

ENSEMBLE MODELLING OF HYGROTHERMAL SYSTEM FOR MULTI-
OBJECTIVES MODEL PREDICTIVE CONTROLLERS

SHAMSUL FAISAL BIN MOHD HUSSEIN

UNIVERSITI TEKNOLOGI MALAYSIA

ENSEMBLE MODELLING OF HYGROTHERMAL SYSTEM FOR MULTI-
OBJECTIVES MODEL PREDICTIVE CONTROLLERS

SHAMSUL FAISAL BIN MOHD HUSSEIN

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

Malaysia-Japan International Institute of Technology
Universiti Teknologi Malaysia

NOVEMBER 2022

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, Associate Professor Dr. Shahrum Shah bin Abdullah, for encouragement, guidance, critics and friendship. I am also very thankful to my co-supervisor Dr Noorazizi bin Mohd Samsuddin for his guidance, advices and motivation. Without their continued support and interest, this thesis would not have been the same as presented here.

I am also indebted to Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) for funding my Ph.D study. My sincere appreciation also extends to all my colleagues and others who have provided assistance at various occasions. Their views and tips are useful indeed. Unfortunately, it is not possible to list all of them in this limited space. I am grateful to all my family member.

ABSTRACT

An air conditioner maintains occupants' thermal comfort; however, it is also power-hungry in which leads to high electricity consumption. Maintaining thermal comfort while minimising electrical power consumption is difficult, especially when the weather-related inputs are not predictable. This leads to overcooling due to undershoot and undercooling due to overshoot. Undercooling causes discomfort, while overcooling causes discomfort and high-power usage. To minimise this problem, the implementation of model-based predictive controllers can be developed to produce necessary pre-emptive control decisions based on the output of the embedded simulation model in the controller. However, the simulation model must be accurate for the best result. This project develops accuracy-improved mathematical models that represent the dynamic hygrothermal behaviour of a laboratory in aiding future potential energy-efficient predictive controllers. This is to maintain the thermal comfort level in the laboratory while minimising power consumption. Two thermal comfort variables were modelled to maintain two different desired setpoints simultaneously in the future. First, the empirical modelling was developed to capture the dynamics of the temperature and humidity behaviours of the laboratory using three existing standard methods, which were: (1) autoregressive-moving-average (ARMA) model; (2) transfer function (TF) model; and (3) nonlinear autoregressive exogenous model (NARX) model. Second, the ensemble methods were implemented to increase the simulation accuracy of the developed modelling by summing up the output values from all three developed models – prior to summation, the output of each of the models was multiplied by the weight value assigned for each of the models. The values of these weights were determined using the following three ensemble methods: (1) weighted average; (2) least square technique (LST) / least square method (LSM); and (3) genetic algorithm (GA). All models' simulation outputs were compared with the actual data for accuracy benchmarking. Results showed that the most accurate ensemble models have better accuracies than the most accurate individual models developed in this research while being simulated with the testing data set in each simulation case. The improvements in the air temperature simulation models are by 3.40%, 7.38%, and 8.69% each for one-, five-, and ten-minute(s) simulation ahead, while the improvements in the relative humidity simulation models are by 0.96%, 1.35%, and 2.38% each for one-, five-, and ten-minute(s) simulation ahead. The accuracy-improved models can then be utilised in model-based predictive controllers for maintaining occupants' thermal comfort in a building while minimising the air conditioners' power consumption for energy saving and environmental conservation.

ABSTRAK

Pendingin hawa mengekalkan keselesaan haba penghuni-penghuni dalam bangunan; walau bagaimanapun, pendingin hawa menggunakan kuasa elektrik yang tinggi dan mengakibatkan bil elektrik yang tinggi. Mengekalkan keselesaan haba sambil meminimumkan penggunaan kuasa elektrik adalah sukar, lebih-lebih lagi apabila gangguan daripada input-input yang berkaitan dengan cuaca tidak dapat diramal. Ini mengakibatkan penyejukan berlebihan akibat kurang lajukan dan kekurangan penyejukan akibat lebih lajukan. Kekurangan penyejukan mengakibatkan ketidakselesaan manakala penyejukan berlebihan mengakibatkan kedua-dua ketidakselesaan dan penggunaan kuasa yang tinggi. Untuk meminimumkan masalah ini, pelaksanaan pengawal ramalan berasaskan model boleh dibangunkan bagi menghasilkan keputusan kawalan pendahuluan yang perlu berdasarkan output model penyelakuan yang terbenam kalam pengawal. Walaubagaimanapun, model penyelakuan mestilah tepat untuk keputusan yang terbaik. Projek ini membangunkan model-model matematik yang ditambahbaik ketepatan bagi mewakili perlakuan dinamik higrotermal untuk sebuah makmal bagi membantu pelaksanaan pengawal peramal cekap tenaga yang berpotensi pada masa akan datang. Ini dilakukan untuk mengekalkan tahap keselesaan haba dalam makmal sambil meminimumkan penggunaan kuasa. Dua pemboleh ubah keselesaan haba telah dimodelkan bagi mengekalkan dua titik tolak berbeza yang dikehendaki serentak pada masa akan datang. Mula-mula, pemodelan empirikal telah dibangunkan bagi merakam dinamik kelakuan-kelakuan suhu udara dan kelembapan relatif dalam makmal menggunakan tiga kaedah standard yang sedia ada, iaitu: (1) model autoregresif-purata-bergerak (*autoregressive-moving-average (ARMA) model*); (2) model rangkap pindah (*transfer function (TF) model*); dan (3) model eksogen autoregresif tak linear (*nonlinear autoregressive exogenous (NARX) model*). Kemudian, kaedah-kaedah *ensemble* dilaksanakan bagi meningkatkan ketepatan pemodelan dengan menjumlahkan nilai output daripada ketiga-tiga model yang telah dibangunkan – sebelum dijumlahkan, output bagi setiap model didarabkan dengan nilai pemberat yang telah ditentukan bagi setiap model. Nilai pemberat-pemberat ini telah ditentukan menggunakan tiga kaedah *ensemble* berikut: (1) berpemberat purata (*weighted average*); (2) teknik kuasa dua terkecil (*least square technique (LST)*) / kaedah kuasa dua terkecil (*least square method (LSM)*); dan (3) algoritma genetik (*genetic algorithm (GA)*). Output penyelakuan daripada kesemua model dibandingkan dengan data sebenar bagi tujuan penandaan aras. Keputusan-keputusan menunjukkan bahawa model-model *ensemble* yang paling tepat mempunyai ketepatan yang lebih baik berbanding model-model individu yang paling tepat yang dibangunkan dalam penyelidikan ini ketika diselakukan dengan set data ujian dalam setiap kes penyelakuan. Penambahbaikan model penyelakuan suhu udara adalah sebanyak 3.40%, 7.38%, dan 8.69% masing-masing untuk penyelakuan satu, lima, dan sepuluh minit ke hadapan manakala penambahbaikan model penyelakuan kelembapan relatif adalah sebanyak 0.96%, 1.35%, dan 2.38% masing-masing untuk penyelakuan satu, lima, dan sepuluh minit ke hadapan. Model-model penyelakuan yang telah ditambahbaik ketepatan kemudiannya boleh dimanfaatkan dalam pengawal ramalan berasaskan model bagi mengekalkan keselesaan haba penghuni-penghuni dalam bangunan sambil meminimumkan penggunaan kuasa pendingin hawa demi penjimatan tenaga dan pemuliharaan alam sekitar.

