FUZZY MODEL BASED PREDICTIVE CONTROL OF GREENHOUSE TEMPRATURE AND HUMIDITY

A MASTER'S THESIS

BY

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FUZZY MODEL BASED PREDICTIVE CONTROL OF GREENHOUSE TEMPERATURE AND HUMIDITY

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By

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CERTIFICATE

This is to certify that the thesis prepared by **Mr. Dejenie Fikir Addis** entitled "**Fuzzy Model Predictive Control of Greenhouse Temperature and Humidity"** and submitted in fulfillment of the requirements for the Degree of Master of Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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DECLARATION

I hereby declare that the work entitled "**Fuzzy model Based predictive control of greenhouse temperature and humidity"** is our original work with the help of my advisor. I have not copied from any other students' work or from any other sources except where due reference or acknowledgement is made explicitly in the text, nor has any part been written for us by another person.

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Addis Ababa, Ethiopia Dec. 2018

Place Date of submission

This work has been submitted for examination with my approval as a University advisor.

Prof. Venkata L.N.K

Advisor Name Signature

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ABSTRACT

Greenhouse is the most widely used system for agricultural plants due to its quality production, accuracy and disease resistant behavior. This plant factory specializing in a complex environment have temperature and humidity as a basic parameters to be controlled. Many controllers like fuzzy logic, Adaptive, PID, feedforward and neural networks was already proposed and applied to evaluate in real field test. The obtained result indicated the effectiveness of the control system although constraint, optimization and interaction of parameters are not considered. It is not feasible to extend the same approach to control the parameters currently.

Model predictive control was applied as a solution to regulate greenhouse temperature and humidity for the above problem. Its performances strongly depended on the precision of the mathematical model of the greenhouse dynamics, and thus, a fuzzy modelling and identification strategy using Takagi-Sugeno fuzzy modelling was introduced to model and update the parameters. But the model which is designed by fuzzy modelling and identification toolbox is highly non-linear and it is linearized using fuzzy linearization algorithm.

The control results in the MATLAB simulation indicated that the proposed method performed well and showed an average decrease of the settling time and rise time by 96% and 60 % respectively. Furthermore the modelling error also approximately decrease by 25% which is a great performance index for advanced controlling mechanism.

Key-words: Model predictive control, Greenhouses, Takagi-Sugeno fuzzy model, Fuzzy modelling and Identification.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ARX	Autoregressive with Exogenous inputs
CARIMA	Controlled Auto Regressive Integral Moving Average
EHDA	Ethiopian Horticulture Development Agency
FLC	Fuzzy logic controller
FMID	Fuzzy modelling and Identification
IMC	Internal model control
LSIT	Linear system identification toolbox
MBPC	Model based predictive control
MIMO	Multi input Multi output
MMPC	Multiple Model Predictive control
MPC	Model Predictive Control
NARX	Non-linear autoregressive
PI	Proportional Integral
PSO	Particle swarm optimization
RLS	Recursive least square
TS	Takagi-Sugeno
USD	United states dollar
VAF	Variance Accounted for

CHAPTER ONE

INTRODUCTION

1.1. Background

Various types of vegetable crops are grown in Ethiopia under rain-fed and/or irrigation systems [30]. The major economically important vegetables include hot and sweet peppers (Capsiculm spp.), Ethiopian Mustard/Kale (Brassica carinata), onion (Allium cepa), tomato (solanum lycopersicum), chili (C.chinense), carrot (Davcus carota), garlic (A.Sativum), cabbage (B.oleracea var.capitata) and flowers. According to Ethiopian investment agency (2013) Ethiopia exported 220,213tons of vegetables and generated USD 438 million Ethiopia Revenue and customs Authority 2013.

Ethiopian horticulture Development Corporation has been carrying out production and marketing activities of horticultural crops since its establishment in 1980 [31]. Commercial production of horticultural crops, including vegetables, has also been increasing in recent years because of expansion of state farms and private investment in the sector by national and international entrepreneurs. Most vegetables have their own temperature and humidity range for growing condition in different seasons.

- Hot weather vegetables like tomato, hot pepper and snap beans are produced in hot semiarid areas
- Cool weather vegetables such as Ethiopian mustard, cabbage, potato, garlic onion, shallot, carrot and beet root [32].

In recent years, awareness of nutrition and health benefits of vegetables in Ethiopia has been increasing due to public health advocacy on the role of vegetables in human nutrition and health through its provision of antioxidants such as vitamin A,C and E that are important in neutralizing free radicals (oxidants) known to cause cancer, cataracts, heart disease, hypertension, stroke and diabetes and partly because of rising prices of livestock products such as meat, milk and eggs, which traditionally forms a major components of most Ethiopian diets. As such the increasing consumption of vegetables helps to fight hidden hunger, malnutrition. Vegetables are also used as a source of raw materials for the local processing industry. Moreover, the enhancement of horticultural products boosted private investment. This partially affirms government policy of increasing household income and improving nutrition. But in Ethiopia, there is inadequate knowledge on improved production systems and marketing, especially in the humid tropics that was the target area. With increasing population and decline land size, a better understanding of the production system, marketing channels and endowed opportunities for growth with go a long way to contribute the improve return on investment for value chain sectors in the subsector.

Ethiopian horticultural crops experiences the most common world diseases and pests. However, to control diseases and insects pest so far the country was mainly concentrated in the use of cultural control methods as well as use of resistant crop varieties. In the view of existing deficit of food crops due to adverse weather condition and high population pressure the need of developing new commodities and technologies to increase population and productivity in both the high and low potential areas is permanent important.

Recently, Ethiopia started some progress in diversifying the exports in to non-traditional horticultural products like cut flower, ornamental fruits, roses and vegetables. This activity attracts a lot of foreign investors and they were producing different flower products in Oromia region.

Among them few companies use modern controlling mechanism using scada and other distributing control like Maranque plants, Desa plants, Ethiopian cutting, Floresis Ethiopia, Floresis Abyssinia and Red fox. However, other private companies especially Enyi Ethio Roses, Lafto Roses, Olij Roses Ethiopia and friendship flowers PLC use natural resources to regulate the inside humidity and temperature. But the natural light energy, humidity and other factors have not enough to stabilize the system for better quality product. So the controlling mechanism should be updated.

1.2. Problem Statement

It is known that flower production is one of the dominant source of economy in Ethiopia. It is ranked as second level for exportation. But the quality is not competitive with other countries' flower product due to seasonally variable weather condition. Recently, the weather condition of Ethiopia has been changing dynamically which is not comfortable for domestic plants. Researchers' shows that in central and eastern part of Ethiopia there is higher humidity. It has -4 degree centigrade mean temperature from October to mid of January in the morning time.

It is known, the dynamic model of the greenhouse is highly non-linear because of the coupling between the temperature and humidity and other related parameters. Previously many different modelling and control algorithms has been used to improve the performance of the greenhouse. For example, as the dynamic model of the system is non-linear, a natural approach is the exact feedback linearization control method, by which the original non-linear model can be transformed into a linear model through proper coordinate transformation. However, in general, the dynamics of the greenhouse may not be fully known, since some parameters a appearing in the equation will be changed when the wind speed, air flow, solar radiation and rain volume alters. The modelling that uses physical and linear system identification tool has low accuracy (performance) when the system is coupled complex non-linear system with multiple operating points.

To solve this problem, most widely employed systems for controlling temperature and humidity is the conventional proportional integral (PI) controller. But, the performance of PI controller diminishes under the uncertainties of greenhouse parameter, the uncertainties that include unknown disturbance and its temperature variations. It is also sensitive to disturbances, parameter variations and system nonlinearity.

The limitation of PI controller can be overcome by introducing the concept of artificial intelligence like ANN, FLC and so on. It does not need exact mathematical model of the system. However, a simple fuzzy logic controller (FLC) has a narrow temperature operation and needs much more manual adjustment by trial and error when high performance is needed. The above controllers have no constraint handling mechanism and optimization. Which results utilization of more power in addition to decoupling error (offset error).

1.3. Objective

1.3.1. General objective

Control temperature and humidity of the greenhouse using Fuzzy model based predictive control

1.3.2. Specific objective

- Modelling and studying of greenhouse system characteristics
- Linearizing and Approximate the non-linear plant model using Fuzzy modelling and identification toolbox
- Simulating the greenhouse system by model predictive controller using MATLAB/SIMULINK
- Comparison of the proposed method with previous works

1.4. Methodology

For the accomplishment of this work different tasks has been performed. The first task is describing the statement of problem and define the objective of the research. In this section many international journals, conference papers, articles and text books related to greenhouse control has been reviewed. Next, a detail mathematical model of greenhouse parameters are discussed, which is done by fuzzy modelling and identification toolbox. This model is linearized using degree of freedom (DOF) and consequent parameters (th). As generalized in block diagram shown in fig 1.1. below the controller parameters are tuned using MPC designer toolbox in MATLAB.

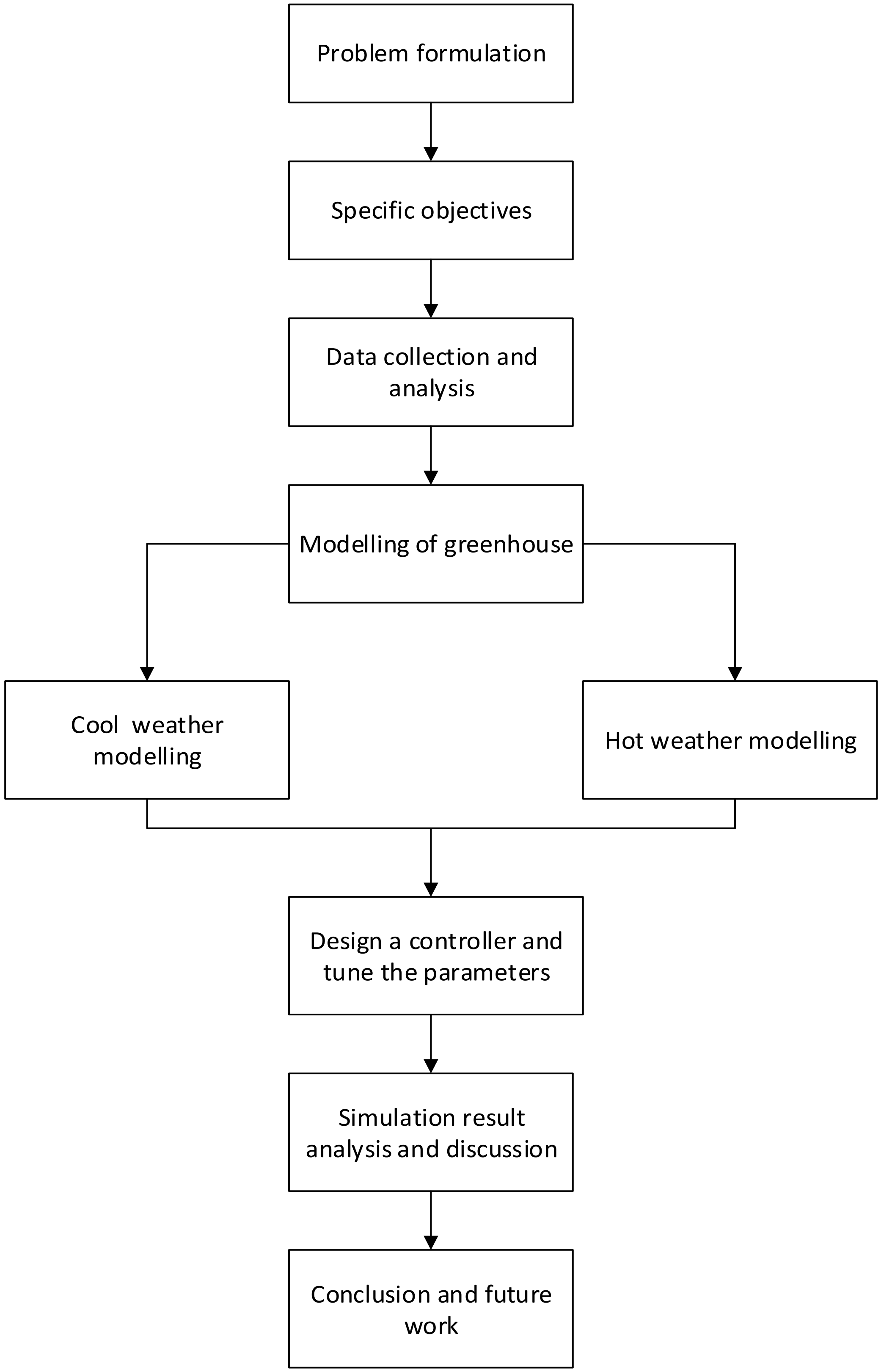

Figure 1. 1 Methodology

1.5. Significance of the study

The contribution of this work is to model and control the greenhouse basic parameters using Fuzzy model based predictive controller. The Takagi-Sugeno fuzzy model is formulated and given to MPC after linearization. Because of variable weather condition, greenhouse dynamic model is highly non-linear, interactive (coupled) and complex which is difficult to control using ordinary (classical) controllers. To avoid this challenge we use fuzzy modelling technique to approximate the non-linear plant to linear one. This modelling approach has a number of advantages in comparison with global non-linear models, like neural network.

- The model structure is easy to understand and interpret both qualitatively and quantitatively.
- Various types of knowledge can be integrated in the model, including empirical knowledge, measured data and available mathematical model.
- The approach has computational advantages.

Model predictive controller have a lot of contribution for highly coupled MIMO systems. It can answer the question of controlling coupled system with input output constraints which is impossible by other controllers without decoupler. Error, energy utilization and life time of the valve are improved using internal optimization. Since the system is totally automated based on various operating regions labor force, plant disease and crop instability is reduced.

1.6. Thesis Organization

This thesis has organized in to six different chapters.

Chapter one is the introduction of this work, and presents the background, statement of the problem, objective of the study, the contribution the study, methodology and Significance of the study including the thesis organization.

Chapter two describes a general introduction of greenhouse and review of previous work. This chapter contains information on component, types and benefit of greenhouse in east Africa. The features of greenhouse with its alternative systems are considered, and the reasons for selecting preferred system for this work are summarized.

Chapter three focused on the development and analysis of greenhouse modelling. It covers fuzzy clustering, Fuzzy modelling algorithm, Model validation and global linearization of fuzzy model. Finally the model is transformed to discrete form.

Chapter four presents about MPC, with its algorithm GPC. The controlling mechanism for greenhouse parameters (temperature and humidity) in different seasons are discussed.

The simulation results obtained from MATLAB/SIMULINK during modelling and controlling with detail discussion of the result are presented in chapter five.

Chapter six states the conclusion drawn from this work and suggests possible directions for future research.

CHAPTER TWO

GREENHOUSE OVERVIEW AND LITERATURE REVIEW

2.1. Overview of Greenhouse System

Cultivation of crops is mainly climate dependent in normal conditions. All fruits and vegetables have their own seasons in which they can be grown [22].

A greenhouse is a structure with a glass or plastic roof and side walls that is used for the production of ornamentals and food crops and may be used seasonally or year round. It is a structure covered with transparent material. With the greenhouse technology, farmers can grow almost any fruits, ornamentals and vegetables in any season. This technology has made possible to have all vegetables throughout the year [22].

Greenhouse technology provides a controlled and favorable environment for the crops to grow in all seasons. The technology saves crops from heat in winter, from cold in summer and from rain in monsoon. Unlike European countries, in tropical area the technology is primarily used in cooling off the environment, as normal temperature is high [22].

Greenhouse technology is more suited to vegetables crops (such as tomato, cauliflower, capsicum, cabbage, chillies, spinach etc.), flowers (like rose, gerbera, carnation etc.) and nursery for all vegetable crops, because of their small life-span. This technology is mainly suitable for commercial farming, as it requires investment in setting up the entire framework. The primary environmental parameter traditionally controlled is temperature, usually providing heat to overcome extreme cold conditions. However, environmental control can also include cooling to mitigate excessive temperatures, light control either shading or adding supplemental light, carbon dioxide levels, relative humidity, water, plant nutrients and pest control [27].

2.2. Classification of Greenhouse

Classification of greenhouse possibly by structure, covering material, heating rate, building cost and height [28], [27]:

2.2.1. Classification of greenhouse by structure

a) Quonset and curved roof type

b) Gable roof type

2.2.2. Classification based on covering material

a) Glass glazing

b) Fiberglass reinforced plastic glazing

i. Plain sheet

ii. Corrugated sheet

c) Plastic film

2.3. Description of the system

The greenhouse is a multi-input and multi-output (MIMO) system which is equipped with several sensors and actuators. There are [16]:

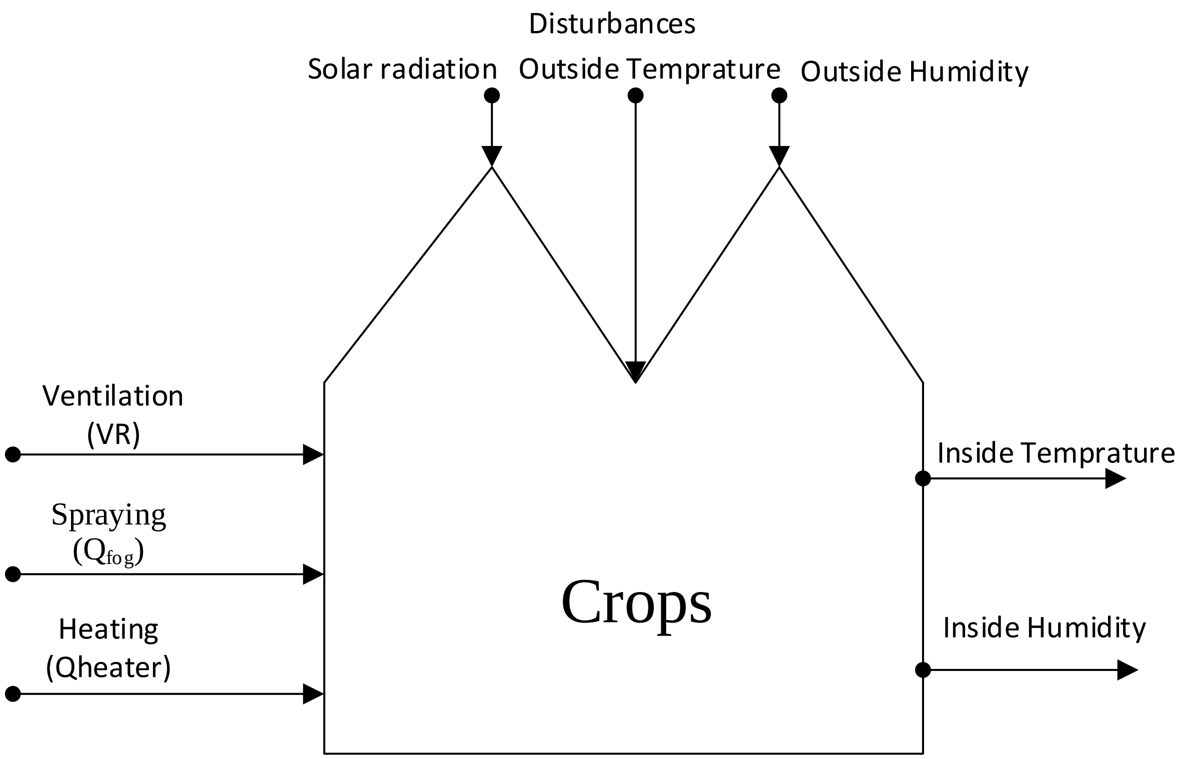

Figure 2.1. Input output component of greenhouse

Three actuators:

1. Heating (thermal power 58kw): Qheater

2. Fog system: Q_{fog}

3. Ventilation VR

Three meteorological disturbance sensors

1. External Temperature: Tout(0c)

2. External hygrometer: Hout(g/m^3)

3. Solar radiation: LR(W/m2)

Two internal climate sensors:

1. Internal temperature: Tin(^{o}c)
2. Internal hygrometer: Hin(g/m^3)

The system is non-stationery and strongly disturbed. For instance, quite high solar radiation and external temperature during a year 2017. These meteorological conditions have a significant effect on the inside greenhouse climate which are clear on figures below:

2.4. Climate management problem

In our greenhouse, the temperature and the hygrometer managements are treated together, because these two quantities are strongly correlated:

- The heating has a dehumidifier effect
- The opening system has a cooling and dehumidifier effect
- The fog system has a cooling effect
- The ventilation has also cooling effect

Controlling the temperature and the hygrometer is therefore of utmost importance. In order to choose the suitable output reference, two main strategies exist.

2.4.1. Classic strategy

Growers refer to their knowledge to fix the hygrometer and temperature references.
Hygrometer reference: there is no real recommendation by species. It appears nevertheless that:

- For the multiplication phase, the hygrometer must be greater than 80%
- For the growth phase, the reference is comprised between 60% and 80%
- For the tomato, the reference is rather comprised between 50% and 70%

Let us mention some other advices: avoid

- Condensations
- A humidity level close to saturation (100%)
- A humidity level below 40% for seedling
- Absolutely a hygrometer below 20%

Temperature reference: the below table displays references among suppliers, which are based on the species. The difficulties for tuning an efficient controllers may be attributed to the following causes:

- Various references
  - In a day
  - According to the species
- System parameter variations according to the plant growth

The system uses data such as seasons, crop stage, and the daily period (divided in to three sub periods). The characteristics of the greenhouse system (location, heating system) and dynamic information (past climate, crop system …) show the reference changes according to the time of day or the plant growth [16].

Table 2.1. Temperature reference of different plants

Species	Night reference	Day reference	Remarks
Auberqine	21 ^{o}c	22 ^{o}c	During 4 weeks after the plant
	19 ^{o}c	21 ^{o}c	To the end
Cucumber	21 ^{o}c	23 ^{o}c	During f4 weeks ater the plant
	20 ^{o}c	22 ^{o}c	During the next 6 weeks
	19 ^{o}c	21 ^{o}c	To the end
Lettuce	10 ^{o}c	10 ^{o}c	During 2 weeks after the plant
	6 ^{o}c	12 ^{o}c	To the end
Pepper	20 ^{o}c	23 ^{o}c	During 3 weeks after
	18 ^{o}c	22 ^{o}c	To the end
Tomato	20 ^{o}c	20 ^{o}c	During one week after the plant
	18.5 ^{o}c	19.5 ^{o}c	During the next five weeks
	17.5 ^{o}c	18.5 ^{o}c	To the end
Azalea	18/21 ^{o}c	>18 ^{o}c	
Chrysanthemum	17 ^{o}c	18 ^{o}c	
Gerbera	13/15 ^{o}c		
Antirrhinum	10/11 ^{o}c		
Carnation	12/13 ^{o}c	18 ^{o}c	
Rosebush	17 ^{o}c	21 ^{o}c	
Cutting flower	18 ^{o}c	28 ^{o}c	

2.5. Greenhouse performance determining components

Sky temperature: due to the huge roof surface and low thermal performance of the greenhouse shells, long wave heat exchanges is one of the major gain and loss mechanism in the greenhouse.

Photosynthesis and respiration: photosynthesis is the process of capturing light energy and converting it into sugar energy using co_2 and water. In general, the crop does not require the whole spectrum of solar radiation for growth. The whole solar spectrum can be divided into three parts for crop growth: ultra violet (UV), photo synthetically active spectrum (PAR) and Near Infrared radiation (NIR).

Transpiration: transpiration essentially describes the loss of water that occurs as a result of evaporation of water vapor, largely from leaves and stomata. Transpiration is crucial to the plant's development for two main reasons. It allows the plant to transfer nutrients from roots to the parts of the plant above ground, and it allows plant to cool down.

Condensation: due to the transpiration from the crops, relative humidity of the greenhouse is always high. When the surface temperature of the greenhouse shell is lower than the dew point temperature of the air, water droplets are formed by the moisture on the greenhouse shell. Atypical greenhouse cover is fully or partly wet about 50% of the year and the amount of condensation water is $100l/m^2$ of the greenhouse shell. Since this condensation decreases inside humidity, it is important in terms of moisture balance. In addition, the condensation release energy that comes from evaporative cooling to the shell, thereby warming up the cover and somewhat decreasing the heating demand of the greenhouse.

