SOFT COMPUTING BASED CONTROLLERS FOR AUTOMOTIVE AIR CONDITIONING SYSTEM WITH VARIABLE SPEED COMPRESSOR

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To my beloved parents and siblings.

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ABSTRACT

The inefficient On/Off control for the compressor operation has long been regarded as the major factor contributing to energy loss and poor cabin temperature control of an automotive air conditioning (AAC) system. In this study, two soft computing based controllers, namely the proportional-integral-derivative (PID) based controllers tuned using differential evolution (DE) algorithm and an adaptive neural network based model predictive controller (A-NNMPC), are proposed to be used in the regulation of cabin temperature through proper compressor speed modulation. The implementation of the control schemes in conjunction with DE and neural network aims to improve the AAC performance in terms of reference tracking and power efficiency in comparison to the conventional On/Off operation. An AAC experimental rig equipped with variable speed compressor has been developed for the implementation of the proposed controllers. The dynamics of the AAC system is modelled using a nonlinear autoregressive with exogenous inputs (NARX) neural network. Based on the plant model, the PID gains are offline optimized using the DE algorithm. Experimental results show that the DE tuned PID based controller gives better tracking performance than the Ziegler-Nichols tuning method. For A-NNMPC, the identified NARX model is incorporated as a predictive model in the control system. It is trained in real time throughout the control process and therefore able to adaptively capture the time varying dynamics of the AAC system. Consequently, optimal performance can be achieved even when the operating point is drifted away from the nominal condition. Finally, the comparative assessment indicates clearly that A-NNMPC outperforms its counterparts, followed by DE tuned PID based controller and the On/Off controller. Both proposed control schemes achieve up to 47% power saving over the On/Off operation, indicating that the proposed control schemes can be potential alternatives to replace the On/Off operation in an AAC system.

ABSTRAK

Ketidakcekapan pengawal On/Off dalam operasi pemampat telah lama dianggap sebagai faktor utama yang menyumbang kepada kehilangan tenaga dan kelemahan kawalan suhu kabin dalam sistem penyaman udara automotif (AAC). Dalam kajian ini, dua pengawal berasaskan pengkomputeraan lembut, iaitu pengawal terbitan kamiran berkadaran (PID) yang ditala dengan algoritma evolusi kebezaan (DE) dan pengawal adaptif rangkaian saraf ramalan (A-NNMPC), telah dicadangkan untuk mengawal suhu kabin melalui modulasi kelajuan pemampat. Perlaksanaan skim kawalan bergabungan dengan DE dan rangkaian saraf bertujuan untuk meningkatkan prestasi sistem AAC dari segi penjejakan rujukan dan kecekapan kuasa berbanding dengan operasi On/Off yang konvensional. Satu sistem ujikaji AAC yang dilengkapi dengan pemampat elektrik kelajuan boleh ubah telah dibangunkan dan digunakan dalam perlaksanaan pegawal yang dicadangkan. Satu autoregresi tak lurus dengan input luaran (NARX) rangkaian saraf digunapakai untuk pemodelan dinamik AAC. Berdasarkan model ini, parameter PID dioptimalkan secara luar talian dengan menggunakan algoritma DE. Hasil ujikaji menunjukkan talaan pengawal PID berasaskan DE memberikan prestasi penjejakan rujukan yang lebih baik dibandingkan dengan kaedah penalaan Ziegler-Nichols. Bagi A-NNMPC, model NARX yang sudah dikenalpasti itu dijadikan sebagai model ramalan dalam sistem kawalan. Ia dilatih secara dalam talian sepanjang proses kawalan. Dengan itu, system dinamik yang berubah-ubah dari masa ke semasa dapat diperolehi secara adaptif. Dengan ini, prestasi optimum dapat dicapai walaupun titik operasi optimum beralih jauh dari keadaan nominal. Akhir sekali, penilaian perbandingan menunjukkan bahawa prestasi paling baik diperolehi daripada A-NNMPC, dan diikuti oleh pengawal PID yang ditalakan dengan DE and pengawal On/Off. Jika dibandingkan dengan pengawal On/Off, penjimatan kuasa sebanyak 48% dapat dicapai oleh skim kawalan yang dicadangkan. Ini menunjukkan bahawa pengawal yang dicadangkan adalah alternatif yang berpotensi dalam sistem AAC berbanding dengan pengawal On/Off.