TABLE OF CONTENTS

| | TITLE | PAGE |
|------------------|--|--------------|
| | DECLARATION | iii |
| | DEDICATION | iv |
| | ACKNOWLEDGEMENT | v |
| | ABSTRACT | vi |
| | ABSTRAK | vii |
| | TABLE OF CONTENTS | viii |
| | LIST OF TABLES | xiii |
| | LIST OF FIGURES | xv |
| | LIST OF ABBREVIATIONS | xxiii |
| CHAPTER 1 | INTRODUCTION | 1 |
| | 1.1 Background of Study | 1 |
| | 1.2 Research Objectives | 3 |
| | 1.3 Research Significance | 4 |
| | 1.4 Research Scopes | 5 |
| | 1.5 Thesis Outline | 7 |
| CHAPTER 2 | LITERATURE REVIEW | 9 |
| | 2.1 Introduction | 9 |
| | 2.2 Modelling and Simulation | 9 |
| | 2.3 The Autoregressive–moving-average (ARMA) Model | 10 |
| | 2.4 The Linear Time-invariant Transfer Function (LTI TF) Model | 11 |
| | 2.5 The Nonlinear Autoregressive Exogenous (NARX) Model | 12 |
| | 2.6 The Ensemble Learning Model | 15 |
| | 2.6.1 The Committee Machine | 16 |
| | 2.6.1.1 The Ensemble Averaging | 17 |

| | | |
|------------------|--|-----------|
| 2.7 | Modelling and Simulating the Dynamic Indoor Hygrothermal Behaviour of a Building. | 21 |
| 2.7.1 | White box model | 24 |
| 2.7.2 | Black box model | 29 |
| 2.7.3 | Grey box model | 30 |
| 2.8 | Summary | 31 |
| CHAPTER 3 | RESEARCH METHODOLOGY | 33 |
| 3.1 | Introduction | 33 |
| 3.2 | The Plant to be Modelled and Simulated | 34 |
| 3.3 | The Data Recording Devices | 37 |
| 3.4 | The Data Recording Period | 44 |
| 3.5 | The Inputs-output Data Selection | 44 |
| 3.6 | The Solar Radiation | 64 |
| 3.6.1 | Calculating the Direct Solar Radiation from the Global Solar Radiation | 66 |
| 3.6.2 | Calculating the Amount of Direct Solar Radiation that Lands on a Surface | 75 |
| 3.6.3 | Calculating the Diffuse Solar Radiation from the Measured Global Solar Radiation and Calculated Direct Solar Radiation | 76 |
| 3.6.4 | Calculating the Amount of Diffuse Solar Radiation that Lands on a Surface | 77 |
| 3.7 | The Recorded and Calculated Data | 77 |
| 3.7.1 | The Recorded and Calculated Data for the Indoor Air Temperature Simulation Models | 78 |
| 3.7.2 | The Recorded and Calculated Data for the Indoor Relative Simulation Models | 103 |
| 3.8 | The Black Box Models Construction | 113 |
| 3.8.1 | The Autoregressive–moving-average (ARMA) Construction | 113 |
| 3.8.1.1 | The Air Temperature Autoregressive–moving-average (ARMA) Construction | 114 |
| 3.8.1.2 | The Relative Humidity Autoregressive–moving-average (ARMA) Construction | 115 |

| | | |
|---------|---|-----|
| 3.8.2 | The Linear Time-invariant Transfer Function (LTI TF) Construction | 116 |
| 3.8.2.1 | The Air Temperature Linear Time-invariant Transfer Function (LTI TF) Construction | 118 |
| 3.8.2.2 | The Relative Humidity Linear Time-invariant Transfer Function (LTI TF) Construction | 119 |
| 3.8.3 | The Nonlinear Autoregressive Exogenous (NARX) Model Construction | 121 |
| 3.8.3.1 | The Air Temperature Nonlinear Autoregressive Exogenous (NARX) Model Construction | 124 |
| 3.8.3.2 | The Relative Humidity Nonlinear Autoregressive Exogenous (NARX) Model Construction | 126 |
| 3.8.4 | The Ensemble Learning Model Construction | 128 |
| 3.8.4.1 | The Air Temperature Ensemble Model Construction | 130 |
| 3.8.4.2 | The Relative Humidity Ensemble Model Construction | 131 |
| 3.9 | The Model Estimation | 133 |
| 3.9.1 | The Autoregressive–moving-average (ARMA) Estimation | 133 |
| 3.9.1.1 | The Air Temperature Autoregressive–moving-average (ARMA) Estimation | 134 |
| 3.9.1.2 | The Relative Humidity Autoregressive–moving-average (ARMA) Estimation | 136 |
| 3.9.2 | The Linear Time-invariant Transfer Function (LTI TF) Estimation | 139 |
| 3.9.2.1 | The Air Temperature Linear Time-invariant Transfer Function (LTI TF) Estimation | 139 |
| 3.9.2.2 | The Relative Humidity Linear Time-invariant Transfer Function (LTI TF) Estimation | 140 |
| 3.9.3 | The Nonlinear Autoregressive Exogenous (NARX) Model Estimation | 141 |

| | | |
|------------------|--|------------|
| 3.9.3.1 | The Temperature Nonlinear Autoregressive Exogenous (NARX) Model Estimation | 143 |
| 3.9.3.2 | The Humidity Nonlinear Autoregressive Exogenous (NARX) Model Estimation | 147 |
| 3.9.4 | The Ensemble Model Estimation | 150 |
| 3.9.4.1 | The Air Temperature Ensemble Model Estimation | 152 |
| 3.9.4.2 | The Relative Humidity Ensemble Model Estimation | 154 |
| 3.10 | The Black Box Model Testing | 156 |
| 3.11 | Summary | 157 |
| CHAPTER 4 | RESULTS AND DISCUSSION | 159 |
| 4.1 | Introduction | 159 |
| 4.2 | The Modelling and Simulation Results for the Indoor Air Temperature of the Industrial Instrumentation Laboratory | 160 |
| 4.2.1 | The One Minute Ahead Simulation Models for the Indoor Air Temperature of the Industrial Instrumentation Laboratory | 162 |
| 4.2.2 | The Five Minutes Ahead Simulation Models for the Indoor Air Temperature of the Industrial Instrumentation Laboratory | 176 |
| 4.2.3 | The Ten Minutes Ahead Simulation Models for the Indoor Air Temperature of the Industrial Instrumentation Laboratory | 189 |
| 4.3 | The Modelling and Simulation Results for the Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 202 |
| 4.3.1 | The One Minute Ahead Simulation Models for the Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 203 |
| 4.3.2 | The Five Minutes Ahead Simulation Models for the Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 217 |
| 4.3.3 | The Ten Minutes Ahead Simulation Models for the Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 230 |

| | | |
|---|---|------------|
| 4.4 | The Discussions for Modelling and Simulation Results of the Indoor Air Temperature of the Industrial Instrumentation Laboratory | 243 |
| 4.4.1 | The Individual Simulation Models Representing the Dynamic Indoor Air Temperature of the Industrial Instrumentation Laboratory | 243 |
| 4.4.2 | The Ensemble Models Representing the Dynamic Indoor Air Temperature of the Industrial Instrumentation Laboratory | 245 |
| 4.5 | The Discussions for Modelling and Simulation Results of the Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 252 |
| 4.5.1 | The Individual Simulation Models Representing the Dynamic Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 252 |
| 4.5.2 | The Ensemble Models Representing the Dynamic Indoor Relative Humidity of the Industrial Instrumentation Laboratory | 255 |
| 4.6 | Summary | 261 |
| CHAPTER 5 CONCLUSION AND FUTURE RECOMMENDATION | | 263 |
| 5.1 | Conclusion | 263 |
| 5.2 | Future Work | 265 |
| REFERENCES | | 269 |
| LIST OF PUBLICATIONS | | 277 |

