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Research article

Intelligent Control for Gas Collector Pressure of Coke Oven

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Abstract

This paper presents a robust control scheme for controlling the pressure of gas collectors of a coke oven which is a multivariable non-linear process. The effectiveness of the traditional PI (Proportional Integral) control for controlling gas collector pressure of the coke oven is difficult to reach the perfection. A hybrid control scheme based on fuzzy PI and conventional PI methods (called fuzzy PI-PI) is presented. Based on the application of the fuzzy PI-PI and type-2 fuzzy PI-PI control approaches, a high performance pressure control has been obtained.A comparative study between the conventional PI, fuzzy PI-PI and Type-2 fuzzy PI-PI control paradigms has been carried out and. The comparison shows that the Type-2 fuzzy PI outperforms its rival.

Key Words: Coke Oven, Conventional PI Control, Fuzzy PI Control, Type-2 Fuzzy, Gas Collector Pressure.

1. Introduction

Gas pressure is an important parameter of coke oven. Stabilizing it is necessary to enlarge the using of coke oven, reducing the gas reversing, environment protection, saving energy and the life of Coke oven. Extremely low pressure of gas allows air to enter coke oven chambers and cause unsatisfied coke burning, which shortens lifetime of ovens. Also high pressure of gas ovens causes leakage of the gas, pollutes environment, and wastes energy. Modeling such process is hard to do because of its nature of high nonlinearity, being multivariable, time varying and long dead time, therefore, the process mathematical model is not extracted yet [1][2][4][5]. Using traditional control is difficult to reach expected and effective control system. Last researches (Coking experts group, 1978) indicates that normal pressure of the gas collector should be between 80 and 120 Pa (normal operation band) [1][3][5]. The surveys [6] show that the best conventional controller for gas pressure is generally PI controller. This fact has not been considered in the previous researches. Gas pressure control of coke oven has stability problem with PID controller. Therefore, we have applied the PI control in this paper.
The recent research with combined fuzzy control and PID control until now [1] was not completely successful because of process variable offset and instability. Several methods have been proposed to solve the problem, but due to the nonlinearity of the process, designers have to utilize modern control system in order to control all parameters. It seems linearization of gas collector pressure of coke oven with the use of analyzing and try and error methods

leads to stabilization of process. In this research, we have used the combination of the conventional PI controller and fuzzy PI control. Finally, we have compared this hybrid method (T1FPI-PI) with the hybrid system has replaced Type-1 fuzzy by Type-2 fuzzy method (T2FPI-PI).

2. Fuzzy Logic Systems

2.1. Introduction

The fuzzy theory was first presented in 1965 by Professor Lotfi A. Zadeh, who suggested a set theory that was practical over the range [0,1] [10] whereas Boolean logic conclusion is limited to 0 and 1. Fuzzy logic explains the idea that there should be an intermediate value between exact judgments such as absolute true and absolute false. This signifies that fuzzy theory can represent real examples in our daily life such as "very tall", "tall", "very short", and "short". Fuzzy logic is based on degrees of truth and applies linguistics variables. This theory was a vague in the engineering world. Ebrahim Mamdani in 1974, [11] used this method to control a steam engine. This was a foundation for fuzzy logic controlling system. Classical control theory uses a mathematical method to explain the connection between the input and the output of the system. One of its negative points is that they can be used only for liner system. If we have an accurate linear mathematical model of a system, conventional PID controller functions quite acceptable. Usually in real life, we don’t have an exact mathematical model of control process. Perhaps it may not exist! The nonlinear system is uncertain and has incomplete data to model it. There is no way to come up with a proper PID controller design, if the designer does not know the mathematical model. The fuzzy logic control (FLC) is able to control system using some limited an expert human operator. FLCs are economically low cost. They are based on cheap sensors .Type-2 fuzzy logic system (T2FLS) was presented by Zadeh 1975. To be a complement of T1FL sets, Mendel and Karmic have improved the theory of type-2 fuzzy sets more in [12]. The theory of interval T2FLC is described in [13]. T2FLCs possesses better method than type-1 FLCs for handling uncertainty [14, 15]. In [16, 17] the results of uncertainty in type-1 and type-2 are simulated to conduct comparative analysis. As a result, the use of T2FLCs in real world usage [18] which shows modeling uncertainties can have a better dynamic than T1FLCs when the level of uncertainty is high. T1FLCs cannot give an appropriate response [8]. In these situations, the use of T2FLCs is a better method in literature in various aspects like forecasting of time series [19] and controlling of robots [20]. The real time implementation studies indicate that a conventional T1FLCs cannot handle the uncertainties in the system while T2FLCs results in a better performance.

2.2. Type-1 Fuzzy Sets

A type-1 fuzzy set, A, which is in terms of a single variable, x ∈ X, may be defined and shown as:

$$A = \{(x, \mu_A(x))| \ \forall x \in X)\} \qquad (1)$$

A, can also be determined as:

$$A = \int_{x \in X} \mu_A(x)/(X) \qquad (2)$$

where $\int$ means union over all acceptable x. ("/" does not mean division)

As can be seen from Figure 1, a type-1 Gaussian membership function, $\mu_A(x)$, is between 0 and 1 for all x ∈ X, and is a two-dimensional function. This kind of membership function does not include any uncertainty. In other words, there is a vivid membership value for every input data point.