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LIST OF ABBREVIATIONS

AAC	-	Automotive air conditioning system
AC	-	Alternating current
AC&R	-	Air conditioning and refrigeration
ANN	-	Artificial neural network
A-NNMPC	-	Adaptive neural predictive controller
CFO	-	Cost function optimizer
COP	-	Coefficient of performance
D	-	Derivative
DAQ	-	Data acquisition
DC	-	Direct current
DE	-	Differential evolution
DE-PI	-	Proportional-integral controller tuned using differential evolution algorithm.
DE-PID	-	Proportional-integral-derivative controller tuned using differential evolution algorithm.
GA	-	Genetic algorithm
I	-	Integral
MLP	-	Multilayer perceptron
MPC	-	Model predictive control
MPO	-	Model predicted output
NARX	-	Nonlinear autoregressive with exogenous inputs.
NI	-	National instrument
O-NNMPC	-	Predictive controller based on offline trained neural network
OSA	-	One step ahead
P	-	Proportional

PI	-	Proportional-integral
PID	-	Proportional-integral-derivative
PSO	-	Particle swarm optimisation
RBN	-	Radial basis network
Ref	-	Reference
RTD	-	Resistance temperature detectors
TXV	-	Thermostatic expansion valve
VSC	-	Variable speed compressor
ZN	-	Ziegler-Nichols
ZN-PI	-	Proportional-integral controller tuned using Ziegler-Nichols tuning rules.
ZN-PID	-	Proportional-integral-derivative controller tuned using Ziegler-Nichols tuning rules.

LIST OF SYMBOLS

A	-	Cross section
a_{ZN}	-	Intercepting point of the steepest descent slope of the response curve with the vertical axis
$b_{i,L}, b_{i,H}$	-	Lower and upper bound of each tuning parameters
b_1, b_2, b_3, b_4	-	Biases of the neural network at different layer
CR	-	Crossover constant
c_{pa}	-	Specific heat capacity of the air
D	-	Dimension of problem
e	-	Tracking error
e_{Up}	-	Upper bound of temperature error
e_{Low}	-	Lower bound of temperature error
err_{index}	-	Error index
E	-	Vector of the training error
F	-	Mutation constant
Fit	-	Fitness value
$f_{\log sig}$	-	Logsig transfer function
$f_{NN,OSA}, f_{NN,MPO}$	-	Function with series parallel and series-parallel Architectures
G	-	Generation
G_max	-	Maximum number of generation
H	-	Height of the rectangular ducting cross section
HD	-	Hydraulic diameter
$h_{evap,g,i}$	-	specific enthalpy of the evaporator inlet water vapour

$h_{evap,g,o}$	-	specific enthalpy of the evaporator outlet water vapour
h_{wa}	-	Specific enthalpy of the condensate
I	-	Individual
I_{comp}	-	Current supply to the compressor
$IAE,\ IAE_s$	-	Integral absolute error for experimental and simulation tests.
J	-	Objective function of the predictive controller
Jac	-	Jacobian matrix with first derivative of the training errors with respect to the ANN weights.
K_d	-	Derivative gain
K_i	-	Integral gain
K_p	-	Proportional gain
k	-	Iteration of optimisation
$k_{\max}$	-	Maximum iteration
M_p	-	Over/undershoot
$\dot{m}_a$	-	Mass flow rate of the air
$\dot{m}_r$	-	Mass flow rate of refrigerant
m_u, m_y	-	Model order
$MSE_{Train},\ MSE_{Test}$	-	Mean square error computed based on training and testing sets
N_{comp}	-	Compressor speed
N_i, N_o	-	Dimension of the input and output layer
$N_{neuron,h}$	-	Number of neuron in the hidden layer
N_u	-	Control horizon
N_p	-	Prediction horizon
NP	-	Population size
$NP_{MLP}\ NP_{RBN}$	-	Network complexity of MLP and RBN model
n	-	time instant

$PI_{x\max}$	-	Performance index when operational parameter is maximum
$PI_{x\min}$	-	Performance index when operational parameter is minimum
$\dot{Q}_{cool}$	-	Instantaneous cooling capacity
$\dot{Q}_{cool,av}$	-	Average cooling capacity
R	-	Experimental result
r	-	Set point
T_c	-	Cabin temperature
$T_{c,steady}$	-	Steady state cabin temperature
$T_{evap,a,i}$	-	Evaporator inlet air temperature
$T_{evap,a,o}$	-	Evaporator outlet air temperature
T_s	-	Sampling time
t_{const}	-	Time constant
$t_{const,\min}$	-	Minimum time constant
$t_{h,\min}$	-	Minimum hold time
t_{Opt}	-	Optimisation duration
t_r	-	Rise time
t_{sett}	-	Settling time
t_1, t_2	-	Start and end time
U	-	Trial individual
U_v	-	Vector of control signal
u	-	Control signal, model input
$u_{i,j}$	-	Element of the trial individual
$u_{\min}, u_{\max}$	-	Lower and upper limit of the control signal
V	-	Mutant vector
VP	-	Variation of AAC performance indices
$v_{i,j}$	-	Element in the mutant vector
v_{cond}	-	Condenser face velocity

