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A comparative study on applications of artificial intelligence-based multiple models predictive control schemes to a class of industrial complicated systems

A. H. Mazinan[1] · A. R. Khalaji[2]

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Abstract The purpose of the present research is to demonstrate a comparative study on applications of artificial intelligence-based multiple models predictive control schemes, which are considered in a number of referenced materials. These control schemes are to implement on a class of industrial complicated systems, as long as the traditional related cases are not to guarantee the desired tracking performance, efficiently. In reality, the research proposed here, in its present form, outlines the achieved results of the control schemes, which are all organized based on both the multiple models strategy and the linear model based predictive control approach, as well. In one such case, the outcomes are focused on an industrial tubular heat exchanger system, which has so many applicabilities in real and academic environments. The traditional schemes are almost implemented on the system to control the outlet temperature of the inner tube by either the temperature or the flow of the fluid flowing, concurrently, through the shell tube. In some situations, the appropriate control scheme realization is not possible, due to the fact that the whole of system coefficients variation cannot quite be covered by the control action. In case of the matter presented, the techniques need to be organized, which the tracking performance both in the system coefficients and also in the desired set point variations could acceptably be guaranteed. Hereinafter, the performance mentioned and also the weight of realization of each one of the proposed control schemes have been surveyed, while all of them are presented in shortened version and therefore their details are not thoroughly given here. In such a case, some schemes are now available in the corresponding research, that are fully referenced, in

✉ A. H. Mazinan
mazinan@azad.ac.ir; ahmazian@gmail.com; ah_mazinan@yahoo.com

1 Department of Control Engineering, Faculty of Electrical Engineering, South Tehran Branch, Islamic Azad University (IAU), No. 209, North Iranshahr St, P.O. Box 11365/4435, Tehran, Iran

2 Department of Control Engineering, South Tehran Branch, Islamic Azad University (IAU), No. 209, North Iranshahr St, P.O. Box 11365/4435, Tehran, Iran

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the present investigation. In agreement with the acquired results, the validity of the control schemes are tangibly verified and also compared with respect to each other. Consequently, the finalized control schemes are suggested, where the advantages and its disadvantages of each one of them over the system are accurately investigated in line with the related reasons.

Keywords A set of model based predictive control schemes · Intelligence-based approach · Nonlinear generalized predictive control scheme · Multiple models strategy · Industrial complicated systems

1 Introduction

This investigation is organized based on applications of a set of control techniques proposed here to deal with a class of industrial complicated systems. While the tubular heat exchanger system is chosen as an example of the complex system, so many applicabilities, in a number of real and academic environments are easily existed such as food processing, automotive, pulp and paper, chemicals-petrochemicals and so on. These control schemes considered here are realized with a focus on the multiple models strategy as well as the model based predictive control (LMBPC) approach. In fact, the main concept of dealing with the proposed schemes is to design the multiple models strategy and the corresponding LMBPC approach, where the linear generalized predictive control (LGPC), as the powerful approach, in the LMBPC family is realized in most of the present control schemes. Nowadays, the LGPC approach could only be realized in association with the explicit linear model of the system to predict the controlled variables over a specified range of time horizon. Regarding the background of the research, it should be noted that Nagy et al. study on output feedback nonlinear model predictive control in temperature tracking with its application to an industrial batch reactor, while Chen et al. consider multiple models predictive control in the area of a hybrid proton exchange membrane fuel cell system [1,2]. Nunez et al. propose fuzzy model-based hybrid predictive control, where Ning et al. reveal multiple models predictive control in association with the Takagi-Sugeno fuzzy models [3,4]. Moreover, Kassem designates a control approach for a stand-alone wind energy conversion system via the functional model predictive control, as long as Prakash et al. focus on nonlinear PID controller as well as nonlinear model predictive controller in a continuous stirred tank reactor [5,6]. Now, based on the LGPC approach, it has to assume that each one of the operating environments of the system is either time invariant or slowly time variant in the span of time. Therefore, as a result, the LGPC approach is well behaved based on the linear models of the system, but when the operating environment region is extended, the nonlinearity of the system cannot actually be ignored. Hereinafter, the appropriate scheme tracking performance could purposefully be guaranteed, as long as we are using both the LGPC approach and the highly nonlinear or the time variant system. In the practical applications such as the industrial tubular heat exchanger system, due to the coefficients variations, the system needs to operate in multiple operating environments, which may change, abruptly, from one to another. In the same way, the system tracking performance of the LGPC approach cannot logically be guaranteed, while we are abruptly encountered with this coefficients variation. In reality, the main aim of realizing the proposed control schemes is to improve the LGPC performance, both in desired set point variation and in system coefficients variation, while we are dealing with a nonlinear or a time variant system. These control schemes are fully organized in eight distinctive techniques, where the main topic in each one of them is the same version as others. Based on the matter presented, the first control scheme is realized based on a single model LGPC (SMLGPC) approach, where one linear model is used to represent the system [7]. The second control scheme is realized based on the several predefined linear models and the corresponding LGPC approaches, where the chosen model identification mechanism is designed based on a fuzzy-based decision system [8]. Hereinafter, the third control scheme is realized based on the several predefined linear models and the Takagi-Sugeno-Kang (TSK) fuzzy-based GPC approach, while the fourth control scheme is also realized based on both the TSK fuzzy-based model and the TSK fuzzy-based GPC approaches, respectively [9,10]. In this investigation, the fifth control scheme is organized in case of the multiple fuzzy-based predictive control (FPC) and the multiple fuzzy-based predictive model (FPM) approaches, where the chosen model of the system is identified by a fuzzy-based decision system [11]. Also, the sixth control scheme is organized in association with the some linear fixed/adaptive models and the corresponding fixed/adaptive LGPC approaches, where the chosen model identification mechanism is realized based on a fuzzy-based decision maker system [12]. Furthermore, the seventh control scheme is organized in line with the nonlinear GPC (NLGPC) as a benchmark approach in the some of the schemes [13]. Finally, the eighth control scheme is organized in accordance with the some linear fixed/adaptive models and the corresponding fixed/adaptive LGPC approaches, where the chosen model identification mechanism is designed based on both a fuzzy-based adaptive Kalman filter (FAKF) approach as well as a recursive weight generator (RWG) approach [14]. There are a number of referenced materials that are now avoided presenting to reach concise presentation.

The remainder of this paper is organized as follows. The proposed multiple models based predictive control schemes and the simulation results are presented in Sects. 2 and 3, respectively. The comparative analysis on the proposed control schemes and also the concluding remarks are finally presented in Sects. 4 and 5, respectively.

2 The proposed multiple models based predictive control schemes

The proposed control schemes are fully organized based on the model based predictive control (LMBPC) approach, while the most of them are partially organized based on the multiple models strategy. These control schemes are demonstrated to deal with the industrial tubular heat exchanger system with the several applicabilities in both real and academic environments. In this investigation, all the schemes are presented, in their brief forms. Now, let us outline their titles by the following

- *Control scheme 1*
  The single model LGPC (SMLGPC) approach [7].

- *Control scheme 2*
  The multiple predefined linear models and the corresponding LGPC approaches within the fuzzy-based decision system [8].
- *Control scheme 3*
  The multiple predefined linear models and the Takagi-Sugeno-Kang (TSK) fuzzy-based GPC approach [9].
- *Control scheme 4*
  The TSK fuzzy-based model approach and the TSK fuzzy-based GPC approach [10].
- *Control scheme 5*
  The multiple fuzzy-based predictive models (FPMs) and the corresponding fuzzy-based predictive controls (FPCs) within the fuzzy-based decision system [11].
- *Control scheme 6*
  The multiple linear fixed/adaptive models and the corresponding fixed/adaptive LGPC approaches within a fuzzy-based decision maker system [12].
- *Control scheme 7*
  The nonlinear GPC (NLGPC) approach [13].
- *Control scheme 8*
  The multiple linear fixed/adaptive models and the corresponding fixed/adaptive LGPC approaches within the chosen model identification mechanism realized by both a fuzzy-based adaptive Kalman filter approach as well as a recursive weight generator approach [14].

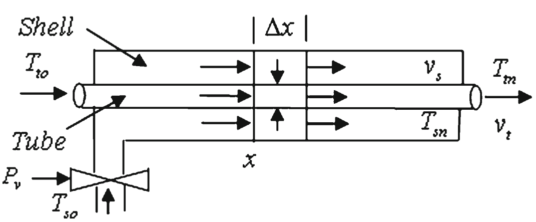
Prior to presenting the proposed control schemes, the industrial tubular heat exchanger system modeling is investigated in the proceeding section.

