Research proposal

Adaptive Fuzzy Control of Nitriding Furnace

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# TABLE OF CONTENTS

**TABLE OF CONTENTS** .................................................................................................................................................................1

**INTRODUCTION** ............................................................................................................................................................................2

**LITERATURE REVIEW** .......................................................................................................................................................................3

- Temperature Control in Heat Treatment Furnaces .....................................................................................................................3
- Adaptive Fuzzy Control .......................................................................................................................................................................14
  - Adaptation of Scaling Factors ..........................................................................................................................................................14
  - Adaptation of FIS Parameters ......................................................................................................................................................15
  - Adaptation of Rules ......................................................................................................................................................................15
- Direct and Indirect Adaptive Fuzzy Model Based Control ........................................................................................................16
- Fuzzy Adaptive Model Predictive Control ..................................................................................................................................16
- The Sugeno Fuzzy Model .................................................................................................................................................................18
- Genetic Fuzzy Systems (GFS) ............................................................................................................................................................19
- Summary of Literature Review .......................................................................................................................................................21

**RESEARCH METHODOLOGY** ...........................................................................................................................................................23

- Problem Definition ...........................................................................................................................................................................23
- Suggested Methodology ....................................................................................................................................................................25
  - Furnace Predictive Fuzzy model ..................................................................................................................................................26
  - Validation .....................................................................................................................................................................................31
  - Rule generation ............................................................................................................................................................................31
  - Parameter optimization ...............................................................................................................................................................31
- Conclusion .......................................................................................................................................................................................31
  - Contribution ................................................................................................................................................................................33
  - Time chart ..................................................................................................................................................................................33

**REFERENCES** ..................................................................................................................................................................................34
Introduction

NITREX is a leading company in modern surface treatment of metal and an equipment manufacturer. NITREX Metal specializes in providing solutions to whose product manufacturing process involves heat treating of ferrous or non-ferrous materials. A fuzzy logic controller is taking over the task of temperature control for furnaces in NITREX.

In NITREX, the task of temperature control in furnace is dealing with three different problems:

The first problem is to track the desired temperature rise and also preventing overshoot.

The second problem originated in use of different loads for nitriding process, which changes the characteristics of the furnace and its response to input power.

The third problem is the variety of furnaces. Since there are different models of furnaces with different characteristic therefore the knowledge base has not the same effect on all the furnaces, which means each furnace individually needs the modification on knowledge base.

Hence designing a new structure for the control system as an adaptive controller is intended to overcome mentioned problems.
Literature review

Temperature control in heat treatment furnaces

Temperature control of heat treatment furnaces have been the subject of many studies and received special attention during the past decades.

A comprehensive review on this matter show that the most of work done deal with influence of temperature control on chemical or metallurgical process as well as hardware control systems (i.e., sensors, digital controllers), system identification and modeling method, efficiency, environment and energy saving and temperature control system.

A review on temperature control system indicates that very less attention has been paid to “temperature control in nitriding furnaces”.

In general, temperature control systems consist of:

- Improvement on existing classical controllers, such as PID and using soft computing techniques for tuning [1-11].
- Defining new strategies for controllers, such as hierarchical structures, multi-sectional thermal system [12-20].
- Model-Based Control, i.e., predictive/adaptive control, on-line modeling [21-33].
- Soft computing and intelligent control, i.e., Fuzzy control, Genetic Algorithm, Neural Networks and Expert System [34-53].

In general, non-linear control systems are robust, adaptive and predictive controls, discrete event and artificial intelligent control. The latter consists of expert systems, neural networks and fuzzy control. Although most industrial applications of fuzzy control have been based on rule-based control, in which controllers have been designed on the basis of operator experience or knowledge of control engineer. There is a growing interest in model-based fuzzy designs. Fuzzy models and control methods for temperature control systems are found in the literature [35-40,43,48,49].

Temperature control for most kind of furnaces, such as heat-treatment furnaces deal with presence of non-linearity with unknown structure, multivariable, time-varying behaviour of the process, large delays in dynamic channels as well as interaction between the
different variables, i.e., cross relationship between control parameters. Non-linearity in heat treatment furnaces is a consequence of convection and radiation heat-transfer [35,41,42,45,46,49,53].

The task of control system is to maintain the reference rate of temperature change (i.e., temperature slope) and attain the temperature reference without overshooting. In this manner, the initial sets of fuzzy rules have been compiled by compromising between fast attaining of the desired temperature and avoiding its overshoot.

Loading furnace with different type of loads changes its characteristics and makes it more sluggish and it could lead to the changes of the temperature response in the closed loop with the fuzzy controller [42,45].

In continuous, reheating, refineries and open fire furnaces with burning process, temperature measurement is very difficult or even impossible and also long time delay is a challenging factor, therefore a large portion of researches in this area is about modeling a furnace by different system identification methods, model-based control methods, predictive control and tuning parameters of the existing PID controllers [7,10,15,22,27,35,39-45,49].

The problems with PID controller applications originate from the object non-linearity, resulting in mismatches of the real responses and the projected ones.

Apart from non-linearity, there is a problem of furnace characteristics alteration. The feasible solution is an application of gain-scheduling methods, used in the manner that the parameters are determined from the set of previously performed measurements or measurements during the real-time regulated process [2,7,10].

In most applications, a linear model has been used to represent the dynamic behaviour of the process, namely impulse/step response function, transfer function and state space model. However, because of severe non-linearities, a fixed linear model for predictive control might not really result the required performance. On the other hand, its tuning by using numerical simulations cannot be precisely performed due to the difficulties in precise modeling of the controlled object [19,27,29,31,37].

In predictive control approach, a model is used to predict output for each action and then decision maker selects the most favourable action. Afterward the selected control action
will be applied to the process and subsequently the whole procedure repeats itself at each control interval [22,24-27,33,49].

The rules of the traditional fuzzy control strategy are stationary and difficult to adapt to different operating modes, whereas in adaptive rule method, rules are changed responding to different situations by the weight factors of the input parameters and make the system adapt to the changing conditions automatically.