W	-	Width of the rectangular ducting cross section
$\dot{W}_{comp}$	-	Compressor power consumption
$\dot{W}_{comp,av}$	-	Average compressor power consumption
$\dot{W}_{motor}$	-	Motor power
W_1, W_2, W_3, W_4	-	Synaptic weights connecting different layers in the neural network
$w_{evap,i}$	-	Specific humidity upstream of the evaporator
$w_{evap,o}$	-	Specific humidity downstream of the evaporator
w_{Train}, w_{Test}	-	Weighting parameters
$X_1, X_2, \ldots, X_J$	-	Independent measurements
$x_{i,j}$	-	Element in the individual
y_m	-	System output
y_n	-	Reference trajectory
$\hat{y}_m$	-	Model output
$\hat{y}_{MLP}, \hat{y}_{RBN}$	-	Predicted output of MLP and RBN models
z^{-1}	-	Time delay
η_{comp}	-	Global compression efficieny
η_e	-	Electrical efficiency
η_m	-	Mechanical efficiency
τ_{ref}	-	Time constant of the reference trajectory
τ_{ZN}	-	Intercepting point of the steepest descent slope of the response curve with the horizontal axis.
σ	-	Spread value
δ	-	Error tolerance
λ	-	Weighting factor

CHAPTER 1

INTRODUCTION

1.1 Introduction

Road transport activity is one of the main contributors to greenhouse gas emissions in the atmosphere. As the effort to counter the issue of greenhouse effect and global energy shortage, a new national fuel economy program has been launched in the United States, which requires an average fuel economy standard of 172 g/km CO_2 emission for new light vehicles by 2016 (Cheah and Heywood, 2011). Similarly, the European Commission, Japan and China have respectively set mandatory standards of 120 g/km, 125 g/km and 167 g/km for the average emissions of new cars to be phased in by the year 2015 (Atabani *et al.*, 2011; Zhang *et al.*, 2014).

Among all the components in a conventional vehicle, the compressor of an automotive air conditioning (AAC) system is the single largest auxiliary load on the engine (Rugh and Hendricks, 2001). A compressor driven by the engine can consume up to 5 to 6 kW peak power draw on a vehicle engine and is equivalent to a vehicle being driven down the road at 56 km/hr (Hensen *et al.*, 2002). According to the findings of National Renewable Energy Laboratory in Golden, Colorado, seven billion gallons of gasoline, a volume representing nearly 5.5% of total national light duty fuel consumption in the United States, are used annually to run the air conditioners of vehicles (Rugh *et al.*, 2007). In addition, the study done by Rugh and Hendricks (2001) indicated that the increment of tailpipe emissions resulting from air conditioning system on average can be up to 70% carbon dioxide (CO_2) and 80% nitrogen oxides (NO_x).

Aiming at reducing the overall vehicle fuel consumption due to the reinforcement of the more stringent environmental regulation, the manufacturers are concerned with the cost effectiveness of AAC system designs and their operating strategies. One of the major functions of air conditioning system in a vehicle is to maintain the desired cabin temperature for the thermal comfort of occupants (Wang *et al.*, 2000). In a conventional vehicle, the compressor is usually powered by a combustion engine and its cooling capacity is controlled via activation and deactivation of the magnetic clutch system. Sensor units are integrated to the air conditioning control panels or/and fitted to the air ducting of the evaporator to monitor the respective local cabin temperature (Daly, 2006). During partial load conditions, the magnetic clutch of the compressor has to undergo engagement and disengagement cycles continuously in order to achieve the desired cooling effect in the cabin. The On/Off control of the compressor has led to several drawbacks, such as cycling losses and poor cabin temperature control (Ananthanarayana, 2005; Buzelin *et al.*, 2005).