2.1 The industrial tubular heat exchanger system modeling

The industrial tubular heat exchanger system in its general form is a device that is used to modify and to control the temperature distribution of one medium by the other [15,16]. This system has both the inner and the shell tubes with concurrent reactions, which fluid of the inner tube flows concurrently through the shell tube, as shown in Fig. 1. In order to model the industrial tubular heat exchanger system, the following parameters need to be defined

ψ: section area of the tube (m^2), ρ: fluid density (kg/m^3), v: fluid velocity (m/s), Δx: incremental element in tube (m), T_x: temperature of x (K), d: internal diameter of

Fig. 1 Diagram of the industrial tubular heat exchanger system



the tube (m), U: overall heat transfer coefficient (W/m^{2}K), C_p: specific heat capacity (J/kgK).

In this case, the temperature distribution of an incremental element Δx, along x, based on the principle of conservation of energy, at the time t, could be given as

$$\psi\rho C_p \Delta x \frac{\partial T}{\delta t} = \psi\rho C_p v(T_x - T_{x+\Delta x}) + U\pi d \Delta x \Delta T \tag{2.1}$$

where $\psi\rho C_p \Delta x \frac{\partial T}{\delta t}$ denotes the accumulation of energy into Δx, $\psi\rho C_p v T_x$ denotes the convection flow of the energy into Δx, $\psi\rho C_p v T_{x+\Delta x}$ also denotes the convection flow of the energy out of Δx and finally $U\pi d \Delta x \Delta T$ represents the heat transfer into Δx. Now, by assuming $\Delta x \longrightarrow \delta x$, the obtained PDEs describing the system could be written as

$$\psi\rho C_p \frac{\partial T}{\delta t} = -\psi\rho C_p v \frac{\delta T}{\delta x} + U\pi d \Delta T \tag{2.2}$$

In such a case, by using T_t and T_s as the temperature parameters in the inner tube and the shell tube, respectively we can have the results in the following

$$\begin{cases} \frac{\partial T_t}{\partial t} = -v_t \frac{\partial T_t}{\partial x} + a_t T_s - a_t T_t; & a_t = \frac{U\pi d}{\psi_t \rho_t C_{p_t}} \left(\frac{1}{sec.}\right) \\ \frac{\partial T_s}{\partial t} = -v_s \frac{\partial T_s}{\partial x} + a_s T_t - a_s T_s; & a_s = \frac{U\pi d}{\psi_s \rho_s C_{ps}} \left(\frac{1}{sec.}\right) \end{cases} \tag{2.3}$$

Also by defining T_t and T_s as the outlet and the inlet of the system and also assuming $s = \frac{\delta}{\delta t}$, we can have

$$\frac{\delta T_t(x,s)}{\delta x} + \frac{s + a_t}{v_t} T_t(x,s) = \frac{a_t}{v_t} T_s(x,s) \tag{2.4}$$

The system modeling results should uniformly be divided into small incremental elements while the boundary conditions are given at $x = kN;\ k = 0, 1, 2, \ldots, n$. Therefore, the system temperature could be represented as

$$T_{tk} = T_t(kN, s), \qquad T_{sk} = T_s(kN, s) \tag{2.5}$$

where T_{tk} and T_{sk} are given as the temperature at the kth point of the inner and the shell tubes, respectively. Now, the system transfer function could be written as

$$\frac{T_{tk}}{T_{sk}} = \frac{a_t}{s + a_t} \left(1 - exp\left(-\frac{kN}{v_t}(s + a_t)\right)\right) \tag{2.6}$$

Moreover, the obtained results could be expressed in terms of the valve pressure, i.e., $\frac{T_{tk}}{P_v}$, by using

$$K_v \lambda P_v - U\pi d \int_0^{kN} (T_{sk} - T_{tk}) dx = C_s \frac{\delta T_{sk}}{\delta t} \tag{2.7}$$

Hereinafter, using (2.6) and (2.7), we could have

$$T_{sk}\left(U\pi d\left(\frac{kNs}{s+a_t}+\frac{a_t v_t}{(s+a_t)^2}\left(1-exp\left(-\frac{kN}{v_t}(s+a_t)\right)\right)\right)+sC_s\right)=K_v\lambda P_v \tag{2.8}$$

As a consequence, the industrial tubular heat exchanger modeling could be resulted using (2.6) and (2.8) as

$$\frac{T_{tk}}{P_v}=\frac{k_1\xi(s)}{aa_t^{-1}s^2+(a+kNa_t^{-1})s+\frac{v_t}{s+a_t}\xi(s)} \tag{2.9}$$

where K_v, λ, P_v and C_s are the valve gain, compressed steam temperature of the shell tube, valve pressure and the shell tube capacitance, respectively. Also $\xi(s)$, k_1 and a are given as $1-\exp(-\frac{kN}{v_t}(s+a_t))$, $\frac{k_v\lambda}{U\pi d}$ and $\frac{C_s}{U\pi d}$, respectively. After the system modeling presented, all the control schemes are now described in the proceeding sections.

2.2 The proposed control scheme 1

In this control scheme, the linear generalized predictive control (LGPC) approach is realized to control the industrial tubular heat exchanger system [17]. In such a case, the sequence of the future model outputs using the system modeling could be obtained by the following j-step ahead predictor

$$\begin{aligned} y(k+j) &= H_j(q^{-1})\Delta u(k-1)+G_j(q^{-1})\Delta u(k+j-1)\\ &\quad +F_j(q^{-1})y(k); \quad j=N_1,\ldots,N_2 \end{aligned} \tag{2.10}$$

where $y(k)$ and $\Delta u(k)$ denote the model output variable and the manipulated variable, respectively. Here, N_2-N_1+1 is given as the prediction horizon. Afterwards, $H_j(q^{-1})$, $G_j(q^{-1})$ and $F_j(q^{-1})$ could be obtained using the following Diophantine equation, i.e.,

$$1=E_j(q^{-1})A(q^{-1})\Delta(q^{-1})+q^{-j}F_j(q^{-1}) \tag{2.11}$$

where $A(q^{-1})$ and $B(q^{-1})$ could be obtained using the RLS identification algorithm in the CARIMA model of the system, given by the following

$$A(q^{-1})y(k)=B(q^{-1})u(k-1)+\frac{e(k)}{\Delta(q^{-1})} \tag{2.12}$$

Here, $e(k)$ denotes the random sequence number and $\Delta(q^{-1})$ denotes $1-q^{-1}$ as well. Based on the matter presented, the LGPC manipulated variable can now be given as

$$\widetilde{U}=K^{LGPC}(R-F) \tag{2.13}$$

where

$$K^{LGPC}=\left(G_j(q^{-1})^T G_j(q^{-1})+\lambda I\right)^{-1}G_j(q^{-1})^T \tag{2.14}$$

Now, the first row of the K^{LGPC} matrix is applied to the system, at each instant of time. In such a case, the LGPC control action could be obtained by

$$u(k) = \frac{1}{1 - q^{-1}} \Delta u(k) \tag{2.15}$$

2.3 The proposed control scheme 2

The proposed control scheme is organized in case of the multiple predefined linear models and the corresponding LGPC approaches, as shown in Fig. 2 [18–20]. In this control scheme, $\mathrm{M}_{\#p}$; $p = 1, 2, \ldots, r$ are the models, which are used in parallel with the system. Hereinafter, $y(t)$ is given as the output of the systems and $u(t)$ is also given as the finalized control action. In designing the proposed control scheme, the chosen model identification mechanism is composed of predefined models, in order to decide which model is closest to the system.

2.3.1 The chosen model identification mechanism

In this control scheme, the chosen model of the system is identified using an fuzzy-based decision mechanism, where by defining three linear models in here, for simplicity, it can be summarized as follows

- Realizing $J_p(t)$; $p = 1, 2, 3$ for each one of the models, correspondingly, given by

$$J_{p,k} = \alpha\, e_{p,k}^2(t) + \beta \sum_{j=0}^{k} \exp(-\lambda(k-j)) e_{p,j}^2; \qquad \alpha \geq 0; \qquad \beta,\ \lambda > 0 \tag{2.16}$$

  Here, $e_{p,k}$ denotes the pth model state estimation error, at the kth instant of time.