LIST OF TABLES

| TABLE NO. | TITLE | PAGE |
|------------------|---|-------------|
| Table 2.1 | The list of works related to white box hygrothermal modelling | 28 |
| Table 2.2 | The list of works related to black box hygrothermal modelling | 30 |
| Table 2.3 | The list of works related to grey box hygrothermal modelling | 30 |
| Table 3.1 | The main and alternate function for each of the 40 male header pins available on the Raspberry Pi single-board computer | 39 |
| Table 3.2 | The function for each pin available on the DHT22 air temperature and humidity sensor | 42 |
| Table 3.3 | Some of the surface angles of interest | 74 |
| Table 3.4 | The genetic algorithm settings that are used to estimate the weights in the air temperature ensemble model in Equation (3.43) | 154 |
| Table 3.5 | The genetic algorithm settings that are used to estimate the weights in the air temperature ensemble model in Equation (3.44) | 156 |
| Table 4.1 | The accuracies of the optimised/estimated Industrial Instrumentation Laboratory's indoor air temperature simulation models developed in this research while being simulated with the training and testing data sets for one, five, and ten minute(s) ahead | 161 |
| Table 4.2 | The weights of the individual optimised ARMA, LTI TF, and NARX models for the estimated WA, LST/LSM, and GA estimated ensemble models developed in this research to represent the dynamic indoor air temperature of the Industrial Instrumentation Laboratory for one, five, and ten minute(s) ahead simulation | 162 |
| Table 4.3 | The structures of all the optimised/estimated one minute ahead indoor air temperature simulation models of the Industrial Instrumentation Laboratory developed in this research | 163 |
| Table 4.4 | The structures of all the optimised/estimated five minutes ahead indoor air temperature simulation models of the | |

| | | |
|------------|--|-----|
| | Industrial Instrumentation Laboratory developed in this research | 176 |
| Table 4.5 | The structures of all the optimised/estimated ten minutes ahead indoor air temperature simulation models of the Industrial Instrumentation Laboratory developed in this research | 189 |
| Table 4.6 | The accuracies of the optimised/estimated Industrial Instrumentation Laboratory's indoor relative humidity simulation models developed in this research while being simulated with the training and testing data sets for one, five, and ten minutes ahead | 202 |
| Table 4.7 | The weight of the individual optimised ARMA, LTI TF, and NARX models for the estimated WA, LST/LSM, and GA estimated ensemble models developed in this research to represent the dynamic indoor relative humidity of the Industrial Instrumentation Laboratory for one, five, and ten minutes ahead simulation | 203 |
| Table 4.8 | The structures of all the optimised/estimated one minute ahead indoor relative humidity simulation models of the Industrial Instrumentation Laboratory developed in this research | 204 |
| Table 4.9 | The structures of all the optimised/estimated five minutes ahead indoor relative humidity simulation models of the Industrial Instrumentation Laboratory developed in this research | 217 |
| Table 4.10 | The structures of all the optimised/estimated ten minutes ahead indoor relative humidity simulation models of the Industrial Instrumentation Laboratory developed in this research | 230 |

LIST OF FIGURES

| FIGURE NO. | TITLE | PAGE |
|-------------------|--|-------------|
| Figure 2.1 | The general architecture of the feedforward neural network [16] | 13 |
| Figure 3.1 | The flowchart depicting the methodology used in this research | 33 |
| Figure 3.2 | The typical floor plan of: (a) the Industrial Instrumentation Laboratory at the 7th floor of the MJIT building; (b) the classroom exactly below the Industrial Instrumentation Laboratory (on the 6th floor of the MJIT building); and (c) the classroom exactly above the Industrial Instrumentation Laboratory (on the 8th floor of the MJIT building) | 35 |
| Figure 3.3 | The Raspberry Pi single-board computer (left) and the labels for all the 40 male header pins available on the board (right) | 39 |
| Figure 3.4 | The example photo of the DHT22 air temperature and relative humidity sensor used in this research together with its pin numbering | 41 |
| Figure 3.5 | The electrical connection from the Raspberry Pi single-board computer to the DHT22 air temperature and humidity sensor | 42 |
| Figure 3.6 | The flowchart explaining the code workflow for the home-made low-cost data loggers made of Raspberry Pi single-board computer and DHT22 air temperature and relative humidity data logger | 43 |
| Figure 3.7 | The heat flow through a building envelope due to the air temperature difference between the two opposite sides of the envelope (a) and its R circuit analogy representation (b) | 45 |
| Figure 3.8 | The heat flow through a building envelope due to the air temperature difference between the two opposite sides of the envelope (a) and its 2R-C circuit analogy representation (b) | 47 |
| Figure 3.9 | The heat flow through a building envelope due to the air temperature difference between the two opposite sides of the envelope (a) and its 3R-2C circuit analogy representation (b) | 49 |

| | | |
|-------------|---|----|
| Figure 3.10 | The heat flow through a building envelope due to the solar radiation that lands on the surface of the envelope (a) and its R circuit analogy representation (b) | 51 |
| Figure 3.11 | The electrical circuit analogy describing the dynamic indoor air temperature behaviour of the Industrial Instrumentation Laboratory | 53 |
| Figure 3.12 | The revised electrical circuit analogy describing the dynamic indoor air temperature behaviour of the Industrial Instrumentation Laboratory | 56 |
| Figure 3.13 | The black box model structure describing the dynamic indoor air temperature behaviour of the Industrial Instrumentation Laboratory | 58 |
| Figure 3.14 | The humidity flow through an air infiltration opening on a building envelope due to the relative humidity difference between the two opposite sides of the envelope (a) and its R circuit analogy representation (b) | 60 |
| Figure 3.15 | The electrical circuit analogy describing the dynamic indoor relative humidity behaviour of the Industrial Instrumentation Laboratory | 62 |
| Figure 3.16 | The black box model structure describing the dynamic indoor relative humidity behaviour of the Industrial Instrumentation Laboratory | 63 |
| Figure 3.17 | The illustration of direct versus diffuse solar radiation | 65 |
| Figure 3.18 | The solar angles [80], [81] | 74 |
| Figure 3.19 | The website of Google Map used to obtained the latitude and longitude of Malaysia-Japan International Institute of Technology (MJIT) building for the related calculations in this section | 75 |
| Figure 3.20 | The recorded data for developing the simulation models representing the dynamic behaviour of the indoor air temperature of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur | 79 |
| Figure 3.21 | The calculated direct and diffuse solar radiation based on the measured global solar radiation based on the mathematical formulas in Subsection 3.6.1 and Subsection 3.6.3 | 90 |
| Figure 3.22 | The calculated direct and diffuse solar radiation that land on the outer walls of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia | |

| | | |
|-------------|--|-----|
| | (UTM) Kuala Lumpur based on the mathematical formulas in Subsection 3.6.2 and Subsection 3.6.4 | 93 |
| Figure 3.23 | The finalised recorded and calculated data for developing the simulation models representing the dynamic behaviour of the indoor air temperature of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur | 98 |
| Figure 3.24 | The recorded data for developing the simulation models representing the dynamic behaviour of the indoor relative humidity of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur | 104 |
| Figure 3.25 | The finalised recorded and calculated data for developing the simulation models representing the dynamic behaviour of the indoor air temperature of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur | 109 |
| Figure 3.26 | The block diagram of the general ensemble models implemented in this research | 129 |
| Figure 3.27 | The block diagram of the air temperature ensemble models implemented in this research | 131 |
| Figure 3.28 | The block diagram of the relative humidity ensemble models implemented in this research | 132 |
| Figure 3.29 | The basic MATLAB® System Identification Toolbox™ settings used to estimate continuous-time linear time-invariant transfer function model representing the dynamic air temperature behaviour of the Industrial Instrumentation Laboratory | 140 |
| Figure 3.30 | The basic MATLAB® System Identification Toolbox™ settings used to estimate continuous-time linear time-invariant transfer function model representing the dynamic relative humidity behaviour of the Industrial Instrumentation Laboratory | 141 |
| Figure 3.31 | The air temperature output data set distribution imported for the NARX model estimation via the MATLAB® Neural Network Time Series Tool™ for the following conditions: (a) the evenly distributed training, testing, and validation data sets using the default setting with the ration of 70:15:15 | 145 |

| | | |
|-------------|---|-----|
| Figure 3.32 | The air temperature data set that is separated into two totally different training and testing data sets as stated in Subsection 3.4 to standardise the training procedure with the other models in this research | 146 |
| Figure 3.33 | The relative humidity output data set distribution imported for the NARX model estimation via the MATLAB® Neural Network Time Series Tool™ for the following conditions: (a) the evenly distributed training, testing, and validation data sets using the default setting with the ration of 70:15:15 | 148 |
| Figure 3.34 | The relative humidity data set that is separated into two totally different training and testing data sets as stated in Subsection 3.4 to standardise the training procedure with the other models in this research | 149 |
| Figure 4.1 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 164 |
| Figure 4.2 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 166 |
| Figure 4.3 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) model while being simulated using the training data set (a) and testing data set (b) | 168 |
| Figure 4.4 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 170 |
| Figure 4.5 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 172 |
| Figure 4.6 | The one minute ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 174 |

| | | |
|-------------|--|-----|
| Figure 4.7 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 177 |
| Figure 4.8 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 179 |
| Figure 4.9 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) model while being simulated using the training data set (a) and testing data set (b) | 181 |
| Figure 4.10 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 183 |
| Figure 4.11 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 185 |
| Figure 4.12 | The five minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 187 |
| Figure 4.13 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 190 |
| Figure 4.14 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 192 |
| Figure 4.15 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) | |

| | | |
|-------------|--|-----|
| | model while being simulated using the training data set (a) and testing data set (b) | 194 |
| Figure 4.16 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 196 |
| Figure 4.17 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 198 |
| Figure 4.18 | The ten minutes ahead indoor air temperature simulation results of the Industrial Instrumentation Laboratory for the genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 200 |
| Figure 4.19 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 205 |
| Figure 4.20 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 207 |
| Figure 4.21 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) model while being simulated using the training data set (a) and testing data set (b) | 209 |
| Figure 4.22 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 211 |
| Figure 4.23 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 213 |
| Figure 4.24 | The one minute ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the | |

| | | |
|-------------|--|-----|
| | genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 215 |
| Figure 4.25 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 218 |
| Figure 4.26 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 220 |
| Figure 4.27 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) model while being simulated using the training data set (a) and testing data set (b) | 222 |
| Figure 4.28 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 224 |
| Figure 4.29 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 226 |
| Figure 4.30 | The five minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 228 |
| Figure 4.31 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised autoregressive–moving-average (ARMA) model while being simulated using the training data set (a) and testing data set (b) | 231 |
| Figure 4.32 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised linear time-invariant transfer function (LTI TF) model while being simulated using the training data set (a) and testing data set (b) | 233 |

| | | |
|-------------|---|-----|
| Figure 4.33 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the optimised nonlinear autoregressive exogenous (NARX) model while being simulated using the training data set (a) and testing data set (b) | 235 |
| Figure 4.34 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the weighted average (WA) ensemble model while being simulated using the training data set (a) and testing data set (b) | 237 |
| Figure 4.35 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the least square technique (LST) / least square method (LSM) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 239 |
| Figure 4.36 | The ten minutes ahead indoor relative humidity simulation results of the Industrial Instrumentation Laboratory for the genetic algorithm (GA) estimated ensemble model while being simulated using the training data set (a) and testing data set (b) | 241 |

LIST OF ABBREVIATIONS

| | | |
|--------|---|---|
| ARMA | - | Autoregressive–moving-average |
| LTI TF | - | Linear time-invariant transfer function |
| NARX | - | Nonlinear Autoregressive Exogenous |
| ARX | - | Autoregressive Exogenous |
| GA | - | Genetic Algorithm |

CHAPTER 1

INTRODUCTION

1.1 Background of Study

The air conditioner is one of the typical thermal comfort equipment used to maintain the occupants' thermal comfort in a building. Even though it is an effective equipment to maintain an indoor space's desired thermal setpoint, it also utilises a high amount of electricity. This high-power consumption is economically bad to the consumer due to the high electricity bill and also environmentally harmful to the nature if the electricity used to power the air conditioner is generated from the non-renewable fossil fuel sources such as natural gas, coal, and diesel. As cooling demands increase because of these developments, the energy sector is being greatly disrupted because the energy sector is thought to be a key contributor to climate change [1], [2]. According to the International Energy Agency (IEA) in the year 2021, 606.490 exajoule of energy is produced worldwide each year [3]. In 2015, it is reported that nearly 40% of the generated energy is utilised by buildings, which also accounts for an equivalent amount of greenhouse gas emissions [4]. Meanwhile, buildings are the world's third most total final energy consumption in 2017, trailing only the industry and transportation sectors [5], [6]. Over 70% of greenhouse gas emissions originate from metropolitan areas, primarily because of continuous use of heating, ventilation, and air conditioning (HVAC) systems. Thus, it is highly desirable to ensure that the air conditioner can be operated at its highest efficiency without sacrificing the users' thermal comfort [1], [7], [8].

The air conditioner system's disturbance is the unpredictable weather-related inputs, such as the outdoor temperature, solar radiation, and rainfall. These disturbances will lead to overshoot and undershoot while maintaining the indoor space's thermal conditions at the desired setpoints – both the overshoot and undershoot will cause discomfort to the occupants in the thermally controlled occupied area. In

contrast, the undershoot will cause unnecessary power usage during the extra cooling. Predictive controllers can be implemented to produce necessary control outputs that can minimise the overshoot and undershoot while maintaining the desired setpoints. However, an accurate simulation model representing the plant's dynamic behaviour is required for the predictive controller to function effectively.