Ventilation control: by capturing solar energy during the day, the greenhouse heats up due to the so called greenhouse effect.

This effect causes high air temperature in the greenhouse, which has a negative effect on the crop growth and quality. If the temperature inside the greenhouse is higher than a certain set-point, the crop suffers leaf distortion and delay of development, and ultimately suffers damage or dies.in addition, high temperature is a causative factor in the decrease of photosynthesis and increase of respiration, both of which are correlated with a reduction of crop production.

Additionally, the crop loses water vapor through the stomata of the leaves during metabolic processes, which increases the inside humidity of the greenhouse. The optimum relative humidity range is between 60% and 90% for crops. However, if the relative humidity is higher than 95%, there is a serious risk of mold growth, which causes disease, decreases photosynthesis rate and lower the absorbed co_2 by closing stomata opening, and finally results in low growth and poor quality of the crop.

For reducing greenhouse air temperature and relative humidity, natural or mechanical ventilation using outside air is employed. Since most of the time outside relative humidity is lower than it is inside greenhouse, ventilation is the best means to control humidity in the greenhouse. Mechanical ventilation works independently regardless of the wind speed outside the greenhouse. When it comes to dehumidification, mechanical ventilation is more efficient way than natural ventilation in that the air exchange by mechanical ventilation occurs close to the crop.

Humidification: when the greenhouse relative humidity becomes too low, crop transpiration increases. When this is the case, the nutrients or minerals do not transfer to the leaves, only the water does, which leads to nutrient deficiencies. In addition, the crop loses moisture and wilts very quickly. Therefore, low relative humidity ultimately results in a decrease of crop quality and quantity.

In order to raise the humidity level, a high pressure fogging system is employed in the greenhouse. This system sprayed water in to the inside air to increase the humidity and reduces the temperature. The control system can regulate both the activation times and the water flow. It has a direct effect on the energy balance through its use of evaporative cooling and on the moisture balance through vapor increase.

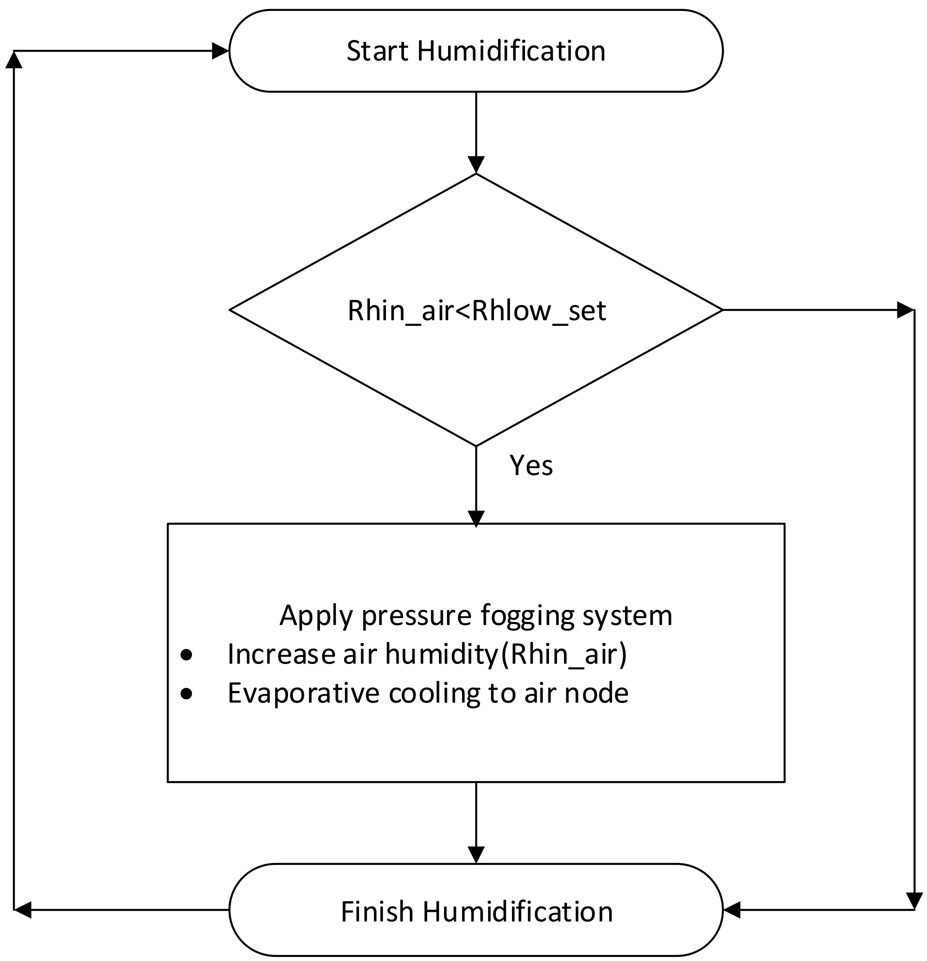

Table 2.2. Humidification process control flowchart

Artificial lighting control: due to the solar radiation that it contains, light has a considerable effect on the crop growth and development. However, the amount of solar radiation available varies a cording to the season.

In order to produce good yields of good quality, the crop must absorb sufficient PAR radiation. Artificial lighting is used in the greenhouse to supply PAR radiation to the crop when the amount of PAR from the natural light is not sufficient. The artificial lighting plays an important role in the energy balance. Only small percentage of light turns to PAR radiation, which is used to enhance crop production. The remaining majority turns into long wave radiation, which is used to increase the greenhouse temperature. Since the main shortage of PAR radiation is summer, lighting helps greenhouse heating as a heat source.

Screen control: three types of screen-thermal, shading and block screen- are used in greenhouses, depending on their purpose. The purposes of screen control are:

- To prevent crop damage from high solar radiation
- To adjust day length for flowering
- To reduce cooling demand in winter
- To block heat loss to outside in summer

Flowering plants can be categorized in to short-day, long-day and day neutral plants, depending on the duration of darkens for flowering.

Short-day (long night) plants form flowers when the day length is less than about 12 hrs. **Long-day (short night) plants** form flowers when day length is more than 12 hrs. While **day-neutral plants** form flowers regardless of day length.

2.6. Heated greenhouse environments

Greenhouse heating is an important issue to consider for your hobby or commercial greenhouse.

The night temperature in a year round greenhouse is the most important factor to determine which heating system is required. The greenhouse gardener also determines whether to winter over plants or to provide a constant growing environment. Cool or frost free greenhouses maintain a night temperature of 40-45ºF (5-7ºC). This is suitable for frost sensitive plants and rooted cuttings. Warm greenhouse requires a night temperature of 55ºF (13ºC). Grow lights are necessary for adequate light conditions in this environment. Hothouse night temperatures are set at 65ºF (18ºC). This will provide a natural habitat for tropical and exotic plants [28].

2.7. Greenhouse Curtain Systems

Are called shades, screens and even blankets. No matter what they are called, they consist of movable panels of fabric or plastic film used to cover and uncover the space enclosed in a greenhouse. Curtains may cover an area as small as a single bench or more than an acre. Small systems are often moved by hand, while large systems are commonly motor driven.

Internal shade systems mount to the greenhouse structure below the rigid or film covering of the house. They are used for heat retention, shade (and the cooling effect of shade) and day length control or blackout when the covering material transmits less than 1% of the incident light. Advancements in drive system and shade cloth technology have made moveable exterior curtain systems practical in the 1990s. Exterior systems are used in two ways. In some cases, the curtain replaces the greenhouse covering, while in others the system is installed above a standard greenhouse structure. Typical applications of the first type of system are to provide a hardening-off area or to add seasonal square footage in jurisdictions where zoning restrictions make it difficult to permit and build a traditional structure. The second type of outdoor system provides shade for light intensity control and blocks the light before it enters the greenhouse, giving an improved cooling effect [28].

2.8. Review of Previous Works

Greenhouses are highly nonlinear and strongly coupled Multi-Input Multi-Output (MIMO) systems that are largely influenced by the outside weather (wind velocity, outside temperature and humidity) and by many other practical constraints (actuators and moistening cycle). Many years ago various advanced control techniques are proposed. To obtain the control objective, many greenhouses use a conventional PID control but this control strategy may not be suitable to guarantee the desired performance due to the interaction between the different variables in the greenhouse. Motivated by these disadvantages, inherent in linear control methods, several techniques, which use advanced control, have been proposed to deal with climate control problems in greenhouses. Recently Model predictive control was applied to evaluate in area field test [2].

The result showed indicated the effectiveness of the control system by improving the disturbance rejection and temperature stabilization as compared to conventional controllers like PI, PID and others. But the optimal solution of this controller was based on a brute force attack and it has larger computation time that exposes the system to time delay. There is also proposed system by combining MPC with genetic algorithm to save water consumption [3].

For better performance and also for nonlinear compensation the adaptive MPC systems have been recently developed for controlling the greenhouse temperature [1]. The adaptation is usually achieved by using the Recursive Least Squares parameter estimation technique. However, adaptation of a single process model over wider operational range may result in a transient error [1]. The conventional sliding mode control (CSMC) scheme is known to be an effective robust non-linear control approach for systems with uncertainties and / or disturbance. But it has a main drawback so-called chattering caused by the high frequency control switching.

This undesirable phenomenon could severely degrade the performance of the control system and may even lead to instability [4]. Many researchers start to change conventional and old system of control mechanism by using feed forward control [5] which is very difficult to measure all disturbances. Adaptive control [6], not advisable for complex non-linear system because of decoupling error and uncertainty. Optimal control [7], robust control [8] and constrained predictive control [9] were also proposed. Traditional greenhouse control methods only consider a single objective [2], which stabilizes some parameters of the facility, such as temperature, humidity, and light intensity, at expected values. Recently, most researchers are not focused on humidity control but it has a great impact on the plants growth and product [1] [2]. To clarify the effect, when the greenhouse relative humidity becomes too low, crop transpiration increases.

When this is the case, the nutrients or minerals do not transfer to the leaves, only the water does, which leads to nutrient deficiencies. In addition, the crop loses moisture and wilts every quickly. Therefore, low relative humidity ultimately results in a decrease of crop quality and quantity [22].

Non-linear predictive control has been designed by many researchers [23], [24]. They have developed non-linear MPC algorithm that used various forms of non-linear models such as non-linear ordinary differential/algebraic equations, partial differential equation, integrate different equations and delay equation models. These models can be accurate over a wide range of operating regimes [24], [25]. However, it is difficult to obtain in many industrial cases. It has two major problems that limit the application of non-linear model predictive controller to non-linear systems.

- It is difficult to get a proper non-linear model in order to predict the output of the system over prediction horizon with sufficient accuracy.
- With a given non-linear model, solving online non-linear optimization problem is a big challenge in each sampling period and it limits on real time applications [25].

Temperature and humidity control using TS fuzzy model. One of the main contribution of this work is the fuzzy of TS fuzzy modelling technique to model the non-linear dynamic greenhouse parameters [20]. The researcher drive a TS fuzzy model from a given non-linear dynamic of an empty greenhouse. The non-linear terms in the dynamic equation are linearized using a method that results a higher offset error. It uses ideal parameters and reject most basic disturbances which is hazard for real application. The stability of the obtained TS fuzzy model is determined by checking a common lyapunov functions for all the subsystems described by the TS fuzzy mode [20].

Non-linear feedback/feed forward technique to decouple and linearize highly non-linear interactive parameters are used for greenhouse system [19]. Decoupling as well as feedback linearization make the system simple and easy to control using classical controllers (PID, PI and PDF). However, computation errors are introduced due to elimination of interaction factors. This control algorithm can tolerate up to 10% uncertainty, but large parameter variations (plant growth, evapotranspiration) cannot handle by this controllers [19].

From the above, most researches didn’t address the basic problems like overshoot, instability, computation time and unexpected disturbance. This research answers the listed problems using new innovative method that preserves the previous advantage and incorporate additional features by combing fuzzy modelling and model predictive control.

CHAPTER THREE

SYSTEM MODELLING

3.1. Description of greenhouse model

The two models for greenhouse system include: cooling and heating model. Heating model is essential when the inside temperature of the greenhouse is very low during summer climate and at night time. Whereas, cooling model is required when the outside temperature is very high which may affect the plants during the winter at day time. Ventilation model is one of the most important components of greenhouse modelling. The main purpose of ventilation is to regulate the temperature at the optimum level, to ensure moment of air and supply of fresh air for photosynthesis and plant respiration. But in this work, ventilation model is combined with heating and cooling model in common [29].

In winter mode operation, Qheater is set to zero. The climate model provided have two variables to be regulated, namely the indoor temperature (Tin) and the humidity (Hin), through the process of ventilation VR (t) and fogging QR(t). In winter, Qfog becomes zero (off), these variables (Tin and Hin) are regulated using ventilation and heating Qheat (t). Therefore ventilation is common for both weathers [29].

This paper performs experimental data in two seasons, which are one day in winter and summer, respectively. The detail input output data gathered from the field area used for modelling the system. From the Table 3.1. Two controlled variables are considered.

Table 3.1. Input output data in different season

Winter			Summer		
Inputs	Outputs	Disturbance	Inputs	Outputs	Disturbance
Ventilation rate	Inside temperature	Outside temperature	Ventilation rate	Inside temperature	Outside temperature
Fogging rate	Inside humidity	Outside humidity	Heater rate	Inside humidity	Outside humidity
		Solar radiation			Solar radiation

Inside temperature: the temperature control is the key for crop growth and maturation. The consequence of excessive cooling or heating vary from the reduction of fruit sizes and quality to harvest losses. An optimal temperature control allows one to obtain off-season crops and even several harvests per year.

Inside humidity: the humidity control, together with the temperature control, is the base of greenhouse farming. An appropriate and balanced level of humidity is required to avoid plant diseases and insect pests.

There are many methods to model the greenhouse. Among them the well-known and usual ones are:

A. Physical modelling
B. Input output data based modelling

Physical modelling: this model describes flow and mass transfer generated by the difference in energy and mass content between the inside and outside air, by control, or by exogenous energy and mass inputs. Most analytic models on analysis and control of the greenhouse environment have been based on the following state space form. $\dot{x} = f(t, u, v)$, where x is state variables such as indoor temperature and humidity: u are control inputs such as energy inputs by the heating system, fogging system, ventilation system and etc: v are external disturbance such as solar radiation, outdoor temperature and humidity; t denotes time and f (,) is non-linear function. A simplified greenhouse climate model adequate for control purpose describes the dynamic behavior of the state variable with the following two differential equations [29]. The following dynamic model indicates temperature and humidity are strongly coupled system. Ventilation rate affects both output parameters.

$$\frac{d}{dt}T_{in}(t) = \frac{1}{\rho C_p V_T}\left[Q_{heater}(t) + S_i(t) - \lambda Q_{fog}(t)\right] - \left(\frac{V_R(t)}{V_T} + \frac{U_A}{\rho C_P V_T}\right).\left[T_{in}(t) - T_{out}(t)\right] \quad (3.1)$$

$$\frac{d}{dt}H_{in}(t) = \frac{1}{V_H}Q_{fog}(t) + \frac{1}{V_H}[E(S_i(t), H_{in}(t))] - \frac{V_R(t)}{V_H}[H_{in}(t) - H_{out}(t)] \quad (3.2)$$

$$E(S_i(t), H_{in}(t)) = \alpha\frac{S_i(t)}{\lambda} - \beta_T H_{in}(t) \quad (3.3)$$

Where [29]:

T_{in}/T_{out}: Indoor / outdoor temperature (^{o}c)

H_{in}/H_{out}: Interior / exterior humidity

Q_{heater}: Heat provided by the greenhouse heater (W/m^2)

Q_{fog}: Water capacity of fog system (g/s)

V_R: Ventilation rate (W/m^2)

UA: the heat transfer coefficient (W K1)

ρ: The air density (1.2 kg m3)

Cp: the specific heat of air (1006 J kg1 K1),

Si: the intercepted solar radiant energy (W)

E(Si,win): the evapotranspiration rate of the plants (g H2O s1)

VT: Air volumes temperatures

VH: Air volumes Humidity

α: overall coefficient to account for shading and leaf area index

β_{T}: the overall coefficient to account for thermodynamic constants

3.2. Input output data based modelling:

This paper deals with the input-output data based modelling using Fuzzy method. Fuzzy modelling techniques have received considerable attention, not only from the scientific community but also from industry. Many systems are not amenable to conventional modelling approaches due to the lack of precise, formal knowledge about the system, due to strongly non-linear behavior, due to the high degree of uncertainty, or due to time varying characteristics. Fuzzy modelling along with other related techniques such as Adaptive and neural network have been recognized as powerful tools which facilitate the effective development of models [26].

Fuzzy modelling uses flexible mathematical structures that can approximate a large class complex non-linear systems to a desired degree of accuracy. In order to automatically generate fuzzy models from measurements, a comprehensive methodology is implemented.

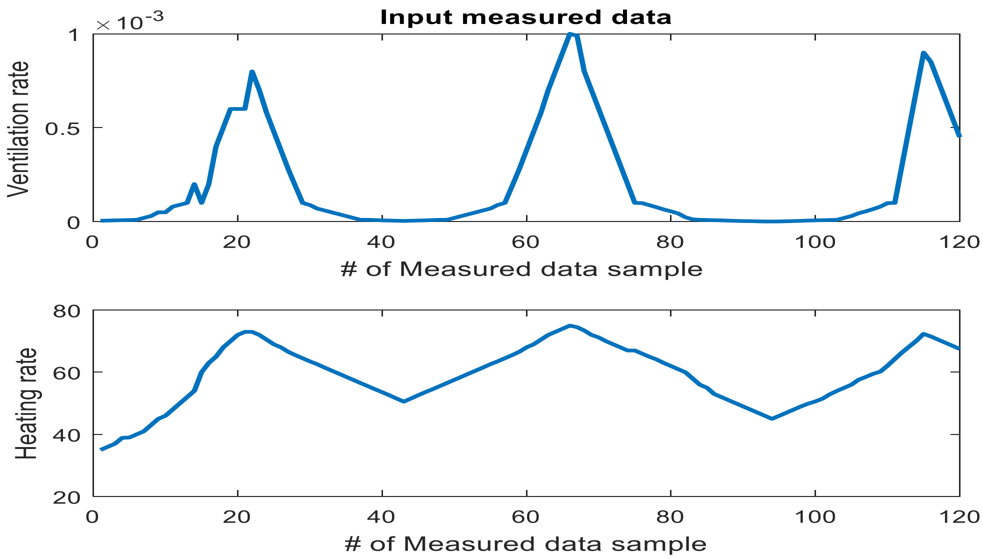

Figure 3.1. Manipulated variable input data

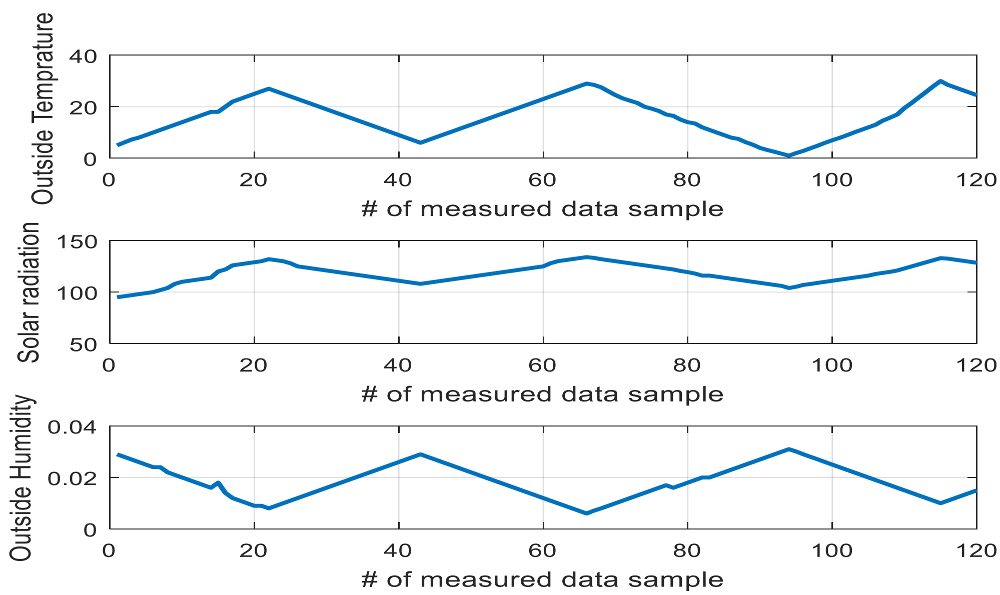

Figure 3.2. Measured disturbance data samples

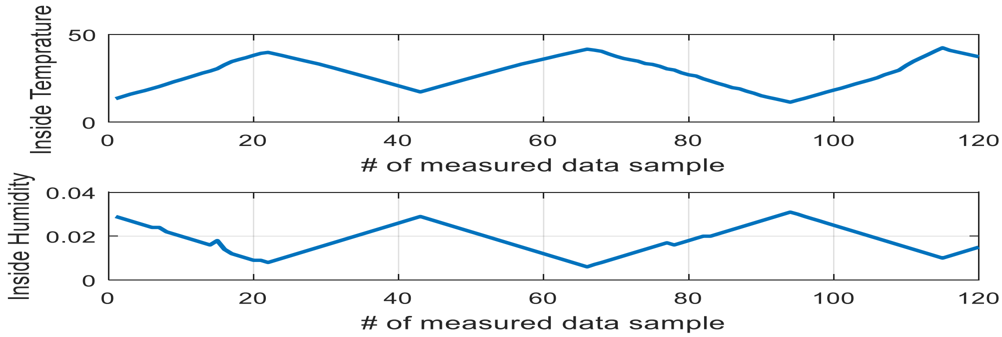

Figure 3.3 Output measured data

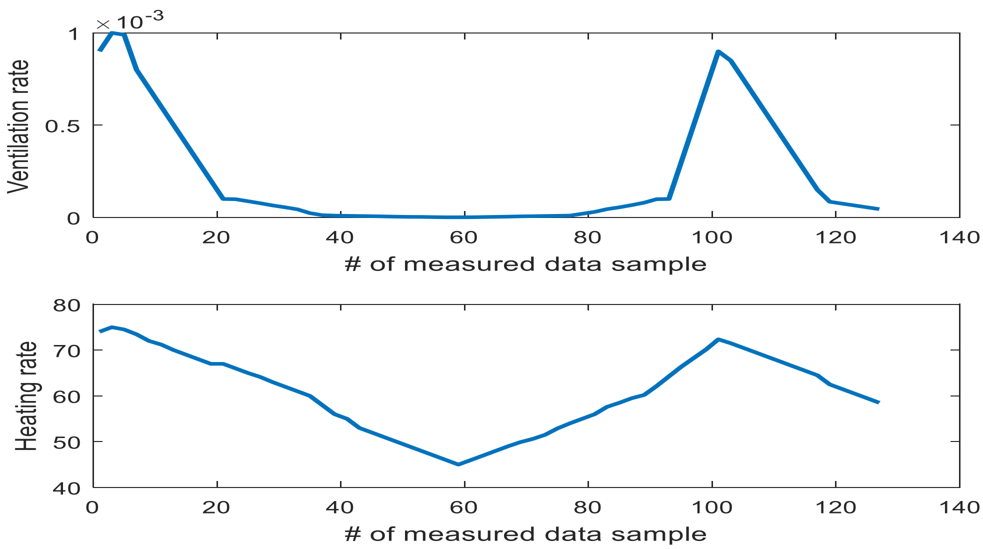

Figure 3.4 Input variable measured validation data

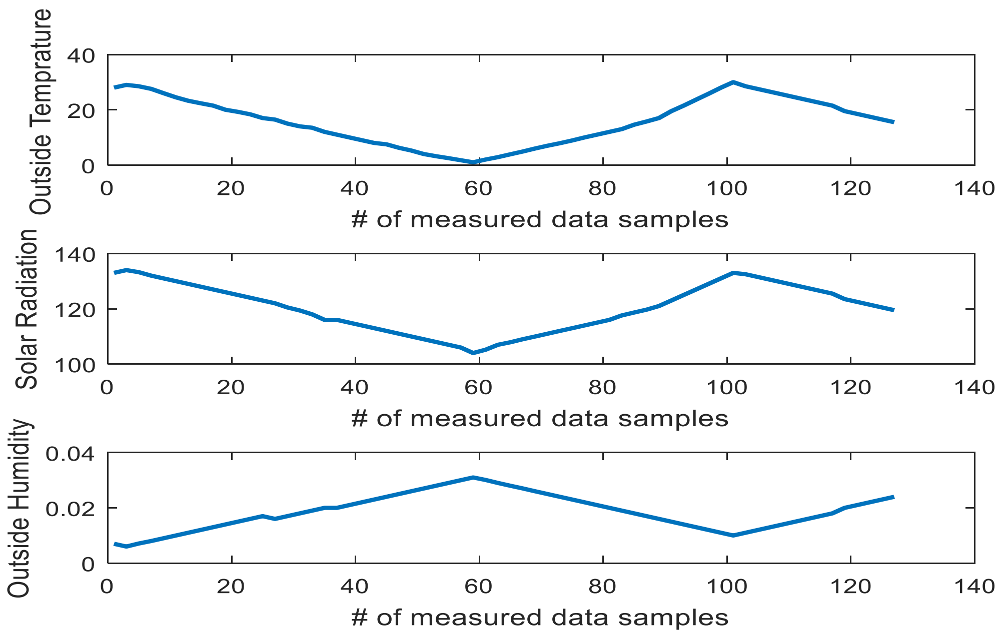

Figure 3.5 Measured Disturbance for validation

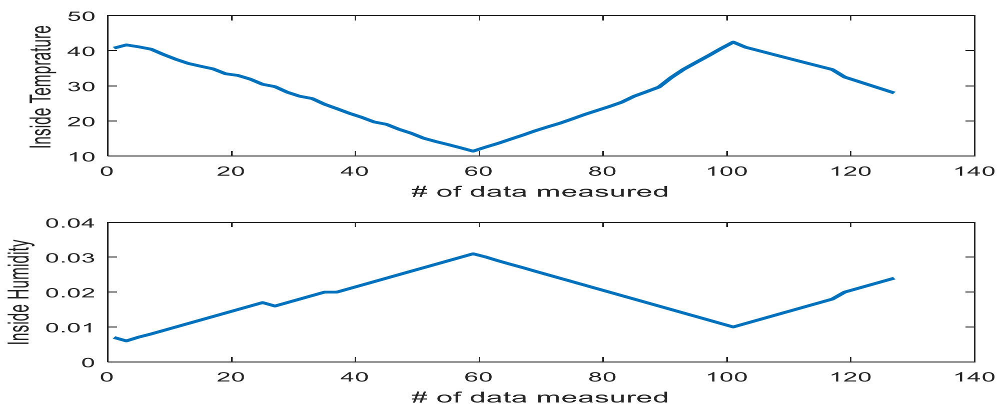

Figure 3.6 Output data measured for validation

3.2.1.Product space clustering for Identification

The decomposition of a nonlinear identification problem into a set of locally linear models by means of product-space fuzzy clustering. The individual steps of the identification procedure, which is iterative in its nature. In a typical modeling session, some of the steps may be repeated for different choices of the various parameters [17]. The steps are shown in Figure 3.1.below:

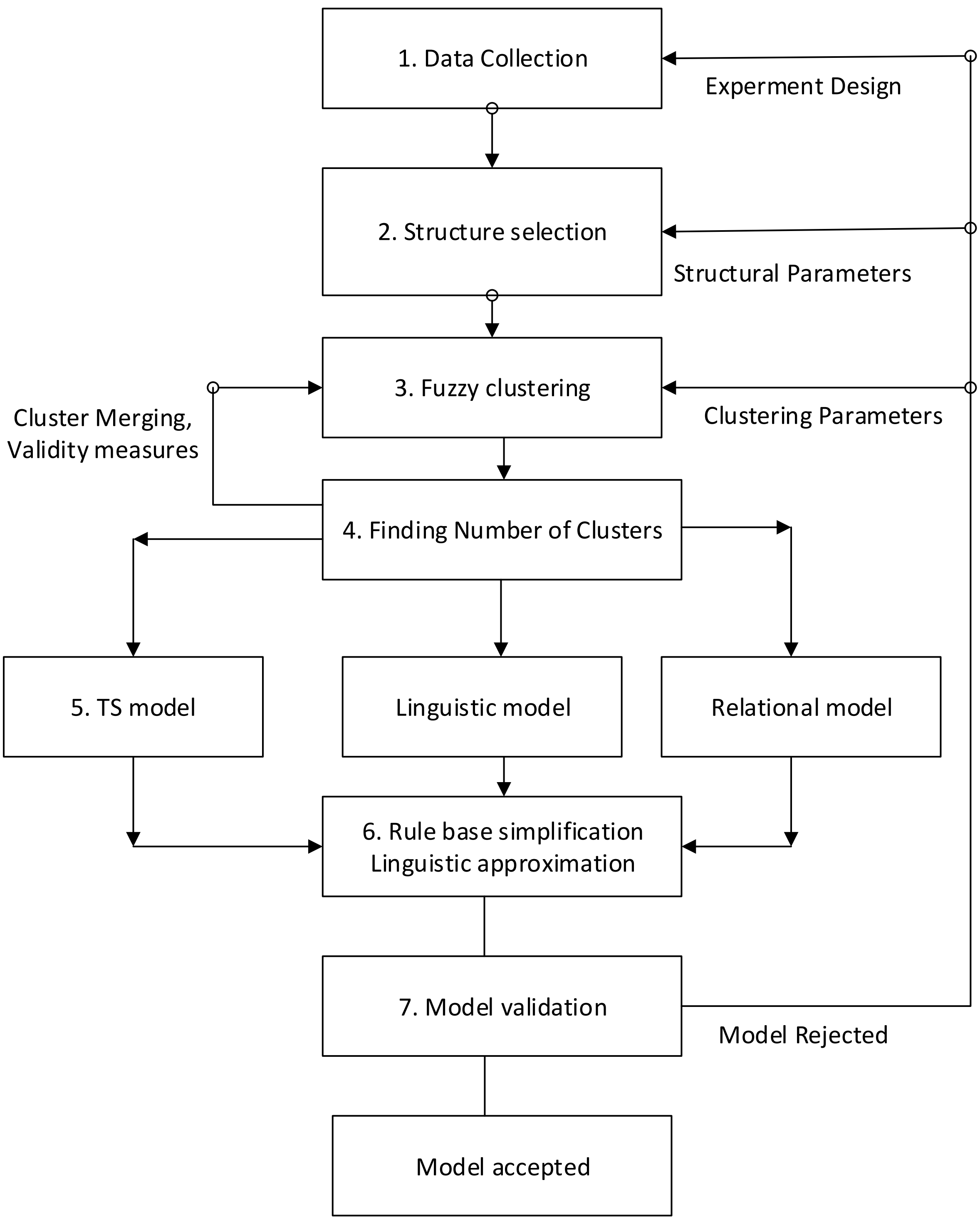

Figure 3.7. Fuzzy modelling steps

Step 1. Design of Identification experiments and data collection.

This initial step determines the information content of the identification data set. Unlike linear techniques, pseudo-random binary excitation signals are not suitable for non-linear identification in general, and for fuzzy clustering in particular. Also the data required for modelling are collected through field experiments [17].

Step 2. Structure Selection:

This step aims to determine the relevant input and output variables with respect to the aim of the modeling exercise. When identifying dynamic systems, the structure and the order of the model dynamics must be chosen. Structure selection allows us to translate the identification of a dynamic system into a regression problem that can be solved in a static or quasi-static manner. In most cases, a reasonable choice can be made by the user, based on the prior knowledge about the process [17].

Step 3. Clustering of the data:

Structure selection leads to a nonlinear static regression problem, which is then approximated by a collection of local linear sub models. The location and the parameters of the sub models are found by partitioning the available data into hyper planar or hypereUipsoidal clusters. Each of the clusters defines a fuzzy region in which the system can be approximated locally by a linear sub model [18].

Step 4. Selection of the number of cluster:

By applying cluster validity measures, compatible cluster merging, or a combination of the two techniques, an appropriate number of clusters can be found. This step typically involves several repetitions of Step 3 for a different number of clusters and a different initial partition matrix [17].

Step 5. Generation of an initial fuzzy model:

Fuzzy clustering divides the available data into groups in which local linear relations exists between the inputs and the output. So as to obtain a model suitable for prediction or controller design, a rule-based fuzzy model of a selected structure is derived from the available fuzzy partition matrix and from the cluster prototypes. The rules, the membership functions and other parameters that constitute the fuzzy model are extracted in an automated way [17], [18].

Step 6: Simplification and Reduction of the initial model:

Initial fuzzy models obtained from data may be redundant in the sense that they contain more membership functions than are necessary to describe the system. Fuzzy similarity measures can be applied to simplify or reduce the initial fuzzy rule base and to obtain linguistic interpretation of the membership functions [17].

Step 7: Model Validation:

Through model validation, the final model is either accepted as appropriate for the given purpose, or it is rejected. In addition to the usual numerical validation by means of simulation, interpretation of fuzzy models plays an important role in the validation step [26].

3.2.1.1. Structure selection

In fuzzy modelling, the problem of structure selection can be divided in to three sub problems:

I. Choice of input output variables

II. Representation of the systems dynamics

III. Choice of the fuzzy model’s granularity

Choice of input output variables: The selection of the input and output variables is based on the aim of the modeling exercise, on the prior knowledge related to the (expected) process dynamics, and on additional variables that may cause the nonlinearity of the system. Statistical techniques, such as correlation analysis, can be used in combination with prior knowledge. This step can also be partially automated. Several candidate models with different input variables can be compared in terms of some performance measure, and the best one is then selected.

Representation of the systems dynamics: A common approach is to transform the identification of a dynamic system into a static regression problem. The choice of this particular transformation is usually based on a combination of a priori knowledge with intuition, insights, and understanding of the process behavior. Mechanistic (physical, first-principle) modeling of the well-understood relationships and physical laws can guide the selection of the relevant variables, and of the model's order. This transformation can be regarded as a mapping from the domain of time signals into a space of variables that fully determine the state of the system. These variables are called the regressors. The choice of the regressors is a crucial step, as an inappropriate choice may hamper the modeling effort. Choosing too poor a structure (too few regressors) results in inaccurate modeling of the process dynamics and nonlinearities. Choosing a structure richer than necessary (too many regressors) leads to badly conditioned estimation problems and to "overfitting" the data [17].

Regressor Selection: there are a number of possibilities for the choice of regressors in the non-linear black-box identification. The NARX (Nonlinear Autoregressive with exogenous input) model is frequently used with many nonlinear identification methods. The NARX model establishes a relation between the past input-output data and the predicted output:

$$\hat{y}(k+1) = F\left(y(k), \dots, y\left(k - n_y + 1\right), u(k), \dots, u(k - n_u + 1)\right) \tag{3.4}$$

Where k denotes discrete time samples, n_u and n_y are integers related to the systems order, and F denotes a fuzzy model. In NARX model, the regression vector is a collection of a finite number of past inputs and outputs,

$$X(k) = [y(k), \dots, y\left(k - n_y + 1\right), u(k), \dots u(k - n_u + 1)]^T \tag{3.5}$$

The regressand is the predicted output$\hat{y}(k+1)$. The unknown function F(.) can be directly inferred from the data by using static regression. However, that n_u may be quite large and is not directly related to the systems order [26].

Granularity of the fuzzy model: This choice is related to the number of linguistic terms defined for each variable and therefore also to the number of rules in the model.

3.2.1.2. Fuzzy clustering

The principle of identification by product-space clustering is to approximate a non-linear regression problem by decomposition it into several local linear sub problems. This approach has a number of advantages in comparison with global non-linear models, such as neural networks [26].

- The model structure is easy to understand and interpret, both qualitatively and quantitatively
- Various types of knowledge can be integrated in the model, including empirical knowledge, measured data and available mathematical models.

- In addition, the approach has computational advantages and lends itself to straight forward adaptive and learning algorithm.

Fuzzy clustering is applied in the product space of the regressors and the regressand: XxY. Let X denote the matrix in R^{Nxp}, having the regression vectors X_k^T in its rows, and let y denote the column vector in R^N, containing the regressands $y_{k:}$

$$X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_N^T \end{bmatrix}, \qquad Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$$

N denotes the number of data samples, p is the dimension of the regression vector. The matrix X contains shifted versions of the input and output data [18].

The available data represents a sample from the regression surface. By clustering the data, local linear models can be found that approximate the regression surface in an optimal way. The set (matrix) of data to be clustered, denoted Z, is constructed by concatenating the regressor data matrix X and the regressand vector y:

$$\mathrm{Z}^{\mathrm{T}} = [\mathrm{X}, \mathrm{y}]$$

This data set is a subset of the Cartesian product space XxY defined by the non-linear functional relationships.

$$Z \subset XxY \ Such \ that \ y \approx f(x)$$

The data set Z is partitioned into fuzzy subsets by applying fuzzy clustering algorithms capable of detecting linear substructures in data. The membership of the data samples in the clusters is described by the fuzzy partition matrix. Each cluster is characterized by its center and covariance matrix which represents the variance of the data in the cluster. A fuzzy clustering algorithm C can be regarded as a mapping $C: (ZxN) \rightarrow \left(M_{fc}xR^{nxc}xPD^{n}\right)$:

$$(U, V, F) = C(Z, c; U^{O}, m, \in)$$

Where c is the number of clusters, U^{O} is the initial partition matrix and $m, \in$ are the parameters of the clustering algorithm. The partition matrix U contains the membership degrees of the data points in the clusters with prototypes V. The cluster covariance matrix F_i conveys information about the shape and orientation of the i^{th} cluster [17].

3.2.1.3. Choice of clustering algorithm

Different algorithms differ in the definition the distance measure and of the prototypical structure for the clusters. Because of these difference, each algorithm performs in a different way for the same data set. So for our work we chose clustering with adaptive distance measure.

3.2.1.3.1. Gustafson-Kessel Algorithm

The GK algorithm appears to be suitable method for identification purposes, because of the following properties [17]:

- The size of the clusters is limited by the definition of the distance measure. The fuzzy sets induced by the partition matrix are compact, have typically one distinct extreme, and hence are easy to interpret.
- In comparison with the other considered algorithms, the GK algorithm is relatively insensitive to the initialization of the partition matrix (or cluster prototypes).
- As the GK algorithm is based on an adaptive distance measure, it is not so sensitive to scaling (normalization, standardization) of the data

- The GK algorithm can detect clusters of different shapes, not only linear subspaces

Clustering techniques can be applied to data that are quantitative (numerical), qualitative (categorical), or a mixture of both. In this paper, the clustering of quantitative data is considered. The data are typically observations of some physical process. Each observation consists of *n* measured variables, grouped into an *n*-dimensional column vector $Z_k = \left[Z_{1k,} \dots . Z_{nk}\right]^T, Z_k \epsilon\ R^n$ A set of *N* observations is denoted by $Z = \{Z_k | k = 1,2, \dots, N\}$, and is represented as an $n \times N$ matrix:

$$\begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1N} \\ Z_{21} & Z_{22} & \cdots & Z_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ Z_{n1} & Z_{n2} & \cdots & Z_{nN} \end{bmatrix} \qquad (3.6)$$

In this work we have 7 measured variables with 120 data samples, so the above matrix becomes 7x120.

$$\begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1,120} \\ Z_{21} & Z_{22} & \cdots & Z_{2,120} \\ \vdots & \vdots & \vdots & \vdots \\ Z_{71} & Z_{72} & \cdots & Z_{7,120} \end{bmatrix} \qquad (3.7)$$

Given the data set **Z**, choose the number of clusters $1 < c < N$, the weighting exponent $m > 1$ and the termination tolerance $\varepsilon > 0$ and the cluster volumes ρ_i. Initialize the partition matrix randomly, such that $\mathbf{U}_{(0)} \in M_{fc}$.

Repeat for $l = 1, 2 \dots$

Step 1: Compute cluster prototypes (means):

$$V_i^{(l)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m}, 1 \le i \le c \qquad (3.8)$$

Step 2: Compute the cluster covariance matrices:

$$F_i = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m (Z_k - V_i^{(l)})(Z_k - V_i^{(l)})^T}{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m}, 1 \leq i \leq c \tag{3.9}$$

Step 3: Compute the distances:

$$D_{ikA_i}^2 = \left(Z_k - V_i^{(l)}\right)^T \left[\rho_i \det(F_i)^{1/n} F_i^{-1}\right] \left(Z_k - V_i^{(l)}\right), 1 \leq i \leq c, 1 \leq k \leq N \tag{3.10}$$

Step 4: Update the partition matrix:

For $1 \leq k \leq N$

If $D_{ikA_i} > 0$ for all i=1,2,…,c

$$\boldsymbol{\mu_{ik}^{(l)}} = \frac{\mathbf{1}}{\sum_{j=1}^{c} \left(\boldsymbol{D_{ikA_i}} / \boldsymbol{D_{jkA_i}}\right)^{\mathbf{2}/(\boldsymbol{m}-\mathbf{1})}} \tag{3.11}$$

Otherwise

$$\mu_{ik}^{(l)} = 0 \text{ if } D_{ikA_i} > 0, \text{and } \mu_{ik}^{(l)} \in [0,1] \text{ with } \sum_{i=1}^{c} \mu_{ik}^{(l)} = 1 \tag{3.12}$$

Until $\left\|U^{(l)} - U^{(l-1)}\right\| < \epsilon$

3.2.1.4. Determining the number of clusters

Before fuzzy clustering can be applied, the number of clusters must be specified. Two methods to determine the number of clusters are considered in this section: cluster validity measures, and compatible cluster merging. Validity measures assess the goodness of the obtained partition by using criteria like the within-cluster distance, the partition density, the entropy, etc.

Cluster merging approaches start with a higher number of clusters than are expected for the particular problem. The initial number of clusters is then reduced by successively merging compatible clusters until some threshold is reached and no more clusters can be merged [17].

Cluster validity measures

Clustering algorithms generally aim at locating well-separated and compact clusters. When the number of clusters is chosen equal to the number of groups that actually exist in the data, it can be expected that the clustering algorithm will identify them correctly. When this is not the case, misclassifications appear, and the clusters are not likely to be well separated and compact. Validity measures that account for these requirements are given below. Fuzzy hyper volume Vh is defined by [19]:

$V_h = \sum_{i=1}^{c} [\det(F_i)]^{1/2}$ where F_i are the cluster co − variance matrix. Good partition are indicated by small values of V_h. The average partition density D_A is defined by.

$D_A = \frac{1}{c} \sum_{i=1}^{c} \frac{S_i}{[\det(F_i)]^{1/2}}$ Where S_i is the sum of membership degrees of the data vectors that lie with in a hyperellipsoid whose radii are the standard deviation of the cluster features.

$S_i = \sum_k \mu_i, \forall_k \textit{ such that } (Z_k - V_i)^T F_i^{-1} (Z_k - V_i) < 1$ The partition density D_p *is defined by*

$$D_p = \frac{\sum_{i=1}^{c} S_i}{V_h} \qquad (3.13)$$

Good partition are indicated by large values of D_A *and* D_p

Compatible cluster merging

A compatible cluster merging algorithm used for finding an appropriate number of linear or planar clusters in 2D or 3D image data. The algorithm starts with $c = c_{max}$, which is greater than the maximum number of clusters expected for the particular problem. The number of clusters is then reduced by successively merging compatible clusters until some threshold is reached and no more clusters can be merged [17].

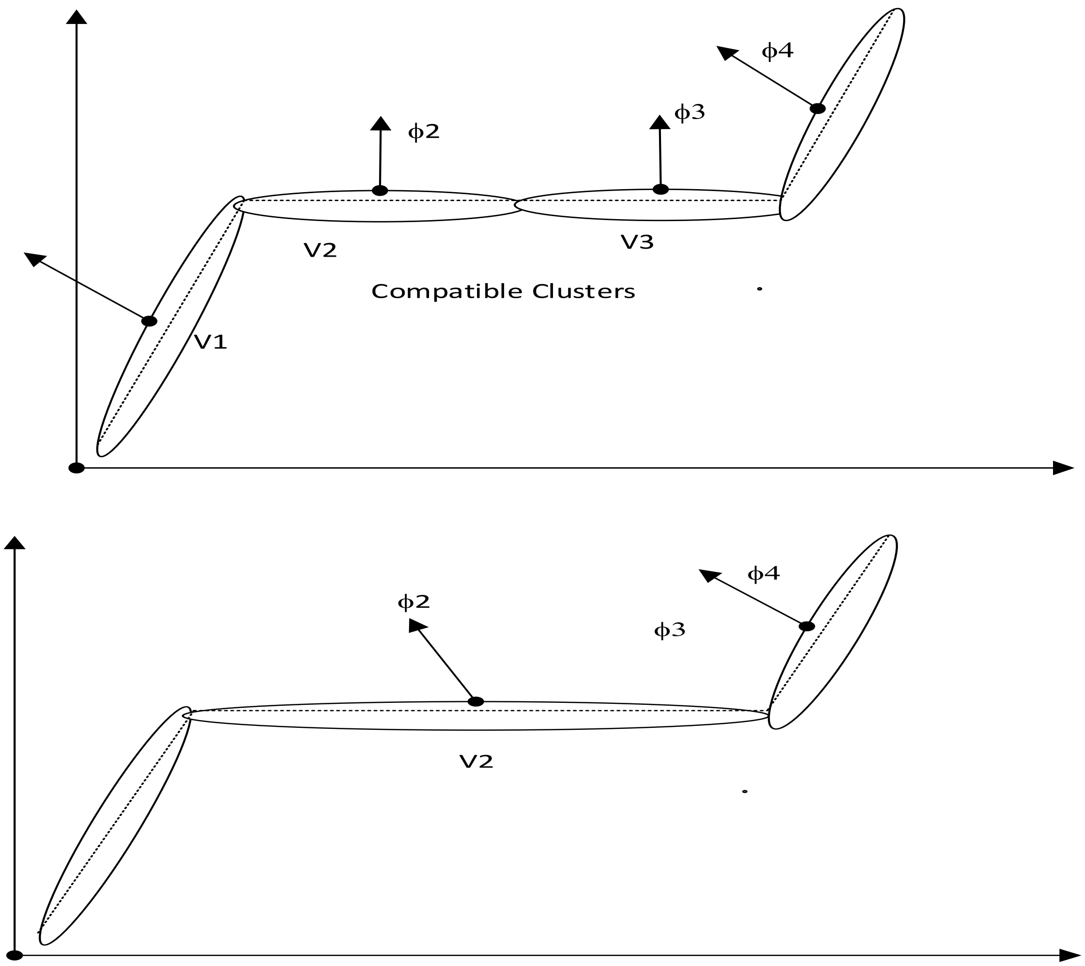

Figure 3.8. Merging of similar data in one group

The key elements of the CCM algorithm are the criteria which measure the degree of compatibility between clusters. This is based on geometrical properties of the clusters, by analyzing the eigenvalues and the unit eigenvectors of the cluster co-variance matrices.

3.2.2.Takagi-Sugeno Modelling

TS fuzzy model uses crisp functions in the consequents. Hence, it can be seen as a combination of linguistic and mathematical regression modelling in the sense that the antecedents describe fuzzy regions in the input space in which consequent functions are valid. The TS rules have the following form.

$$R_i: if\ x\ is\ A_i\ then\ y_i = f_{i(x)}, i = 1,2, \ldots \quad (3.14)$$

Contrary to the linguistic model, the input x is a crisp variable.