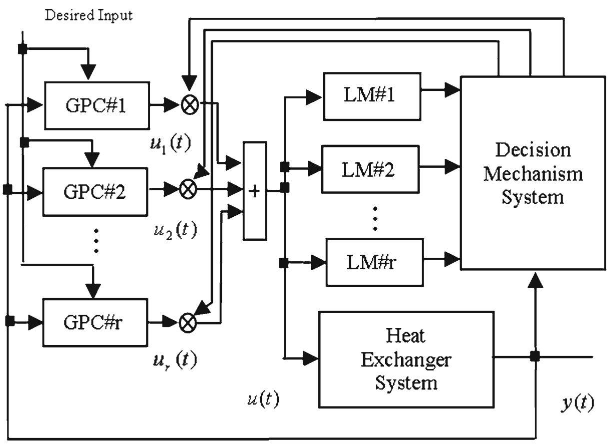


Fig. 2 The schematic of the proposed control scheme 2

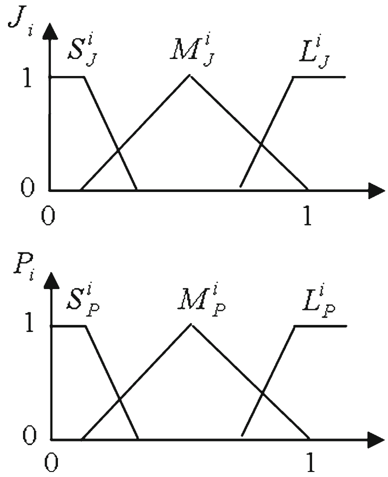


Fig. 3 The input–output fuzzy sets in the fuzzy-based decision mechanism

- Defining the fuzzy sets for input-output of the fuzzy-based decision mechanism; $J_p(t)$ and $P_p(t)$; $p = 1, 2, 3$.
- Realizing the fuzzy rules, which can be given by the following
  Rule 1:
  IF J_1(t) is S_J^1 AND J_2(t) is L_J^1 AND J_3(t) is L_J^1 THEN P_1(t) is L_P^1, P_2(t) is S_P^1, P_3(t) is S_P^1 (i.e., $M \triangleq LM_{\#1}$, $C \triangleq GPC_{\#1}$)
  Rule 2:
  IF J_1(t) is L_J^2 AND J_2(t) is S_J^2 AND J_3(t) is L_J^2 THEN P_1(t) is S_P^2, P_2(t) is L_P^2, P_3(t) is S_P^2 (i.e., $M \triangleq LM_{\#2}$, $C \triangleq GPC_{\#2}$)
  Rule 3:
  IF J_1(t) is L_J^3 AND J_2(t) is L_J^3 AND J_3(t) is S_J^3 THEN P_1(t) is S_P^3, P_2(t) is S_P^3, P_3(t) is L_P^3 (i.e., $M \triangleq LM_{\#3}$, $C \triangleq GPC_{\#3}$)

In this way, the input-output fuzzy sets of the proposed fuzzy-based decision mechanism are given here, as shown in Fig. 3.

2.3.2 The finalized control action

The finalized control action is acquired based on the soft switching technique, i.e.,

$$u(t) = \sum_{p=1}^{r} P_p(t)\, u_p(t) \tag{2.17}$$

where

$$\sum_{p=1}^{r} P_p(k) = 1 \tag{2.18}$$

In the same way, r is given as the number of appropriate local LGPC approaches, $P_p(t)$ is given as the appropriate weight of the pth local LGPC approach, at the kth

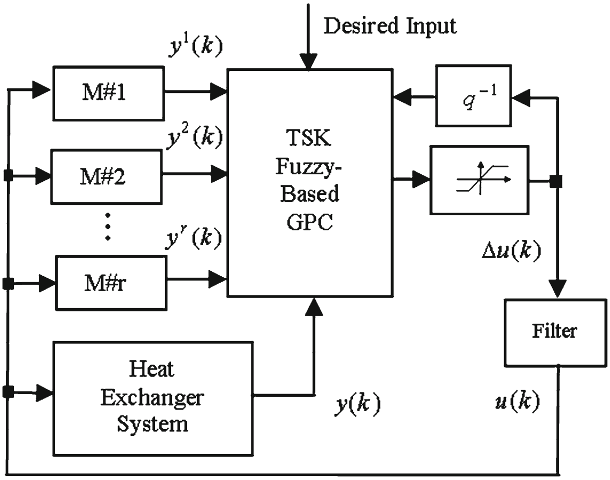


Fig. 4 The schematic of the proposed control scheme 3

instant of time, $u_p(t)$ is also given as the pth local LGPC output and finally $u(t)$ is given as the finalized control action.

2.4 The proposed control scheme 3

In this control scheme, the multiple predefined linear models of the system are used to derive the TSK fuzzy-based GPC scheme as the control approach [21,22]. Figure 4 represents the scheme, while $\mathrm{M}_{\#p};\ p = 1, 2, \ldots, r$ denotes the pth CARIMA model of the system.

By assuming $N_2 - N_1 + 1 = N_u = n$, the ith rule of the proposed TSK fuzzy-based GPC approach could now be written as

GPC Rule i: IF $y(k)$ is C^i THEN

$$\Delta u^i(k) = \sum_{\lambda=1}^{n} s_\lambda^i\, r(k+\lambda) + \sum_{\lambda=0}^{n} f_\lambda^i\, y^i(k-\lambda) + t_0^i\, \Delta u(k-1)$$

where $r(k)$, $y^i(k)$, $\Delta u(k)$ and n are all defined as the desired set point, the ith model output, the manipulated variable and finally the model order, respectively. Also s_λ, f_λ and t_0 denote the controller coefficients. After several experiments, the fuzzy sets; $\mathrm{C}^i;\ i = 1, 2, \ldots, r$, used in the proposed strategy are obtained, as shown in Fig. 5. Now, by using the centroid defuzzification and the product type of inference, the TSK fuzzy-based GPC approach could be obtained as

$$\Delta u(k) = \sum_{i=1}^{r} w^i\, \Delta u^i(k) \tag{2.19}$$

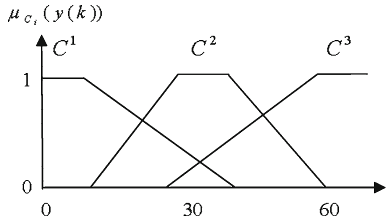


Fig. 5 The fuzzy sets used in the TSK fuzzy-based GPC scheme

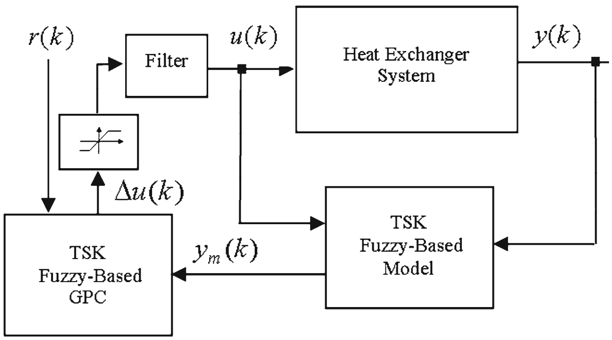


Fig. 6 The schematic of the proposed control scheme 4

where

$$w^i = \frac{\mu_{C^i}(\Delta u(k))}{\sum_{i=1}^{r} \mu_{C^i}(\Delta u(k))} \tag{2.20}$$

2.5 The proposed control scheme 4

Figure 6 shows the proposed control scheme, where the Takagi-Sugeno-Kang (TSK) fuzzy-based model and also the TSK fuzzy-based GPC approaches are used to control the system, in the scheme presented [23,24].

In the control scheme proposed, the fuzzy-based model approach is also realized using the IF-THEN rules, where the corresponding fuzzy sets are the same type as the fuzzy sets used in the TSK fuzzy-based GPC scheme. In this way, the rule of the TSK fuzzy-based model approach could be realized as

Model Rule i: IF $y(k)$ is C^i THEN

$$y^i(k) = y_0^i + \sum_{\lambda=1}^{n} a_\lambda^i \, y^i(k-\lambda) + \sum_{\lambda=1}^{m} b_\lambda^i \, u(k-\lambda)$$

where $y^i(k)$, $u(k)$, m and n denote the ith model output, the control action, the delay input and finally the delay output of the model, respectively. Hereinafter, by using the centroid defuzzification and the product type of inference, the TSK fuzzy-based model approach could now be obtained as

$$y(k) = \sum_{i=1}^{M} w^i y^i(k) \tag{2.21}$$

where

$$w^i = \frac{\mu_{C^i}(y(k))}{\sum_{i=1}^{r} \mu_{C^i}(y(k))} \tag{2.22}$$

Subsequently, the TSK fuzzy-based GPC approach is realized in line with the proposed control scheme 3.

2.6 The proposed control scheme 5

This control scheme is realized by using the multiple fuzzy-based predictive model (FPM) and the multiple fuzzy-based predictive control (FPC) approaches, as shown in Fig. 7. In this scheme, the realizations of the FPC and the FPM approaches are given in the proceeding sections [25,26].