Some of the air conditioning systems today are capable of maintaining the desired indoor air temperature and the desired indoor relative humidity. Besides, there is also the requirement for the air conditioner in the large non-residential spaces to mix a certain percentage of fresh outdoor air into the existing air circulated in the area. The mixing of outdoor and existing air was done to reduce the content of unpleasant odours, harmful microorganisms, and carbon dioxide to an acceptable level to minimise the negative effect on the occupants' health and productivity. These new criteria lead to additional desired setpoints, which then lead to multi-objective setpoints.

This research focuses on constructing the model describing the dynamic indoor hygrothermal (temperature and humidity) behaviour of the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur. The model will be essential for potential predictive controllers in the future to maintain the hygrothermal level at desired setpoints during unpredictable weather conditions and to reduce power wastage due to unnecessary overcooling. The laboratory's two dynamic indoor thermal behaviours, the air temperature, and the relative humidity, were selected to be modelled in this research at this moment. The models representing indoor air temperature and relative humidity can be used for the potential multi-objective predictive controllers in the future. Additional thermal comfort-related indoor dynamic behaviour of the laboratory, such as the content of dust and carbon dioxide in the air of the occupied indoor space, can be added in the future for a higher possible multi-objective predictive controller.

Most works in Malaysia related to building hygrothermal issues and investigations are done using in situ experiments and are not focused on simulation.

Examples of work done in Malaysia include Ali et al. [9], Aktas et al. [10], and Mohammad Yusoff [11].

Ali et al. in [9] focus on in situ experiments combined with hygrothermal analytical methods to assess the thermal envelope quality together with the operative conditions against condensation and mould growth risks of a building. The results show that the building is overcooled, leading to poor envelope hygrothermal performance with associated condensation and mould growth problems on the non-air-conditioned sides of the envelopes. No simulation models were used in their work.

Aktas et al. in [10] focus on tackling urban heat islands in Kuala Lumpur through actual experiments and not using any simulation. They also focus on outdoor temperatures near buildings. Mohammad Yusoff in [11] focuses on a heritage mosque's indoor thermal comfort based on in situ experiments. Again, no simulation models were used in this work.

Hence, this research aims to fill the gap in hygrothermal modelling, focusing on creating and utilising indoor hygrothermal models for simulation in Malaysia.

1.2 Research Objectives

The objectives of this research are:

1. To install relevant sensors at strategic locations to facilitate hygrothermal data collections from an actual laboratory.
2. To develop the mathematical models representing a laboratory's dynamic hygrothermal behaviour using black-box models as accurately as possible with limited knowledge and resources.
3. To improve the simulation output accuracy of the constructed black box models by implementing ensemble methods to emphasise the strength of the

output feature(s) of each of the developed black-box models and validating them with the actual values recorded at the laboratory.

1.3 Research Significance

The contributions of this research are:

1. The installation of the relevant sensors at strategic locations to facilitate hygrothermal data collections from an actual laboratory. This setup may be upgraded with newer types of sensors in the future to collect newer types of data for newer research objectives. This setup can also be converted into a smart laboratory facility for various research purposes in the future.
2. The construction of the mathematical models representing the dynamic hygrothermal behaviour of an actual laboratory using several types of black-box models. The models are developed with minimal physical knowledge related to the hygrothermal behaviour of the laboratory. The simulation outputs from these black-box models have been compared with the actual output recorded at the laboratory for accurate benchmarking. Since the models developed in this research are simple models with less parameters compared to the high-fidelity white box models, they are suitable to be implemented in model-based predictive controllers cost effectively because simple models require less computational power and can be implemented using low-cost computers, microprocessors, and microcontrollers.
3. The improvement of the simulation output accuracy of the constructed black-box models using ensemble methods to emphasise the strength of the output feature(s) of each of the developed black-box models. The output values are then combined into a single output value based on the strength of each model's output. The simulation outputs from these ensemble models have also been compared with the actual output recorded at the laboratory for benchmarking

purposes. These accuracy-improved black box models are still simple, require less computational power and can be implemented using low-cost computers, microprocessors, and microcontrollers.

1.4 Research Scopes

First, the Industrial Instrumentation Laboratory at Malaysia-Japan International Institute of Technology (MJIIT), Universiti Teknologi Malaysia (UTM) Kuala Lumpur, is selected as the plant to be modelled in this research and will be described in more detail in Subsection 3.2. The laboratory was selected since it is conveniently located in the city centre, where the climate is hot and humid, which is the focus of this research.

Second, only the weather-related inputs are used for the model developed in this research. The Industrial Instrumentation Laboratory is equipped with air conditioners and ventilation fans. However, the data available by the time this research are done is recorded when these thermal comfort equipment are not operated.

Third, only two dynamic behaviours related to the laboratory's thermal comfort control are modelled for this research due to time constraint, which are temperature and humidity. Additional hardware for recording other dynamic behaviours related to thermal comforts, such as indoor air quality (IAQ), will be developed and installed for data collection as a future work.

Fourth, only the data recorded for 11 days are used for this research for the black box models development. Due to time constraint, only the data recorded for 11 days are available by the time this research is done. Additional data could not be recorded because the plant to be modelled (the laboratory) at the campus was not accessible due to the multiple movement control orders (MCOs) during the COVID-

19 pandemic. This additional data will be recorded in the future for models' improvement.

Fifth, even though some of the wall surfaces of the plant to be modelled (the laboratory) has a few doors, windows, and ventilation fans, all these items are incorporated into the walls and assumed to be part of the walls with uniform heat conductivity rate to maintain the models simplicity – instead of having multiple mathematical terms to represent the heat conductivity characteristic through multiple types of surface (the surfaces of the walls, doors, windows, and ventilation fans), the number of the mathematical terms representing the heat conductivity through the surface are reduced when the doors, windows, and ventilation fans are incorporated into the walls and assumed to be part of the walls with uniform heat conductivity rate.

Sixth, the surface areas of the outer walls of the plant to be modelled (the laboratory) are considered to receive either no solar radiation (0% radiated area) or complete solar radiation (100% radiated area), also to maintain the simplicity during the models' development. There is a complex set of mathematical formula to calculate how much the surface of an area receives sunlight at a given time of the day based on the surface inclination, surface bearing, the sun inclination, the sun bearing, the position of nearby object(s) that can partially/fully block the direct sunlight to the surface, etc., but this calculation is not implemented in this research due to time constraint.

Seventh, only three types of black-box models and three ensemble algorithms are implemented and investigated in this research due to time constraint. The three types of black-box models are: (1) the autoregressive–moving-average (ARMA) model; (2) the linear time-invariant transfer function (LTI TF) model; and (3) the nonlinear autoregressive exogenous (NARX) model. Meanwhile, the three types of ensemble algorithms are: (1) the weighted average (WA) ensemble model; (2) the least square technique (LST) / least square method (LSM) estimated ensemble model; and (3) the genetic algorithm (GA) estimated ensemble model.

Finally, the simulation models developed in this research only simulate output at every one-minute interval and produce output for one, five, and ten minute(s) ahead due to time constraint.