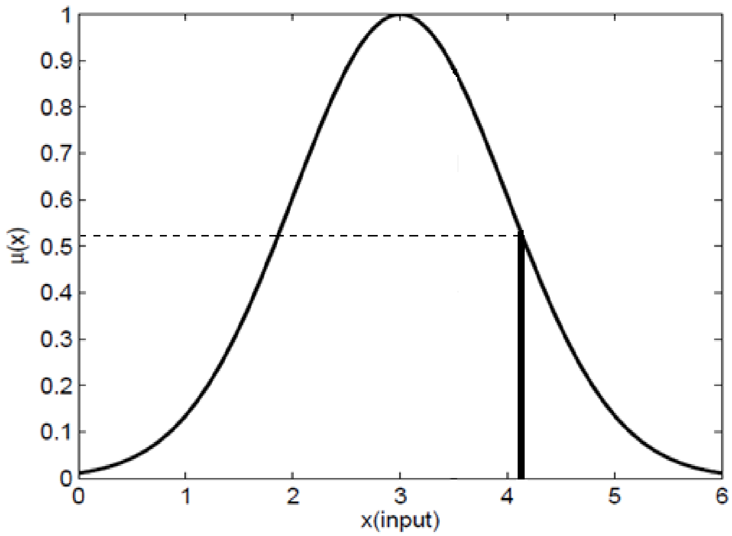

Figure 1: A Gaussian type-1 fuzzy membership function

2.3. Type-2 Fuzzy Sets

A type-2 fuzzy set, $\tilde{A}$, may be shown as: [21]

$$\tilde{A} = \{ ((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \quad (3)$$

where $\mu_{\tilde{A}}(x,u)$ is the type-2 fuzzy membership function in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$.

$\tilde{A}$, can also be determined as [21]:

$$\tilde{A} = \int_{x \in X} \int_{u \in JX} \mu_{\tilde{A}}(x,u)/(x,u) J_x \subseteq [0,1] \qquad (4)$$

Where $\iint$ means union over all acceptable x and u [21].

J_x is called primary membership of x [21]. In addition, there is a secondary membership value according to each primary membership value that explains the possibility for primary membership value [22]. While the secondary membership functions can take values in the interval of [0,1] in generalized T2FLSs, they are similar functions that only take on values of 1 in interval T2FLSs. The general T2FLSs are very demanding, but the use of interval T2FLSs is seen more in the literature, due to the fact that the computations are more manageable. If the circumstances are so fuzzy, the places of the membership functions may not be certain precisely. In such cases, the membership degree cannot be chosen as a crisp number in [0, 1], then the use of type-2 fuzzy sets forced to be a higher option. If the standard deviation of the Gaussian function in figure 1 is blurred, figure 2 can be produced. In figure 2, the membership function does not have a unique value for a specific value of x. The values on the intersection of vertical line and the region of membership function do not need all be weighted same. Thus, a weight distribution can be defined for those points. So a three-dimensional membership function (type-2 membership function) that indicates the characteristics of a type-2 fuzzy set is created if all x ∈ X have assigned its own distribution [2].

The footprint of uncertainty (FOU), the union of all primary memberships, is said to be the bounded region that represents the uncertainty in the incipient memberships of a type-2 fuzzy set (Figure 2). An upper membership function and a lower membership function are two type-1 membership functions that are the bounds for the footprint of uncertainty of a type-2 fuzzy set [7] [23].

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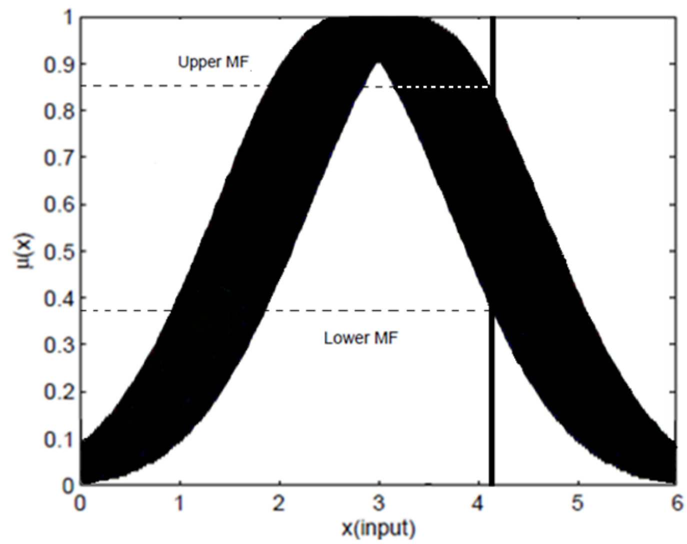

Figure 2: A Gaussian interval type-2 fuzzy membership function

2.4. Interval Type-2 Fuzzy Sets

When all $\mu_{\tilde{A}}(x,u)$ are equal to 1, then $\tilde{A}$ is an interval T2FLS. The special case of equation (4) might be determined for the interval T2FLSs as:

$$\tilde{A} = \int_{x\in X}\int_{u\in JX} 1/(x,u) \quad Jx \subseteq [1,0] \qquad (5)$$

The researchers are familiar to the calculated duty of general T2FLS. Therefore, interval T2FLSs is generally used in literature. Each the general and interval Type-2 fuzzy membership functions are 3-dimensional. As can be seen from figure 3, the only difference between them is that the secondary membership value of the interval type-2 membership function is always equal to 1.