2.6.1 The fuzzy-based predictive control approach

In correspondence with the control scheme presented, $w(t+N)$ is given as the desired set point and $y_m(t+N)$ is also given as the prediction output of the FPM approach. In such a case, the manipulated variable of the FPC approach, i.e., $\Delta u(t)$ could be updated using the fuzzy rule-based, given by

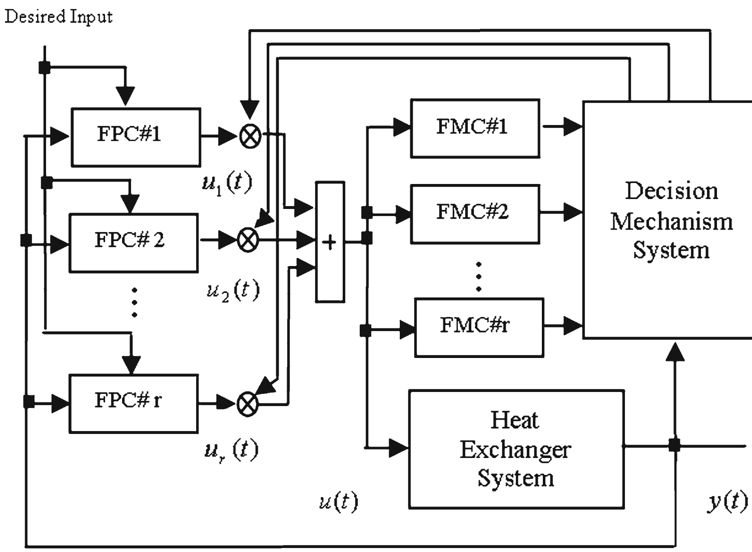


Fig. 7 The schematic of the proposed control scheme 5

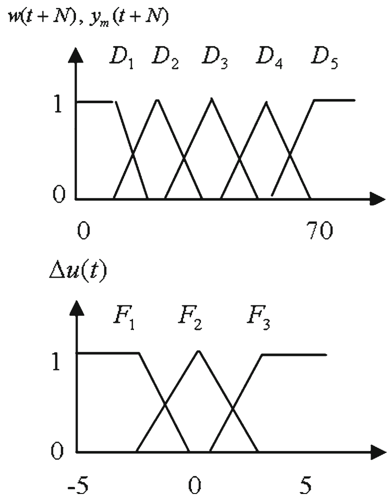


Fig. 8 The input-output fuzzy sets used in the FPC

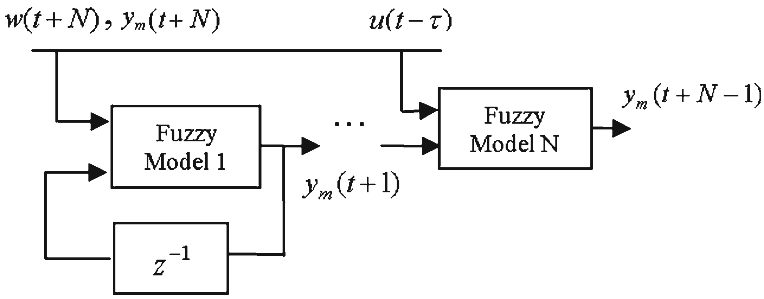


Fig. 9 The overall fuzzy-based predictive model

Rule i:

$$\text{IF } w(t+N) \text{ is } \mathrm{D}_j^i \text{ AND } y_m(t+N) \text{ is } \mathrm{E}_j^i \text{ THEN } \Delta u(t) \text{ is } \mathrm{F}_j^i$$

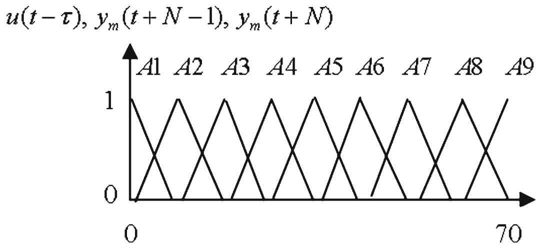
where i is given as the rule number, j is given as the fuzzy set number, D_j^i, E_j^i and F_j^i are all given as the input-output fuzzy sets, respectively, as shown in Fig. 8.

2.6.2 The fuzzy-based predictive model approach

In accordance with the control approach presented, $u(t-\tau)$ is used as the valid input of the system and τ is also used as its delay parameter. Furthermore, $y_m(t)$ is used as the output of the system. Now, by realizing the following fuzzy system, the overall FPM could be finalized in Fig. 9.

In this case, the proposed fuzzy rule-based of the model presented is given as follows

Fig. 10 The input–output fuzzy sets used in the FPM



Rule i:

$$\text{IF } u(t-\tau) \text{ is } \mathrm{A}_j^i \text{ AND } y_m(t-1) \text{ is } \mathrm{B}_j^i \text{ THEN } y_m(t) \text{ is } \mathrm{C}_j^i$$

where i is given as the rule number, j is given as the fuzzy set number, A_j^i, B_j^i and C_j^i are all given as the input-output fuzzy sets, shown in Fig. 10.

In the mean time, the appropriate finalized control action and also the chosen model identification mechanism are realized the same methods as the proposed control scheme 1.

2.7 The proposed control scheme 6

This control scheme is organized in accordance with the multiple models adaptive predictive control scheme, as shown in Fig. 11 [27,28].

In designing this control scheme, the chosen model identification mechanism is realized by a decision system, namely intelligent decision maker scheme (IDMS) in Fig. 11, in order to decide which model is closest to the system. In agreement with this figure, $F/A\ Model_{\#1}, \ldots, F/A\ Model_{\#r}$ are the r fixed/adaptive linear models, which are used in parallel with the system through the IDSM. Also $F/A\ Cont_{\#1}, \ldots, F/A\ Cont_{\#r}$ are used as the corresponding LGPCs, in the control scheme presented. Hereinafter, the models and the corresponding LGPCs could be used on the fixed or adaptive via a selector system that is used in the IDMS. As soon as $F/A\ Model_{\#p};\ p = 1, 2, \ldots, r$ is identified as the chosen model through the IDMS, the corresponding outputs of the selector system, i.e., $c_{mp};\ p = 1, 2, \ldots, r;\ c_{cp};\ p = 1, 2, \ldots, r$ are used to change the status of the chosen model and the corresponding LGPCs to adaptive status. Realization of the multiple models strategy based on the IDMS is now described in the proceeding sections.

The responsibility of the intelligent decision maker scheme (IDMS) could briefly be introduced as follows

- Realizing the chosen model identification mechanism, using the fuzzy-based adaptive Kalman filter approach as well as the fuzzy-based weight generator approach.
- Selecting the models and the corresponding controllers status in the fixed or the adaptive situations.
- Generating the finalized control action, using the soft switching technique.

- stabling the system performance under both the system coefficients and the desired set point variations.

As it can be seen from the proposed multiple models control strategy, the desired set point, the finalized control action; u, c_{mp}; $p = 1, 2, \ldots, r$ and finally c_{cp} are used as the output signals of the IDMS. Also y_{mp} and u_{cp}; $p = 1, 2, \ldots, r$ are used as the input signals of the IDMS.

2.7.1 The chosen model identification mechanism

The chosen model identification mechanism is realized to identify the better model of the system (BM) and also the deviated models from the better model of the system (DFBM), at each instant of time. In the mechanism presented, the controller weight parameters; $w_{p,k},\ \ p = 1, 2, \ldots, r, k = 1, 2, \ldots, \infty$ should accurately be varied to the ones, as soon as the corresponding model state estimation error; $e_{p,k}$, is close to the acceptable minimum values. Realization of the chosen model identification mechanism is now described in the proceeding sections.