1.5 Thesis Outline

This thesis is organized into five chapters. Their contents are outlined as follows:

1. Chapter 1 contains the introduction of the research, which includes brief executive summary information where the project's scope is also discussed. It also explains the objectives of the research. The research's significance has also been discussed in this chapter.
2. Chapter 2 provides a literature review and briefly discusses modelling methods of dynamic systems. In particular, the autoregressive-moving-average (ARMA) model, the linear time-invariant transfer function (LTI TF) model, the nonlinear autoregressive network with exogenous inputs (NARX) model, and the ensemble learning will be introduced. Recent works on modelling and simulating the dynamic indoor hygrothermal behaviour of a building, focusing on hot and humid environments, will be reviewed next. Finally, the issues that remain in this area will be discussed, highlighting research gaps and the possibility of improvements.
3. Chapter 3 briefly explains the methodology for the research in every research stage. This chapter briefs the construction, testing, and optimisation processes for each type of simulation model utilised in this research.
4. Chapter 4 presents the results and discussions of the research. This chapter presents the hygrothermal model's simulation results, comparing the individual black-box models, the ensemble models, and the actual values obtained from the laboratory. The focus is on how the proposed ensemble learning improved the prediction output of the lab's humidity and temperature.

5. Chapter 5 concludes the thesis by reviewing the objectives and their fulfilment, a summary of the work that has been accomplished, and the recommended future work.

REFERENCES

- [1] S. K. Verma, Y. Anand, N. Gupta, B. B. Jindal, V. V. Tyagi, and S. Anand, “Hygrothermal dynamics for developing energy-efficient buildings: Building materials and ventilation system considerations,” *Energy Build.*, vol. 260, p. 111932, 2022.
- [2] J. F. Feenstra, I. Burton, J. B. Smith, and R. S. J. Tol, “Handbook on Methods for Climate Change Impact Assessment and Adaptation Strategies (Version 2.0),” 1998.
- [3] I. E. Agency, “Key World Energy Statistics 2021 – Statistics Report,” *IEA Publ.*, pp. 1–82, 2021.
- [4] V. S. K. V. Harish and A. Kumar, “A review on modeling and simulation of building energy systems,” *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1272–1292, 2016.
- [5] United Nations, *Energy Statistics Pocketbook*. 2021.
- [6] M. A. Hamdaoui, M. H. Benzaama, Y. El Mendili, and D. Chateigner, “A review on physical and data-driven modeling of buildings hygrothermal behavior: Models, approaches and simulation tools,” *Energy Build.*, vol. 251, p. 111343, 2021.
- [7] A. Mardiana-Idayu and S. B. Riffat, “Review on heat recovery technologies for building applications,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 2, pp. 1241–1255, 2012.
- [8] E. Frühwald, C. Brischke, L. Meyer, T. Isaksson, S. Thelandersson, and D. Kavurmaci, “Durability of timber outdoor structures - modelling performance and climate impacts,” 2012.
- [9] M. Ali, M. O. Oladokun, S. B. Osman, S. A. Mohd Din, M. S. Ibrahim, and F. Yusof, “Hygrothermal performance of building envelopes in the tropics under operative conditions: Condensation and mould growth risk appraisal,” *J. Teknol.*, vol. 78, no. 5, pp. 271–279, 2016.
- [10] Y. D. Aktas *et al.*, “Outdoor thermal comfort and building energy use potential in different land-use areas in tropical cities: Case of Kuala Lumpur,” *Atmosphere (Basel)*, vol. 11, no. 6, pp. 1–17, 2020.

- [11] W. Fatimah and M. Yusoff, "Initial assessment of indoor environmental condition and thermal comfort of Malaysia heritage mosque," *J. Kejuruter.*, vol. 32, no. 2, pp. 271–280, 2020.
- [12] D. E. Seborg, D. A. Mellichamp, T. F. Edgar, and F. J. Doyle, *Process Dynamics and Control*. John Wiley & Sons Incorporated, 2010.
- [13] N. S. Nise, *Control Systems Engineering*, 3rd ed. John Wiley & Sons Incorporated, 2000.
- [14] P. Whittle, *Hypothesis Testing in Time Series Analysis*. Almqvist & Wiksells, 1951.
- [15] G. E. P. Box and G. M. Jenkins, *Time series analysis: forecasting and control*. Holden-Day, 1970.
- [16] H. B. Demuth and M. H. Beale, *Neural Network Toolbox 4 User's Guide*. The MathWorks, Inc., 2004.
- [17] D. Opitz and R. Maclin, "Popular Ensemble Methods: An Empirical Study," *J. Artif. Intell. Res.*, vol. 11, pp. 169–198, Aug. 1999.
- [18] R. Polikar, "Ensemble based systems in decision making," *IEEE Circuits Syst. Mag.*, vol. 6, no. 3, pp. 21–45, 2006.
- [19] L. Rokach, "Ensemble-based classifiers," *Artif. Intell. Rev.*, vol. 33, no. 1–2, pp. 1–39, Feb. 2010.
- [20] A. van den Bosch, B. Hengst, J. Lloyd, R. Miikkulainen, H. Blockeel, and H. Blockeel, "Hypothesis Space," in *Encyclopedia of Machine Learning*, C. Sammut and G. I. Webb, Eds. Boston, MA: Springer US, 2011, pp. 511–513.
- [21] L. I. Kuncheva, "Measures of Diversity in Classifier Ensembles and Their Relationship with the Ensemble Accuracy," in *DERA/IEE Workshop Intelligent Sensor Processing*, 2001, vol. 2001, no. 50, pp. 10–10.
- [22] P. Sollich and A. Krogh, "Learning with Ensembles: How Over-fitting Can Be Useful," in *Proceedings of the 8th International Conference on Neural Information Processing Systems*, 1995, pp. 190–196.
- [23] G. Brown, J. Wyatt, R. Harris, and X. Yao, "Diversity Creation Methods: A Survey and Categorisation," *Inf. Fusion*, vol. 6, no. 1, pp. 5–20, Mar. 2005.
- [24] J. J. Garcia Adeva, U. Cervino Beresi, and R. A. Calvo, "Accuracy and Diversity in Ensembles of Text Categorisers," *CLEI Electron. J.*, vol. 8, no. 2, pp. 1–12, Dec. 2005.
- [25] S. Haykin, *Neural Networks: A Comprehensive Foundation*. I E E E, 1999.