Inference Mechanism

The inference formula of the TS model is a straightforward extension of the singleton model inference [19]:

$$y = \frac{\sum_{i=1}^{k} \beta_i y_i}{\sum_{i=1}^{k} \beta_i} = \frac{\sum_{i=1}^{k} \beta_i (a_i^T x + b_i)}{\sum_{i=1}^{k} \beta_i} \quad (3.15)$$

When the antecedent fuzzy sets define distinct but overlapping regions in the antecedent space and the parameters. The affine TS model with a common consequent structure can be expressed as a pseudo linear model with input-dependent parameters:

$$y = \sum_{i=1}^{k} (\lambda_i(x) a_i^T) x + \sum_{i=1}^{k} \lambda_i(x) b_i = a^T(x) x + b(x) \quad (3.16)$$

An *n*-output, *m*-input nonlinear process can be approximately modeled by *n* set of coupled Multiple-Input Single-Output (**MISO**) models. For the *i*th output, *yi* (*i*= 1, …,n) the decomposed models at the time instant *k* can be described as, $y_i(k) = f(\varphi_i(k))$

Where the regression vector, $\varphi_i(k)$ are coupled with the previous n_A^i time instances values of the *i*th output, and n_B^{ij} time instances values of all inputs u_j (*j*=1, …. , *m*) of the process and is given by,

$$\varphi_i(k+1) = \left[\tilde{Y}_i(k)\ \tilde{U}_1(k), \ldots, \quad \tilde{U}_m(k)\ \right] \quad (3.17)$$

Where

$$\tilde{Y}_i(k) = \left[y_i(k-1), \ldots, y_i(k - n_A^i)\right]$$

$$\widetilde{U}_j(k) = \left[u_j\left(k - k_d^{ij} - 1\right), \dots, u_j\left(k - k_d^{ij} - n_B^{ij}\right)\right]$$

The delay time k_d^{ij} for the ith process output is expressed in sampling time unit and is given by the relation $\tau_d^{ij} = Tk_d^{ij}$where the dead time, τ_d^{ij} is the integer multiple of the sampling time, T. The unknown function, $f(.)$can be approximated by using the TS type fuzzy model. The model comprises a number of logical rules for the approximation where each rule possesses nonlinear process variables in the antecedent space and piecewise linear function in the consequent space. The antecedents of fuzzy rules divide the input space into a number of fuzzy regions while the consequent functions approximate the local behavior of the process [19]. The rule base TS fuzzy model comprises.

$$L_r: If\ y_i(k-1)\ is\ C_1^i(k)\ and\ \dots and\ y_i\left(k - n_A^i\right)\ is\ C_{n_A^i}^i(r)\ and\ u_1\left(k - k_d^{i1} - 1\right)\ is\ D_{11}^i(r)\ and\ \dots and\ u_1\left(k - k_d^{i1} - n_B^{i1}\right)\ is\ D_{1n_B^{i1}}^i(r)\ and\ \dots and\ u_m\left(k - k_d^{im} - 1\right)\ is\ D_{m1}^i(r)\ and\ \dots and\ u_m\left(k - k_d^{im} - n_B^{im}\right)\ is\ D_{mn_B^{im}}^i(r)\ then$$

$$\hat{y}_i^r(k) = \sum_{l=1}^{n_A^i} \hat{a}_l^i(r) y_i(k-1) + \sum_{j=1}^{m} . \sum_{l=0}^{n_B^{ij}} \hat{b}_l^{ij}(r) u_j\left(k - l - k_d^{ij} - 1\right)$$

Where, $C_1^i(k), \dots, C_{n_A^i}^i(r)\ and\ D_{11}^i(r)$, …., $D_{1n_B^{i1}}^i(r)$, …., $D_{mn_B^{im}}^i(r)$ are the antecedent fuzzy sets representing the fuzzy subspace in which the implications Lir for r=1, … , R can be applied for reasoning, $\hat{y}_i^r(k)$ presents the linear local model for the rth rule consequent and $\hat{a}_l^i(r)$ and $\hat{b}_l^{ij}(r)$are the consequent linear model parameters of the rth rule. The consequent parameters for all R rules can be expressed in the following compact matrix form [19]:

$$\hat{\theta}_i = \begin{bmatrix} \hat{A}_i(1) & \hat{B}_{i1}(1)\cdots & \hat{B}_{im}(1) \\ \vdots & \ddots & \vdots \\ \hat{A}_i(R) & \hat{B}_{i1}(R)\cdots & \hat{B}_{im}(R) \end{bmatrix} \tag{3.18}$$

The choice of the right **NARX** structure is very important. One can use physical knowledge to choose a proper structure .Another method is a search through a (large) set of possible structures. Furthermore, the quality of the model is highly dependent on the information content of the input-output data set. It is difficult to design a good identification signal, especially for MIMO systems. Filtered random signals with additional white noise seem to be appropriate at the moment. These signals go slowly through the whole control domain and continuously excite the system. The performance **of** the models is measured by the variance accounted for (VAF) index given by [26]:

$$VAF = 100\%.\left[1 - \frac{var(Y - Y_m}{var(Y)}\right] \tag{3.19}$$

Where Y is the true output and Y_m is the simulated output.

3.3. Linear Model Based Predictive Control

Local linearization of Takagi-Sugeno fuzzy models is investigated in order to extend the operation range of linear model based predictive controllers.

3.4. Linear State Space MBPC

In Linear MBPC**,** a linear model **is** used to predict the output ***as*** a function of the predicted control signal $\widehat{U}(k, \ldots., k + H_p)$**,** with Hp the prediction horizon. The objective function, given **is** minimized for a given reference trajectory. The signal U may change over the control horizon $H_c(H_c \leq H_p)$ and remains constant between H_c, and H_p. A linear model in state-space description is given by [35]:

$$x(k+1) = Ax(k) + Bu(k) \tag{3.20}$$

$$y(k) = Cx(k) \tag{3.21}$$

For the locally linearized system, these equations become:

$$x(k+1) = x(k) + A^*(x(k) - x_0) + B^*(u(k) - u_0) \tag{3.22}$$

$$y(k) = Cx(k)$$

Where x_0 and u_0 define the linearization point.

3.4.1. Linearization of TS Model

At each sample time, the local A* and B* matrices are calculated as follows: Calculate the degrees of fulfillment $\omega_i(x(k))$ of the antecedents, using product as the fuzzy logic and operator. The rule inference gives [35]:

$$y_l(k+1) = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).\, y_{li}(k+1)}{\sum_{i=1}^{k_l} \omega_{li}(x_l(k))} \tag{3.23}$$

$$y_{li}(k+1) = \zeta_{li} y(k) + \eta_{li}\big(u(k)\big) + \theta_{li} \tag{3.24}$$

Define $\zeta_l^* \ and \ \eta_l^* \ as$:

$$\zeta_l^* = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).\, \zeta_{li}}{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).} \tag{3.25}$$

$$\eta_l^* = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).\, \eta_{li}}{\sum_{i=1}^{k} \omega_{li}(x_l(k))} \tag{3.26}$$

Define **x, u** and **y** for the state-space description **as:**

$$x(k) = \big[x_1(k), x_1(k-1), \dots., x_1\big(k - n_{y1}\big), \dots\dots, x_{n_0}(k), x_{n_0}(k-1), \dots., x_{n_0}(k - n_{yn_0})\big]^T$$

$$u(k) = \big[u_1(k - n_{d1} + 1), u_1(k - n_{d1}), \ldots . u_1(k - n_{d1} - n_{u1} + 1), \ldots . , u_{ni}\big(k - n_{d_{ni}} + 1\big), u_{ni}\big(k - n_{d_{ni}}\big), \ldots . . , u_{ni}(k - n_{d_{ni}} - n_{u_{ni}} + 1)\big]^T$$

$$y(k) = \big[x_1(k), x_2(k), \ldots . . , x_{n_0}(k)\big]^T$$

The local linear system matrices are now derived **as** follows [35]:

A* is a $\sum_{j=1}^{n_0} n_{yi}\, x \sum_{j=1}^{n_0} n_{yi} (= a_1) matrix$

$$A^* = \begin{bmatrix} \zeta_{1,1}^* & \zeta_{1,2}^* & \cdots & \cdots & \cdots & \cdots & \zeta_{1,a1}^* \\ 1 & 0 & 0 & & \cdots & & 0 \\ 0 & 1 & \vdots & & \ddots & & 0 \\ 0 & \ldots & \ddots & & \ddots & & \vdots \\ \zeta_{2,1}^* & \zeta_{2,2}^* & \cdots & \cdots & \cdots & \cdots & \zeta_{2,a1}^* \\ 0 & \vdots & \ddots & & \ddots & & \vdots \\ \zeta_{n0,1}^* & \zeta_{n0,2}^* & \cdots & \cdots & \cdots & \cdots & \zeta_{n0,a1}^* \\ 0 & \cdots & 0 & 1 & \cdots & 0 & 0 \\ \vdots & & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \tag{3.27}$$

B* is a $\sum_{j=1}^{n_0} n_{ui}\, x \sum_{j=1}^{ni} n_{ui} (= a_2) matrix$

$$B^* = \begin{bmatrix} \eta_{1,1}^* & \eta_{1,2}^* & \cdots & \eta_{1,a2}^* \\ 0 & \cdots & \cdots & 0 \\ \vdots & \cdots & & \vdots \\ 0 & & \cdots & 0 \\ \eta_{2,1}^* & \eta_{2,2}^* & \cdots & \eta_{2,a2}^* \\ \vdots & \ddots & \ddots & \vdots \\ \eta_{n0,1}^* & \eta_{n0,2}^* & \cdots & \eta_{n0,a2}^* \\ \vdots & \ddots & \ddots & \vdots \end{bmatrix} \tag{3.28}$$

And C is a $n_0 x \sum_{j=1}^{n_0} n_{yj}\;\; matrix$

$$C = \begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ \vdots & & \ddots & & \ddots & & \vdots \\ 0 & \cdots & \cdots & 1 & 0 & \cdots & 0 \end{bmatrix} \tag{3.29}$$

The one in C are positioned such that $y_l(k) = \; x_l(k)$ [35]

Based on the above algorithm we have linearized model as follows:

3.4.1.1. Cool weather Model

$$y1(k) = 0.9y1(k-1) - 0.2y1(k-2) + 32y2(k-1) - 9.5y2(k-2) + 1209.7u1(k-1) - 2699.27u1(k-2) - 0.1u2(k-1) + 0.3u2(k-2) + 0.1v1(k-1) - 0.3v1(k-2) - 0.2v2(k-1) - 0.01v2(k-2) - 288v3(k-1) + 265.3v3(k-2) + 17.2$$

$$y2(k) = -0.5726u1(k-1) - 0.249u1(k-2) - 0.0001u2(k-2) - 0.0005v1(k-1) + 0.0004v1(k-2) + 0.0001v2(k-2) - 0.354v3(k-1) + 0.1905v3(k-2)$$

$$A^* = \sum_{j=1}^{n_o} n_y \, X \sum_{j=1}^{n_o} n_y = \sum_{j=1}^{2} n_y \, x \sum_{j=1}^{2} n_y = (2+2)x(2+2) = 4x4$$

$$B^* = \sum_{j=1}^{n_o} n_y \, x \sum_{j=1}^{n_i} n_u = \sum_{j=1}^{2} n_y \, x \sum_{j=1}^{5} n_u = (2+2)x(2+2+2+2+2) = 4x10$$

$$A^* = \begin{bmatrix} 0.9 & -0.2 & 32 & -9.5 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$B^* = \begin{bmatrix} 1209.7 & -2699.27 & -0.1 & 0.3 & 0.1 & -0.3 & -0.2 & -0.01 & -288 & 265.3 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.5726 & -0.249 & 0 & -0.0001 & -0.0005 & 0.0004 & 0 & 0.0001 & -0.354 & 0.1905 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

States:

$$x(k+1) = \begin{bmatrix} y1(k) \\ y1(k-1) \\ y2(k) \\ y2(k-1) \end{bmatrix} \qquad x(k) = \begin{bmatrix} y1(k-1) \\ y1(k-2) \\ y2(k-1) \\ y2(k-2) \end{bmatrix}$$

Transformation to "z" domain and finding transfer function

$$\frac{y1(z)}{y2(z)} = \frac{32z-9.5}{z^2-0.9z+0.2} \quad \frac{y1(z)}{u1(z)} = \frac{1209.7z-2699.27}{z^2-0.9z+0.2} \quad \frac{y1(z)}{u2(z)} = \frac{-0.1z+0.3}{z^2-0.9z+0.2} \quad \frac{y1(z)}{v1(z)} = \frac{0.1z-0.3}{z^2-0.9z+0.2} \quad \frac{y1(z)}{v2(z)} = \frac{-0.2z-0.01}{z^2-0.9z+0.2}$$

$\frac{y1(z)}{v3(z)} = \frac{-288z+265.3}{z^2-0.9z+0.2}$ Offset value $\frac{y1(z)}{1} = \frac{17.2}{z^2-0.9z+0.2}$ when input values are zero

$$\frac{y2(z)}{u1(z)} = \frac{-0.5726z-0.249}{z^2-0.919z+0.2271} \quad \frac{y1(z)}{u2(z)} = \frac{-0.0001}{z^2-0.919z+0.2271} \quad \frac{y2(z)}{v1(z} = \frac{-0.0005z+0.0004}{z^2-0.919z+0.2271} \quad \frac{y2(z)}{v2(z)} = \frac{0.0001}{z^2-0.919z+0.2271}$$

$$\frac{y2(z)}{v3(z)} = \frac{-0.354z+0.1905}{z^2-0.919z+0.2271}$$

3.4.1.2. Hot weather Linearized Model

It has the same matrix dimension and input output numbers. The only difference is the parameter values.

$$\begin{aligned} y1(k) = {} & 0.9y1(k-2) - 0.2y1(k-2) - 72.2y2(k-1) + 68.2y2(k-2) - 28.5u1(k-1) \\ & + 1125.6u1(k-2) - 0.1u2(k-1) + 0.3u2(k-2) + 0.3v1(k-1) \\ & - 0.4v1(k-2) - 0.2v2(k-2) - 158.9v3(k-1) - 66.4v3(k-1) \\ & - 74.5v3(k-2) + 23.6 \end{aligned}$$

$$\begin{aligned} y2(k) = {} & 1.0394y2(k-1) - 0.3351y2(k-2) + 0.2584u1(k-1) - 0.6784u1(k-2) \\ & - 0.0001u2(k-1) + 0.0001u2(k-2) - 0.0003v1(k-1) \\ & + 0.0004v1(k-2) + 0.0003v2(k-1) - 0.0002v2(k-2) - 0.08v3(k-1) \\ & + 0.0642v3(k-2) + 0.0005 \end{aligned}$$

$$A^* = \begin{bmatrix} 0.9 & -0.2 & -73.2 & 68.2 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1.0394 & -0.335 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

B^*

$$= \begin{bmatrix} -28.5 & 1125.6 & -0.1 & 0.3 & 0.3 & -0.4 & 0 & -0.2 & -66.4 & -74.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.0314 & 0 & -0.0001 & 0.0001 & -0.2995 & -0.1391 & 0.1391 & 0.1856 & 0.0125 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad offset = \begin{bmatrix} 23.6 \\ 0.0005 \end{bmatrix}$$

Transforming the model to z domain transfer function

$\frac{y1(z)}{y2(z)} = \frac{-73.2z+68.2}{z^2-0.9z+0.2}$ $\frac{y1(z)}{u1(z)} = \frac{-28.5z+1125.6}{z^2-0.9z+0.2}$ $\frac{y1(z)}{u2(z)} = \frac{-0.1z+0.3}{z^2-0.9z+0.2}$ $\frac{y1(z)}{v1(z)} = \frac{0.3z-0.4}{z^2-0.9z+0.2}$ $\frac{y1(z)}{v2(z)} = \frac{0.2}{z^2-0.9z+0.2}$

$\frac{y1(z)}{v3(z)} = \frac{-66.4z-74.5}{z^2-0.9z+0.2}$ the off set value when the inputs are zero, $\frac{y1(z)}{1} = \frac{23.6}{z^2-0.9z+0.2}$

The humidity transfer function (y2 (z))

$\frac{y2(z)}{u1(z)} = \frac{0.2584z-0.6784}{z^2-1.0394z+0.335}$ $\frac{y2(z)}{u2(z)} = \frac{-0.0001z+0.0001}{z^2-1.0394z+0.335}$ $\frac{y2(z)}{v1(z)} = \frac{-0.0003z+0.0004}{z^2-1.0394z+0.335}$ $\frac{y2(z)}{v2(z)} =$

$\frac{0.0003z-0.0002}{z^2-1.0394z+0.335}$ $\frac{y2(z)}{v3(z)} = \frac{-0.08z+0.0642}{z^2-1.0394z+0.335}$

the off set value when the inputs are zero, $\frac{y2(z)}{1} = \frac{0.0005}{z^2-1.0394z+0.335}$

CHAPTER FOUR

CONTROLLING MECHANISM

4.1. Model predictive control

The term Model Predictive Control does not designate a specific control strategy but a very ample range of control methods which make an explicit use of a model of the process to obtain the control signal by minimizing an objective function. These design methods lead to linear controllers which have practically the same structure and present adequate degree of freedom. The idea appearing in greater or lesser degree in all the predictive control family are basically:

- Explicit use of a model to predict the process output at future time instants (horizon)
- Calculation of a control sequence minimizing an objective function
- Receding strategy, so that at each instant the horizon is displaced towards the future, which involves the application of the first control signal of the sequence calculated at each step.

MPC presents a series of advantages over other methods, amongst which stand out:

- It particularly attractive to staff with only a limited knowledge of control because the concepts are very intuitive and at the same time the tuning is relatively easy.
- It can be used to control a great variety of processes, from those with relatively simple dynamics to other more complex ones, including systems with long delay times or of non-minimum phase or unstable ones.
- The multivariable case can easily be dealt with.
- It intrinsically has compensation for dead times
- It introduces feed forward control in a natural way to compensate for measured disturbances.

- The resulting controller is an easy to implement linear control law
- The extension to the treatment of constraints is conceptually simple and these can be systematically included during the design process.
- It is very useful when future reference (robotics or batch processes) are known.
- It is a totally open methodology based on certain basic principles which allow for future extensions.

As is logical, however, it also has its drawbacks. One of these is that although the resulting control law is easy to implement and requires little computation, its derivation is more complex than that of the classical PID controllers. When constraints are considered, the amount of computation required is even higher. Even so, the greatest drawback is the need for an appropriate model of the process to be available. The design algorithm is based on a prior knowledge of the model and it is independent of it, but it is obvious that the benefits obtained will be affected by the discrepancies existing between the real process and the model used [33].

4.1.1. MPC strategy

The methodology of all the controllers belonging to the MPC family is characterized by the following strategy, represented in figure 4.4.:

1. The future outputs for a determined horizon N, called the prediction horizon, are predicted at each instant t using the process model. These predicted output $y(t+k|t)$ for k=1…N depend on the known values up to instant t(past inputs and outputs) and on the future control signals $u(t+k|t), k=0 \dots N-1,$ which are those to be sent to the system and to be calculated.
2. The set of future signals is calculated by optimizing determined criterion in order to keep the process as close as possible to the reference trajectory $w(t+k)$ (which can be the set point

itself or a close approximation of it). This criterion usually takes the form of a quadratic function of the errors between the predicted output signal and the predicted reference trajectory. An explicit solution can be obtained if the criterion is quadratic, the model is linear and there are no constraints, otherwise an iterative optimization method has to be used.

3. The control signal $u(t|t)$ is sent to the process whilst the next control signals calculated are rejected, because at the next sampling instant $y(t+1)$ is already known and step 1 is repeated with this new value and all the sequences are brought up to date. Thus $u(t+1|t+1)$ is calculated (which in principle will be different to the $u(t+1|t)$ because of the new information available) using the receding horizon concept.

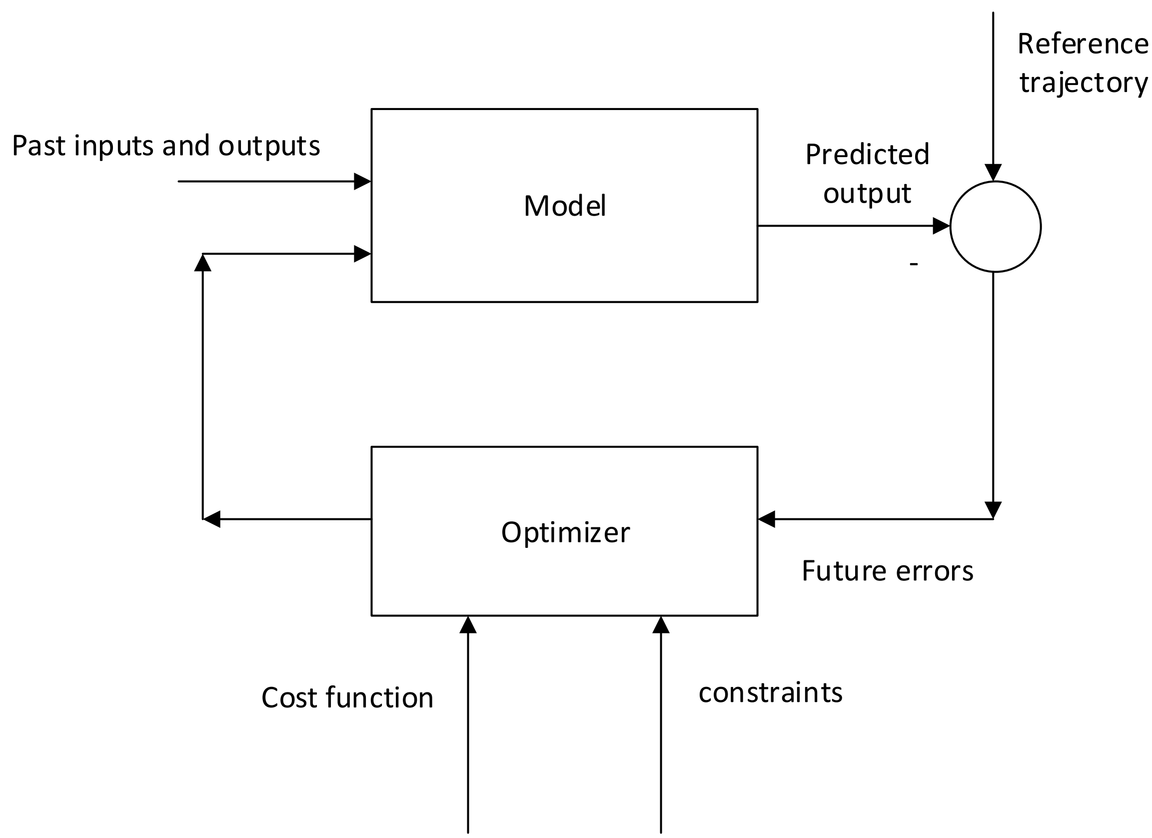

Figure 4.1. MPC controller strategy

A model is used to predict the future plant outputs, based on past and current values and on the proposed optimal future control actions as shown in figure 4.1. These actions are calculated by the optimizer taking into account the cost function (where the future tracking error is considered) as well as the constraints [33].

4.1.2. MPC Calculations

The MPC calculations are based on current measurements and predictions of the future values of the outputs. The objective of the MPC control calculations is to determine a sequence of control moves (that is, manipulated input changes) so that the predicted response moves to the set point in an optimal manner. The actual output y, predicted output $\hat{y}$, and manipulated input u.

1. At the k-th sampling instant, the values of the manipulated variables, u, at the next M sampling instants, {u (k), u (k+1)… u (k+M -1)} are calculated. This set of M "control moves" is calculated so as to minimize the predicted deviations from the reference trajectory over the next P sampling instants while satisfying the constraints. Typically, an LP or QP problem is solved at each sampling instant. Terminology: M = control horizon, P = prediction horizon. Then the first "control move", u (k), is implemented.
2. At the next sampling instant, k+1, the M-step control policy is re-calculated for the next M sampling instants, k+1 to k+M, and implement the first control move, u(k+1).
3. Then Steps 1 and 2 are repeated for subsequent sampling instants. Note: This approach is an example of a receding horizon approach.