A feasible alternative to the less efficient On/Off operation is the variable speed control of the compressor with the basic function of varying the refrigerant flow rate in the refrigerant circuit. Cabin temperature control through proper modulation of the compressor speed has emerged to be a popular choice due to its superior power efficiency (Qureshi and Tassou, 1995).

Application of On/Off compressor in a conventional vechicle remains a popular choice worldwide (Daly, 2006; Nasution, 2005) due to the fact that the implementation of variable speed compressor (VSC) is restricted by the 12 V power supply. In view of this limitation, reciprocating compressor driven by vehicle engine is still widely applied in many foreign and local vehicles. Technically, VSC is only applicable for heavy trucks, buses, electric and hybrid vehicles, in which high voltage battery supply is available to drive the VSC. Recently, it has become a prospective application in conventional vehicles, as the key German carmakers are working on stepping up the existing 12 V power supply to the proposed 48 V power net system (Hammerschmidt, 2011). The effort of the power net transition makes the application of VSC become more attractive, as it will facilitate the integration of an electric VSC in the conventional vehicle powered fully by a 48 V battery.

In view of the stricter emission standards of today's automotive industry and the promising improvement brought about by the VSC application, the design of efficient and optimised control strategies for the implementation of VSC is desirable. With the advent of powerful computers, rapid development of advanced control techniques such as the use of soft computing approaches is spawn to achieve more satisfactory process controls (Silva, 2000). Soft computing emerges to receive growing acceptance in the industry due to its capability to tolerate with the ambiguous real life situation such as imprecision and uncertainty (Malhotra *et al.*, 2011). The principle constituents of soft computing include artificial neural networks (ANN), fuzzy logic, evolutionary algorithms and probabilistic computing (Ray, 2014), which have been well recognized as powerful tools to handle nonlinearity, complex optimization problems and uncertain environmental condition. There is an extensive literature in soft computing from theoretical as well as applied viewpoint (Dote and Ovaska, 2001; Fortuna *et al.*, 2001; Ray, 2014). However the main focus of this study will be on differential evolution (a subset of evolutionary algorithm) and ANN. Both soft computing approaches are adopted and incorporated in the proposed control schemes for the VSC operation. Further review on the recent development of conventional and soft computing based control methods and their respective applications in air conditioning and refrigeration (AC&R) systems is presented in Chapter 2.

1.2 Problem Statement

The main issue needs to be addressed in this study is the inefficient operation of the engine driven compressor integrated in a conventional vehicle. When the AAC system is operated under partial load condition, the compressor has to be cycled 'On' and 'Off' via magnetic clutch. The major drawback of this control method is the energy loss associated with the pressure equalization during compressor stoppage and power losses due to the pulley belt friction. Additionally, the transient start-up and shut-down of the compressor often results in the fluctuating cabin temperature. Another major disadvantage of this system is that the location of the air conditioning system is restricted due to the engine shaft-pulley-belt-compressor configuration. In addition, the continuous ‘On’ and ‘Off’ switching process may reduce the lifetime of the mechanical parts.

Innovative solutions are necessary to improve fuel consumption and the cabin temperature control of a conventional AAC system. A possible alternative is by converting the conventional On/Off cycling to a variable speed operating mode (Buzelin *et al.*, 2005; Nasution and Hassan, 2006). The reason for energy saving lies in the fact that establishment of a proper speed control for the VSC can insure a continuous matching between the cooling capacity and the time varying thermal load. Furthermore, variable speed operation is expected to deliver better temperature control, as the compressor speed is no longer a function of the engine speed and thus can be freely regulated in response to the set point change as well as the variation of the operating condition.

Optimal thermal control of a mobile AAC system through proper modulation of the comrpessor speed is a rather complex job, as the system is consistently subjected to a wide range of transient disturbances such as the sun radiation, changing ambient temperature and incoming air speed of condenser (Shah *et al.*, 2004). Under the consideration of the inherently nonlinear dynamics of the air conditioning system (He *et al.*, 1997; Li *et al.*, 2012), application of simple controller such as proportional-integral-derivative (PID) control in regulating the compressor speed requires proper optimisation of the control parameters. Repetition of experimental tests for parameter tuning based on trial and error can be costly and time consuming (Saad *et al.*, 2012). Thus, implementation of a proper tuning method is essential for determining the optimal parameter setting for the PID controller.