For automatic adaptation of fuzzy logic, genetic algorithm (GA) and neural network (NN) techniques are used to fix the adaptive parameters in the fuzzy control system [34,37,38,40,43].

Fang [34] studied neural-fuzzy regulator to control temperature of resistance furnace. For raising learning speed, an improved back propagation algorithm is proposed. The result of practical operation shows that the system with the neural-fuzzy regulator has a better static and dynamic characteristic than similar models.

Wang [35] investigated application of fuzzy inference compound method to resistance furnace temperature control system. According to the characteristics of the resistance furnace temperature control, i.e. one way temperature rise, large time delay and time varying parameters, the fuzzy inference compound method was employed to build fuzzy model and design fuzzy controller. The basic procedure to build fuzzy model and the table of inquisition were presented. A fuzzy variable was introduced to enhance further accuracy of fuzzy control and the fuzzy control system with parameters online self-adjustment was constructed. The simulation result shows that the fuzzy control system with parameters self-adjustment removes small amplitude oscillation in the system without parameters self-adjustment and improves steady precision.

Hu [36] developed a fuzzy-neural network intelligent temperature control system of quench furnace. The weight values of neural networks, parameters of fuzzy membership functions and inference rules can be automatically adjusted by combined genetic algorithm with back-propagation algorithm, which results the optimal control of temperature. The results show that this control system can run effectively with satisfied temperature precision; in temperature uprising stage, overshoot of temperature is under
4°C; in stable stage, the scope of temperature change is controlled within +2°C, which meets the need of control veracity of temperature.

Kayama [37] investigated adjusting neural networks for accurate control model tuning in reheating furnace plants. He proposed adjusting neural networks (AJNNs), which are extended model of conventional multi-layered neural networks (CNNs), for accurate model tuning with small tuning numbers. The AJNN consists of two multi-layered neural networks, namely, a CNN and an error calculation neural network (ECNN) which is added in parallel to the CNN. The ECNN calculates the output error of the CNN and subtracts it from the output of the CNN, to obtain accurate tuning values. A training method for the AJNN is also proposed, where the modified back-propagation developed for reducing the error of the AJNN and the conventional back-propagation for decreasing the output of the ECNN, are applied to the AJNN alternately. The AJNN is evaluated with model tuning of temperature control for reheating furnace plants and is demonstrated to be effective to improve the accuracy of tuning and decrease tuning numbers.

Liu [38] presented a high-order-fuzzy CMAC adaptive control, using the fuzzy subset to partition input state spaces, employing the multi-layer quantification to quantify input states and utilizing the algebraic product and algebraic sum to integrate the result of multi-layer quantification. In general, cerebellar model articulation controller (CMAC) is a linear combination of overlapped basis function. It is a type of local neural network, which means only a local set of neurons, is activated by a particular input. The high-order-fuzzy CMAC adaptive controller has better capability of generalization than the ordinary CMAC. Due to the use of multi-layer quantification, the controller has better control performance than that simply based on the generalized basic function fuzzy CMAC. Temperature control experiments on an industrial furnace prove the effectiveness of the proposed method.

Wang [39] conducted a research on soft sensor model for slab temperature in reheating furnace. In his work a slab temperature neural network soft sensor model based on fuzzy clustering has been studied. The approach consists of two components: an FCM (Fuzzy C-Means) clustering, which classifies training objects into a couple of clusters, and a
distributed Radial Basis Function (RBF) network, which is used to train each cluster. In
the online stage, the values of membership are computed using an adaptive fuzzy
clustering algorithm for the new object. The proposed approach has been applied to the
slab temperature estimation in an actual reheating furnace. Simulations show that the
approach is effective.
Ma [40] investigated genetic-based fuzzy bed temperature control system of circulating
fluidized bed boiler. A kernel problem in fuzzy control system design is generating the
control rules library. Genetic algorithm is a global optimization algorithm based on
evolutionism. GA can be used to designing fuzzy controller, but the convergence process
usually takes a great deal of time, especially when the standard GA is used to generate the
control rules of MIMO system. It is due to the huge multivariable search space. To
overcome this disadvantage, an improved GA is proposed in which excellent patterns in
chromosome are defined and the genetic operations in GA are regulated by the excellent
patterns, as a result, the convergence of search process is evidently accelerated. Bed
temperature, which determines the operation security and continuance of circulating
fluidized bed boiler, is a very important parameter of CFB. A new regulation strategy of
bed temperature is put forward according to the working characters of CFB, and a fuzzy
bed temperature controller is designed using the improved GA. In the new designing
method, the genetic operations are guided with human experience and heuristic
information. Consequently, fuzzy control rules are created with higher speed. The
simulation results indicate the proposed scheme has good efficiency. It can keep the
stabilization of main steam pressure and bed temperature and meet the need of load.
Fuzzy control of a multiple hearth furnace has been studied by Ramirez [41]. The
schematic of a multiple hearth furnace has been shown in Fig. 1. The system is divided
into different local domains; each one is described by its own rule base. Meta-rules of
classical non-fuzzy inference provide dynamical switching of the most suitable sub-base
among the whole set of sub-bases. The program has two kinds of user interfaces: the
developer’s interface and the operator’s interface. The developer’s interface contains
information that is needed for tuning the fuzzy control system, where controller’s
parameters (e.g., scaling factors, knowledge bases, etc.) are accessible for changes. In the
operator’s interface only basic information is presented. Operators can switch the control system on or off, and change the settings (e.g., set point, limit values of technological restrictions, etc.) [41]. The objective of process control in a reduction furnace is to optimize nickel recovery, while minimising fuel consumption and environmental contamination. This entails the exact control of temperature and gas composition in the furnace. Controlling the temperature of a multiple hearth furnace is a difficult task. Fast and extensive changes in operating conditions occur, complicated by non-linear and time-varying behaviour of the process and interaction between the different variables. Failing to solve the control problem with a normal PID controller led to development of a knowledge-based fuzzy controller, which keeps the temperature as close to the set profile as possible. Such controller is endowed with a set of 60 rule bases, which are dynamically switched depending on technological constraints and/or operating regions. The algorithm used for the resulting MIMO controller has a Mamdani-type inference system.