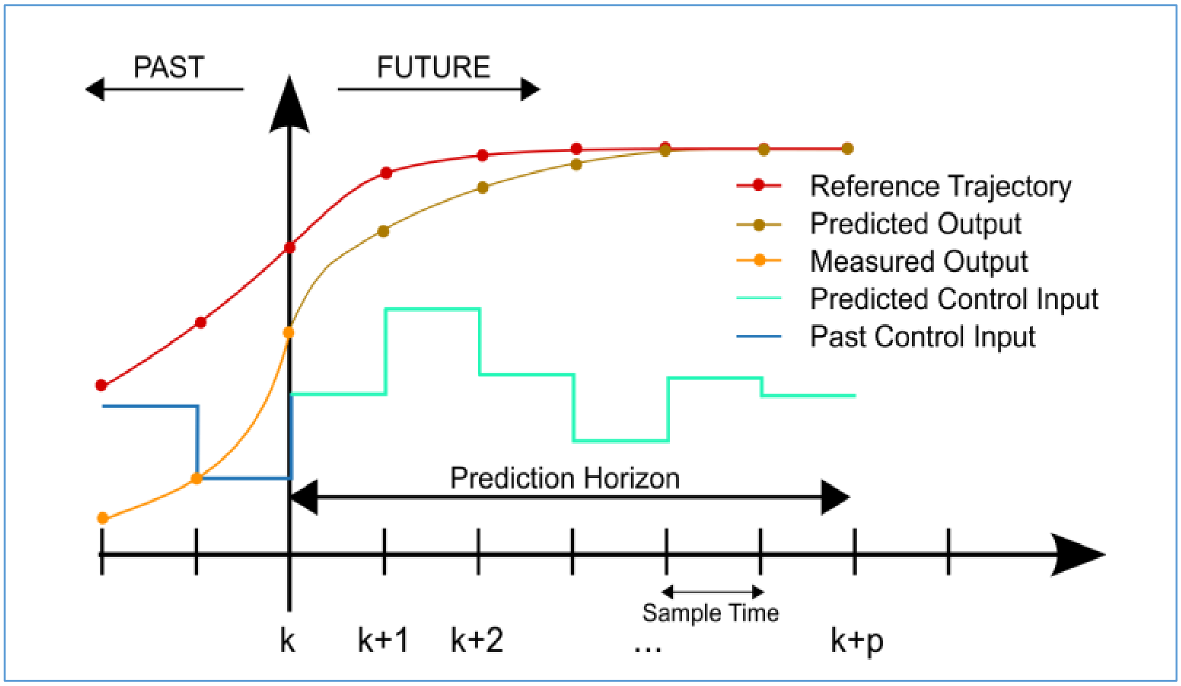

Figure 4.2. Graphical description MPC controller

4.1.3. Selection of Design Parameters

Model predictive control techniques include a number of design parameters [33], [34]:

- N : model horizon
- Δt : sampling period
- P : prediction horizon (number of predictions)
- M : control horizon (number of control moves)
- Q : weighting matrix for predicted errors (Q > 0)
- R : weighting matrix for control moves (R > 0)

N and Δt: These parameters should be selected so that N *Δt > open-loop settling time. Typical values of N: 30 < N < 120

Prediction Horizon, *P*: Increasing *P* results in less aggressive control action Set *P* = *N* + *M*

Control Horizon, *M*: Increasing *M* makes the controller more aggressive and increases computational effort, typically: 5 < *M* < 20 or *N*/3 < *M* < *N*/2

Weighting matrices *Q* and *R*: Diagonal matrices with largest elements corresponding to most important variables

- Output weighting matrix ***Q*** : the most important variables having the largest weights
- Input weighting matrix (move suppression matrix) ***R:*** increasing the values of weights tends to make the MPC controller more conservative by reducing the magnitudes of the input moves.

4.1.4. Generalized Predictive Control Algorithm

The generalized predictive control (GPC) algorithm consists of applying a control sequence that minimizes a multistage cost function of the form [33]:

$$J(N_1, N_2, N_u) = \sum_{j=N_1}^{N_2} \delta(j)[\hat{y}(t+j|t) - w(t+j)]^2 + \sum_{j=1}^{N_u} \lambda(j)[\Delta u(t+j-1)]^2 \tag{4.1}$$

Where y(t+j|t) is an optimum j-step ahead prediction of the system output on data up to time t, N1 and N2 are the minimum and maximum costing horizons, Nu is the control horizon, $\delta(j)$ and $\lambda(j)$ are weighting sequences and $w(t+j)$ is the future reference trajectory, which can be calculated . $\delta(j)$ is considered to be 1 and $\lambda(j)$ is considered to be constant [33].

The objective of prediction control is to compute the future control sequence $u(t), u(t+1), \ldots$ in such a way that the future plant output y(t+j) is driven close to w(t+j). This is accomplished by minimizing $J(N_1, N_2, N_u)$. In order to optimize the cost function the optimal prediction of $y(t+j)$ for $j \geq N_1 and\ N_2$ will be obtained. Consider the following Diophantine equation.

$$1 = E_j(z^{-1})\tilde{A}(z^{-1}) + z^{-j}F_j(z^{-1})\ with\ \check{A}(z^{-1}) = \Delta A(z^{-1}) \tag{4.2}$$

The polynomials E_j and F_j are uniquely defined with degrees j-1 and n_a respectively. They can be obtained dividing 1 by $\check{A}(z^{-1})$ until the remainder can be factorized as $z^{-j}F_j(z^{-1})$. the quotient of the division is the polynomial$E_j(z^{-1})$. Consider a process described by the following. In this case the CARIMA model must be changed to include the disturbance.

$$A(z^{-1})y(t) = B(z^{-1})u(t-1) + D(z^{-1})v(t) + \frac{1}{\Delta}C(z^{-1})e(t) \tag{4.3}$$

Where the variable v (t) is the measured disturbance at time t and $D(z^{-1})$ is a polynomial defined as:

$$D(z^{-1}) = d_0 + d_1z^{-1} + d_2z^2 + \cdots + \ d_{nd}z^{-1} \tag{4.4}$$

Multiplying equation 1 by$\Delta E_j(z^{-1})z^j$:

$$\begin{aligned} E_j(z^{-1})\tilde{A}(z^{-1})y(t+j) \\ &= E_j(z^{-1})B(z^{-1})\Delta \mathrm{u(t+j-1)} + E_j(z^{-1})D(z^{-1})\Delta v(t+j) \\ &+ E_j(z^{-1})e(t+j) \end{aligned} \tag{4.5}$$

By using 4.3 and after some manipulation we get:

$$\begin{aligned} y(t+j) = F_j(z^{-1})y(t) + E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) \\ + E_j(z^{-1})D(z^{-1})\Delta v(t+j) + E_j(z^{-1})e(t+j) \end{aligned} \tag{4.6}$$

Notice that because the degree of $E_j(z^{-1})$ is j-1, the noise terms are all in the future. By talking the expectation operator and considering that $E[e(t)] = 0$, the expected value for $y(t+j)$ is given by:

$$\hat{y}(t+j|t) = E[y(t+j)]$$

$$= F_j(z^{-1})y(t) + E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) + E_j(z^{-1})D(z^{-1})\Delta v(t+j) \quad (4.7)$$

By making the polynomial $E_j(z^{-1})D(z^{-1}) = H_j(z^{-1}) + z^{-j}H'_j(z^{-1})$, with $\delta(H_j(z^{-1}) = j-1$, the prediction equation can now be written as:

$$\hat{y}(t+j\backslash t) = G_j(z^{-1})\Delta u(t+j-1) + H_j(z^{-1})\Delta v(t+j) + G'_j(z^{-1})\Delta u(t-1) + H'_j(z^{-1})\Delta v(t) + F_j(z^{-1})y(t) \quad (4.8)$$

Notice that the last three terms of the right hand side of this equation depend on the past values of the process output, measured disturbances and input variables and correspond to the free response of the process considered if the control signals and measured disturbances are kept constant; while the first term only depends on future values of the control signal and can be interpreted as the forced repose [33]. That is, the response obtained when the initial conditions are zero $y(t-j) = 0, \Delta u(t-j-1) = 0, \Delta v(t-j) for\ j > 0$.

The second term of equation (4.8) depends on the future deterministic disturbances. In some cases, when they are related to the process load, future disturbance are known. In other cases, they can be predicted using trends or by other means. If this is the case, the term corresponding to future deterministic disturbances can be computed. If the future load disturbances are supposed to be constant and equal to the last measured value (i.e. $v(t+j) = v(t)), then\ \Delta v(t+j) = 0$ and the second term of this equation vanishes. Equation (4.8) can be rewritten as:

$$\hat{y}(t+j|t) = G_j(z^{-1})\Delta u(t+j-1) + H_j(z^{-1})\Delta v(t+j) + f_j \quad (4.9)$$

With $f_j = G'_j(z^{-1})\Delta u(t-1) + H'_j(z^{-1})\Delta v(t) + F_j(z^{-1})y(t)$

Let us now consider a set of N_j ahead predictions:

$$\hat{y}(t+1|t) = G_1(z^{-1})\Delta u(t) + H_j(z^{-1})\Delta v(t+1) + f_1$$

$$\hat{y}(t+2|t) = G_2(z^{-1})\Delta u(t+1) + H_j(z^{-1})\Delta v(t+2) + f_2$$

$$\vdots \qquad (4.10)$$

$$\hat{y}(t+N|t) = G_N(z^{-1})\Delta u(t+N-1) + H_j(z^{-1})\Delta v(t+N) + f_N$$

Because of the recursive properties of the E_j polynomial, these expressions can be rewritten as:

$$\begin{bmatrix} \hat{y}(t+1|t) \\ \hat{y}(t+2|t) \\ \vdots \\ \hat{y}(t+j|t) \\ \vdots \\ \hat{y}(t+N|t) \end{bmatrix} = \begin{bmatrix} g_0 & 0 & \dots & 0 & \dots & 0 \\ g_0 & g_0 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ g_{j-1} & g_{j-2} & \dots & g_0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ g_{N-1} & g_{N-2} & \dots & \dots & \dots & g_0 \end{bmatrix} \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ \vdots \\ \Delta u(t+j-1) \\ \vdots \\ \Delta u(t+N-1) \end{bmatrix}$$

$$+ \begin{bmatrix} h_0 & 0 & \dots & 0 & \dots & 0 \\ h_1 & h_0 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ h_{j-1} & \dots & h_1 & h_0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ h_{N-1} & \dots & \dots & \dots & h_1 & h_0 \end{bmatrix} \begin{bmatrix} \Delta v(t+1) \\ \Delta \mathrm{v}(\mathrm{t}+2) \\ \vdots \\ \Delta v(t+j-1) \\ \vdots \\ \Delta v(t+N) \end{bmatrix} + \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_j \\ \vdots \\ f_N \end{bmatrix}$$

Where $H_j(z^{-1}) = \sum_{i=1}^{j} h_i z^{-i}$, being h_i the coefficients of the system step response to the disturbance. By making $f' = H_V + f$, the prediction equation is now:

$$y = G_u + f' \qquad (4.11)$$

Which has the same shape as the general prediction equation used in the case of zero measured disturbance. The future control signal can be found in the same way, simply using as free response the process response due to initial conditions (including external disturbances) and future "known" disturbances [33].

The overall system block diagram including linearization and clustering loop is shown in the figure below.

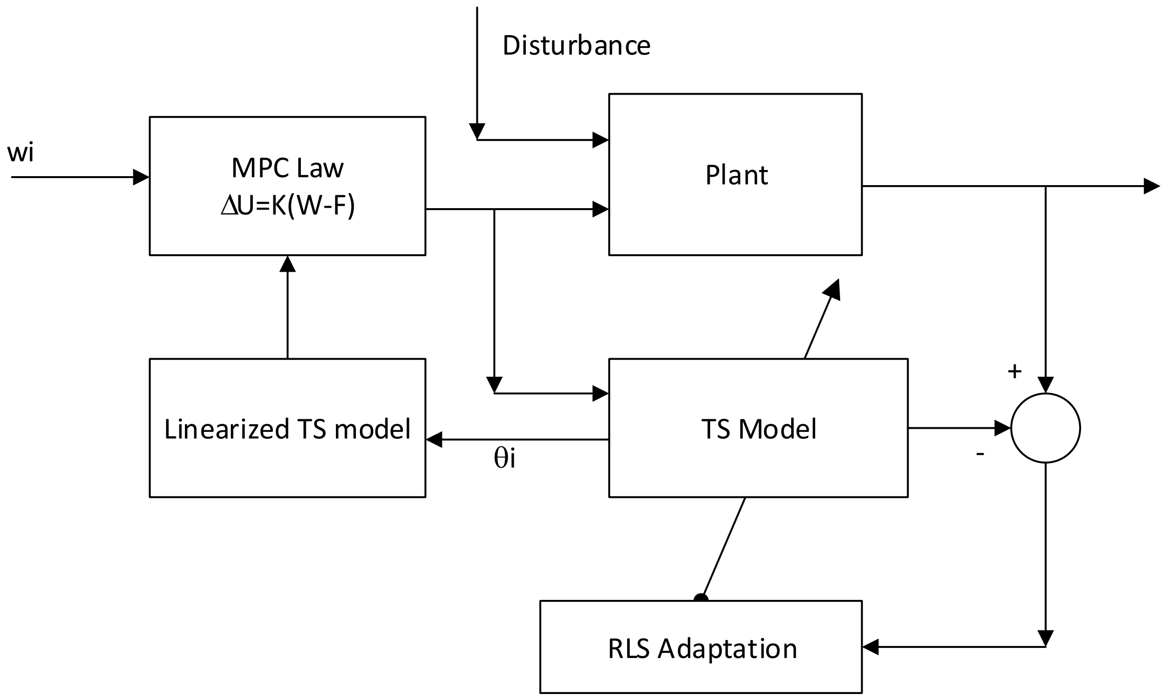

Figure 4.3. Overall block diagram of the system

CHAPTER FIVE

SIMULATION RESULT AND DISCUSSION

This chapter concerned with the simulation results of the closed loop control of the system using Fuzzy Model based MPC with MATLAB/Simulink. SIMULINK® is a toolbox extension of the MATLAB program. It is a program for simulating dynamic systems which has the advantages of computing complex dynamic system simulations, graphical environment with visual real time programming and broad selection of tool boxes. Its graphical interface allows for selection of functional blocks, their placement on a worksheet, selection of their functional parameters interactively, and description of signal flow by connecting their data lines using a mouse device. Simulink simulates analogue systems and discrete digital systems. Furthermore, it gives the opportunity to transform other programming language and .m files of MATLAB in to a block to use in the Simulink environment.

In the simulation part only two seasons are considered with different model. Using those seasons modelling and identification, model predictive controller response and control of the system using MMPC at different operating conditions have discussed in this chapter.

5.1. Modelling and Validation

A model of this system was simulated in MATLAB SIMULINK in order to obtain input-output data sequences for identification using FMID (fuzzy modelling and Identification) MATLAB toolbox to measure temperature and humidity. The number of samples available for identification is 120 and the sample time is 1s. The structure of the MIMO model is selected by using detail analysis and characteristics studying in the physical structure of the system.

The following model orders are selected to achieve better VAF which is one of the modelling performance indicator through long time trial and error. Linear system identification tool (ARX model) gives an information about the order and delay numerical values of the greenhouse model. When the LSIT have remarkable result in the modelling, the resulted order used as the initial order input for fuzzy modelling and identification algorithms. After long process the following orders are selected.

$$n_{hy} = \begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix} \qquad n_{hu} = \begin{bmatrix} 2 & 2 & 2 & 2 & 2 \\ 2 & 2 & 2 & 2 & 2 \end{bmatrix} \qquad n_{hd} = \begin{bmatrix} 15 & 15 & 15 & 15 & 15 \\ 15 & 15 & 15 & 15 & 15 \end{bmatrix}$$

$$n_{wy} = \begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix} \qquad n_{wu} = \begin{bmatrix} 2 & 2 & 2 & 2 & 2 \\ 1 & 0 & 3 & 0 & 3 \end{bmatrix} \qquad n_{wd} = \begin{bmatrix} 15 & 15 & 15 & 15 & 15 \\ 15 & 15 & 15 & 15 & 15 \end{bmatrix}$$

The first row of the *ny* matrix states that temperature, which depends on $u1(k), u2(k), v1(k), v2(k)$ and $v3(k)$. Similarly, the 2nd row of this matrix states that $Hi(k)$ depends on all the input variables like temperature. The meaning of *nu* and *nd* are defined below.

n_{hy}: Output number of delay in humid season

n_{hu}: input number of delay in humid season

n_{hd}: Number of transport delay in humid season

n_{wu}: Output number of delay in warm season

n_{wu}: input number of delay in warm season

n_{wd}: Number of transport delay in warm season

To construct the fuzzy model, the identification data set is first loaded and the structural parameters of the model are defined using built in function programs.

The model is validated by variance accounted for (VAF) between two signals. The VAF of two equal signals is 100% if the fuzzy model is exactly fit with the system. It is used to evaluate the quality of a model, by comparing the true output with the output of the fuzzy model. VAF can be expressed mathematically as follows:

$$VAF = 100\%.\left[1 - \frac{var(y1 - y2)}{var(y1)}\right]$$

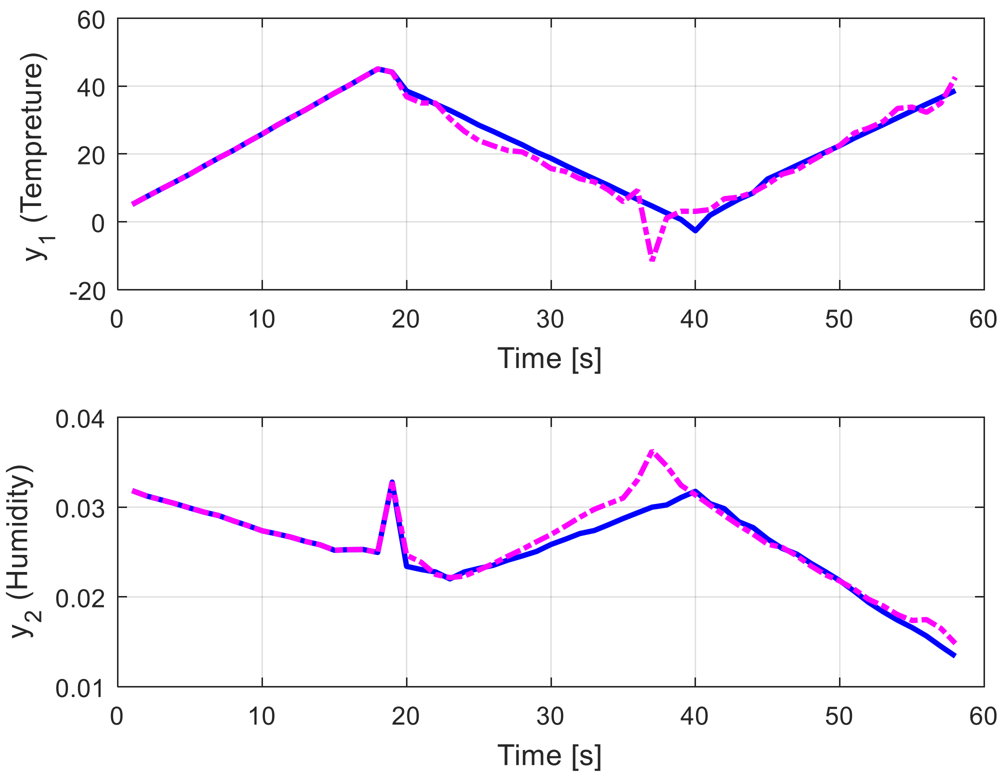

Figure 5.1. The process (solid line) and model output (dashed line) in hot weather

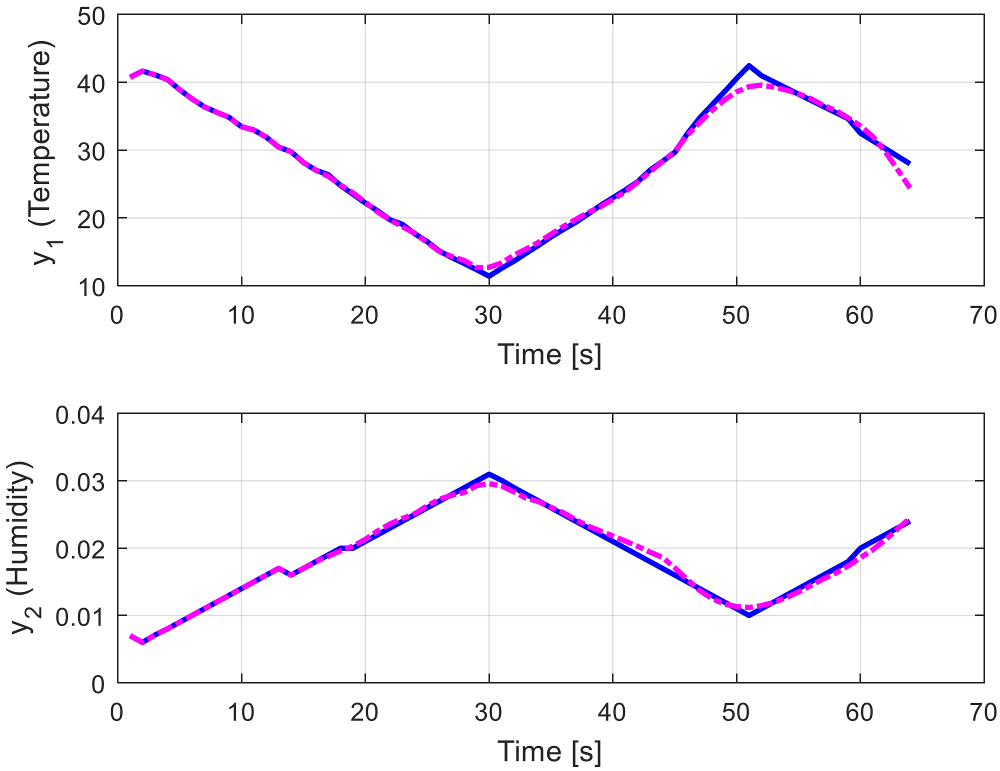

Figure 5.2. The process (solid line) and model output (dashed line) in cool weather

VAF (variance accounted for performance index) for output parameters is as follows: VAF for inside temperature and humidity are 99.2223 and 99.1121 respectively with 2 clusters in cool weather. From the above figure 5.1., the modelling error partially goes to zero and the fuzzy model tracks the actual process model (real process) with excellent fitting percentage. This shows that the modelling performance index of the proposed system exactly represent the actual process model which is considerably more accurate than the linear one in cool weather. The VAF ([94.9344; 91.9091] index in hot weather as shown in figure 5.2. performs better modelling quality even though it is less than the cool weather. It is because of the output data values of the plant dynamically changing as the temperature in the greenhouse is highly variable and difficult to control.

Fuzzy modelling have noticeable improved result in comparison with linear system identification tool. ARX modelling linearizes the non-linear system model globally at one operating point. This increases the offset error aggressively. But the proposed modelling merges similar data sets in different group which are locally linear to simplify the error generated by global linearization. This modelling result shows that the non-linear dynamic MIMO system designed by Fuzzy modelling technique tracks the real process model with insignificant errors.

5.2. Response of Greenhouse Process using Model Predictive Controller

5.2.1. Cool Weather Model Response

In this work, Model Predictive Designer toolbox parameters are like prediction horizon, control horizon and sampling time tuned manually using try and error method. The resulted remarkable tuning parameter values are: N=80, N_u=8 and Ts=1.