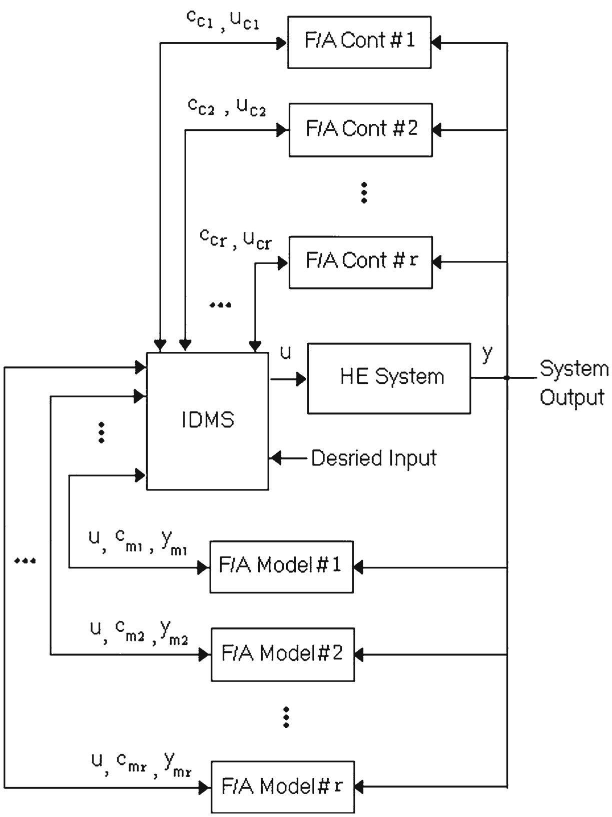


Fig. 11 The schematic of the proposed scheme 6

2.7.2 The fuzzy-based weight generator approach

The fuzzy-based weight generator (FWG) approach presented here is used to generate the appropriate weight signals; $w_{p,k},\ p=1,2,\ldots,r$, as long as we are suddenly encountered with variation in the system coefficients and also in the desired set point, concurrently. Now, the approach is realized based on a fuzzy-based algorithm, given by

- Defining the some performance indices, i.e., $J_{p,k};\ p=1,2,\ldots,r,\ k=1,2,\ldots,\infty$.
- Determining the minimum value of performance indices and also the maximum acceptable value of performance indices, i.e., J_{min} and J_{max}, respectively.
- Defining the acceptable, the conditionally acceptable and the unacceptable fuzzy sets, i.e., AFS, CAFS and UAFS, respectively, for each one of the performance indices.
- If the performance indices, i.e., $J_{p,k}$ is obtained in the AFS, the corresponding model; $F/A\ Model_{\#p},\ p=1,2,\ldots,r$, should now be identified as the chosen model of the system and the algorithm will be stopped, otherwise the rest of the algorithm must be followed.
- Defining the some decision maker parameters; $\xi(p)=J_{p,k}-J_{min};\ p=1,2,\ldots,r$.
- Defining the fuzzy sets corresponding to the acceptable decision and the unacceptable decision; ADFS, UDFS, respectively, for each one of the decision maker parameters; $\xi(p)$.
- Identifying the predefined model of the system; $F/A\ Model_{\#p};\ p=1,2,\ldots,r$ in the following fuzzy rule based system

  IF $J_{p,k}$ is AFS THEN $F/A\ Model_{\#p} \triangleq$ BM
  IF $J_{p,k}$ is CAFS AND $\xi(p)$ is ADFS THEN $F/A\ Model_{\#p} \triangleq$ BM
  IF $J_{p,k}$ is CAFS AND $\xi(p)$ is UDFS THEN $F/A\ Model_{\#p} \triangleq$ DBFM
  IF $J_{p,k}$ is UAFS THEN $F/A\ Model_{\#p} \triangleq$ DFBM
- Defining the fuzzy sets corresponding to low value and high value; LVFS, HVFS, respectively, to generate the controller weights parameters.
- Calculating the controller weights parameters based on the predefined models; $F/A\ Model_{\#p}$, in the following fuzzy rule based system

  IF $F/A\ Model_{\#1} \triangleq$ BM AND $F/A\ Model_{\#2} \triangleq$ DFBM AND, …, AND $F/A\ Model_{\#r} \triangleq$ DFBM THEN $w_{1,k}$ is HVFS, $w_{2,k}$ is LVFS, …, $w_{p,k}$ is LVFS
  IF $F/A\ Model_{\#1} \triangleq$ DFBM AND $F/A\ Model_{\#2} \triangleq$ BM AND, …, AND $F/A\ Model_{\#r} \triangleq$ DFBM THEN $w_{1,k}$ is LVFS, $w_{2,k}$ is HVFS, …, $w_{p,k}$ is LVFS
  ⋮
  IF $F/A\ Model_{\#1} \triangleq$ DFBM AND $F/A\ Model_{\#2} \triangleq$ DFBM AND, …, AND $F/A\ Model_{\#r} \triangleq$ BM THEN $w_{1,k}$ is LVFS, $w_{2,k}$ is LVFS, …, $w_{p,k}$ is HVFS

where the fuzzy sets of the performance indices; $J_{p,k}$, the decision maker parameters; $\xi(p)$, and finally the controller weight parameters; $w_{p,k}$, are all given in Fig. 12.

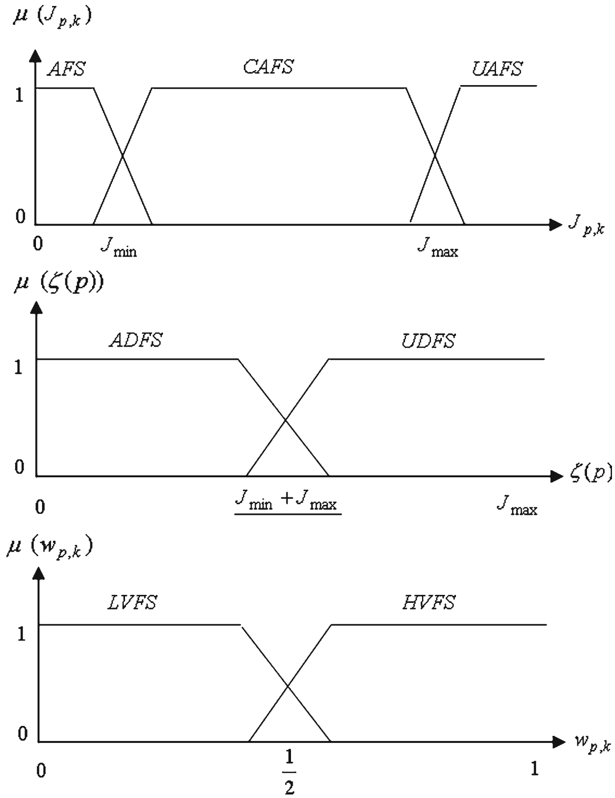


Fig. 12 The scheme of the fuzzy sets of the performance indices, the decision maker parameters and the controller weight parameters

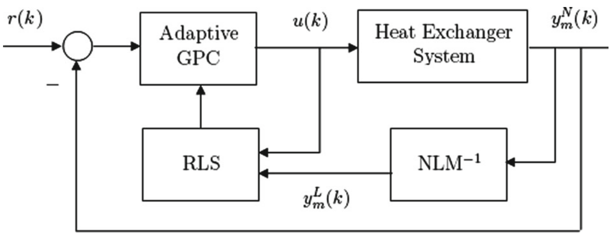


Fig. 13 The schematic of the proposed control scheme 7

2.8 The proposed control scheme 7

The proposed control strategy is shown in Fig. 13. In this figure, $u(k)$, $y_m^L(k)$ and $y_m^N(k)$ denote the control action, the linear model output and finally the nonlinear model output, respectively [29–31].

Here, by using the recursive least square (RLS) identification algorithm, the linear part of the Wiener model could be identified. In addition, the nonlinear part of the

Wiener model could also be expressed as

$$\widehat{y_m^N}(k) = f(\widehat{y_m^L}(k)) = \widehat{y_m^N}(0) + \gamma_0 \ \tanh(\beta_0 \ (\widehat{y_m^L}(k) - \widehat{y_m^L}(0))) \tag{2.23}$$

where γ_0 and β_0 denote the nonlinear model coefficients. A sequence of future nonlinear part of the Wiener model output could be given as

$$\widehat{y_m^N}(k+j) = f(\widehat{y_m^L}(k+j)) = \widehat{y_m^N}(0) + \gamma_0 \ \tanh(\beta_0 \ (\widehat{y_m^L}(k+j) - \widehat{y_m^L}(0))) \tag{2.24}$$

Afterwards, the manipulated variable; $\Delta u(k)$, could be obtained by optimizing the following cost function

$$J_{NLGPC} = \sum_{j=N_1}^{N_2} (\widehat{y_m^N}(k+j) - r(k+j))^2 - \lambda \sum_{j=1}^{N_u} \Delta u^2(k+j-1) \tag{2.25}$$

where $r(k)$ and λ denote the desired set point and control weight coefficients, respectively.

2.9 The proposed control scheme 8

This control scheme is realized based on the multiple linear fixed/adaptive models and the multiple fixed/adaptive controllers, as shown in Fig. 14 [32–34].