Abilov [42] investigated fuzzy temperature control of industrial refineries furnaces through combined feedforward/feedback multivariable cascade systems. The proposed structure has been depicted in Fig. 2.
In this work, the application of the multivariable cascade fuzzy advanced control structure for an industrial AVT furnace is investigated. The feedforward controller takes care of the large and frequent measurable disturbances. The feedback controller takes care of any errors that come through the process because of inaccuracies in the feedforward controller or other unmeasured disturbances. In addition, the feedforward controller has no effect on the closed loop stability of the system for linear systems. The denominators of the closed loop transfer functions are unchanged. In a nonlinear system, the addition of a feedforward fuzzy controller often permits tighter tuning of the feedback controller because the magnitude of the disturbances is reduced [42]. The purpose was to improve and apply a multivariable advanced control structure on the basis of fuzzy logic technique for two flow tubular furnace having widespread applications in petroleum refinery industries. After analyzing the dynamic properties of furnaces, it has been concluded that these furnaces are the MIMO processes which have two inputs and two outputs. There are a lot of reciprocal interactions between input and output variables. For this reason, equivalent system methods were used to develop advanced control structures for these furnaces. According to this method, symmetric MIMO system was divided into two equivalent separate systems.

An adaptive fuzzy approach for the incineration temperature control process has been studied by Shen [43]. The fuzzy logic strategy with the adaptive factors is used to
improve the incineration temperature control system and a new correction model is adopted to determine the proper adaptive factors. There are many factors affecting the combustion process in incinerators; one of them is how to control the temperature of the incineration and reduce the emissions. In his work, a second-order model of the adaptive fuzzy control strategy is adopted to stabilize the combustion temperature and the results demonstrate that the adaptive control strategy with the adaptive factors is a good method to achieve the goal of incineration temperature control. The fundamental configuration of adaptive fuzzy controller for the incineration temperature control process is shown in Fig. 3.

![Fuzzy control system](image)

Figure 3: Fuzzy self-adaptive control proposed by Shen

Application of temperature fuzzy controller in an indirect resistance furnace has been investigated by Radakovic [44]. The application results of a fuzzy controller of temperature and its rate of change in indirect resistance chamber furnaces have been presented. Controller basic structure in an indirect resistance furnace is shown in Fig. 4. The method of an initial controller tuning based on the computer simulations is described, where the modelling of the furnace appears as a special problem. Further controller
tuning was done based on tests performed on the real furnace. The quality of the finally-adopted controller on the real furnace is assessed by its tracking of the desired response, regulation robustness with respect to the presence of load in the furnace as well as by a comparison with the ideal implementation of the Dahlin algorithm for classic PID control. The experimental part of the work is made using a 5 kW indirect resistance chamber furnace.

![Duty-separated Fuzzy control proposed by Radakovic](image)

**Figure 4: Duty-separated Fuzzy control proposed by Radakovic**

In the domain far from the commanded temperature, the control task is to maintain the temperature slope (maximum or commanded). In the domain close to the commanded temperature, the slope must not be tracked in order to avoid temperature overshoot, i.e. it is primary to obtain a convenient approach to the commanded temperature. As a consequence of separated scopes of duty, control can be implemented via two separate fuzzy controllers [44].

Gao [45] studied a stable self-tuning fuzzy logic control system for industrial temperature regulation. A closed-loop control system incorporating fuzzy logic has been developed for a class of industrial temperature control problems. A unique fuzzy logic controller (FLC) structure with an efficient realization and a small rule base that can be easily implemented in existing industrial controllers was proposed. The potential of FLC in both software simulation and hardware test in an industrial setting was demonstrated. This
includes compensating for thermo mass changes in the system, dealing with unknown and variable delays, operating at very different temperature set points without retuning, etc. It is achieved by implementing, in the FLC, a classical control strategy and an adaptation mechanism to compensate for the dynamic changes in the system. The proposed FLC was applied to two different temperature processes and performance and robustness improvements were observed in both cases. Furthermore, the stability of the FLC is investigated and a safeguard is established.

An intelligent ladle furnace (ILF) control system has been presented by Sun [46]. The main functions and system structure has been introduced. The system applied combined artificial intelligent technology for ladle furnace heat balance calculation and steel temperature prediction, dynamic energy input optimization and intelligent electrode control. The application results achieved are given to demonstrate the capability of this intelligent control system.

The design of functional module of the intelligent fuzzy micro controller based on 80C196 for heat treatment furnace was introduced by Zhu [47]. The rule self-seeking-optimization fuzzy control algorithm has been studied, simulated and applied to heat treatment furnace. The running results indicate that the system has reasonable control scheme, high reliability, advanced control algorithm, self-learning capability, good tracking property, high static accuracy, small overshoot, friendly man-machine interface and easy operation.

Balazinski [48] developed fuzzy logic control of industrial heat treatment furnaces. The application of fuzzy logic to the control system for industrial heat treatment furnaces has been presented. A modified fuzzy decision support system has been developed to control the temperature in an industrial nitriding furnace. The results obtained using the fuzzy logic controller are very good and the system is fully automatic and maintains a very stable temperature control.

Zou [49] studied fuzzy predictive functional control strategy for decomposing furnace temperature system of cement rotary kiln. A new fuzzy predictive control method has been proposed for the decomposing furnace in cement rotary kiln system. A Takagi-Sugeno fuzzy model for the decomposing furnace is established, which merges
several linear models together with fuzzy logic. The parameters of fuzzy model can be modified, depending on the flow of raw material. Based on the dynamic fuzzy model, incremental predictive functional control arithmetic has been developed to control the decomposing furnace temperature, improving the robustness of the control system without adding computational load. Real time control software of this arithmetic has been developed on the platform of Plantscape discrete control system of Honeywell Corporation. Application results exhibit the superiority of the proposed method over conventional ones even on the condition of existing large delay and time-varying parameter. The cement decomposing rate is improved from 81.5% to 89.1%, and the control precision of the decomposing furnace temperature is ensured.