- [26] U. Naftaly, N. Intrator, and D. Horn, "Optimal ensemble averaging of neural networks," *Netw. Comput. Neural Syst.*, vol. 8, no. 3, pp. 283–296, Jan. 1997.
- [27] S. A. Jafari, S. Mashohor, and M. J. Varnamkhasti, "Committee Neural Networks with Fuzzy Genetic Algorithm," *J. Pet. Sci. Eng.*, vol. 76, no. 3–4, pp. 217–223, Mar. 2011.
- [28] A. Tatar, M. R. Yassin, M. Rezaee, A. H. Aghajafari, and A. Shokrollahi, "Applying a Robust Solution Based on Expert Systems and GA Evolutionary Algorithm for Prognosticating Residual Gas Saturation in Water Drive Gas Reservoirs," *J. Nat. Gas Sci. Eng.*, vol. 21, pp. 79–94, Nov. 2014.
- [29] S. Hashem, "Optimal Linear Combinations of Neural Networks," *Neural Networks*, vol. 10, no. 4, pp. 599–614, Jun. 1997.
- [30] S. Geman, E. Bienenstock, and R. Doursat, "Neural Networks and the Bias/Variance Dilemma," *Neural Comput.*, vol. 4, no. 1, pp. 1–58, Jan. 1992.
- [31] R. T. Clemen, "Combining forecasts: A review and annotated bibliography," *Int. J. Forecast.*, vol. 5, no. 4, pp. 559–583, Jan. 1989.
- [32] A. A. Nadiri, E. Fijani, F. T.-C. Tsai, and A. Asghari Moghaddam, "Supervised committee machine with artificial intelligence for prediction of fluoride concentration," *J. Hydroinformatics*, vol. 15, no. 4, pp. 1474–1490, Oct. 2013.
- [33] C.-H. Chen and Z.-S. Lin, "A committee machine with empirical formulas for permeability prediction," *Comput. Geosci.*, vol. 32, no. 4, pp. 485–496, May 2006.
- [34] A. Gholami, H. R. Ansari, and S. Ahmadi, "Combining of intelligent models through committee machine for estimation of wax deposition," *J. Chinese Chem. Soc.*, vol. 65, no. 8, pp. 925–931, 2018.
- [35] B. a Pearlmutter and R. Rosenfeld, "Chaitin-Kolmogorov Complexity and Generalization in Neural Networks," in *Advances in Neural Information Processing Systems 3*, 1991, vol. 3, pp. 925–931.
- [36] L. Rincón, A. Carrobé, M. Medrano, C. Solé, A. Castell, and I. Martorell, "Analysis of the thermal behavior of an earthbag building in Mediterranean continental climate: Monitoring and simulation," *Energies*, vol. 13, no. 1, 2019.
- [37] R. A. Barrientos-González, R. E. Vega-Azamar, J. C. Cruz-Argüello, N. A. Oropeza-García, M. Chan-Juárez, and D. L. Trejo-Arroyo, "Indoor temperature validation of low-income detached dwellings under tropical weather conditions," *Climate*, vol. 7, no. 8, 2019.

- [38] M. Qin, P. Hou, Z. Wu, and J. Wang, "Precise humidity control materials for autonomous regulation of indoor moisture," *Build. Environ.*, vol. 169, no. November 2019, p. 106581, 2020.
- [39] M. D'Orazio and G. Maracchini, "An experimental investigation on the indoor hygrothermal environment of a reinforced-EPS based temporary housing solution," *Energy Build.*, vol. 204, p. 109500, 2019.
- [40] M. Qin, G. Walton, R. Belarbi, and F. Allard, "Simulation of whole building coupled hygrothermal-airflow transfer in different climates," *Energy Convers. Manag.*, vol. 52, no. 2, pp. 1470–1478, 2011.
- [41] A. Romano, A. Bras, S. Grammatikos, A. Shaw, and M. Riley, "Dynamic behaviour of bio-based and recycled materials for indoor environmental comfort," *Constr. Build. Mater.*, vol. 211, no. 2019, pp. 730–743, 2019.
- [42] R. Z. Freire, G. H. C. Oliveira, and N. Mendes, "Development of regression equations for predicting energy and hygrothermal performance of buildings," *Energy Build.*, vol. 40, no. 5, pp. 810–820, 2008.
- [43] C. Rode and K. Grau, "Whole-building Hygrothermal Simulation Model," in *ASHRAE Transactions*, 2003, vol. 109, no. 1, pp. 572–582.
- [44] M. Winkler, M. Pazold, A. Zegowitz, S. Giglmeier, and F. Antretter, "Use of a radiator for user-centric cooling - Measurement and Simulation," *E3S Web Conf.*, vol. 172, pp. 1–6, 2020.
- [45] R. Kramer, J. van Schijndel, and H. Schellen, "Simplified thermal and hygric building models: A literature review," *Front. Archit. Res.*, vol. 1, no. 4, pp. 318–325, 2012.
- [46] F. Bruckmayer, "The Equivalent Brick Wall," *Gesundheits-Ingenieur*, vol. 63, pp. 61–65, 1940.
- [47] G. Mitalas and D. Stephenson, "Room Thermal Response Factors," *ASHRAE Trans.*, vol. 73, no. III.2, pp. 1–10, 1967.
- [48] J. Clarke, *Energy Simulation in Building Design*. Routledge, 2007.
- [49] J. A. Crabb, N. Murdoch, and J. M. Penman, "A simplified thermal response model," *Build. Serv. Eng. Res. Technol.*, vol. 8, no. 1, pp. 13–19, 1987.
- [50] S. Wang and Y. Chen, "A novel and simple building load calculation model for building and system dynamic simulation," *Appl. Therm. Eng.*, vol. 21, no. 6, pp. 683–702, 2001.
- [51] E. H. Mathews, P. G. Richards, and C. Lombard, "A first-order thermal model

- for building design,” *Energy Build.*, vol. 21, no. 2, pp. 133–145, 1994.
- [52] L. Ljung, *System Identification Toolbox 9 User’s Guide*. The MathWorks, Inc., 2014.
- [53] M. Benchekroun, S. Chergui, F. Ruggiero, and S. Di Turi, “Indoor Microclimate Conditions and the Impact of Transformations on Hygrothermal Comfort in the Old Ottoman Houses in Algiers,” *Int. J. Archit. Herit.*, vol. 14, no. 9, pp. 1296–1319, 2020.
- [54] A. H. Holm, H. M. Künzl, and K. Sedlbauer, “Predicting indoor temperature and humidity conditions including hygrothermal interactions with the building envelope,” *ASHRAE Trans.*, vol. 110 PART I, pp. 820–826, 2004.
- [55] H. M. Künzl, A. Holm, D. Zirkelbach, and A. N. Karagiozis, “Simulation of indoor temperature and humidity conditions including hygrothermal interactions with the building envelope,” *Sol. Energy*, vol. 78, no. 4 SPEC. ISS., pp. 554–561, 2005.
- [56] M. Qin, R. Belarbi, and A. Aît-Mokhtar, “Modeling of simultaneous heat and moisture transfer in air-conditioned buildings,” *J. Harbin Inst. Technol.*, vol. 14, no. sup., pp. 72–76, 2007.
- [57] S. M. Cornick and M. K. Kumaran, “A Comparison of Empirical Indoor Relative Humidity Models with Measured Data,” *J. Build. Phys.*, vol. 31, no. 3, pp. 243–268, 2008.
- [58] F. Antretter, F. Sauer, T. Schöpfer, and A. Holm, “Validation of a hygrothermal whole building simulation software,” *Proc. Build. Simul. 2011 12th Conf. Int. Build. Perform. Simul. Assoc.*, pp. 1694–1701, 2011.
- [59] A. Bishara and R. Mujahn, “Development of a Model for the Prediction of Indoor Climate to Enhance Design Tasks in Southern Climates,” in *2nd International ASHRAE Conference Efficient Building Design: Materials and HVAC Equipment Technologies*, 2016.
- [60] S. Salakij, N. Yu, S. Paolucci, and P. Antsaklis, “Model-Based Predictive Control for building energy management. I: Energy modeling and optimal control,” *Energy Build.*, vol. 133, pp. 345–358, 2016.
- [61] N. Carbonare, T. Pflug, C. Bongs, and A. Wagner, “Simulative study of a novel fuzzy demand controlled ventilation for façade-integrated decentralized systems in renovated residential buildings,” *Sci. Technol. Built Environ.*, vol. 26, no. 10, pp. 1412–1426, Nov. 2020.