Apart from the PID control system, advanced control strategies such as model based controllers require preliminarily a detailed nonlinear physical model of the vapour compression cycles derived from first principles. However, developing an adequate physical model with satisfactory prediction accuracy is a challenging task, as air conditioning system is highly nonlinear and it consists of complex subsystems that mutually influence one another (He *et al.*, 1997; Rasmussen *et al.*, 2002). Consequently, establishment of a model adequately representing the nonlinear AAC system is essential to ensure satisfactory cabin temperature control of the AAC system.

Soft computing is a practical method in solving computationally complex and mathematically intractable problems. In this study, differential evolution (DE) algorithm and artificial neural networks (ANN) are integrated with the conventional control system in a complementary hybrid framework to handle the complex control problems. Two soft computing based control schemes, namely PID based controllers tuned using DE algorithm and an adaptive neural network based model predictive controller (A-NNMPC), have been proposed for the implementation of VSC. In contrast to the conventional On/Off operation, the implementation of the proposed control schemes allows the compressor speed to be regulated optimally within the predefined range in order to achieve the target cabin temperature.

1.3 Research Objectives

The main goal of this research is to implement the proposed control schemes for the VSC operation in an AAC system. Accordingly, following objectives are to be accomplished:

1. To design an AAC experimental rig integrated with a VSC. The rig serves as a platform for the implementation of VSC using the proposed control schemes.

2. To develop an ANN model simulating the dynamics of the AAC system. This model is intended to be applied for the design and implementation of the proposed controllers.

3. To develop PID based controllers tuned using DE algorithm and an adaptive neural network based model predictive control system (A-NNMPC) that can effectively regulate the cabin temperature by modulating the compressor speed. Additionally, a conventional On/Off controller is introduced as a benchmark to evaluate the performance delivered by the proposed controllers.

4. To compare the reference tracking performance, robustness and power efficiency of the proposed control schemes with the conventional On/Off controller.

1.4 Scope of the Study

The scopes of the research are as follows:

1. In this study, an experimental setup, comprising refrigeration circuit, ducting systems and measurement instrumentation, is developed to resemble an AAC system equipped with a VSC. All the proposed control schemes are implemented and tested on this experimental rig.

2. For the analysis of the AAC steady state performance, the variation of three operational parameters are taken into account, namely the compressor speed, air temperature upstream of the evaporator, and inlet air velocity of the condenser. The range of the respective operational parameters is 2400–5750 rpm for the compressor, 20.5–31.5 °C for the air temperature upstream of the evaporator, and 3–6.2 m/s for the inlet air velocity of the condenser.

3. A nonlinear autoregressive with exogenous inputs (NARX) neural network is used to model the dynamic behaviour of the experimental AAC system. Two network architectures considered in this study are the multilayer perceptron (MLP) and radial basis network (RBN). The RBN and MLP based NARX models are used to capture the transient dry bulb cabin temperature under random modulation of the compressor speed. Selection of the optimal network architecture is determined based on the prediction capability,

network complexity and computational effort for the ANN training. The prediction capability of the NARX neural networks is evaluated using the one-step-ahead and model-predictive-output prediction tests, while the network complexity is determined based on the number of connection weight and biases.

4. Two control schemes, namely PID based controllers (PI and PID) tuned using DE algorithm and an adaptive neural network based model predictive controller (A-NNMPC), are developed. The soft computing approaches incorporated in the control schemes involve the DE algorithm and the ANN model. By implementing the proposed controllers, the average dry bulb cabin temperature is controlled through proper modulation of the compressor speed.

5. Offline tuning of the PI and PID controllers is performed using DE algorithm. The identified NARX neural network is used as the plant model during the optimization process. The reference tracking performance of the DE tuned PID based controllers is evaluated by being compared to the conventional ZN tuning rules.

6. The A-NNMPC is developed by adopting the Newton-Rahpson method to solve the nonlinear cost optimisation problem. The identified NARX neural network is incorporated as a plant predictive model in the control system. Levenberg-Marquardt algorithm and sliding stack window technique are adopted for the online ANN training scheme. The necessity of using the online AAN training scheme in the control system is highlighted based on the comparative study between the proposed controller and a model predictive controller using an offline trained neural network (O-NNMPC).

7. All the experimental tests involving both proposed controllers are performed under nominal condition as well as in the presence of disturbance. Nominal condition can be understood as the operating condition, under which data collection is performed for the identification of an ANN model. This working condition is achieved by fixing the flow rate and temperature of the incoming air upstream of the condenser at 4.0 m/s and 33 °C respectively. A total of three heaters in the environmental chamber are switched on in order to

produce 1650 W thermal load. Air flow over the evaporator is driven at a speed of 4.25 m/s. It is recirculated without channelling additional air from the ambient. On the other hand, the disturbances introduced for the robustness tests comprise the variation of air speed (3 m/s−4.25 m/s) upstream of the evaporator and the thermal load (550 W−2200 W) in the cabin. The operating condition is varied via the adjustment of the evaporator fan and On/Off switching of the cabin heaters.