A multivariable fuzzy decoupling control system has been developed and applied to temperature control of hydrogen sintering furnace by Li [50]. The authors learn from experienced operators of hydrogen sintering furnace and abstract with them from their observation a number of rules of decoupling control. Then the fuzzy mathematics is used to make a table whose tabulated values are compensating values for fuzzy decoupling values. Through using compensating values, control values can be computed and so much coupling can be eliminated as to make the control of each variable practically independent.

Wang [51] developed a hybrid intelligent control (HIC) by using the techniques of expert control and fuzzy neural network for industrial rotary kiln plant. The HIC consists of a knowledge base, information pre-processor, and intelligent coordinator in a hierarchical structure. The basic idea is to give an effective control strategy to complex controlled plant using knowledge-based coordinator so as to achieve the desired performance. The results of simulation as well as temperature control for industrial rotary kiln furnace were performed to demonstrate the feasibility and effectiveness of the proposed scheme.

A new developed and designed real-time expert intelligent control system (REICS) for industrial process control has been introduced by Cai [52]. The global architectures of the hardware and software of the system have been proposed. A multi-level method of knowledge representation based on the combination of frame, production rules and real-time procedures has been discussed, and used to represent the control knowledge and
algorithms of the control system. Meanwhile, the reasoning mechanism, control strategy and its flow chart have been presented. The simulation and the practical application of an industrial rotary kiln furnace for the proposed tool and method have been described. Zheng [53] studied a real-time fuzzy control for a kind of multivariable object. This paper describes the application of fuzzy control to a complex object, that of temperature control for furnace, and develops a three-dimensional fuzzy control table. Electrical furnace with multiple temperature zones (EFMTZ) is a typical kind of multivariable control object. It has some characteristics which are harmful to control such as strong coupling, nonlinearity, time-variant parameters, and so on. For this kind of object, the control strategy will be divided into two steps. At first, it employs a decoupling strategy based on feedforward compensation to reduce the coupling between adjacent temperature zones. Then it applies the fuzzy control strategy to each temperature zone after compensation, and a three-dimensional fuzzy control table-E, EC, T is specially presented. The results of practical run show that the control strategy is encouraging.

**Adaptive Fuzzy Control**

Anderson [54] indicates that adaptive fuzzy controllers are fuzzy controllers with a mechanism for changing their own characteristics during operation. According to Driankov [55], adaptive fuzzy controllers may be classified according to which parameters are adjusted. This classification method results in three major groups:

**Adaptation of Scaling Factors**

To design a temperature controller for a chemical reactor, Yamashita et al. [56] have found that different controller gains are required for different stages of operation. To allow this, an adaptation mechanism was added to the system. This mechanism monitored the performance of the system and consequently altered the scaling factor on this basis by using an additional set of fuzzy rules. The alteration of the scaling factors effected a change in the controller gains and it was found that this approach improved overall performance significantly. Schemes which adapt the scaling factors on the basis of the parameters of an adaptive linear process model are given in [57,58].
**Adaptation of FIS Parameters**

Some significant publications that describe methods of adapting the FIS parameters are: which apart from presenting the Fuzzy Model-Reference Learning Control (FMRLC) method, provides a useful overview of other similar methods [59]; which aims to improve FMRLC by implementing three methods of focusing the attention of the learning paradigm [60]; which presents a method identical in concept to the neural feedback-error learning architecture described in [54] section 3.1.12 [61]; and which defines a set of heuristic adaptation actions selected by a set of rules based on a series of performance criteria [62].

Ordonez [63] presents an excellent comparison of indirect and direct adaptive fuzzy control (IAFC and DAFC respectively) paradigms. In particular, this work compares these methodologies with each other and with more traditional control methods. It is found that direct and indirect adaptive fuzzy control methods yield comparable performance in the case of rotational inverted pendulum and ball-and-beam balancing problems, and that both methods outperform their non-fuzzy counterparts.

**Adaptation of Rules**

The first adaptive fuzzy controller was designed by Mamdani and *et al.* in 1975; it is called the Self-Organizing Controller (SOC) [55,64-66]. Instead of changing the characteristics of the existing FIS, the SOC automatically replaces poorly performing rules with better ones. This is achieved by utilizing a performance monitor and an adaptation mechanism. The purpose of the performance monitor is to indicate how much the plant output needs to be changed in order to achieve good performance. The adaptation mechanism then translates this desired change in the plant output into a required change in the control signal using a plant model, and generates a new rule which will effect this change.
Direct and Indirect Adaptive Fuzzy Model Based Control

Conceptually, there are two distinct approaches that have been formulated in the design of a fuzzy adaptive control system: direct and indirect schemes. In the direct method, a fuzzy system is used to describe the control action and the parameters of the fuzzy system are adjusted directly to meet the required control objective [67-73]. In contrast with the direct adaptive scheme, the indirect adaptive approach uses fuzzy systems to estimate the plant dynamics and then synthesizes a control law based on these estimates [67-71,73-77]. The indirect fuzzy adaptive controller for SISO uncertain nonlinear systems has been developed in many investigations [68,71,75,76]. The multi-input multi-output (MIMO) nonlinear systems are investigated in several articles [67,69,70,74,77].

Fuzzy Adaptive Model Predictive Control

Model Predictive Control (MPC) has recently become one of effective control methods for handling multivariable control problems. The simplest MPC system uses a linear plant model. For a highly nonlinear process the linear assumption may lead to unsatisfactory performance. For better performance and also for nonlinear compensation the adaptive MPC systems have been recently developed [78-80]. The adaptation is usually achieved by using the Recursive Least Squares (RLS) parameter estimation technique. However, adaptation of a single process model over wider operational range may result in a transient error [81]. Alternatively, fuzzy logic can be used for modeling a non-linear process system where different rules can be conveniently allocated to represent different local models of the process [81]. Although there are many representations in fuzzy systems, Takagi-Sugeno (TS) type fuzzy systems [82] have been widely used in modeling nonlinear process systems [83]. The TS fuzzy model allows a high dimensional nonlinear modeling problem to be decomposed into a set of simpler linear local models and the fuzzy inference interpolates the fuzzy outputs of the local models in a smooth fashion. Therefore, TS type fuzzy model based MPC strategy recently generated considerable interests among the researchers [81,83-86]. In many cases [81,83,85] the parameters of the linear model extracted from the nonlinear fuzzy model are used for linear MPC formulation at every sampling instant. In other cases,[86] a Nonlinear MPC (NMPC)
problem is solved at every step with the nonlinear fuzzy model [84,86]. When the process is time variant the predefined linear local models will become applicable only for a small operating region. Introducing more local models may increase the accuracy but at the cost of heavy computation.