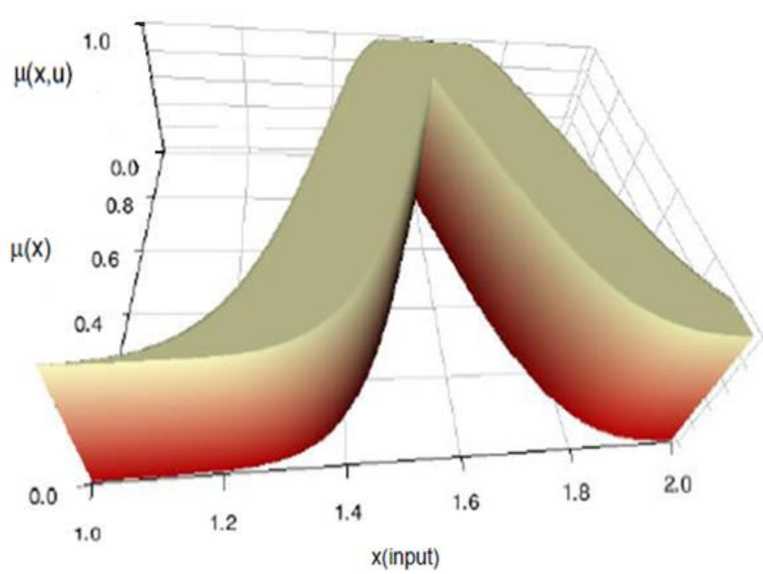

Figure 3: Three-dimensional representation of interval type-2 fuzzy membership functions

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2.5. Type-2 Fuzzy Logic System Block Diagram

The type-1 and type-2 fuzzy logic system are shown in figure 4 and figure 5, respectively. As can seen from figure 5, an additional block (type reduction) is needed in type-2 FLS design. Though the structure in figure 5 brings some benefits when dealing with uncertainties, it also increases the computational costs. The basic blocks of a T2FLS are as below:

- **a) Fuzzifier:** It maps crisp inputs into type-2 fuzzy sets which activates the inference engine.
- **b) Rule base:** The rules in a T2FLS remain the same as in T1FLS, but antecedents and consequents are represented by interval type-2 fuzzy sets.
- **c) Inference:** Inference blocks connect fuzzy inputs to fuzzy outputs using the rules in the rule base and the operators such as union and intersection. In type-2 fuzzy sets, join (⊔) and meet (⊓) operators, which are new concepts in fuzzy logic theory, are used instead of union and intersection operators. These two new operators are used in secondary membership functions. For a more detail about them, refer to [24].
- **d) Type-reducer:** The type-2 fuzzy outputs of the inference engine are converted into type-1 fuzzy sets that are called the type-reduced sets. There are two common methods for the type-reduction operation in the interval type2 fuzzy logic system: One is the Karmic-Mendel iteration algorithm and the other is Wu-Mendel uncertainty bounds method. Calculation of the centroid is the base of these two methods.
- **e) Defuzzification**: The type-reduced fuzzy sets are inputs of defuzzification block. Since the type-reduced sets are determined by their left end and right endpoints, the defuzzified value is calculated from mean extracting of these points [7].

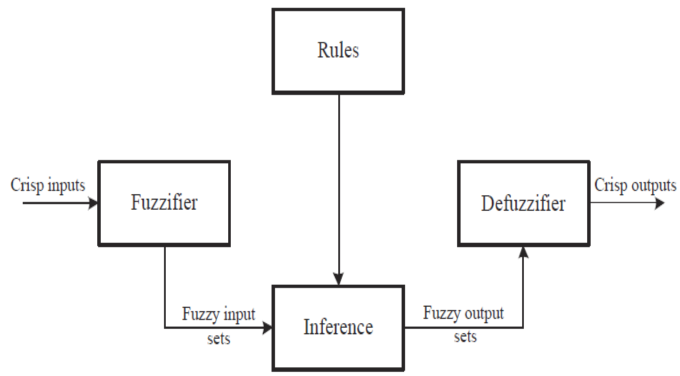

Figure 4: T1FLS block diagram

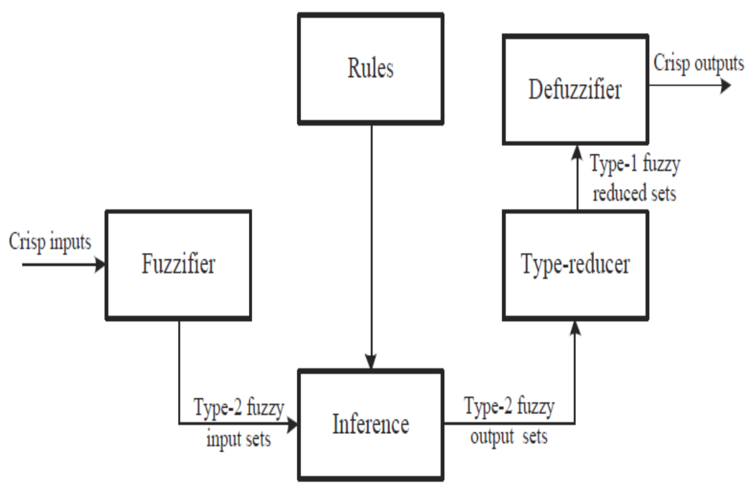

Figure 5: T2FLS block diagram

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3. The Characteristic Analysis to the Control Object and Control Requirement