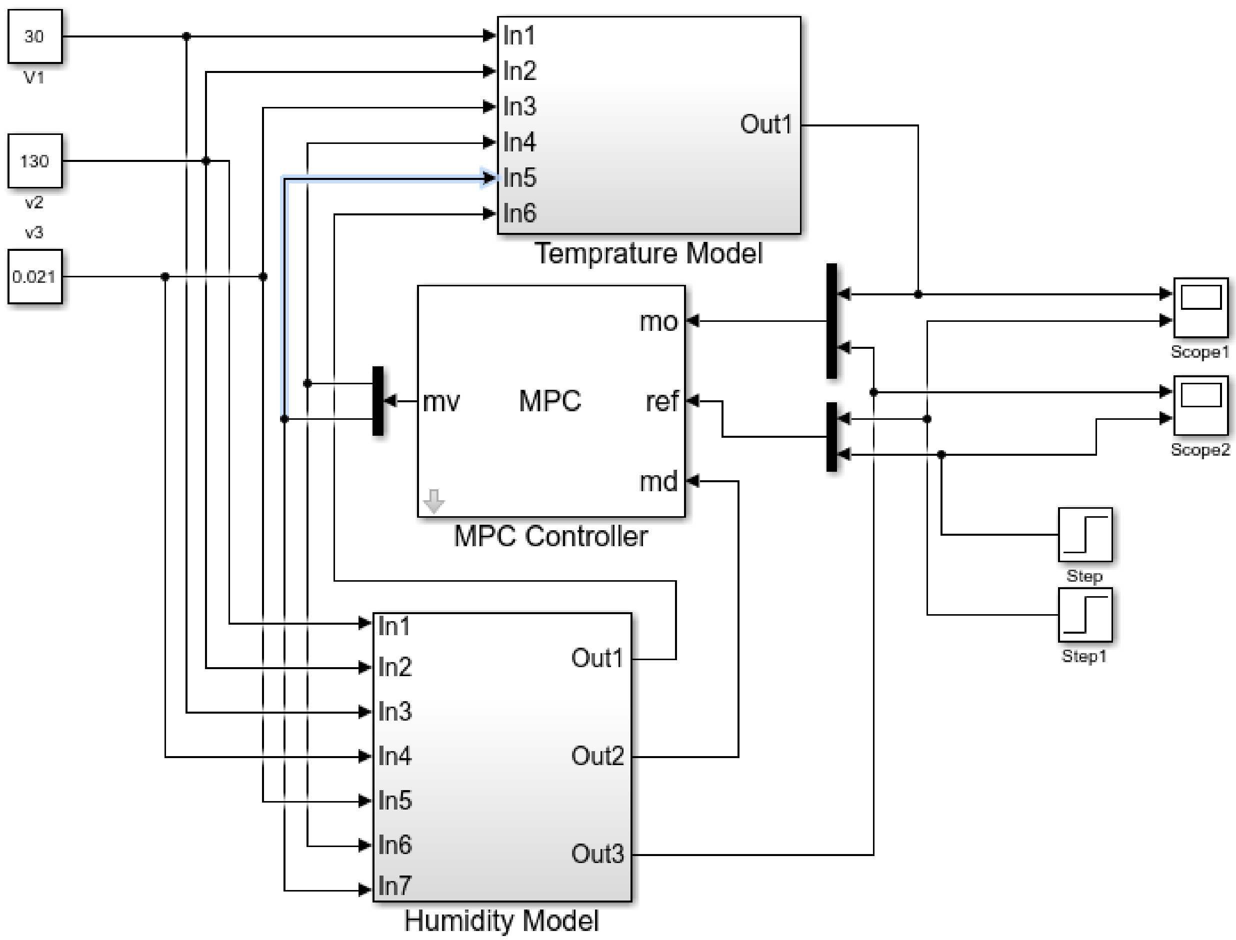

Figure 5.3.Cool weather greenhouse controlling diagram

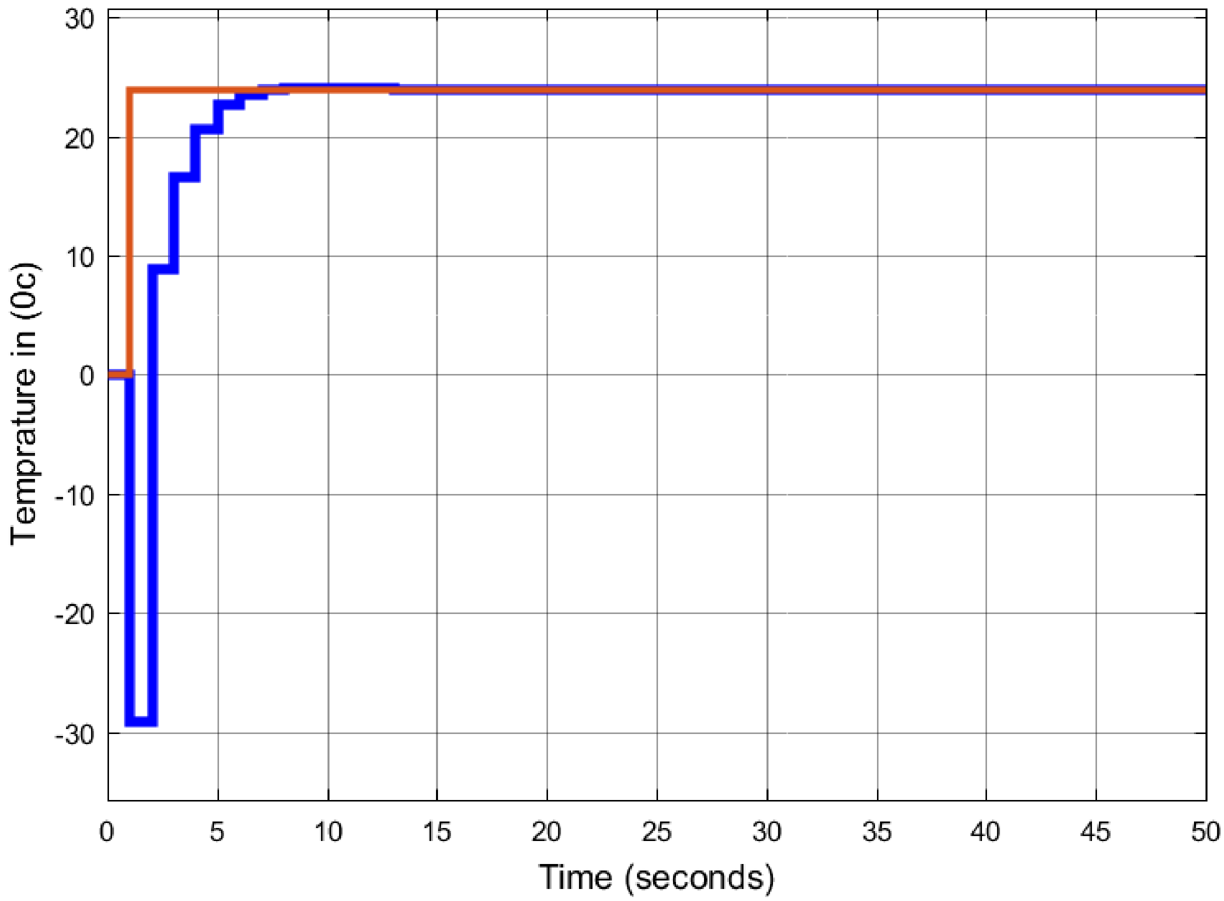

Figure 5.4. Response of the temperature in cool weather

The response of temperature with MPC has the following time domain characteristics in cool weather. These are: Rise time =2.237second, overshoot = 0.505%, steady state error=0 and settling time = 7 second with 24^0c reference (trajectory).

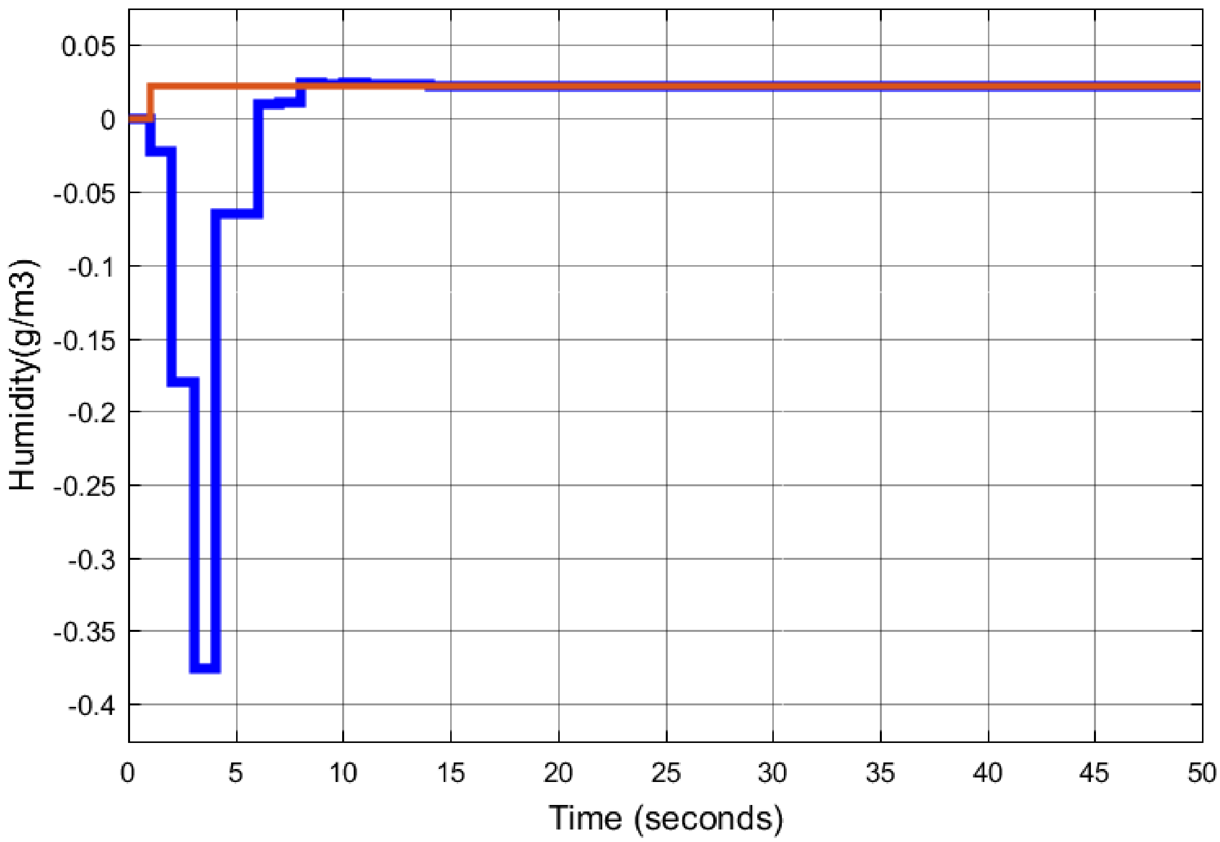

Figure 5.5. Response of the humidity in hot weather

The response of humidity with MPC has the following time domain characteristics Rise time =2.5second, overshoot = 0.505%, steady state error=0 and settling time = 10 second with 0.22 reference trajectory.

5.2.2.Hot Weather Model Response

The MPC controller tuning parameters value after many trial and error are N=95, Nu=8 and Ts=1second with the nominal weight rating of the manipulated variables (input weight) U1=2.517 and U2= 2.51742.

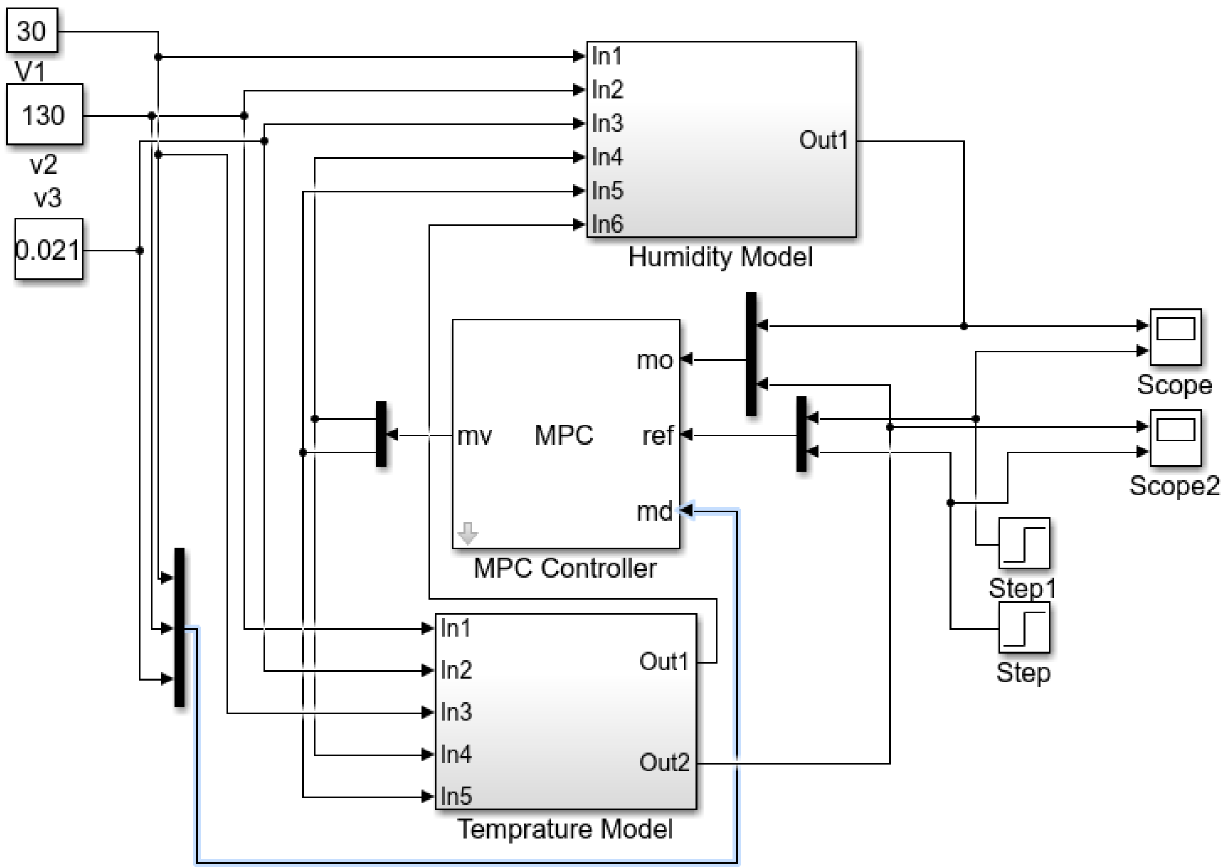

Figure 5.6. Simulink hot weather greenhouse modeling and controlling diagram

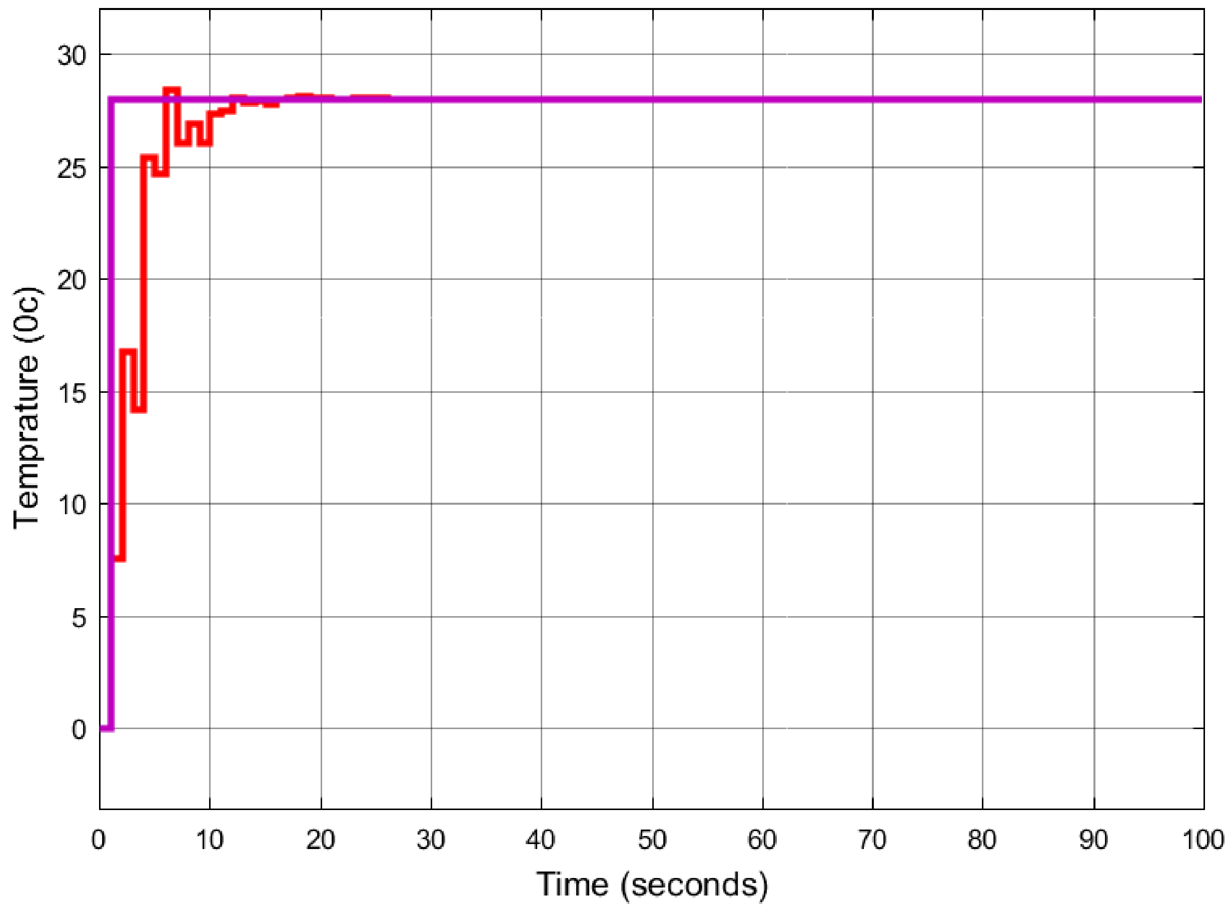

Figure 5.7. Response of temperature in hot weather

From the figure 5.7.the response of temperature with MPC has the following time domain characteristics in hot weather conditions: rise time =5.466second, overshoot = 0.505%, steady state error=0 and settling time = 11 second with 28^0c reference trajectory.

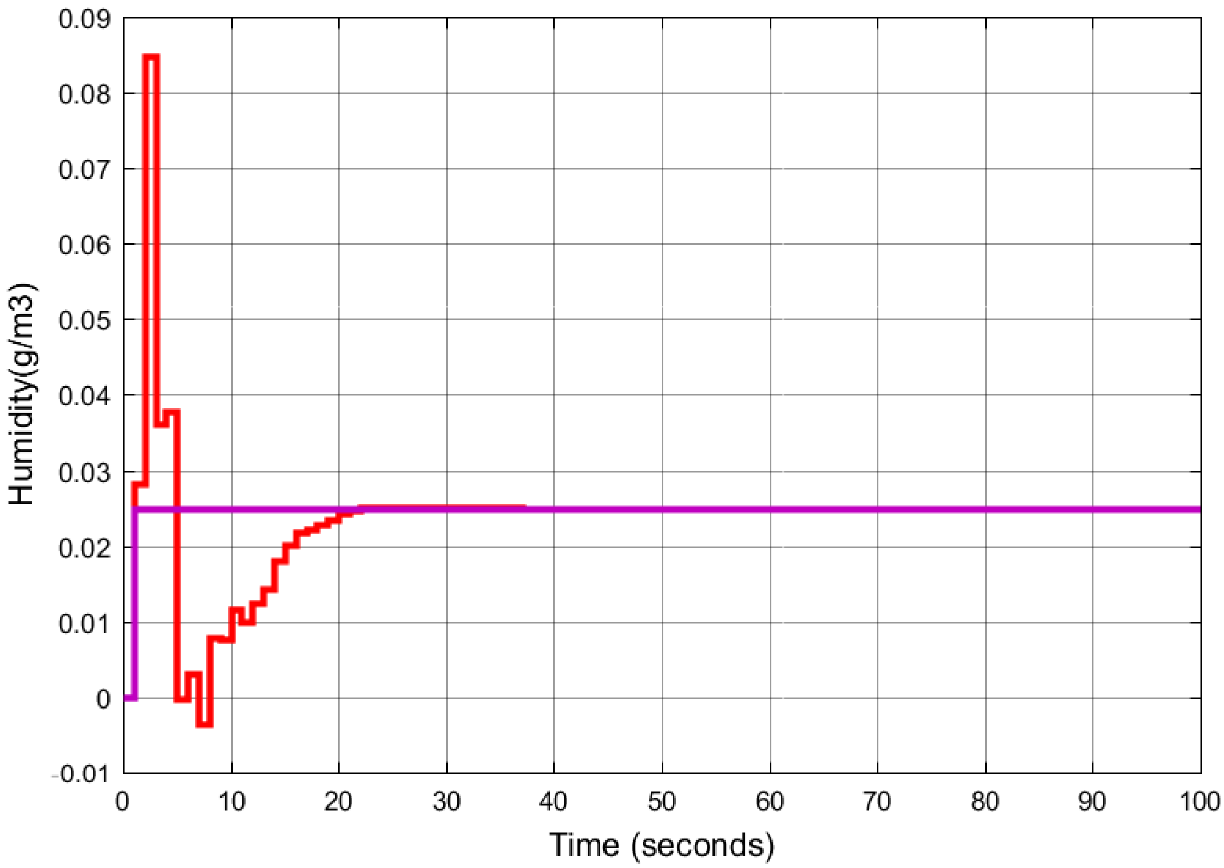

Figure 5.8. Response of humidity in hot weather

The response of humidity with MPC has the following time domain characteristics in hot weather conditions are rise time =0.83916second, overshoot = 0.746%, steady state error=0 and settling time = 22 second with 0.22 reference trajectory.

5.3. Quantitative Comparison of Greenhouse Controlling Methods

Three different control schemes were employed for comparative study of a closed loop feedback greenhouse system. The numerical comparative study elucidates the effectiveness of each controller in targeting and maintaining the desired value. In our simulation based study, TS-fuzzy modelling and control [20] with various parameters showing a delayed response with high rise and settling time while the system overshoot drastically improved to zero in humidity response. The other controller IMC-PI using PSO [29] improves the response time from delayed to moderate as compared to TS fuzzy control. However, it does not contribute much in overshoot reduction for humidity response.

The new proposed system (Fuzzy model based Model predictive control) from figure 5.4., 5.5., 5.7. and 5.8. provides much faster response with no steady state error percentage as compared to the other two controllers but still it has overshoot in humidity response (cool weather) (figure 5.8.). These finding were due to the real time analysis of the greenhouse system. Each controller shows its own merits and demerits in terms of different time domain specification as shown in the table 5.1. But fuzzy model based Model predictive control system have better overall performance. The comparative analysis of the closed loop results along with the time domain characteristics illustrated in Table 5.1. Evidently demonstrates and validates the enhanced efficacy of fuzzy model based Model predictive controller.