Roy et al. [87] present design of a rule-adaptive fuzzy Model Predictive Control (MPC) algorithm for controlling temperatures of a multivariable soil-heating process system. The system uses Takagi-Sugeno (TS) type fuzzy model structure. The control objective is to track a desired temperature profile at three locations in the soil sample using three heat sources located at the outer surface of the soil cell. The system recognizes the active fuzzy rules which are recursively adapted for handling the time-variant behavior of the process. In order to show the effectiveness, the performance of the proposed scheme is compared against the non-adaptive fuzzy model based MPC scheme. A classical non-adaptive MPC is also developed to confirm the superiority of the fuzzy model based MPC controllers.

Takagi [82] introduced a novel fuzzy logic-based modeling methodology, where a nonlinear system is divided into a number of linear or nearly linear subsystems. A quasi-linear empirical model is then developed by means of fuzzy logic for each subsystem. The model is a rule-based fuzzy implication (FI). The whole process behavior is characterized by a weighted sum of the outputs from all quasi-linear FIs. The methodology facilitates the development of a nonlinear model that is essentially a collection of a number of quasi-linear models regulated by fuzzy logic. It also provides an opportunity to simplify the design of model predictive controllers. More recently, Huang et al. [88] have introduced a fuzzy model predictive control (FMPC) approach to design a control system for a highly nonlinear process system. The approach utilizes the Takagi–Sugeno modeling methodology to generate a fuzzy convolution model. With this model, a novel hierarchical control design approach is described.
The Sugeno Fuzzy Model

Jang [89] proposed an adaptive-network-based fuzzy inference system, which is a fuzzy inference system implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed fuzzy system could construct an input-output mapping based on both human knowledge and stipulated input-output data pairs and could be used to identify nonlinear components on-line in a control system.

Sugeno fuzzy model proposed by Takagi, Sugeno and Kang [90] is an effort to develop a systematic approach to generating fuzzy rules from a given input output data set. Roubos [91] indicates that Takagi Sugeno-fuzzy models are suitable to model a large class of nonlinear systems [84,92,93]. Fuzzy modeling and identification from measured data are effective tools for the approximation of uncertain nonlinear systems. So far, most attention has been devoted to single-input, single-output (SISO) or multi-input, single-output (MISO) systems. Recently, also methods have been proposed to deal with multi-input, multi-output (MIMO) systems [94-96]. Most articles deal with various aspects of multivariable relational models, such as the decomposition of fuzzy relations, simplification of the models to avoid memory overload, etc. Relatively little attention has been devoted to the identification of MIMO fuzzy models from input-output data. Babuška, R. et al. [97] developed a MIMO identification algorithm which uses input-output data. This algorithm is used to obtain MIMO Takagi-Sugeno models which can be used for control purposes.

Abonyi [98] presents an adaptation method for Sugeno fuzzy inference systems that maintain the readability and interpretability of the fuzzy model during and after the learning process. This approach can be used for the modeling of dynamical systems and for building adaptive model-based control algorithms for chemical processes. The gradient-descent based learning algorithm can be used on-line to form an adaptive fuzzy controller. This ability allows these controllers to be used in applications where the knowledge to control the process does not exist or the process is subject to changes in its dynamic characteristics. The proposed approach was applied in an internal model (IMC) fuzzy control structure based on the inversion of the fuzzy model. The adaptive fuzzy
controller was applied in the control of a non-linear plant and is shown to be capable of providing good overall system performance.

**Genetic Fuzzy Systems (GFS)**

A genetic algorithm (GA) is a parallel, global search technique that emulates operators [99]. Because, it simultaneously evaluates many points in the search space, it is more likely to converge toward the global solution. A GA applies operators inspired by the mechanics of natural selection to a population of binary string encoding the parameter space at each generation; it explores different areas of the parameter space, and then directs the search to regions where there is a high probability of finding improved performance. By working with a population of solutions, the algorithm can effectively seek many local minima, thereby increasing the likelihood of finding the global minimum.

A GFS is basically a fuzzy system augmented by a learning process based on a genetic algorithm (GA). GAs are search algorithms, based on natural genetics, that provide robust search capabilities in complex spaces, and thereby offer a valid approach to problems requiring efficient and effective search processes [100-102]. Genetic learning processes cover different levels of complexity according to the structural changes produced by the algorithm [103], from the simplest case of parameter optimization to the highest level of complexity of learning the rule set of a rule based system. Parameter optimization has been the approach utilized to adapt a wide range of different fuzzy systems, as in genetic fuzzy clustering or genetic neuro-fuzzy systems [104].

Analysis of the literature shows that the most prominent types of GFSs are genetic fuzzy rule-based systems (GFRBSs) [105], whose genetic process learns or tunes different components of a fuzzy rule-based system (FRBS). Fig. 5 shows this conception of a system where genetic design and fuzzy processing are the two fundamental constituents [104]. Inside GFRBSs it is possible to distinguish between either parameter optimization or rule generation processes, that is, adaptation and learning.
Belarbi [106] indicates that GA have been used diversely for FLC design either off-line or on-line although in the latter case computation time is sometimes prohibitive. Off-line learning is carried through closed loop simulation using a simplified model of the plant for fitness computation. The search is carried out either in the set of the parameters of the membership functions and/or the set of rules. Thrift [107], Nishiyama et al. [108], Lee and Tagaki [109], and Tagaki and Lee [110] used GA through off-line learning to find an optimal rule base. Karr [111,112] applied GA with binary coding to find good parameters for the membership functions. The problem is to locate support points for the membership functions. Since there is an underlying ordering of the fuzzy sets to be maintained, each point is constrained to lie between a lower and an upper bound.