In the control strategy proposed here, $y(k)$ is given as the output of the system and $u(k)$ is given as the finalized control action. Here, $M_{\#1}, \ldots, M_{\#r}$ are given as the r fix/adaptive linear models, which are used in parallel with the system. Also $LGPC_{\#1}, \ldots, LGPC_{\#r}$ are used as the corresponding controllers, in this scheme. At each instant of time, a linear model of the system is identified as the chosen model using the intelligence decision mechanism (IDM). Hereinafter, the models and the corresponding controllers could be used on the fixed or adaptive via a selector system used in the IDM, where it is the same version as the proposed control scheme 6. Realization of the model identification mechanism is now described as follows.

2.9.1 The model identification mechanism

The model identification mechanism is realized by an intelligent decision mechanism (IDM), shown in Fig. 15. The inputs and the outputs of the IDM are given as the model data parameters; $md_{p,k}$, and the weight parameters; $w_{p,k}$, while $k = 1, 2, \ldots, \infty$ and $p = 1, 2, \ldots, r$ denote the discrete-time index and the model index and also $e_{p,k}$ denotes the state estimation error.

The main idea in the proposed IDM is to identify both the better model (BM) and no better model (NBM), as long as we are suddenly encountered with the variation in the inputs of the system, at each instant of time, described as follows.

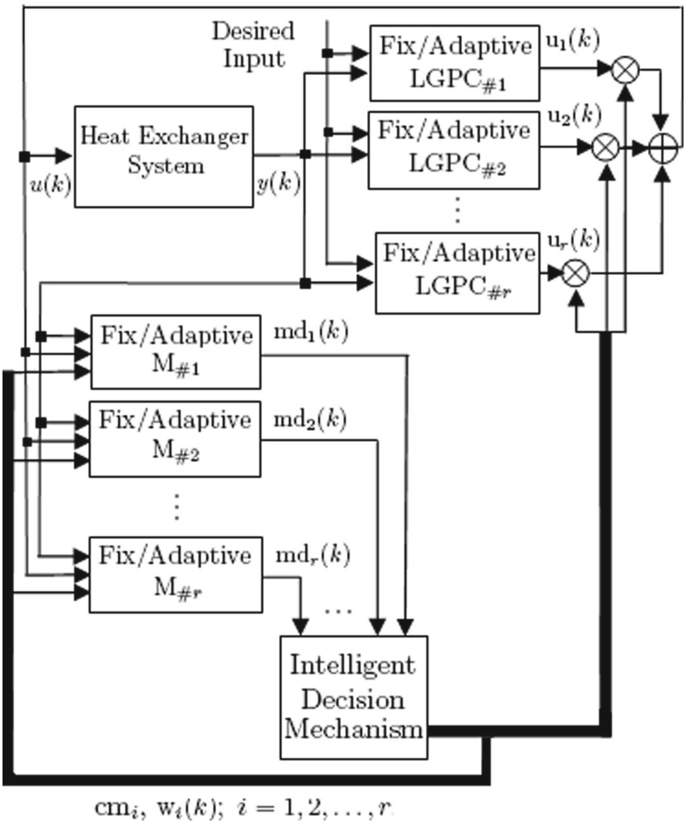


Fig. 14 The schematic of the proposed control scheme 8

2.9.2 Recursive weight generator approach

The proposed recursive weight generator; RWG, approach is realized by using a recursive formula, as long as the adaptation of the pth weight parameter; $p = 1, 2, \ldots, r$ at $(k + 1)$th instant of time is given by

$$w_{p,k+1} = w_{p,k}\ \delta_{p,k} \tag{2.26}$$

Now, let us introduce a plenary adaptive term; $\delta_{p,k}$, i.e.,

$$\delta_{p,k} = \frac{A_{p,k}}{\sum_{l=1}^{r} A_{l,k} w_{l,k}} \tag{2.27}$$

where

$$0 \leq A_{i,k} \leq 1; \qquad i = 1, 2, \ldots, r \tag{2.28}$$

In such a case, the probability of $M_{\#p}$ becoming the better model, at kth instant of time, is given by $A_{p,k}$, where the predefined assumptions (PA) are tabulated in Table 1.

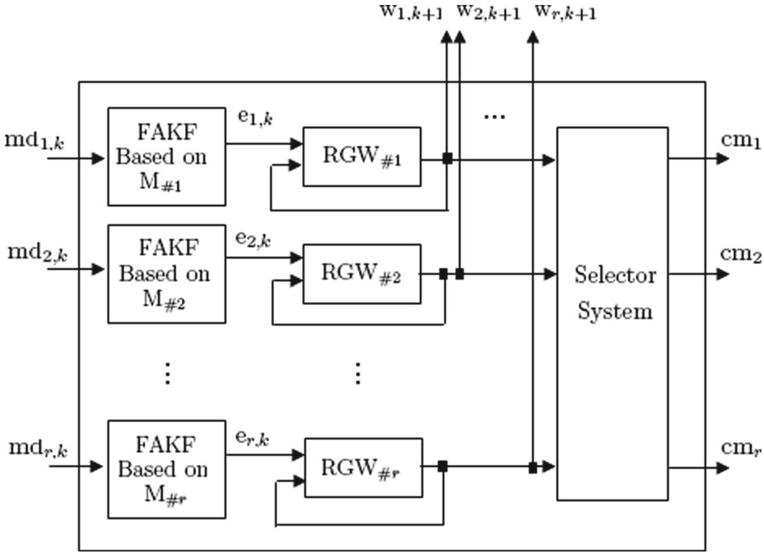


Fig. 15 The intelligent decision mechanism scheme

Table 1 The adaptive terms realization

PA				$\delta_{p,k}$			
$A_{1,k}$	$A_{2,k}$	$\dots$	$A_{r,k}$	$p=1$	$p=2$	$\dots$	$p=r$
1	0		0	$\frac{1}{w_{1,k}}$	0		
0	1		0	0	$\frac{1}{w_{2,k}}$		0
	$\vdots$				$\vdots$		
0	0		1	0	0		$\frac{1}{w_{r,k}}$

Hereinafter, we need to obtain $A_{p,k}$, while $\underline{J_p}$ and its components are assumed to be the random variables with Gaussian distribution, given by

$$\underline{J_p} = [J_{p,1}, \dots, J_{p,k}]^T \tag{2.29}$$

In such a case, the Gaussian probability density functions of the $\underline{J_p}$ could be obtained as

$$P_{p,k} = \frac{exp\left(-\frac{1}{2}\widetilde{J_p}^T C_{J_p}^{-1}\widetilde{J_p}\right)}{\sqrt{(2\Pi)^k det(C_{J_p})}} \tag{2.30}$$

where we have the following

$$\widetilde{J_p} = \underline{J_p} - \overline{J_p}; \quad \overline{J_p} = E(J_p); \quad C_{J_p}^{-1} = [\alpha_{p_{ij}}]_{k\times k}; \quad C_{J_p} = [Cov(\underline{J_p})]_{k\times k} \tag{2.31}$$

Here, C_{J_p} and E denote the steady-state covariance matrix and the expectation value, respectively. Now, using (2.39), (2.40) and (2.41), we could deduce as

$$\begin{cases} P_{p,k} = \dfrac{exp\left(-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_{p_{ij}}(J_{p,i}-\overline{J_{p,i}}\right)(J_{p,j}-\overline{J_{p,j}}))}{\sqrt{(2\Pi)^k det(C_{J_p})}} \\ \overline{J_{p,\mu}} = E(J_{p,\mu}); \quad \mu = i, j \end{cases} \tag{2.32}$$

Also by denoting

$$\underline{w_p} = [w_{p,1}, \ldots, w_{p,k}] \tag{2.33}$$

the following adaptive term, using (2.37), (2.42) and (2.43), could be resulted

$$\delta_{p,k} = f_p(\underline{J_p}, \underline{w_p}, k) = \frac{\int_0^{J_{min}} exp\left(-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_{p_{ij}}(J_{p,i}-\overline{J_{p,i}})(J_{p,j}-\overline{J_{p,j}})\right)dJ_p}{\sum_{l=1}^{r} w_{l,k}\int_0^{J_{min}} exp\left(-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_{l_{ij}}(J_{l,i}-\overline{J_{l,i}})(J_{l,j}-\overline{J_{l,j}})\right)dJ_p} \tag{2.34}$$

where J_{min} denotes the minimum acceptable error value and the weight parameters could initially be defined as

$$w_{p,0} = r^{-1} \tag{2.35}$$

3 The simulation results

In order to consider the suitability of the proposed control schemes, the industrial tubular heat exchanger system, which has the so many applicabilities in real environments such as food processing, automotive, aerospace, metallurgy, pulp and paper, fertilizers, chemicals-petrochemicals and finally cement is considered for the purpose of the simulations. In case of this matter, the fluid of the inner tube at $x = Ln = 2.5$ m, $\psi_t = 0.15$ m^2 and $v_t = 0.1$ m/s has a wide variation with respect to time, as long as the several distinctive fluids are used in the inner tube and the steam is used as the fluid of the shell tube in these simulations. In such a case, the inner tube fluid is used as an outlet of the system and also the shell tube fluid is used as an inlet of the system. In the simulations presented here, the tracking performance of the proposed control schemes, using both the desired set points variation and also the following system coefficients variation are now considered [35]