- [62] D. Chung, J. Wen, and L. J. Lo, “Development and verification of the open source platform, HAM-Tools, for hygrothermal performance simulation of buildings using a stochastic approach,” *Build. Simul.*, vol. 13, no. 3, pp. 497–514, 2020.
- [63] H. E. Huerto-Cardenas *et al.*, “Validation of dynamic hygrothermal simulation models for historical buildings: State of the art, research challenges and recommendations,” *Build. Environ.*, vol. 180, no. March, p. 107081, 2020.
- [64] N. Grzegorz, S. Paweł, and M. Małgorzata, “Experimental Study of Thermal and Humidity Conditions in a Historic Wooden Building in,” pp. 1–14, 2020.
- [65] M. Pazold, M. Winkler, and F. Antretter, “Investigating overheating by measurement and simulation in classrooms,” vol. 3005, pp. 1–8, 2020.
- [66] E. Schito, P. Conti, L. Urbanucci, and D. Testi, “Multi-objective optimization of HVAC control in museum environment for artwork preservation , visitors ’ thermal comfort and energy efficiency,” *Build. Environ.*, vol. 180, no. June, p. 107018, 2020.
- [67] S. Wijesuriya, P. C. Tabares-velasco, K. Biswas, D. Heim, and O. Ridge, “Empirical validation and comparison of PCM modeling algorithms commonly used in building energy and hygrothermal software,” *Build. Environ.*, vol. 173, no. November 2019, p. 106750, 2020.
- [68] I. Costa-Carrapiço, B. Croxford, R. Raslan, and J. Neila González, “Hygrothermal calibration and validation of vernacular dwellings: A genetic algorithm-based optimisation methodology,” *J. Build. Eng.*, vol. 55, no. May, p. 104717, Sep. 2022.
- [69] M. Zhao, S. R. Mehra, and H. M. Künzeli, “Energy-saving potential of deeply retrofitting building enclosures of traditional courtyard houses – A case study in the Chinese Hot-Summer-Cold-Winter zone,” *Build. Environ.*, vol. 217, no. March, p. 109106, 2022.
- [70] I. Oubrahim, T. Duforestel, and R. Belarbi, “Integration of water sorption hysteresis for heat and mass transfer modeling,” *Heat Mass Transf. und Stoffuebertragung*, no. 0123456789, 2022.
- [71] R. Z. Freire, L. dos S. Coelho, G. H. dos Santos, and V. C. Mariani, “Predicting building’s corners hygrothermal behavior by using a Fuzzy inference system combined with clustering and Kalman filter,” *Int. Commun. Heat Mass Transf.*, vol. 71, pp. 225–233, 2016.

- [72] M. H. Benzaama, L. Rajaoarisoa, F. Boukhelf, and Y. El Mendili, “Hygrothermal transfer modelling through a bio-based building material: Validation of a switching-linear model,” *J. Build. Eng.*, vol. 55, no. March, p. 104691, 2022.
- [73] A. Tijsskens, S. Roels, and H. Janssen, “Neural networks for metamodelling the hygrothermal behaviour of building components,” *Build. Environ.*, vol. 162, no. June, p. 106282, 2019.
- [74] A. Ghofrani, S. D. Nazemi, and M. A. Jafari, “Prediction of building indoor temperature response in variable air volume systems,” *J. Build. Perform. Simul.*, vol. 13, no. 1, pp. 34–47, 2020.
- [75] X. Lü, T. Lu, C. Kibert, K. Vahtikari, M. Hughes, and Y. Zhao, “A dynamic modelling approach for simulating climate change impact on energy and hygrothermal performances of wood buildings,” *Build. Simul.*, vol. 11, no. 3, pp. 497–506, 2018.
- [76] D. O. Woo and L. Junghans, “Framework for model predictive control (MPC)-based surface condensation prevention for thermo-active building systems (TABS),” *Energy Build.*, vol. 215, p. 109898, 2020.
- [77] E. L. Maxwell, “A quasi-physical model for converting hourly global horizontal to direct normal insolation,” Oct. 1987.
- [78] J. W. Spencer, “Fourier series representation of the position of the sun,” *Search*, vol. 2, no. 5, p. 172+, May 1971.
- [79] F. Kasten, “A new table and approximation formula for the relative optical air mass,” *Arch. für Meteorol. Geophys. und Bioklimatologie, Ser. B*, vol. 14, no. 2, pp. 206–223, 1965.
- [80] K. Holbert and D. Srinivasan, “Solar energy calculations,” in *Handbook of Renewable Energy Technology*, World Scientific Publishing Co., 2011, pp. 189–204.
- [81] A. W. Culp, *Principles of Energy Conversion*. McGraw-Hill, 1991.
- [82] M.-J. Chang *et al.*, “A Support Vector Machine Forecasting Model for Typhoon Flood Inundation Mapping and Early Flood Warning Systems,” *Water*, vol. 10, no. 12, p. 1734, Nov. 2018.

LIST OF PUBLICATIONS

Journals:

- [1] **S. F. M. Hussein**, H. Nguyen, S. S. Abdullah, Y. Lim, and Y. Tan, “Black Box Modelling the Thermal Behaviour of iHouse using Auto Regressive and Moving Average (ARMA) Model,” *J. Teknol.*, vol. 78, no. 6–13, pp. 51–58, 2016.
- [2] **S. F. M. Hussein**, N. B. Sharifmuddin, A. O. Al rabeei, A. Faruq, M. S. Noorazizi, S. A. Zaki, and S. S. Abdullah, “Black Box Modelling and Simulating the Dynamic Indoor Air Temperature of a Laboratory using Autoregressive–moving-average (ARMA) Model,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 21, no. 2, pp. 791–800, Feb. 2021.

Conference Proceedings:

- [1] **S. F. M. Hussein**, M. A. Abu Bakar, Y. Makino, H. Nguyen, S. S. Abdullah, Y. Lim, and Y. Tan, “Simplifying the Auto Regressive and Moving Average (ARMA) Model Representing the Dynamic Thermal Behaviour of iHouse Based on Theoretical Knowledge,” in *17th Asia Simulation Conference, AsiaSim 2017, Melaka, Malaysia, August 27 – 29, 2017, Proceedings, Part II*, vol. 752, 2017, pp. 697–711.
- [2] **S. F. M. Hussein**, M. K. Mohd Fitri Alif, A. O. Al rabeei, A. Faruq, S. M. Zulkapli, M. S. Noorazizi, S. A. Zaki, and S. S. Abdullah, “Black Box Modelling and Simulating the Dynamic Indoor Relative Humidity of a Laboratory Using Autoregressive–moving-average (ARMA) Model,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 884, p. 012108, Jul. 2020.
- [3] **S. F. M. Hussein**, N. B. Sharifmuddin, M. K. Mohd Fitri Alif, A. O. Al rabeei, A. Faruq, S. M. Zulkapli, M. S. Noorazizi, S. A. Zaki, and S. S. Abdullah,, “Black Box Modelling and Simulating the Dynamic Indoor Air Temperature of a Laboratory Using the Continuous-Time Transfer Function Model,” in *Proceedings of the Third International Conference on Separation Technology 2020 (ICoST 2020)*, 2020, vol. 200, no. 2, pp. 146–157.