8. The performance of the proposed control schemes and the On/Off controller is analyzed based on reference tracking performance, power efficiency and robustness of the controller against the time varying operating condition. Three criteria used to quantify the power efficiency of the control schemes include the cooling capacity, power consumption and coefficient of performance (*COP*) of the AAC system.

1.5 Research Contributions

A brief outline of the main contributions of this research is given as follows:

1. This research provides detailed development of the AAC test rig equipped with an electric rotary vane compressor. This experimental rig can be used for the steady state performance analysis and the implementation of different control schemes for the operation of VSC.

2. Nonlinear identification technique is introduced for the dynamic modelling of the AAC system using the MLP based and RBN based NARX neural networks. The identified model can be further used for the development of different control schemes, such as the model based controllers and optimisation methods that require an AAC model. The tedious effort required for the physical modelling of an AAC system can be avoided by mean of this identification technique.

3. The research gives the details regarding the implementation of the DE tuned PI and PID controllers for the VSC operation on the AAC experimental rig. Optimisation of the control parameters can be carried out in simulation based on the aforementioned NARX neural network. This tuning method can be an alternative to the widely adopted ZN tuning rules and the cubersome trial and error method.

4. An adaptive neural network based model predictive control scheme (A-NNMPC) is introduced and tested experimentally for the cabin temperature control in an AAC system equipped with a VSC. Experimental resutls are provided to highlight the robustness of the control schemes against the disturbances and its adaptability to time varying operating conditions.

5. This research provides the outcome of a comparative study between the proposed control schemes and the On/Off control strategy. It highlights the respective performance in term of reference tracking and power efficiency.

1.6 Research Methodology

After extensive review of the past research works, an AAC experimental rig equipped with a VSC was first developed to demonstrate experimentally the practical implementation of the proposed control schemes. In order to ensure that the rig is a good representation of an actual AAC system, the refrigeration circuit was made up of the original key components (condenser, evaporator, thermostatic expansion valve (TXV)) obtained from a compact vehicle. However, the original reciprocating compressor was replaced by an electric rotary vane compressor. The rig was designed in such a way that it resembled an AAC system under the influence of different operational condition, such as the variation of thermal load in the vehicle cabin, air temperature and air velocity upstream of the evaporator and condenser. Measurement instrumentations were installed on the experimental rig for control application, performance evaluation and monitoring purpose. The task of signal sampling and analog-to-digital conversion for sensors and actuators were performed with National Instrument data acquisition (DAQ) system. This served to interface the communication with the hardwares for real time actuator regulation, data storing and data analysis.

Several preliminary experimental tests were carried out to make a basic analysis of the system dynamics and performances. Step response tests at different compressor speeds have been performed and the system dynamics was quantified based on the time constant, rise time and the static gain. These parameters were able to provide the basic knowledge regarding the nonlinear nature of the AAC system. Additionaly, steady state performance of the AAC system with respect to different operating conditions was investigated. The three operational parameters considered here included the compressor speed, the incoming air temperature upstream of the evaporator and the condenser inlet air velocity. This test aimed at determining the influence of each operational parameter on the system performance based on a sensitivity analysis. The implementation of VSC would be of great interest if the variation of compressor speed gives predominant effect on the AAC performance as compared to the other operational parameters. This is to ensure that the desired cooling capacity can be achieved effectively via modulation of the compressor speed over a wide range of operating conditions. Subsequently, an uncertaintity analysis was performed on the performance indices of the AAC experimental rig. Such analysis is essential, as various uncertainty sources involved in the computation of the performance indices may result in higher overall uncertainty of the performance indices. Finally, two conventional control schemes were applied on the experimental rig, namely the On/Off operation and a PID controller tuned using ZN rules. This experiment was designed to analyse the performance delivered by both conventional controllers, which are often use as the first solution before the development of a new control scheme. In addition, the drawbacks indicated by both control schemes may motivate further research effort in hybridizing the soft computing approach with the conventional control system to deal with the complexity of the control problem.