Table 5.1. Comparison of proposed system response with previous works

	Temperature				Humidity			
			Hot weather	Cool weather			Hot weather	Cool weather
Performance criterion	TS fuzzy modelling and control	IMC-PI PSO	FMPC (proposed)	FMPC (proposed)	TS fuzzy modelling and control	IMC-PI PSO	FMPC (proposed)	FMPC (proposed)
Rise time(second)	70	24	3.598	2.237	215	18	0.83916	2.5
Settling Time (second)	300	35	16	7	290	27	22	10
Overshoot (%)	1.8518	0.54	1.531	0.505	0	2.24	0.746	0.505

5.4. Overall System Response Using MMPC

The multiple MPC controllers (MMPC) block allows you to control a non-linear plant over a large range of operating points. It is possible to design multiple MPC controllers inside the block, and switch between them in real time using an input switching signal to the block. A controller that initially works well can degrade dramatically if the plant is non-linear and it's operating point changes. In conventional feedback control, you might compensate for non-linear behavior with gain scheduling. Similarly, the MMPC block allows you to transition between multiple MPC controllers in pre-defined ordained manner. Each MPC controller is designed to work well in a particular region. When the plant moves away from this operating point, the control system switches to another MPC controller. The key difference between this block and the standard MPC controller block is the way you designate the controllers to be used. The block contains ordered list of valid MPC object existing in the MATLAB workspace. Each named controller must be designed to use the identical set of plant signals.

For example, same measured outputs and same manipulated variable. Use the knowledge of the process to identify the operating points and design the controllers for the plant.

By designing the controllers for each plant model in the MATLAB workspace, and import the MPC object to the multiple MPC controllers block. After adding the controllers to the MMPC controller's block, determine the switching mechanism for the controllers. Choose one or more measurements from the process to determine when the specific controller is active. This switching signal must round to an integer 1 when the first controller is to be used, to 2 when the second is to be used, and so on. The MMPC block automatically rounds the switching signal to the nearest integer. If the switching signal is less than or equal to zero, or greater than N_c, none of the controllers activates and the block output goes to zero. In general, you will need to use measurement and plant specification information in order to decide on the controller to be used at a given moment. To allow the control system to switch between controllers based on the switching signal when the simulation is running, connect the switching signal to the block's switch import.

The inactive controllers automatically receive the current manipulated variable and measured output signals so they can update their state estimates. This minimizes bumps in controller transitions.

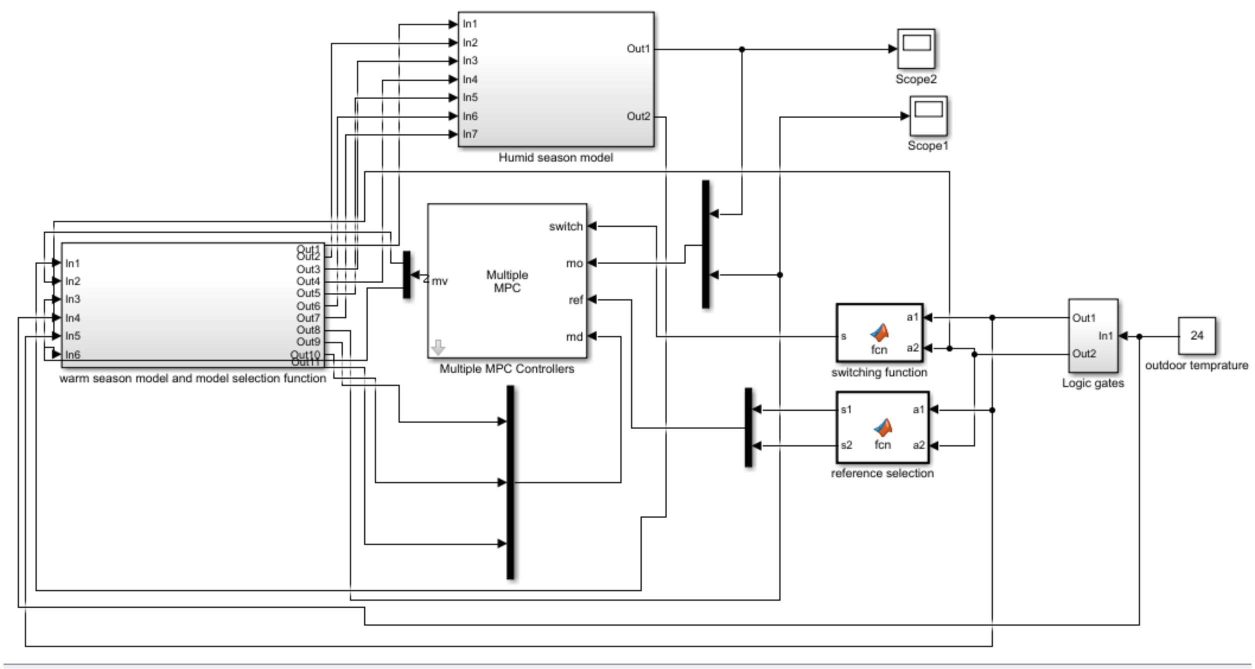

Figure 5.9. Overall Simulink MATLAB model of the system in two seasons

The time domain response of the greenhouse model using multiple MPC have the same result. By using the tuned data gathered from individual MPC controller for both humid and warm season multiple MPC stores those values in two different MPC controller. Then this controller switches the model from humid to warm and vice versa based on the temperature value of the environments. So this controller avoids manual switching from season to season. For this work the temperature value above 26^{o}c considered as warm season and below 26^{o}c could be categorized under humid season. In this season plants having high temperature operating range are assumed. The only merits of this controller is to make the system fully automated.

a. Stability and performance indicators: The stability and performance is evaluated by observing the system responses in the above simulation results and its parameters like overshoot, rise time, settling time, and steady state error (ess). The simulation results show that the FMPC controller have zero steady state with shorter regulating time, and fast recovery from heater flow rate, fog flow rate, ventilation and load disturbance. As it is shown from the results the designed MPC controller is stable.

Table 5.2. Performance indicator parameter values

Performance parameters	Cool weather		Hot weather	
	Temperature	Humidity	Temperature	Humidity
Rise time (second)	2.237	2.5	3.598	0.83916
Settling time (second)	7	10	16	22
Overshot (%)	0.505	0.505	1.531	0.746
Steady state error	0	0	0	0

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

In this work, fuzzy model predictive controller is developed to study the control problems of greenhouse temperature and humidity. The model of the greenhouse system using fuzzy modelling and identification tool has been verified (validated) using VAF value which is the most usual performance index for non-linear modelling using NARX. Based on various performance evaluation criteria Model predictive controller has been compared with Feedforward control, IMC-PI using PSO, fuzzy modelling and control and others.

It is observed that fuzzy modelling is able to minimize the modelling error by more than 20% as compared to linear modelling (ARX). The non-linearity behavior of the greenhouse model increased the difficulty of controller design technique. So, global linearization is mandatory to make the controller mechanism easy. Even though the computational time of MPC is high, the settling time, rise time and steady state error is reduced in both seasons. This significant change (reduction) shows that MPC effectively achieves the desired climate conditions in the greenhouse, which gives the importance of using T-S fuzzy model in the regulation of a very complex process with non-linearity behavior. The performance of fuzzy model predictive controller is found to be better than FFC, FLC and IMC-PI using PSO. Moreover, in terms of practical implementations, FMPC is shown to be useful. The effect of external disturbance in the performance of the controller is investigated using different values of external temperature, humidity and solar radiation. Even in the presence of disturbance, it has seen that FMPC mode control yields better control.

6.2 Recommendation

This research has proposed because of its remarkable values for Ethiopians economy. Currently, greenhouse controlling system uses natural ventilation and manual humidification. Also the reference value of temperature, heating rate, humidity and fogging rate is given by the operator manually. Which have higher probability of exposing to error. This increases labor cost and complexity in the system for the greenhouse. So it is reasonable to advice the horticulture agencies to choice this new technology in order to avoid error, extra labor cost and overloading in managing the system. This design can be extended to future controlling system like:

- Using multi-objective optimization techniques for reducing energy consumption, equipment loss at the same time and increasing the control precision of actuators.
- Controlling the co2 content of the greenhouse
- Practically implementing the research result in the field

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APPENDICES

Appendix A

Modelling of GH in cool weather

This model was generated from 120 data samples. It has 5 inputs and 2 outputs. The sampling period is 1 s. The termination tolerance of the clustering algorithm was 2e-05, and the random initial partition was generated with seed equal to 209871. The output-specific parameters are given in the following table.

Table A.1. Model parameters.

Output	Antecedent	C	M	n_y	n_u
1	1	2	8	{{ [1, 2] [1, 2] },	{{ [15, 16] [15, 16] [15, 16] [15, 16] [15, 16] },
				{ [1, 2] [1, 2] }}	{ [15, 16] [15, 16] [15, 16] [15, 16] [15, 16] }}
2	1	2	8	{{ [1, 2] [1, 2] },	{{ [15, 16] [15, 16] [15, 16] [15, 16] [15, 16] },
				{ [1, 2] [1, 2] }}	{ [15, 16] [15, 16] [15, 16] [15, 16] [15, 16] }}

In the following, the output-specific information is shown for each output. Output1: Rules:

1. **If** is A_{16} **and** $u_2(k-15)$ is A_{17} **and** $u_2(k-16)$ is A_{18} **and** $u_3(k-15)$ is A_{19} **and** $u_3(k-16)$ is A_{110} **and** $u_4(k-15)$ is A_{111} **and** $u_4(k-16)$ is A_{112} **and** $u_5(k-15)$ is A_{113} **and** $u_5(k-16)$ is A_{114} **then** $y_1(k) = -9.0 \cdot 10^{e+2} y_1(k-1) + 7.1 \cdot 10^{e+2} y_1(k-2) - 1.3 \cdot 10^{e+6} y_2(k-1) + 1.8 \cdot 10^{e+6} y_2(k-2) - 3.4 \cdot 10^{e+7} u_1(k-15) + 3.9 \cdot 10^{e+7} u_1(k-16) - 6.3 \cdot 10^{e+2} u_2(k-15) + 1.8 \cdot 10^{e+3} u_2(k-16) - 1.4 \cdot 10^{e+3} u_3(k-15) + 1.5 \cdot 10^{e+3} u_3(k-16) + 1.6 \cdot 10^{e+3} u_4(k-15) - 2.8 \cdot 10^{e+3} u_4(k-16) - 3.6 \cdot 10^{e+6} u_5(k-15) + 4.1 \cdot 10^{e+6} u_5(k-16) + 5.8 \cdot 10^{e+4}$

2. **If** $y_1(k-1)$ is A_{21} **and** $y_1(k-2)$ is A_{22} **and** $y_2(k-1)$ is A_{23} **and** $y_2(k-2)$ is A_{24} **and** $u_1(k-15)$ is A_{25} **and** $u_1(k-16)$ is A_{26} **and** $u_2(k-15)$ is A_{27} **and** $u_2(k-16)$ is A_{28} **and** $u_3(k-15)$ is A_{29} **and** $u_3(k-16)$ is A_{210} **and** $u_4(k-15)$ is A_{211} **and** $u_4(k-16)$ is A_{212} **and** $u_5(k-15)$ is A_{213} **and** $u_5(k-16)$ is A_{214} **then** $y_1(k) = 9.0 \cdot 10^{e+2} y_1(k-1) - 7.1 \cdot 10^{e+2} y_1(k-2) + 1.3 \cdot 10^{e+6} y_2(k-1) - 1.8 \cdot 10^{e+6} y_2(k-2) + 3.4 \cdot 10^{e+7} u_1(k-15) - 3.9 \cdot 10^{e+7} u_1(k-16) + 6.3 \cdot 10^{e+2} u_2(k-15) - 1.8 \cdot 10^{e+3} u_2(k-16) + 1.4 \cdot 10^{e+3} u_3(k-15) - 1.5 \cdot 10^{e+3} u_3(k-16) - 1.6 \cdot 10^{e+3} u_4(k-15) + 2.8 \cdot 10^{e+3} u_4(k-16) + 3.6 \cdot 10^{e+6} u_5(k-15) - 4.1 \cdot 10^{e+6} u_5(k-16) - 5.8 \cdot 10^{e+4}$

Table A.2. Consequent parameters.

Rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-15)$	$u_1(k-16)$	$u_2(k-15)$
1	$-9.0 \cdot 10^{e+2}$	$7.1 \cdot 10^{e+2}$	$-1.3 \cdot 10^{e+6}$	$1.8 \cdot 10^{e+6}$	$-3.4 \cdot 10^{e+7}$	$3.9 \cdot 10^{e+7}$	$-6.3 \cdot 10^{e+2}$
2	$9.0 \cdot 10^{e+2}$	$-7.1 \cdot 10^{e+2}$	$1.3 \cdot 10^{e+6}$	$-1.8 \cdot 10^{e+6}$	$3.4 \cdot 10^{e+7}$	$-3.9 \cdot 10^{e+7}$	$6.3 \cdot 10^{e+2}$

$u_2(k-16)$	$u_3(k-15)$	$u_3(k-16)$	$u_4(k-15)$	$u_4(k-16)$	$u_5(k-15)$	$u_5(k-16)$	Offset
$1.8 \cdot 10^{e+3}$	$-1.4 \cdot 10^{e+3}$	$1.5 \cdot 10^{e+3}$	$1.6 \cdot 10^{e+3}$	$-2.8 \cdot 10^{e+3}$	$-3.6 \cdot 10^{e+6}$	$4.1 \cdot 10^{e+6}$	$5.8 \cdot 10^{e+4}$
$-1.8 \cdot 10^{e+3}$	$1.4 \cdot 10^{e+3}$	$-1.5 \cdot 10^{e+3}$	$-1.6 \cdot 10^{e+3}$	$2.8 \cdot 10^{e+3}$	$3.6 \cdot 10^{e+6}$	$-4.1 \cdot 10^{e+6}$	$-5.8 \cdot 10^{e+4}$

Output2:

Table A.3. Cluster centers.

Rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-15)$	$u_1(k-16)$	$u_2(k-15)$	$u_2(k-16)$
1	$2.8 \cdot 10^{e+1}$	$2.8 \cdot 10^{e+1}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-4}$	$1.7 \cdot 10^{e-4}$	$5.8 \cdot 10^{e+1}$	$5.8 \cdot 10^{e+1}$
2	$2.8 \cdot 10^{e+1}$	$2.8 \cdot 10^{e+1}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-4}$	$1.7 \cdot 10^{e-4}$	$5.8 \cdot 10^{e+1}$	$5.8 \cdot 10^{e+1}$

$u_3(k-15)$	$u_3(k-16)$	$u_4(k-15)$	$u_4(k-16)$	$u_5(k-15)$	$u_5(k-16)$
$1.5 \cdot 10^{e+1}$	$1.4 \cdot 10^{e+1}$	$1.1 \cdot 10^{e+2}$	$1.1 \cdot 10^{e+2}$	$1.9 \cdot 10^{e-2}$	$1.9 \cdot 10^{e-2}$
$1.5 \cdot 10^{e+1}$	$1.4 \cdot 10^{e+1}$	$1.1 \cdot 10^{e+2}$	$1.1 \cdot 10^{e+2}$	$1.9 \cdot 10^{e-2}$	$1.9 \cdot 10^{e-2}$

Rules:

1. **If** $y_1(k-1)$ is A_{11} **and** $y_1(k-2)$ is A_{12} **and** $y_2(k-1)$ is A_{13} **and** $y_2(k-2)$ is A_{14} **and** $u_1(k-15)$ is A_{15} **and** $u_1(k-16)$ is A_{16} **and** $u_2(k-15)$ is A_{17} **and** $u_2(k-16)$ is A_{18} **and** $u_3(k-15)$ is A_{19} **and** $u_3(k-16)$ is A_{110} **and** $u_4(k-15)$ is A_{111} **and** $u_4(k-16)$ is A_{112} **and** $u_5(k-15)$ is A_{113} **and** $u_5(k-16)$ is A_{114} **then** $y_2(k) = 4.2 \cdot 10^{e+}y_1(k-1) - 4.3 \cdot 10^{e+}y_1(k-2) + 4.4 \cdot 10^{e+3}y_2(k-1) - 4.9 \cdot 10^{e+3}y_2(k-2) + 4.2 \cdot 10^{e+4}u_1(k-15) - 4.2 \cdot 10^{e+4}u_1(k-16) - 1.3 \cdot 10^{e+}u_2(k-15) - 2.2 \cdot 10^{e-1}u_2(k-16) + 4.8 \cdot 10^{e+}u_3(k-15) - 5.1 \cdot 10^{e+}u_3(k-16) + 5.7 \cdot 10^{e-1}u_4(k-15) + 1.4 \cdot 10^{e+}u_4(k-16) + 4.6 \cdot 10^{e+3}u_5(k-15) - 4.4 \cdot 10^{e+3}u_5(k-16) - 1.2 \cdot 10^{e+2}$

2. **If** $y_1(k-1)$ is A_{21} **and** $y_1(k-2)$ is A_{22} **and** $y_2(k-1)$ is A_{23} **and** $y_2(k-2)$ is A_{24} **and** $u_1(k-15)$ is A_{25} **and** $u_1(k-16)$ is A_{26} **and** $u_2(k-15)$ is A_{27} **and** $u_2(k-16)$ is A_{28} **and** $u_3(k-15)$ is A_{29} **and** $u_3(k-16)$ is A_{210} **and** $u_4(k-15)$ is A_{211} **and** $u_4(k-16)$ is A_{212} **and** $u_5(k-15)$ is A_{213} **and** $u_5(k-16)$ is A_{214} **then** $y_2(k) = -4.2 \cdot 10^{e+}y_1(k-1) + 4.3 \cdot 10^{e+}y_1(k-2) - 4.4 \cdot 10^{e+3}y_2(k-1) + 4.9 \cdot 10^{e+3}y_2(k-2) - 4.2 \cdot 10^{e+4}u_1(k-15) + 4.2 \cdot 10^{e+4}u_1(k-16) + 1.3 \cdot 10^{e+}u_2(k-15) + 2.2 \cdot 10^{e-1}u_2(k-16) - 4.8 \cdot 10^{e+}u_3(k-15) + 5.1 \cdot 10^{e+}u_3(k-16) - 5.7 \cdot 10^{e-1}u_4(k-15) - 1.4 \cdot 10^{e+}u_4(k-16) - 4.6 \cdot 10^{e+3}u_5(k-15) + 4.4 \cdot 10^{e+3}u_5(k-16) + 1.2 \cdot 10^{e+2}$

Table A.4. Consequent parameters.

Rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-15)$	$u_1(k-16)$	$u_2(k-15)$
1	$4.2 \cdot 10^{e+}$	$-4.3 \cdot 10^{e+}$	$4.4 \cdot 10^{e+3}$	$-4.9 \cdot 10^{e+3}$	$4.2 \cdot 10^{e+4}$	$-4.2 \cdot 10^{e+4}$	$-1.3 \cdot 10^{e+}$
2	$-4.2 \cdot 10^{e+}$	$4.3 \cdot 10^{e+}$	$-4.4 \cdot 10^{e+3}$	$4.9 \cdot 10^{e+3}$	$-4.2 \cdot 10^{e+4}$	$4.2 \cdot 10^{e+4}$	$1.3 \cdot 10^{e+}$

$u_2(k-16)$	$u_3(k-15)$	$u_3(k-16)$	$u_4(k-15)$	$u_4(k-16)$	$u_5(k-15)$	$u_5(k-16)$	Offset
$-2.2 \cdot 10^{e-1}$	$4.8 \cdot 10^{e+}$	$-5.1 \cdot 10^{e+}$	$5.7 \cdot 10^{e-1}$	$1.4 \cdot 10^{e+}$	$4.6 \cdot 10^{e+3}$	$-4.4 \cdot 10^{e+3}$	$-1.2 \cdot 10^{e+2}$
$2.2 \cdot 10^{e-1}$	$-4.8 \cdot 10^{e+}$	$5.1 \cdot 10^{e+}$	$-5.7 \cdot 10^{e-1}$	$-1.4 \cdot 10^{e+}$	$-4.6 \cdot 10^{e+3}$	$4.4 \cdot 10^{e+3}$	$1.2 \cdot 10^{e+2}$

Table A.5. Cluster centers.

Rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-15)$	$u_1(k-16)$	$u_2(k-15)$
1	$2.8 \cdot 10^{e+1}$	$2.8 \cdot 10^{e+1}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-4}$	$1.7 \cdot 10^{e-4}$	$5.8 \cdot 10^{e+1}$
2	$2.8 \cdot 10^{e+1}$	$2.8 \cdot 10^{e+1}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-4}$	$1.7 \cdot 10^{e-4}$	$5.8 \cdot 10^{e+1}$

$u_2(k-16)$	$u_3(k-15)$	$u_3(k-16)$	$u_4(k-15)$	$u_4(k-16)$	$u_5(k-15)$	$u_5(k-16)$
$5.8 \cdot 10^{e+1}$	$1.5 \cdot 10^{e+1}$	$1.4 \cdot 10^{e+1}$	$1.1 \cdot 10^{e+2}$	$1.1 \cdot 10^{e+2}$	$1.9 \cdot 10^{e-2}$	$1.9 \cdot 10^{e-2}$
$5.8 \cdot 10^{e+1}$	$1.5 \cdot 10^{e+1}$	$1.4 \cdot 10^{e+1}$	$1.1 \cdot 10^{e+2}$	$1.1 \cdot 10^{e+2}$	$1.9 \cdot 10^{e-2}$	$1.9 \cdot 10^{e-2}$

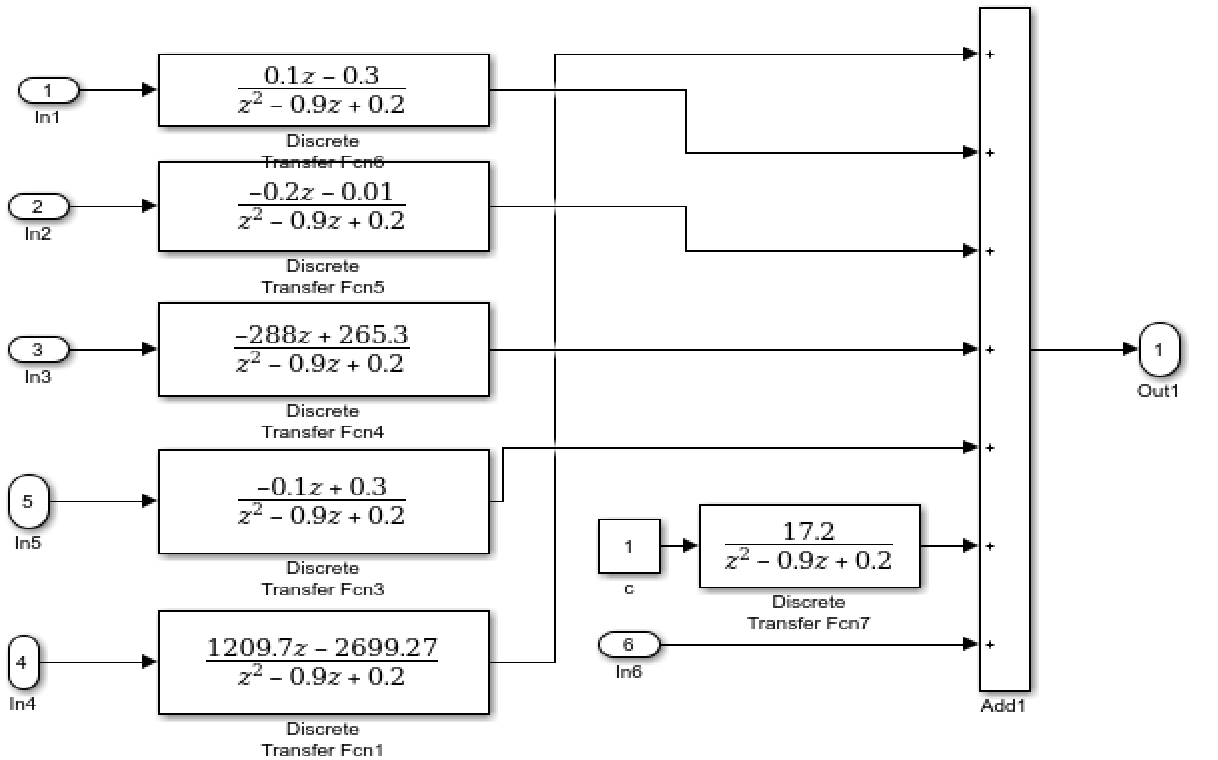

Figure A.1 Cool weather controlling diagram of temperature model in Fig 5.3.

