred.

RESULTS AND OPERATING POINT DEPENDENCY ANALYSIS

All operating points are analysed using the same excitation signal, sampling time, ARX structure, and identification procedure described in Sections 2 and 3. Differences in model performance can therefore be attributed solely to operating point effects.

Identification and Validation at Low Compressor Speed

At the low-speed operating point of 30 Hz, the identified ARX (2,2,0) model achieves validation FIT values of 95.95% for electrical power consumption, 86.84% for thermal power, and 79.82% for cooling power (Figure 1). The results indicate accurate prediction of electrical dynamics, while reduced accuracy is observed for thermal quantities, particularly cooling power, reflecting weaker excitation and stronger relative nonlinear effects at low compressor speed.

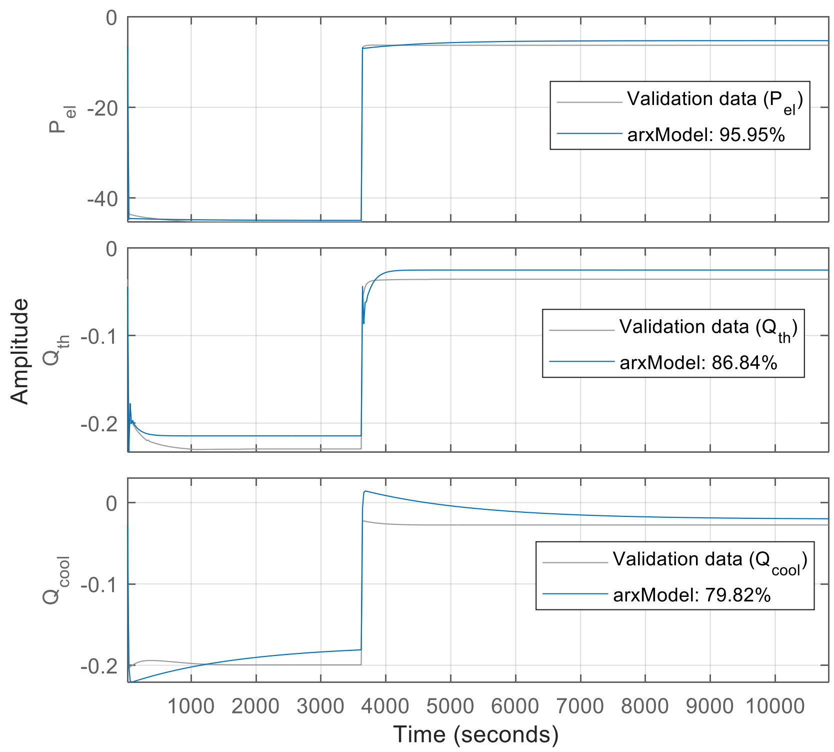

Figure 1. Simulated and predicted outputs at 30 Hz using the ARX (2,2,0) model.

Identification and Validation at Medium Compressor Speed

At 60 Hz, the ARX (2,2,0) model achieves validation FIT values of 97.27% for electrical power consumption, 91.41% for thermal power, and 95.08% for cooling power (Figure 2). Compared to the low-speed case, a clear improvement is observed for the thermal outputs, indicating enhanced identifiability and reduced nonlinear effects at this operating point.

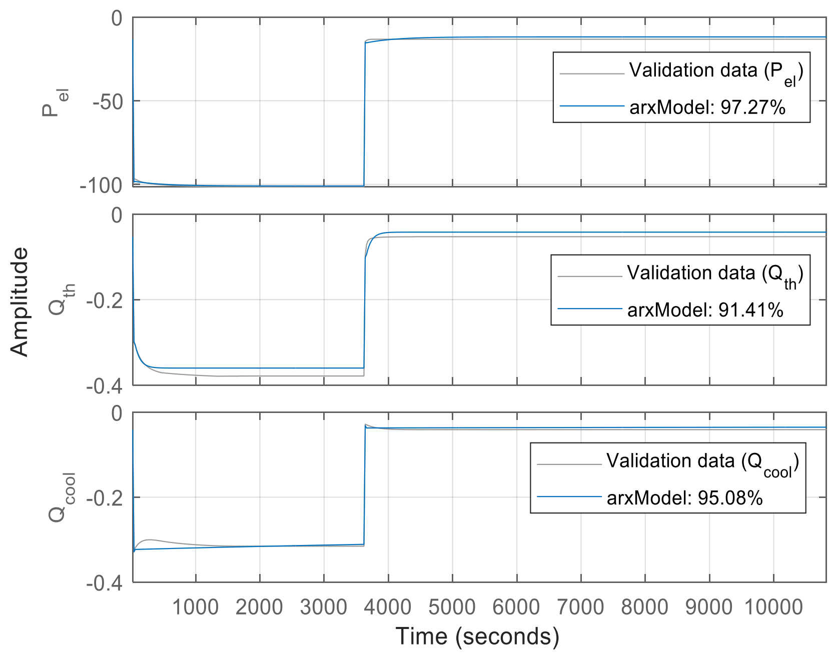

Figure 2. Simulated and predicted outputs at 60 Hz using the ARX (2,2,0) model.