The dynamic behaviour of the AAC system has been identified using a NARX neural network. The input and output data, namely the randomly modulated compressor speed and the corresponding transient dry bulb temperature in the cabin, were collected from the experimental rig. The experimental data was presented to the neural network model during the training phase, so that a notion of memory was incorporated into the networks and thereby leading to the capability of the network model to capture the system dynamics. The two neural network architectures employed for the system identification were MLP and RBN models. The optimality of the network structure was quantified based on model prediction capability, network complexity and computational effort of the ANN training. The NARX model with optimal network architecture was determined and used for further application in the proposed control schemes. If none of the model candidates have delivered satisfactory prediction results, the whole process of the system identification was repeated by either collecting a larger data sets or optimizing the network structures.

Two proposed control schemes: PID based controllers tuned using DE and A-NNMPC were developed and implemented experimentally. PI and PID controllers were tuned in simulation based on the aforementioned NARX neural network. Experimental tests were carried out to compare the performance of DE tuned PI and PID controllers with those tuned using ZN rules. The tracking performance of the respective controllers was evaluated by conducting the tests under nominal condition as well as in the presence of disturbance. The main objective of this comparative study is to exploit the advantages of using the DE tuning method for the PID based controller in conjunction with the identified neural network. Finally, a comparative study was performed between the DE tuned PI and PID controllers to evaluate the necessity of having the derivative component in the control system.

The application of A-NNMPC was realized by adopting the Newton-Rahpson method to solve the nonlinear optimisation problem. The aforementioned NARX neural network was incorporated as a plant predictive model in the control system. Online training of the NARX neural network was implemented using the Levenberg-Marquardt algorithm and sliding stack window technique. The online ANN training scheme helps to minimized the model mismatching due to the time varying operation condition. A parametric study was conducted to evaluate the effect of various adjustable control parameters on the performance of A-NNMPC. Optimal parameter configuration was determined for A-NNMPC based on the results obtained from the parametric study. A comparative assessment was carried out for the proposed controller and a model predictive controller with offline trained ANN model. The comparative study involved set point tracking and disturbance rejection tests, which aimed at highlighting the adaptability of the proposed control scheme in response to the time varying disturbances introduced to the AAC system.

Finally, the proposed control schemes were compared with the On/Off controller by carrying out experimental tests under nominal condition as well as in the presence of disturbance. The performance of each controller was quantified based on the reference tracking capability and power efficiency. The main objective of this comparative study is to determine the overall performance delivered by each control strategy and to identify the advantages and drawbacks of each control schemes. The proposed research strategy in the form of a flow chart is graphically shown in Figure 1.1.