$$\begin{aligned} \rho_t(k) = \rho_t^* + \delta_{\rho_t}(k), \quad C_{p_t}(k) = C_{p_t}^* + \delta_{C_{p_t}}(k), \quad U_t(k) = U_t^* + \delta_{U_t}(k) \\ \underline{\delta_{\rho_t}} \le \delta_{\rho_t}(k) \le \overline{\delta_{\rho_t}}, \quad \underline{\delta_{C_{p_t}}} \le \delta_{C_{p_t}}(k) \le \overline{\delta_{C_{p_t}}}, \quad \underline{\delta_{U_t}} \le \delta_{U_t(k)} \le \overline{\delta_{U_t}} \\ \rho_t^* = 711 \text{ kg/m}^3, \quad C_{p_t}^* = 0.14 \text{ kJ/kgK}, \quad U_t^* = 7.90 \text{ W/m}^2\text{K} \end{aligned} \tag{3.1}$$

To overcome the system coefficients variation, we need to define several system operating environments and to identify the corresponding models. Here, the optimal number of models was obtained to be three for the all schemes. Based on this subject, the system operating environments, i.e., $\text{EV}_{\#p}$; $p = 1, 2, 3$, must be able to cover the whole of the system coefficients variation, given below:

$$EV_{\#1}, \ i.e., \ M_{\#1}: \begin{cases} \delta_{\rho_t}(k) = \underline{\delta_{\rho_t}} = 0 \\ \delta_{C_{p_t}}(k) = \overline{\delta_{C_{p_t}}} = 0 \\ \delta_{U_t}(k) = \underline{\delta_{U_t}} = 0 \end{cases} \tag{3.2}$$

Table 2 The coefficients of the CARIMA models

k	j	a_j^k	b_j^k
1	1	−0.9933	0.2506e−3
1	2	−0.4343	0.3519e−3
1	3	0.0069	0.5283e−3
1	4	0.4219	0.1830e−3
2	1	−0.9947	0.2469e−3
2	2	−0.4327	0.3426e−3
2	3	0.0083	0.5208e−3
2	4	0.4204	0.1738e−3
3	1	−0.9960	0.2434e−3
3	2	−0.4313	0.3336e−3
3	3	0.0097	0.5135e−3
3	4	0.4189	0.1367e−3

Table 3 The model's validation

Model error	M ≠ 1	M ≠ 2	M ≠ 3
$\overline{\sum e^2}(V)$	3.82e−3	7.41e−3	5.12e−3
$\overline{\sum \vert e \vert}(V)$	5.14e−2	9.89e−2	6.46e−2

$$EV_{\#2},\ i.e.,\ M_{\#2}\colon \begin{cases} \delta_{\rho_t}(k) = \frac{\overline{\delta_{\rho_t}} + \underline{\underline{\delta_{\rho_t}}}}{2} = 208 \\ \delta_{C_{p_t}}(k) = \frac{\overline{\delta_{C_{p_t}}} + \underline{\underline{\delta_{C_{p_t}}}}}{2} = 2.02 \\ \delta_{U_t}(k) = \frac{\overline{\delta_{U_t}} + \underline{\underline{\delta_{U_t}}}}{2} = 2000 \end{cases} \tag{3.3}$$

$$EV_{\#3},\ i.e.,\ M_{\#3}\colon \begin{cases} \delta_{\rho_t}(k) = \overline{\delta_{\rho_t}} = 416 \\ \delta_{C_{p_t}}(k) = \overline{\delta_{C_{p_t}}} = 4.04 \\ \delta_{U_t}(k) = \overline{\delta_{U_t}} = 4000 \end{cases} \tag{3.4}$$

where $\underline{\delta_{\rho_t}}$, $\underline{\delta_{C_{p_t}}}$ and $\underline{\delta_{U_t}}$ are given in 0 °C and $\overline{\delta_{\rho_t}}$, $\overline{\delta_{C_{p_t}}}$ and $\overline{\delta_{U_t}}$ are also given in 100 °C, respectively. Now, using the RLS identification algorithm, the following CARIMA models of the system, $p = 1,\ 2,\ 3;\ n = m = 4$, corresponding to different system operating environments; EVs, could be obtained, where the results of this algorithm are tabulated in Table 2.

$$\begin{aligned} A^p(q^{-1})y^p(k) \quad &= B^p(q^{-1})u(k-1) + \frac{e(k)}{\Delta(q^{-1})} \\ A^p(q^{-1}) \quad &= 1 + a_1^p q^{-1} + \cdots + a_n^p q^{-n} \\ B^p(q^{-1}) \quad &= b_0^p + b_1^p q^{-1} + \cdots + b_m^p q^{-m} \end{aligned} \tag{3.5}$$

Here, $y^i(k),\ u(k)$ and $e(k)$ denote the ith model output variable, the control action variable and the random sequence number, respectively. Also $\Delta(q^{-1})$ is taken as $1 - q^{-1}$. Now, to validate the models, the ith model error; $e^i(k)$, with respect to the system output; $y(k)$, are expressed as

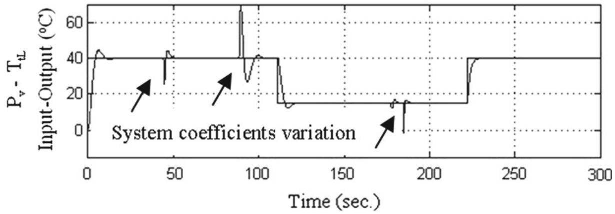


Fig. 16 The tracking performance of the proposed control scheme 1

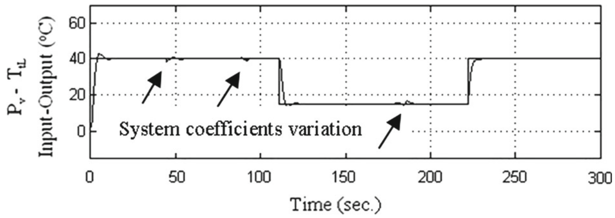


Fig. 17 The tracking performance of the proposed control scheme 2

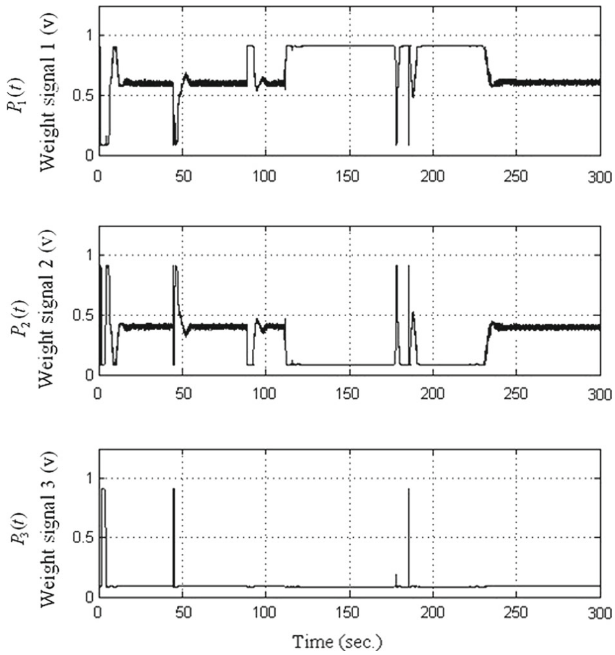


Fig. 18 The weight signals the proposed control scheme 2

$$e^i(k) = y(k) - y^i(k); \quad i = 1, 2, 3 \tag{3.6}$$

The results can verify the validity of the chosen models, as tabulated in Table 3. The coefficients of the CARIMA models. Here, Fig. 16 shows the tracking performance of the proposed control scheme 1, while Figs. 17, 18, 19 represent the tracking perfor-