This paper discuss about coking plant including two coke ovens #1 and #2 with one gas collector for each oven. Gas collecting from main pipe enter to the cooling system. Cooling system contains early cooler and blast blower, which sends gas to the user. As the cooling system and blower of both coke ovens are similar, pressure of one coke oven will affect on the other one so the couple pressure of gas collectors is very important. Coke ovens are parallel together, while gas collectors are in series with the blast blower. Gas collectors are themselves parallel and this shows negative coupling relationship [1]. This type of coupling relationship has most effect on the index of quality. We can control collectors discharge gas pressure by adjusting the butterfly valves of coke ovens. Flow diagram of the coking system is shown in figure 6.

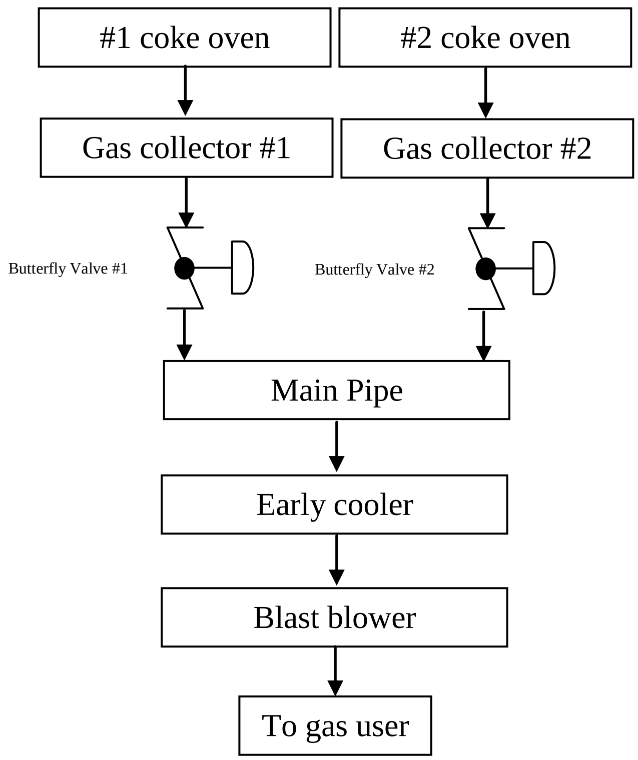

Figure 6: Flow diagram of the coking system

4. The Fuzzy PI Control of the Gas Collectors Pressure

4.1. Design and Choose the Fuzzy PI Control

The basic working theory of the design of fuzzy controller with the auto-tuning PI parameter is that fuzzy auto-tuning PI parameter controller which based on a conventional PI controller as [1]:

$$U(k) = K_P E(k) + K_I \sum \boldsymbol{E}\,(k) \qquad (6)$$

Establish parameters K_P and K_I, which use fuzzy theory. The parameters use deviation absolute value and deviation change absolute value expressive binary continuous function is:

$$\boldsymbol{K_P} = \boldsymbol{f_1}(|\boldsymbol{E}|, |\boldsymbol{E_C}|) \qquad (7)$$

$$\boldsymbol{K_I} = \boldsymbol{f_2}(|\boldsymbol{E}|, |\boldsymbol{E_C}|) \qquad (8)$$

According to the different fuzzy controller with different $|E|\ and\ |E_C|$, online auto-tuning parameters K_P, K_I are different in the fuzzy controller. Online self-revised processes are shown in figure 7.

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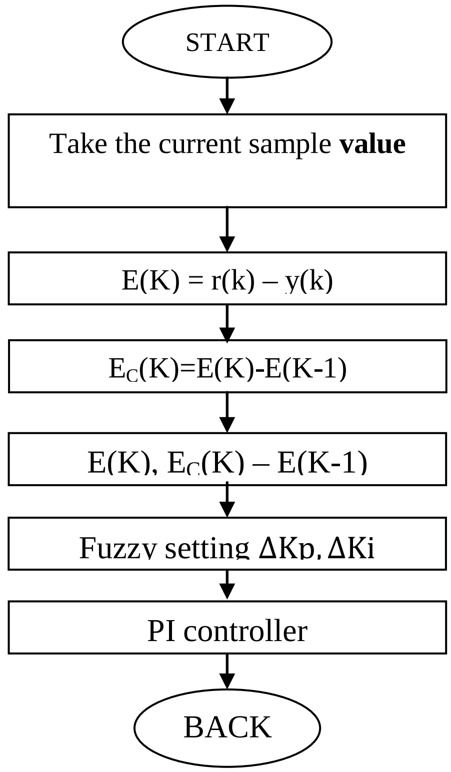

Figure 7: Online self-revised processes

4.2. Determine of Membership Function

In the process of design of the fuzzy controller, two signals E and E_C are selected as inputs of the controller. E and E_C are the system error and the error change rate (error derivative) respectively. E is described by suing seven triangular shaped fuzzy sets membership functions: NB (negative big), NM (negative medium), NS (negative small), ZE (zero), PS (positive small), PM (positive medium), PB (positive big). E_C is described by suing seven triangular shaped fuzzy sets too. The fuzzy-PI control system (FPICS) designed by us is a dual-input and dual-output system. The two fuzzy control input variables are deviation (E) and deviation of change (E_C) and two output variables are K_P and K_I for the PI control. The membership functions are shown in figures 8 & 9.