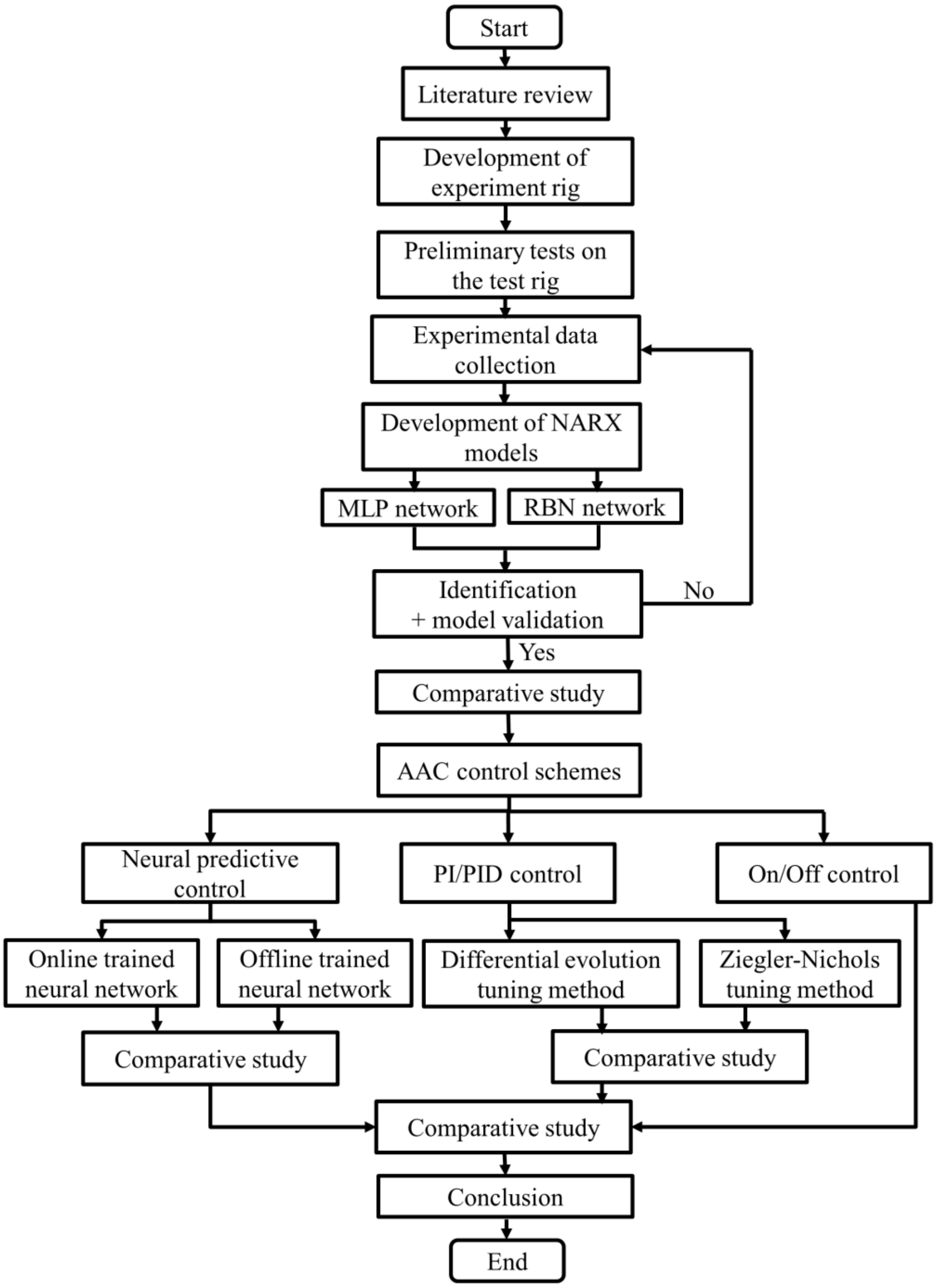

Figure 1.1 Research strategies flowchart.

1.7 Thesis Outline

The thesis is organized into 7 chapters. A brief outline of contents for each chapter is detailed as follows:

Chapter 1 gives an overview of the background study as well as the problem statement of the research. The research objectives, the scopes of the study and its contribution are also presented. Finally, the research methodology and a flow chart representing the research strategies are outlined in this chapter.

In Chapter 2, a review of the existing design of AAC experimental rigs and different approaches of dynamic modelling proposed in previous works are presented. A brief overview of different control strategies for air conditioning and refrigeration system and their respective performance are highlighted. Finally the research gaps on AAC thermal control schemes with VSC operation are identified.

Chapter 3 presents the development of an AAC experimental rig equipped with a VSC. The design of the ducting system, refrigeration circuit, measurement instruments and interfaces between the data signals and computer are further elaborated. Step response tests are performed to have a basic study of the AAC dynamics. Subsequently, the effects of different operating conditions on the AAC rig performance are then evaluated based on experimental results. Finally, two conventional control systems, namely an On/Off controller and a PID control system tuned using ZN tuning rules are implemented on the experimental rig. These tests serve to analyse the performance delivered by both conventional control methods in term of reference tracking performance and power efficiency.

Chapter 4 presents the dynamic modelling of the AAC system using a NARX neural networks. The two network architectures investigated in this research are the MLP and RBN networks. A comparative study is conducted to evaluate the performance of these two classes of NARX models in capturing the dynamics of the AAC system. Following this, the application of PI and PID controllers tuned using

DE algorithm is introduced for the cabin temperature control of an AAC system. The optimisation of the PID based controllers is performed based on the aforementioned NARX model in simultion. The advantages of the proposed controller over the conventional ZN method are highlighted based on the experimental results.

Chapter 5 presents the working principle of A-NNMPC. Experimental tests are carried out to verify the control performance of the proposed control scheme. A parametric study is performed to investigate the effect of each control parameter on the performance of the proposed controller. To show the necessity of adopting an online trained ANN model in the control application, a comparative assessment is performed between the proposed adaptive controller and the predictive controller with an offline trained ANN model.

In Chapter 6, a comparative study is performed between the performance of the two proposed control schemes and the On/Off operation. The comparative results provide several findings which highlight the strengths and weaknesses of the proposed control methods.

The final chapter of this thesis summarises the work presented and draws relevant conclusions. Recommendations of future works for further improvement are discussed.

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