GA has been used to optimize the parameters of the membership functions as well as the rule base. Differences between the approaches lie mainly in the type of coding and the way the membership functions are optimized. Homaifar and Maccormick [113] used nonbinary integer coding to optimize the rule base and membership function parameters of the input variables. The summit of the triangular membership functions is kept constant and only the width of basis is allowed to vary during the search process. While the particular coding reduces the length of the string it implies additional computation in the decoding process and during defuzzification. Moreover, extensive testing [114] has shown that the position of the summit of the triangular fuzzy set of the output variable is
more influential than the width of the basis. Linkens and Nyongesa [115] give more flexibility to the variation of the parameters in particular the summit and the two support points of the triangular fuzzy sets are allowed to vary at the cost of extra computation and longer string. Kim and Ziegler [116] propose a global, hierarchical search that includes the shape and number of fuzzy sets.

**Summary of literature review**

A research was conducted on the subject within 1995-2005 in Compendex (Search strategy: heat treatment furnace, temperature control) and 384 articles were found. A quick review on these articles showed that most of them deal with influence of temperature control on chemical/metallurgical process and behaviour.

The rest of the articles (≈ 150 articles) could be separated in four following categories:

- Hardware control systems
- System identification and modeling methods
- Efficiency and energy saving
- Temperature control systems

A review on “Temperature control systems” shows that during the past 10 years, no research results have been published in the area of “temperature control in nitriding furnaces”, except the work done by Balazinski et al. [48], in which the fuzzy controller has been used in NITREX.

Literature review in temperature control of furnaces leads us to the following results:

Temperature control for most kind of furnaces, such as heat-treatment furnaces deals with the presence of non-linearity, multivariable and time-varying behaviour of the process. Non-linear control systems that used to deal with these problems are mostly adaptive, predictive and fuzzy control.

Apart from non-linearity, there is a problem of furnace characteristics alteration. The feasible solution is an application of gain-scheduling methods and adaptive control, used in the manner that the parameters are determined from the set of previously performed measurements or measurements during the real-time regulated process.
The rules of the traditional fuzzy control strategy are stationary and difficult to adapt to different operating modes, whereas in adaptive rule method, rules are changed responding to different situations by the weight factors of the input parameters and make the system adapt to the changing conditions automatically.

For automatic adaptation of fuzzy logic, genetic algorithm (GA) and neural network (NN) techniques are used to fix the adaptive parameters in the fuzzy control system.

In most applications, a linear model has been used to represent the dynamic behaviour of the process, however, because of severe non-linearities, a fixed linear model for predictive control might not really result the required performance. On the other hand, its tuning by using numerical simulations cannot be precisely performed due to the difficulties in precise modeling of the controlled object.

There is a growing interest in model-based fuzzy designs in most industrial applications of fuzzy control.

A large portion of researches in this area is about modeling a furnace by different system identification methods, model-based control methods, predictive control and tuning parameters of the existing PID controllers.

The problems with PID controller applications originate from the object non-linearity, resulting in mismatches of the real responses and the projected ones. Occurring fast and extensive changes in operating conditions, complicated by non-linear and time-varying behaviour of the process and interaction between the different variables, will resulted normal PID controller fail to solve the control problem and led to development of a knowledge-based fuzzy controller, which keeps the temperature as close to the set profile as possible.

The mentioned statements lead the review to the aspects of fuzzy adaptive control, fuzzy model based control and applications of genetic algorithms in fuzzy control. Finally the results of investigated articles showed that:
• The adaptive fuzzy control system with use of a fuzzy model removes small amplitude oscillation and improves steady precision.
• Fuzzy predictive control with Takagi-Sugeno fuzzy model results the better performance over conventional ones even on the condition of existing large delay and time-varying parameter and ensure the control precision of the furnace temperature.
• Takagi Sugeno-fuzzy models are suitable to model a large class of uncertain nonlinear systems.
• GAs offer a valid approach to problems requiring efficient and effective search processes and thereby researchers use GAs to optimize both the parameters of the membership functions and the rule base.
• Fuzzy control with genetic algorithm adjustment systems can run effectively with satisfied temperature precision; in temperature uprising stage and in stable stage.

Research methodology

Problem definition

NITREX is a leading company in modern surface treatment of metal and an equipment manufacturer. NITREX Metal specializes in providing solutions to whose product manufacturing process involves heat treating of ferrous or non-ferrous materials. A fuzzy logic controller is taking over the task of temperature control for furnaces in NITREX. This controller is based on error and deviation of error between actual temperature and required regime temperature. This controller was developed by Balazinski in 1999 [48].

Figure 6 presents the simplified scheme of current controller in NITREX:
In NITREX, the task of temperature control in furnace is dealing with three different problems:
The first problem is to track the desired temperature rise and also preventing overshoot. Fig. 7 shows a sample of input (u1: power) and output (y1: furnace temperature) for nitriding process.

The second problem originated in use of different loads for nitriding process, which changes the characteristics of the furnace and its response to input power.
The last problem is the variety of furnaces. Since there are different models of furnaces with different characteristic therefore the knowledge base has not the same effect on all the furnaces, which means each furnace individually needs the modification on knowledge base.

In NITREX this modification is mostly applied by changing on database i.e. premises and outputs whereas the rule base remains constant.

Hence designing a general control system is intended which could be used on the different furnaces (or at least similar ones in the sense of physical characteristic).

**Suggested methodology**

Based on literature review and the experience of temperature control with classical controllers and also fuzzy controllers, the suggestions are presented as follows:

Fuzzy Adaptive Model Predictive Control is an effective control method for handling multivariable nonlinear control problems. Table 1 shows the advantage of this method.