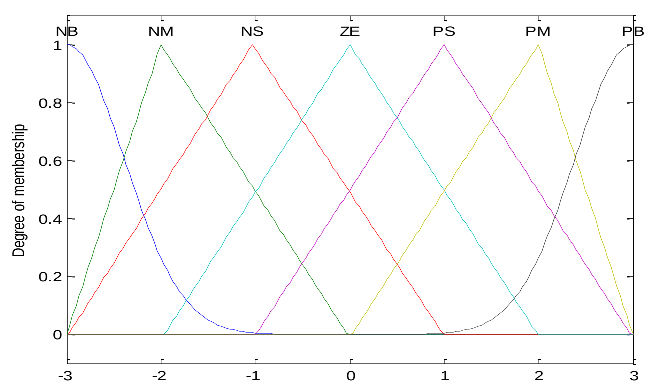

Figure 8: Membership functions of E, E_C and K_I (T1FPI)

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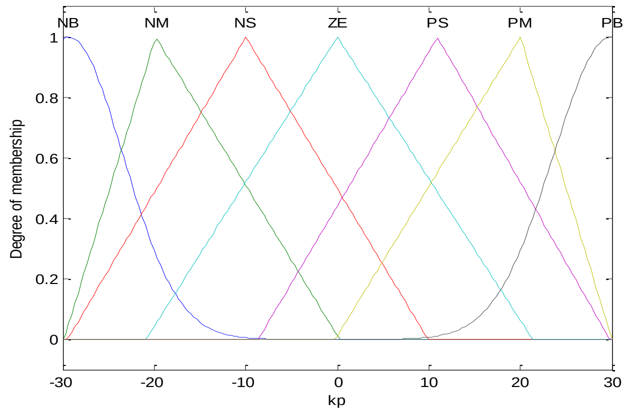

Figure 9: Membership functions of K_P (T1FPI)

4.3. The Establishment of Fuzzy Rules

Fuzzy rules are linguistic IF-THEN constructions that have the general form of "IF *A* THEN *B*" where *A* and *B* are (collections of) propositions containing linguistic variables. *A* is called the premise and *B* is the consequence of the rule. In effect, the use of linguistic variables and fuzzy IF-THEN rules exploits the tolerance for imprecision and uncertainty. In this respect, fuzzy logic mimics the crucial ability of the human mind to summarize data and focus on decision-relevant information. In a more explicit form, if there are I rule each with K premises in a system, the ith rule has the following form.

$$If\ \ (a_1\ \ is\ \ A_{i,1})\ \Theta\ (a_2\ \ is\ \ A_{i,2})\ \Theta\ \ldots.\Theta\ (a_k\ \ is\ \ A_{i,k})\ \ then\ B_i$$

In the above equation a represents the crisp inputs to the rule and *A* and *B* are linguistic variables. The establishment of the fuzzy rules in the self-adaptive fuzzy PI control firstly judged from the knowledge base, which established based on the experts' experience knowledge, and then decided the fuzzy relation between two characters, the error E and the error change ratio E_C. Then during the continuous testing to the E and E_C in the operation, self-tuning two parameters online and according to the certain rules of fuzzy control to satisfy the different E and E_C values, needs two parameters, so that they can make the controlled object have good dynamic and static performances. Base on the setting principles of PI parameters, and on the abstract of the engineering and technical personnel's technical science and practical operation skills, the control rules of the output variables, K_P and K_I are shown in table 1 and table 2.

Table 1: ΔK_P fuzzy control rules

ΔK_P \ E \ E_C	NB	NM	NS	ZE	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZE	ZE
NM	PB	PB	PM	PS	PS	ZE	NS
NS	PM	PM	PM	PS	ZE	NS	NS
ZE	PM	PM	PS	ZE	NS	NM	NM
PS	PS	PS	ZE	NS	NS	NM	NM
PM	PS	ZE	NS	NM	NM	NM	NB
PB	ZE	ZE	NM	NM	NM	NB	NB

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Table 2: ΔK_I fuzzy control rules

ΔK_I (E \ Ec)	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZE	ZE
NM	NB	NB	NM	NS	NS	ZE	ZE
NS	NB	NM	NS	NS	ZE	PS	PS
ZE	NM	NM	NS	ZE	PS	PM	PM
PS	NM	NS	ZE	PS	PS	PM	PB
PM	ZE	ZE	PS	PS	PM	PB	PB
PB	ZE	ZE	PS	PM	PM	PB	PB