Identification and Validation at High Compressor Speed

At 90 Hz, validation FIT values of 98.1% for electrical power consumption and 91.64% for both thermal and cooling power are obtained (Figure 3). The results confirm that the compact ARX structure provides reliable prediction of both electrical and thermal dynamics at higher compressor speeds.

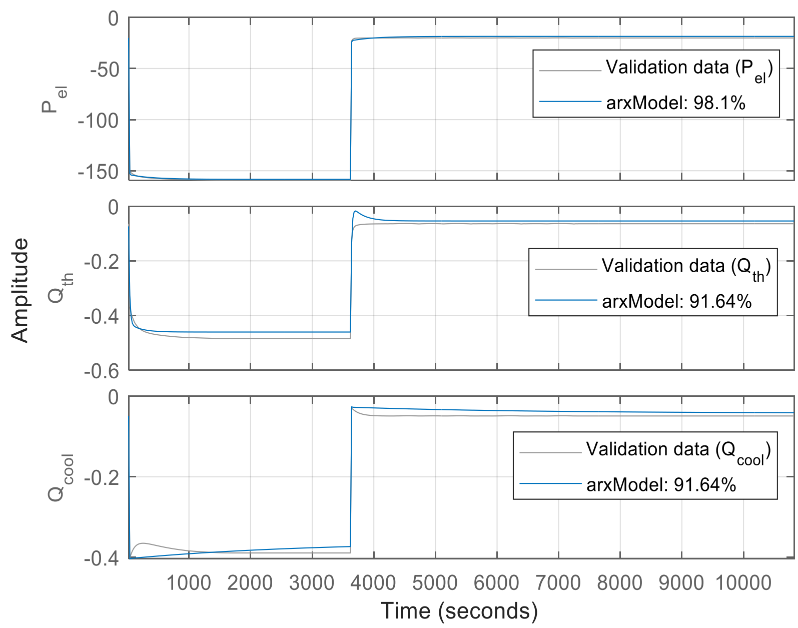

Figure 3. Simulated and predicted outputs at 90 Hz using the ARX (2,2,0) model.

Identification and Validation at Very High Compressor Speed

At 120 Hz, the ARX (2,2,0) model achieves validation FIT values of 98.65% for electrical power consumption, 94.52% for thermal power, and 92.29% for cooling power (Figure 4). High prediction accuracy is maintained across all outputs, confirming the effectiveness of bounded relative excitation and low-order linear modelling at very high compressor speeds.

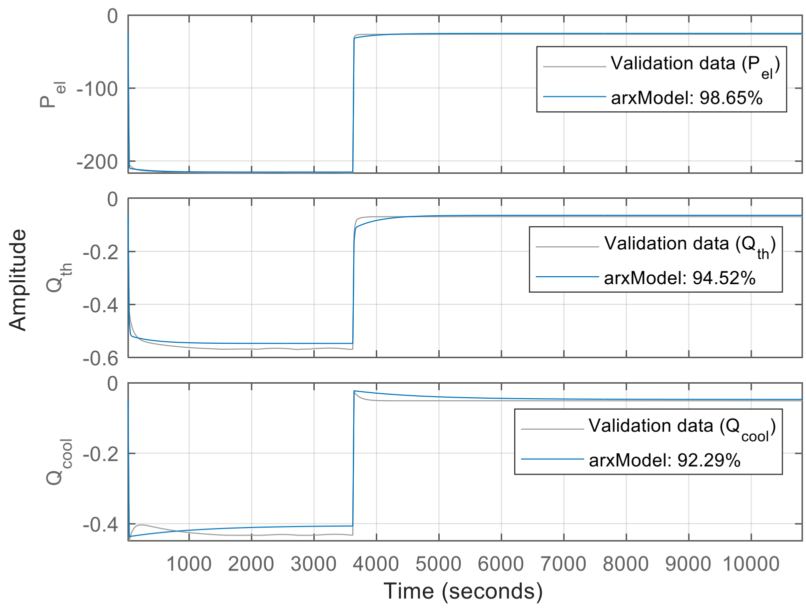

Figure 4. Simulated and predicted outputs at 120 Hz using the ARX (2,2,0) model.

Comparative Analysis and Operating-Point Dependency

Table 1 summarizes the validation FIT values obtained for the ARX (2,2,0) models across all compressor operating points and output variables.