<table>
<thead>
<tr>
<th>Control system</th>
<th>Advantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model predictive control</td>
<td>Accurate</td>
</tr>
<tr>
<td>Model predictive control with fuzzy model</td>
<td>Accurate, nonlinear models</td>
</tr>
<tr>
<td>Model predictive control with Takagi-Sugeno fuzzy model</td>
<td>Accurate, nonlinear models, Consist of different local linear models which could adapt separately</td>
</tr>
</tbody>
</table>

Figure 8 demonstrates the concept of Fuzzy adaptive model predictive control with Takagi-Sugeno fuzzy model. In each step controller tries to generate different predicted outputs and based on the least error with reference line, input with the best fitness would be selected.
**Furnace Predictive Fuzzy model**

Takagi-Sugeno models divide fuzzy model to several linear models and have the ability to switch smoothly between these local models. Hence, in contrast to global model estimation, it can be guaranteed that the local models represent the local behavior of the nonlinear system, and they do not suffer from the effects of compensation.

The idea of prediction is depicted in Fig. 9 based on the past and present temperatures, the model could predict one or more step-ahead, herein we consider one step.

Models built with 15 groups of actual data which gathered from nitriding process in a certain furnace. For comparison 4 groups of data with different loads (not involved in modeling) were used and the output temperature from model was compared in real time to actual output of furnace F1. Table 2 shows the data which gathered and used for modeling and comparison with related load for each process.
<table>
<thead>
<tr>
<th>learning process</th>
<th>LBS</th>
<th>number of pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>100</td>
<td>696</td>
</tr>
<tr>
<td>Training</td>
<td>1294</td>
<td>1292</td>
</tr>
<tr>
<td>Training</td>
<td>640</td>
<td>982</td>
</tr>
<tr>
<td>Training</td>
<td>900</td>
<td>2006</td>
</tr>
<tr>
<td>Training</td>
<td>440</td>
<td>879</td>
</tr>
<tr>
<td>Training</td>
<td>230</td>
<td>1768</td>
</tr>
<tr>
<td>Training</td>
<td>308</td>
<td>838</td>
</tr>
<tr>
<td>Training</td>
<td>442</td>
<td>853</td>
</tr>
<tr>
<td>Training</td>
<td>250</td>
<td>1565</td>
</tr>
<tr>
<td>Checking</td>
<td>350</td>
<td>2598</td>
</tr>
<tr>
<td>Checking</td>
<td>1232</td>
<td>1189</td>
</tr>
<tr>
<td>Checking</td>
<td>656</td>
<td>1060</td>
</tr>
<tr>
<td>Testing</td>
<td>250</td>
<td>2837</td>
</tr>
<tr>
<td>Testing</td>
<td>440</td>
<td>863</td>
</tr>
<tr>
<td>Testing</td>
<td>990</td>
<td>1279</td>
</tr>
<tr>
<td>Validation</td>
<td>1194</td>
<td>1176</td>
</tr>
<tr>
<td>Validation</td>
<td>120</td>
<td>1681</td>
</tr>
<tr>
<td>Validation</td>
<td>550</td>
<td>1025</td>
</tr>
<tr>
<td>Validation</td>
<td>280</td>
<td>1890</td>
</tr>
</tbody>
</table>

Table 2: pair of data used for modeling and comparison

Considering dynamic characteristics of furnace, fuzzy models couldn’t map input/output data based only on input power and output temperature. To overcome this problem, other data should be used as complementary inputs, such as “current temperature”, “last changes in temperature”, “last change in power” and the model output could be considered as “change in the output”, which in each step of simulation, will be added to the last output.

Also, Loading furnace with different type and amount of load change its characteristics (i.e. makes it more sluggish) and it can lead to the changes of the temperature response, therefore, load also could be considered as an input. On the other hand, all these models could be used to predict one or more-step ahead of output.

For calculating rules in each model, suppose for power, 5 membership functions and for the rest 3 will be used, then number of rules for different available models will be:

Model A using: load + output + Δ output + input for prediction with 135 Rules
Model B using: load + output + input for prediction with 45 Rules
Model C using: load + Δ output + input for prediction with 45 Rules
Model D using: load + input for prediction with 15 Rules
Model E using: output + Δ output + input for prediction with 45 Rules
Model F using: output + input for prediction with 15 Rules
Model G using: Δ output + input for prediction with 15 Rules
Model H using: input for prediction with 5 Rules

It should be noted that in these models input means “overall power” and output means “overall temperature” and all the above data used as “input” to fuzzy model and the “output” of fuzzy model is “change in the temperature”.

Considering time delay of the actual furnace, another criterion to choose was how many step ahead prediction should be used for data samples and modeling, which has been investigated as well.

**Fuzzy rule extraction**

The underlying idea of an adaptive fuzzy network is to code the fuzzy if-then rules into a neural network-like structure and then to use a learning algorithm to minimize the output error using training data. The ANFIS approach which was implemented for modeling uses triangular functions for fuzzy sets, zero order linear functions for the rule outputs, and Sugeno's inference mechanism. The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters) and the coefficients of the output linear functions (consequent parameters). The ANFIS learning algorithm is then used to obtain these parameters. This learning algorithm is a hybrid algorithm consisting of the gradient descent and the least-squares estimate techniques. Using this hybrid algorithm, the rule parameters are repeatedly updated until acceptable error is reached. Each iteration involves a forward and a backward pass. In the forward pass, the antecedent parameters are fixed and the consequent parameters are obtained using the linear least-squares estimate. In the backward pass, the consequent parameters are fixed and the output error is propagated back through the network and the antecedent parameters are updated accordingly using the gradient descent method. 100 epochs used for each learning process.
**Fuzzy model optimization**

After comparison between different models, Model E with 7 membership function for input (overall power such as extreme low, very low, low, medium, high, very high, extreme high), 3 membership functions for output (overall temperature such as low, medium, high) and 3 membership functions for change in last output (change in overall temperature as low rate, medium rate, high rate) with triangular shapes with weighted average, defuzzification method and one step ahead of prediction were observed to have the best mapping results (with 63 rules). Results of this comparison for all models were presented in Table 3. Digit numbers which follow the model name are number of step-ahead predictions.