4.4. Surface viewer for K_I shown in figure 10.

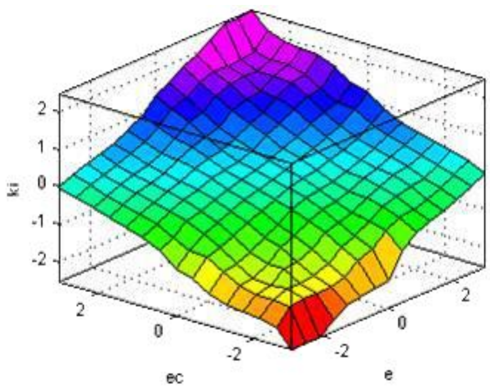

Figure 10: Surface viewer for K_I

4.5. Simulation of Fuzzy PI Control Algorithm

Simulation processes are performed in MATLAB R2010a platform. The gas collector pressure of the coke oven system is a non-linear, multivariable and time-varying system. The system model is extracted through the below steps:

a) Investigation of the researches accomplished about the control process of gas pressure inside coke ovens show that no mathematical model is developed yet.
b) The process is linearized in four areas from minimum to maximum possible values of gas pressure within the chamber of coke ovens that range from 0 to 200 Pa.
c) Process transfer function is developed from PID controller data extracted in [1]. This is done by try and error and changing the coefficients of an assumed 2nd degree linear function until when the output is nearly fit to PID control curve in [1].
d) During the simulation, set point is considered 80 Pa.
e) During its simulation, the transfer function of the coke-side gas collector pressure system in normal operation band is:

$$\left(\frac{1}{8s^2 + 9s + 1.6}\right) e^{-40s}$$

5. The Type-2 Fuzzy PI Control of the Gas Collectors Pressure

5.1. Design and Choose the Type2-Fuzzy PI Control

The type-2 fuzzy PI controller design is the same as fuzzy PI controller. Design difference between the first and second methods is the choice of membership functions. Membership functions for type2-fuzzy PI controller shown in figures 11 & 12.

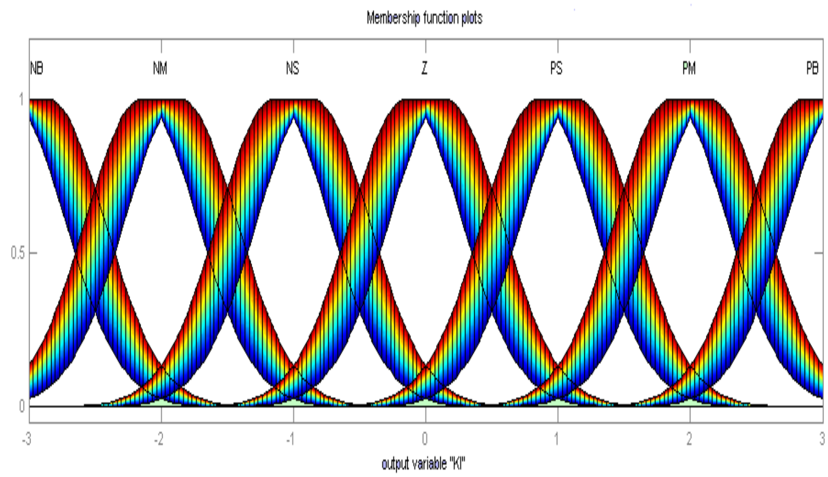

Figure 11: Type-2 membership functions of E, E_C and K_I

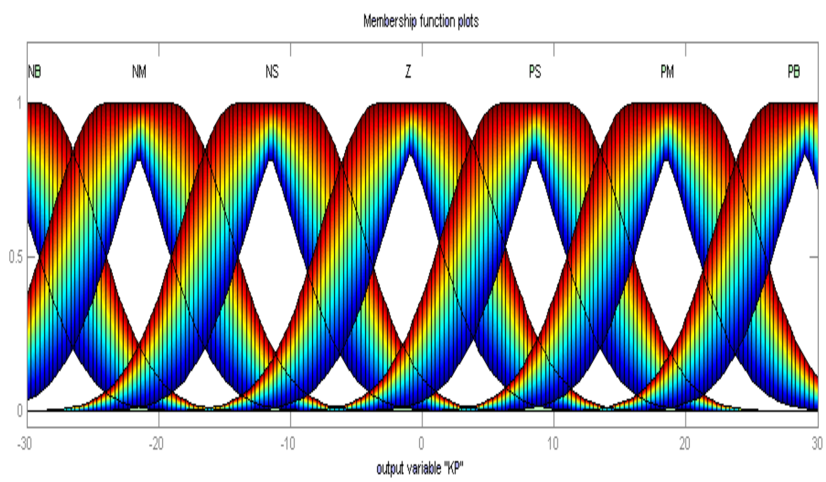

Figure 12: Type-2 membership functions of K_P

6. Simulation Results

6.1. The Response Curve of the Conventional PI System Shown In Figure 13

As can be seen in figure 13, the process variable (coke oven pressure) converges to set point (80 Pa) after approximately 700 s. This long time causes negative pressure in the oven, disorder in coke production, propagation of toxic gases and environment pollution. Therefore, because of high sensitivity of the process and the importance of controlling it at a very high accuracy (about ±1 Pa (0.00001bar)), its control must have a neat and rapid response to process variations. This may be interpreted to reducing rise time and stabilizing process in normal operation band.