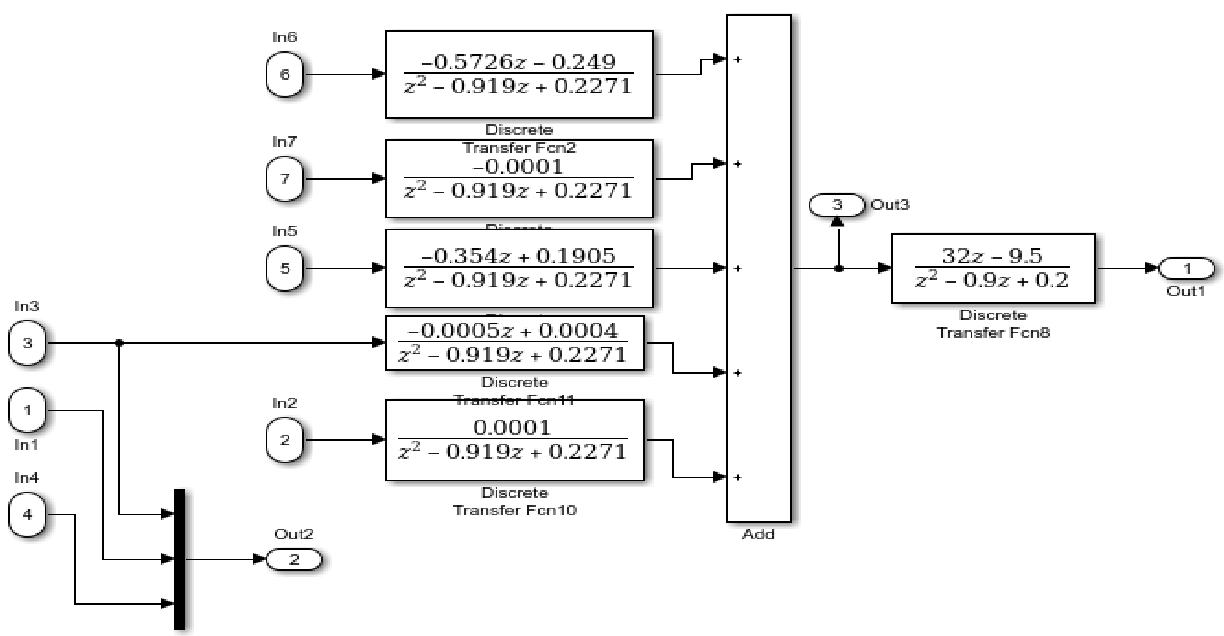

Figure A.2 Cool weather controlling diagram of humidity model in Fig 5.3.

Appendix B

Modelling of GH in hot weather

This model was generated on 3-9-2018 from 120 data samples. It has 5 inputs and 2 outputs. The sampling period is 1 s. The termination tolerance of the clustering algorithm was 2e-05, and the random initial partition was generated with seed equal to 210216. The output-specific parameters are given in the following table.

Table B.1. Model parameters.

Output	Antecedent	c	m	n_y	n_u
1	1	2	6	{{ [1, 2] [1, 2] }, { [1, 2] [1, 2] }}	{{ [17, 18] [17, 18] [17, 18] [17, 18] [17, 18] }, { [17, 18] [17, 18] [17, 18] [17, 18] [17, 18] }}
2	1	2	6	{{ [1, 2] [1, 2] }, 4. { [1, 2] [1, 2] }}	{{ [17] [ ] [17, 18, 19] [ ] [17, 18, 19] }, { [17] [ ] [17, 18, 19] [ ] [17, 18, 19] }}

In the following, the output-specific information is shown for each output. Output1: Rules:

1. **If** $y_1(k-1)$ is A_{11} **and** $y_1(k-2)$ is A_{12} **and** $y_2(k-1)$ is A_{13} **and** $y_2(k-2)$ is A_{14} **and** $u_1(k-17)$ is A_{15} **and** $u_1(k-18)$ is A_{16} **and** $u_2(k-17)$ is A_{17} **and** $u_2(k-18)$ is A_{18} **and** $u_3(k-17)$ is A_{19} **and** $u_3(k-18)$ is A_{110} **and** $u_4(k-17)$ is A_{111} **and** $u_4(k-18)$ is A_{112} **and** $u_5(k-17)$ is A_{113} **and** $u_5(k-18)$ is A_{114} **then** $y_1(k) = -7.2 \cdot 10^{e-1} y_1(k-1) + 1.7 \cdot 10^{e+} y_1(k-2) - 1.3 \cdot 10^{e+4} y_2(k-1) + 7.4 \cdot 10^{e+3} y_2(k-2) - 1.1 \cdot 10^{e+3} u_1(k-17) - 7.1 \cdot 10^{e+3} u_1(k-18) - 1.6 \cdot 10^{e+3} u_2(k-17) + 1.4 \cdot 10^{e+4} u_2(k-18) - 3.1 \cdot 10^{e+} u_3(k-17) + 5.4 \cdot 10^{e+} u_3(k-18) + 1.2 \cdot 10^{e+} u_4(k-17) - 2.6 \cdot 10^{e+} u_4(k-18) - 2.3 \cdot 10^{e+1} u_5(k-17) - 6.7 \cdot 10^{e+3} u_5(k-18) + 4.2 \cdot 10^{e+2}$

2. **If** $y_1(k-1)$ is A_{21} **and** $y_1(k-2)$ is A_{22} **and** $y_2(k-1)$ is A_{23} **and** $y_2(k-2)$ is A_{24} **and** $u_1(k-17)$ is A_{25} **and** $u_1(k-18)$ is A_{26} **and** $u_2(k-17)$ is A_{27} **and** $u_2(k-18)$ is A_{28} **and** $u_3(k-17)$ is A_{29} **and** $u_3(k-18)$ is A_{210} **and** $u_4(k-17)$ is A_{211} **and** $u_4(k-18)$ is A_{212} **and** $u_5(k-17)$ is A_{213} **and** $u_5(k-18)$ is A_{214} **then** $y_1(k) = 8.4 \cdot 10^{e-1} y_1(k-1) - 2.4 \cdot 10^{e+} y_1(k-2) + 1.7 \cdot 10^{e+4} y_2(k-1) - 8.7 \cdot 10^{e+3} y_2(k-2) + 2.0 \cdot 10^{e+2} u_1(k-17) + 7.1 \cdot 10^{e+3} u_1(k-18) + 1.4 \cdot 10^{e+3} u_2(k-17) - 1.2 \cdot 10^{e+4} u_2(k-18) + 3.3 \cdot 10^{e+} u_3(k-17) - 3.9 \cdot 10^{e+} u_3(k-18) - 6.3 \cdot 10^{e-1} u_4(k-17) + 2.0 \cdot 10^{e+} u_4(k-18) - 4.8 \cdot 10^{e+2} u_5(k-17) + 1.6 \cdot 10^{e+4} u_5(k-18) - 7.0 \cdot 10^{e+2}$

Table B.2. Consequent parameters.

rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-17)$	$u_1(k-18)$	$u_2(k-17)$
1	$-7.2 \cdot 10^{e-1}$	$1.7 \cdot 10^{e+}$	$-1.3 \cdot 10^{e+4}$	$7.4 \cdot 10^{e+3}$	$-1.1 \cdot 10^{e+3}$	$-7.1 \cdot 10^{e+3}$	$-1.6 \cdot 10^{e+3}$
2	$8.4 \cdot 10^{e-1}$	$-2.4 \cdot 10^{e+}$	$1.7 \cdot 10^{e+4}$	$-8.7 \cdot 10^{e+3}$	$2.0 \cdot 10^{e+2}$	$7.1 \cdot 10^{e+3}$	$1.4 \cdot 10^{e+3}$

$u_2(k-18)$	$u_3(k-17)$	$u_3(k-18)$	$u_4(k-17)$	$u_4(k-18)$	$u_5(k-17)$	$u_5(k-18)$	Offset
$1.4 \cdot 10^{e+4}$	$-3.1 \cdot 10^{e+}$	$5.4 \cdot 10^{e+}$	$1.2 \cdot 10^{e+}$	$-2.6 \cdot 10^{e+}$	$-2.3 \cdot 10^{e+1}$	$-6.7 \cdot 10^{e+3}$	$4.2 \cdot 10^{e+2}$
$-1.2 \cdot 10^{e+4}$	$3.3 \cdot 10^{e+}$	$-3.9 \cdot 10^{e+}$	$-6.3 \cdot 10^{e-1}$	$2.0 \cdot 10^{e+}$	$-4.8 \cdot 10^{e+2}$	$1.6 \cdot 10^{e+4}$	$-7.0 \cdot 10^{e+2}$

Output2: Rules:

1. **If** $y_1(k-1)$ is A_{11} **and** $y_1(k-2)$ is A_{12} **and** $y_2(k-1)$ is A_{13} **and** $y_2(k-2)$ is A_{14} **and** $u_1(k-17)$ is A_{15} **and** $u_3(k-17)$ is A_{16} **and** $u_3(k-18)$ is A_{17} **and** $u_3(k-19)$ is A_{18} **and** $u_5(k-17)$ is A_{19} **and** $u_5(k-18)$ is A_{110} **and** $u_5(k-19)$ is A_{111} **then**

$y_2(k) = 2.7 \cdot 10^{e-4} y_1(k-1) - 3.1 \cdot 10^{e-4} y_1(k-2) + 1.7 \cdot 10^{e-1} y_2(k-1) - 1.7 \cdot 10^{e-1} y_2(k-2) - 1.4 \cdot 10^{e-1} u_1(k-17) + 1.0 \cdot 10^{e-4} u_3(k-17) - 8.6 \cdot 10^{e-4} u_3(k-18) + 4.6 \cdot 10^{e-4} u_3(k-19) - 1.5 \cdot 10^{e+} u_5(k-17) - 2.6 \cdot 10^{e-1} u_5(k-18) + 8.9 \cdot 10^{e-1} u_5(k-19) + 5.2 \cdot 10^{e-2}$

2. **If** $y_1(k-1)$ is A_{21} **and** $y_1(k-2)$ is A_{22} **and** $y_2(k-1)$ is A_{23} **and** $y_2(k-2)$ is A_{24} **and** $u_1(k-17)$ is A_{25} **and** $u_3(k-17)$ is A_{26} **and** $u_3(k-18)$ is A_{27} **and** $u_3(k-19)$ is A_{28} **and** $u_5(k-17)$ is A_{29} **and** $u_5(k-18)$ is A_{210} **and** $u_5(k-19)$ is A_{211} **then**

$y_2(k) = -2.9 \cdot 10^{e-4} y_1(k-1) + 3.4 \cdot 10^{e-4} y_1(k-2) + 1.3 \cdot 10^{e+} y_2(k-1) - 2.5 \cdot 10^{e-1} y_2(k-2) + 5.7 \cdot 10^{e-2} u_1(k-17) - 6.1 \cdot 10^{e-5} u_3(k-17) + 6.7 \cdot 10^{e-4} u_3(k-18) - 2.3 \cdot 10^{e-4} u_3(k-19) + 7.3 \cdot 10^{e-1} u_5(k-17) - 1.3 \cdot 10^{e-1} u_5(k-18) - 4.1 \cdot 10^{e-1} u_5(k-19) - 1.9 \cdot 10^{e-2}$

Table B.3. Cluster centers.

rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-17)$	$u_1(k-18)$	$u_2(k-17)$
1	$8.7 \cdot 10^{e+}$	$9.9 \cdot 10^{e+}$	$2.7 \cdot 10^{e-2}$	$2.6 \cdot 10^{e-2}$	$2.5 \cdot 10^{e-3}$	$2.3 \cdot 10^{e-3}$	$1.8 \cdot 10^{e-3}$
2	$2.9 \cdot 10^{e+1}$	$2.9 \cdot 10^{e+1}$	$1.8 \cdot 10^{e-2}$	$1.9 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.3 \cdot 10^{e-2}$	$1.1 \cdot 10^{e-2}$

$u_2(k-18)$	$u_3(k-17)$	$u_3(k-18)$	$u_4(k-17)$	$u_4(k-18)$	$u_5(k-17)$	$u_5(k-18)$
$1.7 \cdot 10^{e-3}$	$3.8 \cdot 10^{e+1}$	$3.8 \cdot 10^{e+1}$	$1.8 \cdot 10^{e+2}$	$1.8 \cdot 10^{e+2}$	$1.4 \cdot 10^{e-2}$	$1.4 \cdot 10^{e-2}$
$9.6 \cdot 10^{e-3}$	$2.8 \cdot 10^{e+1}$	$2.8 \cdot 10^{e+1}$	$1.4 \cdot 10^{e+2}$	$1.5 \cdot 10^{e+2}$	$2.6 \cdot 10^{e-2}$	$2.6 \cdot 10^{e-2}$

Table B.4. Consequent parameters.

rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-17)$	$u_3(k-17)$
1	$2.7 \cdot 10^{e-4}$	$-3.1 \cdot 10^{e-4}$	$1.7 \cdot 10^{e-1}$	$-1.7 \cdot 10^{e-1}$	$-1.4 \cdot 10^{e-1}$	$1.0 \cdot 10^{e-4}$
2	$-2.9 \cdot 10^{e-4}$	$3.4 \cdot 10^{e-4}$	$1.3 \cdot 10^{e+}$	$-2.5 \cdot 10^{e-1}$	$5.7 \cdot 10^{e-2}$	$-6.1 \cdot 10^{e-5}$

$u_3(k-18)$	$u_3(k-19)$	$u_5(k-17)$	$u_5(k-18)$	$u_5(k-19)$	Offset
$-8.6 \cdot 10^{e-4}$	$4.6 \cdot 10^{e-4}$	$-1.5 \cdot 10^{e+}$	$-2.6 \cdot 10^{e-1}$	$8.9 \cdot 10^{e-1}$	$5.2 \cdot 10^{e-2}$
$6.7 \cdot 10^{e-4}$	$-2.3 \cdot 10^{e-4}$	$7.3 \cdot 10^{e-1}$	$-1.3 \cdot 10^{e-1}$	$-4.1 \cdot 10^{e-1}$	$-1.9 \cdot 10^{e-2}$

Table B.5. Cluster centers.

rule	$y_1(k-1)$	$y_1(k-2)$	$y_2(k-1)$	$y_2(k-2)$	$u_1(k-17)$	$u_3(k-17)$	$u_3(k-18)$
1	$1.2 \cdot 10^{e+1}$	$1.2 \cdot 10^{e+1}$	$2.5 \cdot 10^{e-2}$	$2.5 \cdot 10^{e-2}$	$4.2 \cdot 10^{e-3}$	$3.5 \cdot 10^{e+1}$	$3.5 \cdot 10^{e+1}$
2	$2.1 \cdot 10^{e+1}$	$2.1 \cdot 10^{e+1}$	$2.3 \cdot 10^{e-2}$	$2.2 \cdot 10^{e-2}$	$9.4 \cdot 10^{e-3}$	$3.3 \cdot 10^{e+1}$	$3.3 \cdot 10^{e+1}$

$u_3(k-19)$	$u_5(k-17)$	$u_5(k-18)$	$u_5(k-19)$
$3.6 \cdot 10^{e+1}$	$1.7 \cdot 10^{e-2}$	$1.7 \cdot 10^{e-2}$	$1.6 \cdot 10^{e-2}$
$3.3 \cdot 10^{e+1}$	$2.0 \cdot 10^{e-2}$	$2.1 \cdot 10^{e-2}$	$2.1 \cdot 10^{e-2}$

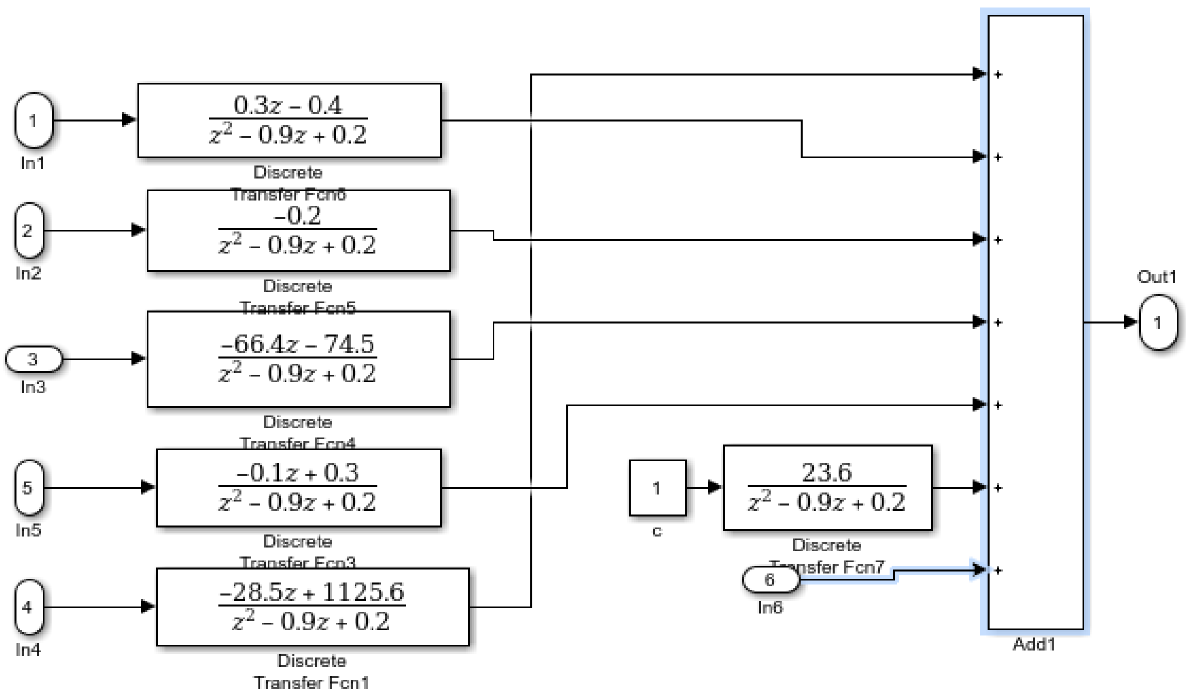

Figure B.1 Hot weather controlling diagram of temperature model in Fig 5.6

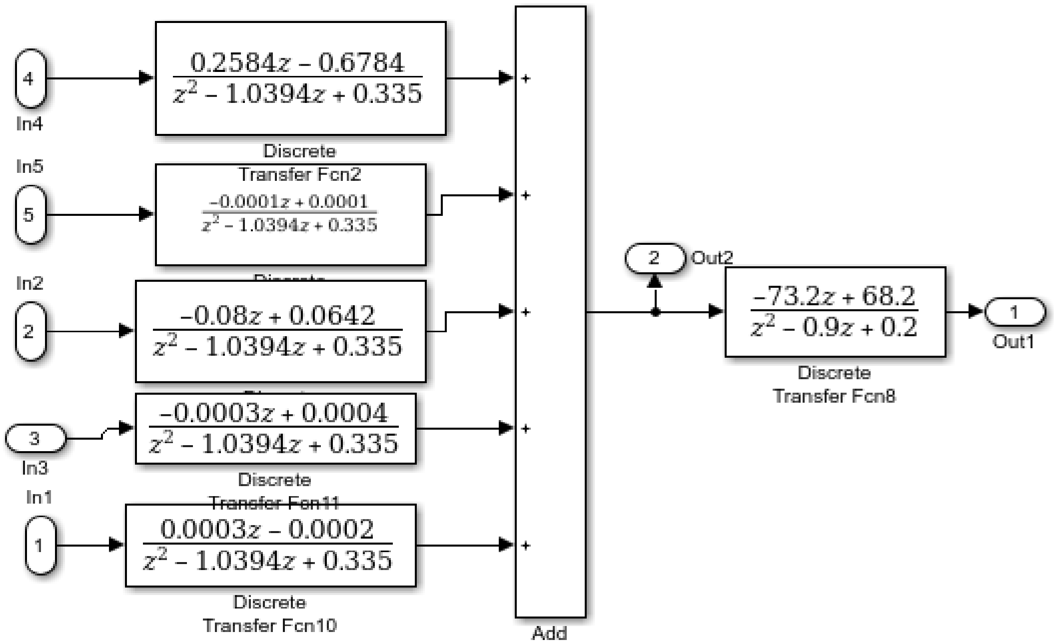

Figure B.2 Hot weather controlling diagram of humidity model in Fig 5.6.

Appendix c

Fuzzy modelling and Identification Mat lab Code

Cool weather greenhouse model

To construct the fuzzy model, the identification data set is first loaded and the structural parameters of the model are defined:

```
clear FM

% generate a fuzzy model for greenhouse system

% define constants
c = [2 2];         % n umber of clusters
m = 8;        % fuzziness parameter
tol = 0.00002;     % termination criterion
Ts = 2;       % sample time [s]
FMtype = [1 1];     % type of fuzzy model:  1 - product-space MFS
                     %           2 - projected MFS
Ny=[2 2;2 2];
Nu=[2 2 2 2 2;2 2 2 2 2];
Nd=[15 15 15 15 15;15 15 15 15 15];% transport delays
             % (set to 1 for y(k+1) = f(u(k),....))
% identification data
% input=u;
% output=y;
% validation data
load 120data;
Dat.U = 120data(:,1:5);
Dat.Y = 120data(:,6:7);
Dat.Ts = 1;          % sample time [s]
% validation data
load 100valdata;
ue = 100valdata(:,1:5);
ye = 100valdata(:,6:7);
% make fuzzy model by means of fuzzy clustering
FM.c = c; FM.m = m; FM.ante = FMtype; FM.tol = tol;
FM.Ny = Ny; FM.Nu = Nu; FM.Nd = Nd;
FM.inputname={'Ventilation rate';'Heater flow rate';'intercepted solar radiant energy';'outside temprature';'outside humidity'};
FM.outputname={'Inside temprature';'Inside Humidity'};
```

```
[FM,Part] = fmclust(Dat,FM);
% simulate the fuzzy model for validation data
 [ym,VAF,dof,yl,ylm] = fmsim(ue,ye,FM,[],[],2); VAF
%[FM,dof]=fmest(FM,Dat,out)
fm2tex(FM,'fuzzymodel5')
grid on
```

Hot weather greenhouse modelling MATLAB code

```
clear FM
% generate a fuzzy model for greenhouse system
% define constants
c = [2 2];          % n umber of clusters
m = 8;        % fuzziness parameter
tol = 0.00002;     % termination criterion
Ts = 2;       % sample time [s]
FMtype = [1 1];     % type of fuzzy model:  1 - product-space MFS
                              %          2 - projected MFS
Ny=[2 2;2 2];
Nu=[2 2 2 2 2;2 1 3 0 3];
Nd=[17 17 17 17 17;17 17 17 17 17];% transport delays
               % (set to 1 for y(k+1) = f(u(k),....))
% identification data
% input=u;
% output=y;
% validation data
load 120data;
Dat.U = 120data(:,1:5);
Dat.Y = 120data(:,6:7);
Dat.Ts = 1;          % sample time [s]
% validation data
load 100valdata;
ue = 100valdata(:,1:5);
ye = 100valdata(:,6:7);
% make fuzzy model by means of fuzzy clustering
FM.c = c; FM.m = m; FM.ante = FMtype; FM.tol = tol;
FM.Ny = Ny; FM.Nu = Nu; FM.Nd = Nd;
FM.inputname={'Ventilation rate';'fogging flow rate';'intercepted solar radiant energy';'outside
temprature';'outside humidity'};
FM.outputname={'Inside temprature';'Inside Humidity'};
[FM,Part] = fmclust(Dat,FM);

% simulate the fuzzy model for validation data
 [ym,VAF,dof,yl,ylm] = fmsim(ue,ye,FM,[],[],2); VAF
%[FM,dof]=fmest(FM,Dat,out)
fm2tex(FM,'fuzzymodel5')
grid on
```