<table>
<thead>
<tr>
<th>model with one step ahead prediction</th>
<th>A1</th>
<th>B1</th>
<th>C1</th>
<th>D1</th>
<th>E1</th>
<th>F1</th>
<th>G1</th>
<th>H1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-255.451</td>
<td>95.82266</td>
<td>85.83427</td>
<td>77.46621</td>
<td>86.2555</td>
<td>95.14666</td>
<td>87.43016</td>
<td>81.0757</td>
</tr>
<tr>
<td>model with two step ahead prediction</td>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
<td>E2</td>
<td>F2</td>
<td>G2</td>
<td>H2</td>
</tr>
<tr>
<td></td>
<td>83.89512</td>
<td>94.92661</td>
<td>92.74462</td>
<td>78.33622</td>
<td>67.54981</td>
<td>95.08485</td>
<td>94.18364</td>
<td>82.74816</td>
</tr>
<tr>
<td>model with three step ahead prediction</td>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
<td>E3</td>
<td>F3</td>
<td>G3</td>
<td>H3</td>
</tr>
<tr>
<td></td>
<td>95.58905</td>
<td>94.87282</td>
<td>92.54401</td>
<td>78.73823</td>
<td>50.69612</td>
<td>95.058</td>
<td>93.60554</td>
<td>83.12422</td>
</tr>
<tr>
<td>model with four step ahead prediction</td>
<td>A4</td>
<td>B4</td>
<td>C4</td>
<td>D4</td>
<td>E4</td>
<td>F4</td>
<td>G4</td>
<td>H4</td>
</tr>
<tr>
<td></td>
<td>95.6297</td>
<td>94.82405</td>
<td>91.63548</td>
<td>79.10944</td>
<td>78.36504</td>
<td>95.00928</td>
<td>93.01039</td>
<td>83.49109</td>
</tr>
<tr>
<td>model E1 with different membership functions</td>
<td>333</td>
<td>335</td>
<td>336</td>
<td>337</td>
<td>355</td>
<td>535</td>
<td>555</td>
<td></td>
</tr>
<tr>
<td></td>
<td>93.80307</td>
<td>66.2487</td>
<td>93.23977</td>
<td>99.57447</td>
<td>89.37164</td>
<td>97.56796</td>
<td>92.20287</td>
<td></td>
</tr>
</tbody>
</table>

The selected fuzzy model has %99.57 fitness to actual output temperature and root mean square error= 0.4º C. (validation with 4 loads which were not used for modeling)

Inputs for this model are: current power, current temperature and last change in temperature and the output for this model are one step-ahead prediction of the change in the temperature.

Fig. 10 demonstrates the idea of Takagi-Sugeno model with 3x3x7=63 rules.
ANFIS (adaptive-network-based fuzzy inference system Fuzzy control) has the ability of on-line and off-line adaptations. It should be considered that the data for modeling gathered during a certain regime of process, this data is not sufficient to map completely the plant. When performing on-line identification, the data distribution can usually not be influenced. Therefore, two difficulties may arise: insufficient excitation in the frequency and in the amplitude range.

The first problem of insufficient dynamic excitation is known from linear model identification. Often, processes are operated at one set point for a long time, and it is obvious that dynamic models cannot be estimated without dynamic excitation.

However, the second problem of insufficient static excitation arises exclusively for nonlinear models. In many practical situations, the process will remain within one operating regime for a long time. The challenge for nonlinear on-line identification is to prevent all the parameters of the model from adapting to this single operation point, and consequently unlearning all the previously trained nonlinear process behavior.

On the other hand, for the off-line identification a representative training data set can be collected that covers a wide frequency and amplitude range. Measurements from many operating conditions can be included, and badly exciting data can be excluded.

Therefore, we consider off-line adaptation for each furnace. Since that ANFIS networks has the ability to adapt, we will provide a strategy to tune the model for each furnace based on input-output data and these models will be implemented in fuzzy control system for each different furnace.
The predictive controller has a feed forward structure. We will add a correction factor to input parameters of plant within an adaptive fuzzy controller. This factor will be adapted based on feedback signal from plant and takes over the task of robustness as well as stability of the system since this controller will be considered as a supervisory controller.

**Validation**

A genetic algorithm (GA) is a parallel, global search technique that emulates operators. Because it simultaneously evaluates many points in the search space, it is more likely to converge toward the global solution. It explores different areas of the parameter space, and then directs the search to regions where there is a high probability of finding improved performance. By working with a population of solutions, the algorithm can effectively seek many local minima, thereby increasing the likelihood of finding the global minimum.

Genetic Algorithms could be used in two different aspects: rule generation and parameter optimization.

**Rule generation**

Genetic algorithms could be used to adjust membership functions and tuning fuzzy rules of supervisory controller. Since this controller will implemented as a correction factor to inputs, GA could generate appropriate fuzzy rules after gathering data of predictive controller.

**Parameter optimization**

Genetic algorithm is an appropriate technique to find best matches on inputs to fuzzy model in each step, instead of searching whole possible inputs which results in time and calculation consumption in each step. Based on the ability of Ga in global search, the results are insured to be the best fit to reference line.

**Conclusion**

Fig. 11 shows the methodology for designing the control system.
Figure 11: Methodology
**Contribution**

Our contribution in this research would be:

1. Define a strategy to model different nitriding furnaces based on Takagi-Sugeno models.
2. Design a predictive fuzzy model based controller adaptive to predicted error.
3. Design an adaptive predictive controller with modified rule base, using Genetic Algorithms to generate data for prediction.

**Time chart**

Finally time chart for this research is presented as follows:
References


[10] Moon, U.-C. and Lee, K. Y., Hybrid algorithm with fuzzy system and conventional PI control for the temperature control of TV glass furnace,


72, 2000.


36
1997.


[51] Wang, Y. N. and Shen, T. T. Hybrid intelligent control for industrial rotary kiln


[77] Tong, S., Tang, J., and Wang, T., Fuzzy adaptive control of multivariable


[90] Takagi, T. and Sugeno, M., Fuzzy identification of systems and its applications to


[102] Holland, J. H. Adaptation in Natural and Artificial Systems, *University of*