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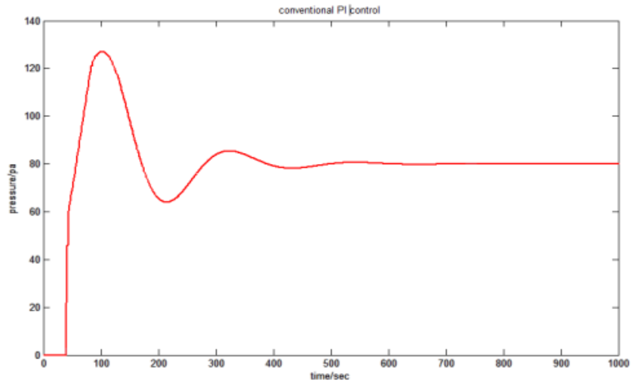

Figure 13: Response curve of traditional PI

6.2. The Response Curve of the Fuzzy PI-PI System Shown In Figure 14

It can be seen from figure 14 that the time to reach set point is reduced dramatically from 700 to 80 s. Compared with previous researches in [1][2][3], it shows that steady-state error is also removed completely and overshoot is very negligible.

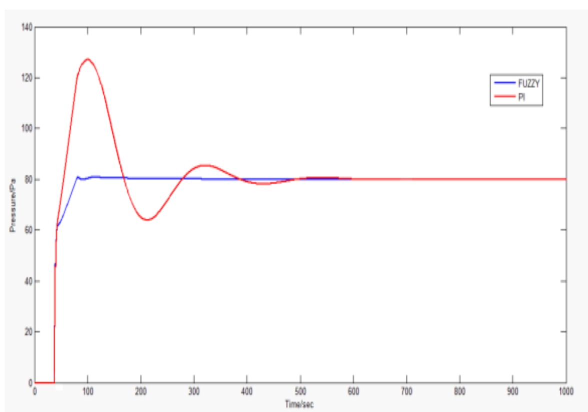

Figure 14- a: Response curve of fuzzy PI (operation of coke ovens)

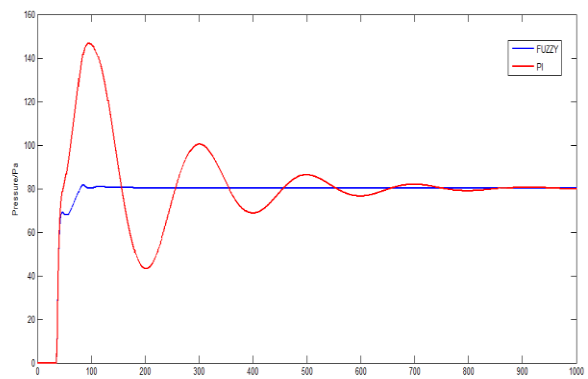

Figure 14- b: Response curve of fuzzy PI (25% above the normal band)

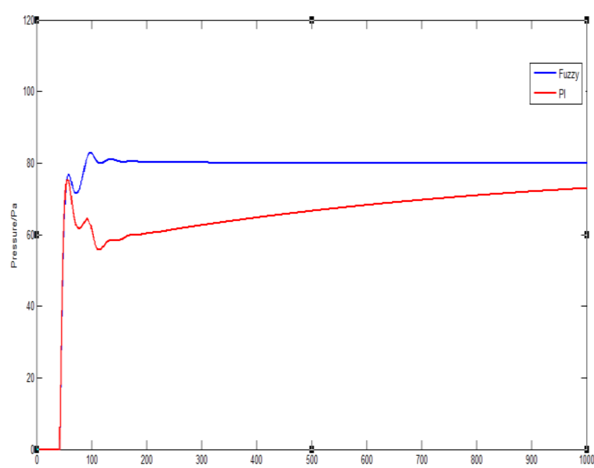

Figure 14- c: Response curve of fuzzy PI (25% below the normal band)

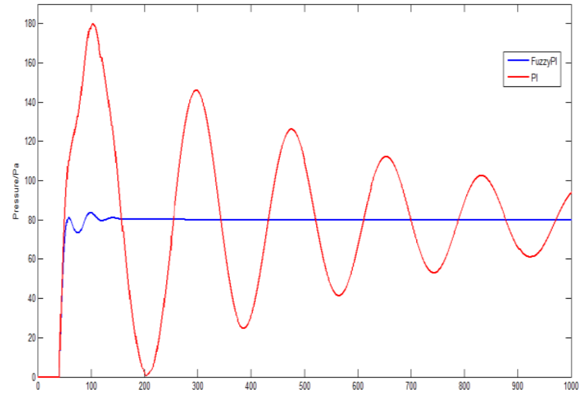

Figure 14- d: Response curve of fuzzy PI (50% above and below the normal band)

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Figure 14: Response curves of the Fuzzy PI system

6.3. The Response Curve of the Type-2 Fuzzy PI-PI System Shown In Figure 15

The results show that the time to reach normal band is reduced from 700 s to 55 s in figure 14-(a) and 45 s in figure 14-(d) where maximum deviation from normal band exists. This is significantly better from performance of type-1 fuzzy controller. Thus, as the uncertainty of conventional controller function becomes more, referred to normal band, type-2 fuzzy controller shows a better performance in stabilizing the process.