Table 1. Validation FIT (%) for ARX (2,2,0) models at different compressor speeds.

Compressor speed (Hz)	P_{el}	Q_{th}	Q_{cool}
30	95.95	86.84	79.82
60	97.27	91.41	95.08
90	98.1	91.64	91.64
120	98.65	94.52	92.29

Across all operating points, electrical power consumption is consistently predicted with high accuracy, with FIT values exceeding 95% and increasing with compressor speed. This behaviour reflects the predominantly linear relationship between compressor speed and electrical power demand, which is well captured by the low-order ARX structure.

Thermal outputs exhibit stronger operating-point dependency. At low compressor speed (30 Hz), both thermal and cooling power are predicted with lower accuracy, particularly for cooling power, due to weaker excitation and stronger relative nonlinear effects. As compressor speed increases, the use of bounded relative excitation improves identifiability of the slow thermal dynamics, resulting in validation FIT values above 90% for both thermal and cooling power at medium and high operating points.

These results indicate that reduced prediction accuracy of linear black-box models at certain operating points is not inherently caused by the ARX structure itself, but is strongly influenced by excitation design and operating regime.

To contextualize the obtained results, a comparison with the authors' previous global identification approach is provided. In [14], a single ARX (3,3,0) model was identified over the full compressor operating range using a fully populated autoregressive matrix. The reported validation FIT values were 94.17% for electrical power consumption, 88.32% for thermal power, and 86.92% for cooling power.

Compared to the present results, the global identification approach yields lower prediction accuracy for thermal outputs, particularly relative to the locally identified models at medium and high compressor speeds. This difference can be attributed to two main factors. First, identifying a single linear model over a wide operating range increases the influence of nonlinear effects that cannot be captured by a fixed linear structure. Second, the use of a fully populated autoregressive matrix introduces cross-coupling between output channels, which may improve global fit but can reduce interpretability and robustness for control-oriented applications.

In contrast, the operating-point-based identification strategy adopted in this work, combined with a diagonal autoregressive structure and bounded relative excitation, allows the linear ARX model to better approximate local dynamics. This comparison highlights the trade-off between global validity and local accuracy and demonstrates that compact locally identified ARX models can outperform a single global model when the objective is accurate prediction within specific operating regimes.

Control-Oriented Implications

The locally identified ARX models obtained at different compressor speeds are well suited for integration into gain-scheduled or switching control frameworks. In such schemes, a model corresponding to the current operating point can be selected based on the measured compressor speed, allowing the controller to use a locally valid linear approximation. Alternatively, supervisory control strategies could interpolate between adjacent models to ensure smooth transitions across operating regimes. Practical challenges include reliable model selection in the presence of noise and avoiding abrupt switching that could introduce transients in the control signal. Nevertheless, the consistent model structure adopted in this work facilitates such integration and supports the use of local linear models in predictive and adaptive control architectures for heat pump systems.

SUMMARY AND CONCLUSION

This paper investigated the operating-point dependency of low-order linear ARX models for control-oriented modelling of an air-source heat pump. Separate ARX (2,2,0) models were identified around four compressor speed operating points using a consistent excitation and identification framework. While this approach allows systematic excitation and repeatable experiments, it does not fully account for practical factors such as measurement noise, sensor dynamics, parameter uncertainty, and unmodelled disturbances. In experimental conditions, these effects are expected to reduce prediction accuracy, particularly for thermal outputs with long time constants. Measurement noise may introduce bias in the estimated parameters, while sensor delays and filtering may alter the apparent system dynamics. In addition, unmodelled disturbances such as ambient fluctuations and load variations may degrade the performance of locally identified linear models. Nevertheless, the relative trends observed in this study regarding operating-point dependency and excitation design are expected to remain valid, and the proposed identification framework provides a useful baseline for experimental implementation.

The results show that electrical power consumption can be predicted with consistently high accuracy across all operating points, while thermal and cooling outputs exhibit stronger operating-point dependency, particularly at low compressor speed. When excitation magnitude is scaled relative to the nominal operating point and model complexity is appropriately constrained, compact linear ARX models provide reliable prediction of both electrical and thermal dynamics at medium and high compressor speeds.

Comparison with a previously published global identification approach highlights the trade-off between global validity and local accuracy. While global models offer acceptable performance over wide operating ranges, locally identified models achieve superior prediction accuracy within specific operating regimes. This demonstrates that reduced accuracy of linear ARX models at certain operating points is primarily driven by excitation design and operating regime rather than by the ARX structure itself.

Additionally, the findings confirm that low-order linear ARX models remain a viable and effective tool for control-oriented heat-pump modelling when identification experiments are properly designed and aligned with the intended operating regime.

Future work will focus on experimental validation and the integration of the identified models into real-time predictive control frameworks.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interest associated with this publication.

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