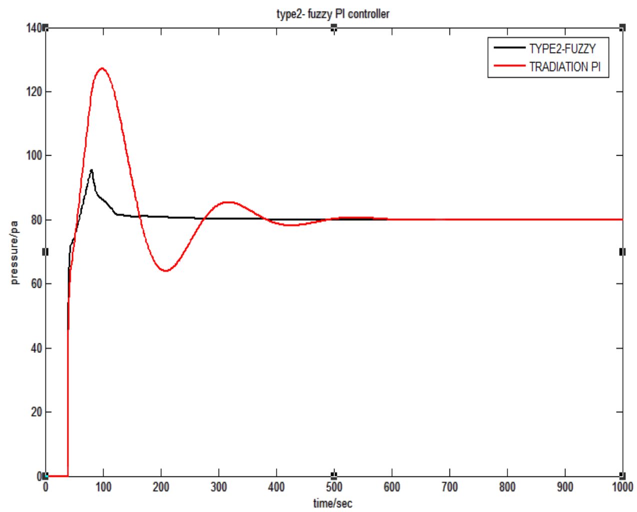

Figure 15- a: Response curve of type-2 fuzzy PI (operation of coke ovens)

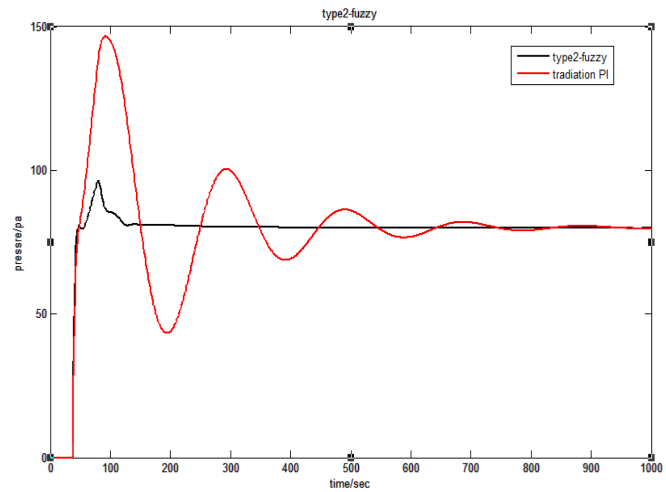

Figure 15- b: Response curve of type-2 fuzzy PI (25% above the normal band)

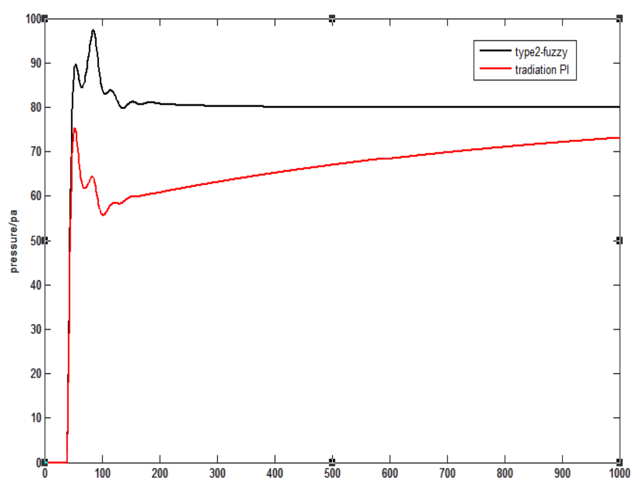

Figure 15- c: Response curve of type-2 fuzzy PI (25% below the normal band)

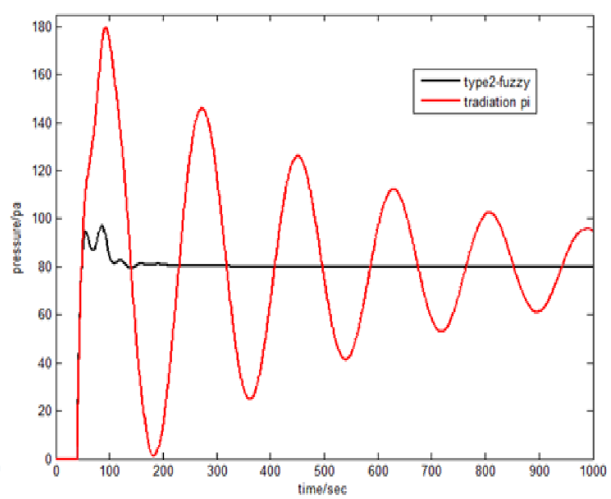

Figure 15- e: Response curve of type-2 fuzzy PI (50% above and below the normal band)

Figure 15: Response curves of the type-2 Fuzzy PI system

7. Conclusion

From the comparison of the simulation results of conventional PI control algorithm and self-tuning fuzzy PI control algorithm with type-2 fuzzy method, we can see that the self-tuning type-2 Fuzzy PI Controller has all the advantages of both conventional PI control and fuzzy PI control. Additionally, the advantages of this controller are removing system overshoot out of normal operation band, shortening rise time, high steady-state precision, good anti interference capability and stability in front of uncertainty. Referring to the conventional method of PI, by which after exactly 700 s process reaches to the 80 Pa steady state, the method "type-2 fuzzy PI-PI" controller reduces time to 45 s. Therefore, offset is eliminated completely. Consequently, long life for coke oven, reduced energy consumption and environment pollution will happen. The state of art of latter method is being simple and economically affordable.

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