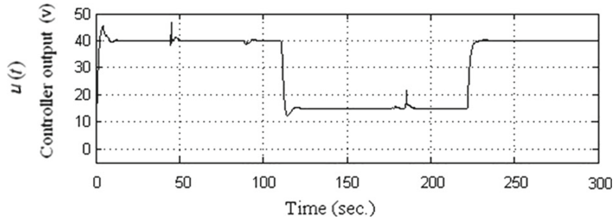


Fig. 19 The finalized control action of the proposed control scheme 2

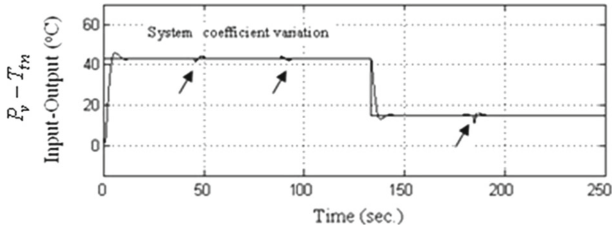


Fig. 20 The tracking performance of the proposed control scheme 3

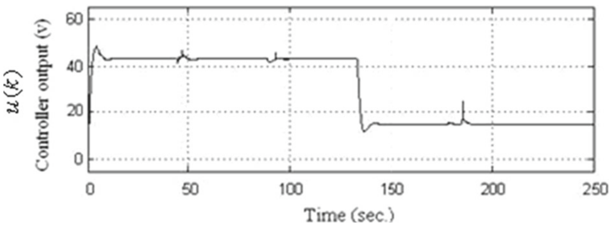


Fig. 21 The control action of the proposed control scheme 3

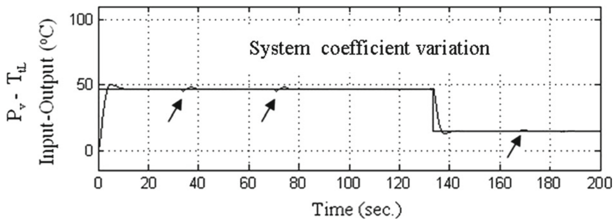


Fig. 22 The tracking performance of the proposed control scheme 4

mance, the weight signals and also the finalized control action of the proposed control scheme 2, respectively. In the same way, Figs. 20, 21 show the tracking performance and the control action of the proposed control scheme 3, while Figs. 22, 23 represent the tracking performance and also the control action of the proposed control scheme 4, respectively. In this way, Figs. 24, 25, 26 show the tracking performance, the weight signal and the finalized control action of the proposed control scheme 5, while Figs. 27, 28, 29 represent the tracking performance, the weight signals and also the finalized control action of the proposed control scheme 6, respectively. Finally, Fig. 30 shows

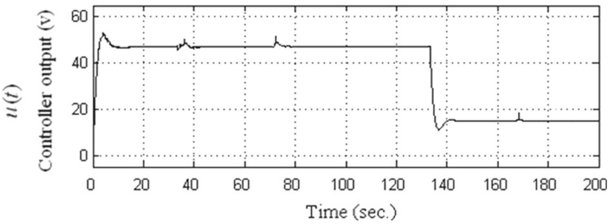


Fig. 23 The control action of the proposed control scheme 4

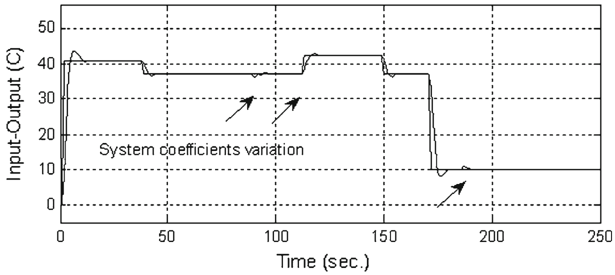


Fig. 24 The tracking performance of the proposed control scheme 5

the tracking performance of the proposed control scheme 7, while Figs. 31, 32, 33 represent the tracking performance, the weight signals and also the finalized control action of the proposed control scheme 8, respectively.

Regarding the results, each one of the proposed control schemes has to well be challenged with the variations, where the closed loop tracking performances have to acceptably be guaranteed. In the mean time, the details of the simulations could thoroughly be found in the published research papers that are referenced, in this paper.

4 The comparative analysis on the proposed control schemes

In this section, the comparative analysis on the proposed control schemes (PCSs) are implemented, where the advantages and also the disadvantages of each one of them are fully surveyed. In such a case, the tracking performance in both the system coefficients variation (SCV) and in the desired set point variations (DSPV) are investigated. Furthermore, the weight of the PCSs realization (WPCSR) and the cover of the system coefficients variation (CSCV) are given, with respect to each other. Based on this matter, the comparative results are tabulated by Table 4. Regarding this table, the PCSs are all investigated in line with the system tracking performance, while the SCV and also the DSPV are abruptly taken place, in the system. With this purpose, the percentage of the maximum overshoot (mo), the settling time (ts) and the steady state error (ess) for each one of the PCSs are experimentally achieved. Also, the rise time (tr) for each one of the PCSs are given, while the system are encountered with variation in desired set point. Meanwhile, the WPCSR and also the CSCV with respect to each other are given by Table 4. In the same way, the WPCSR and the CSCV of the $PCS_{\#8}$ are defined as hundred in percentage, where the mentioned parameters are approximately given

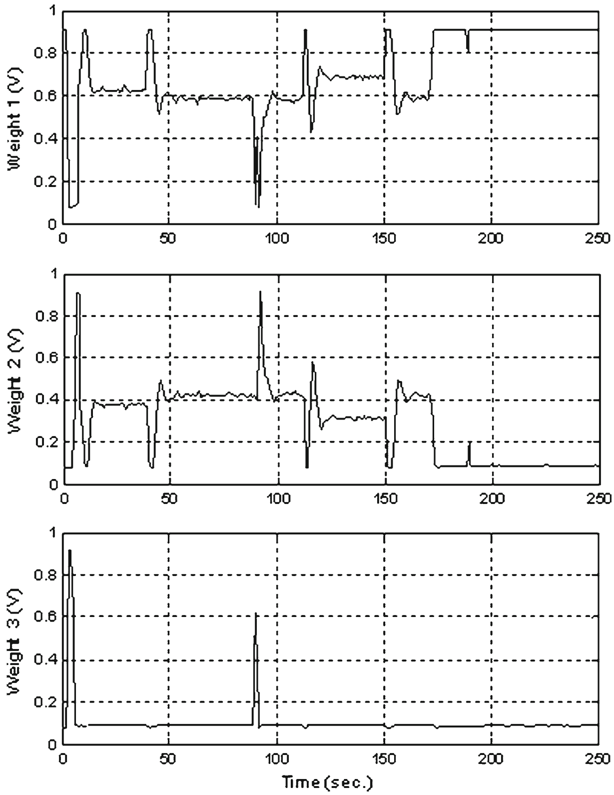


Fig. 25 The weight signals the proposed control scheme 5

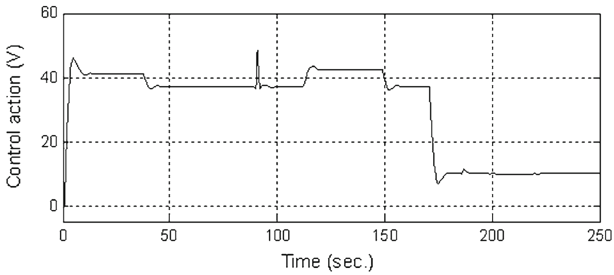


Fig. 26 The finalized control action of the proposed control scheme 5

for all the PCSs in terms of the $PCS_{\#8}$, in this paper. In fact, the WPCSR points out the quantity of the scheme realization and also the CSCV points out the quality of the scheme realization, as long as the PCSs are analyzed in line with each other.

In case of the comparative results presented, the system is well controlled by the most of control schemes, where each one of them has the good tracking performance in the specified situations. Here, we want to develop these comparative studies on the

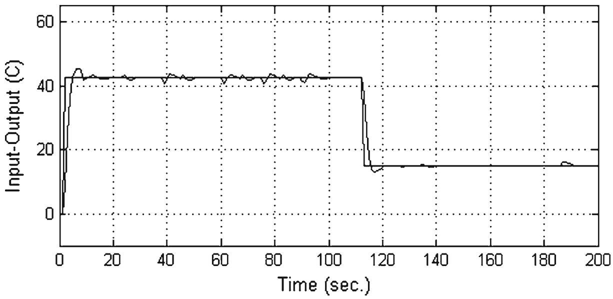


Fig. 27 The tracking performance of the proposed control scheme 6

proposed schemes as follows, where the results are significant with respect to each other, i.e.,

The advantages of the proposed control schemes are outlined as

1. The control scheme is applicable in the systems with the fixed coefficients.
2. The control scheme is applicable in the systems with the mediocre coefficients variation.
3. The control scheme is applicable in the systems with the wide coefficients variation.
4. The control scheme is applicable in the systems with the wide and the fast coefficients variation.
5. Realization of the proposed scheme is not elaborated with respect to others.
6. Realization of the proposed scheme is not relatively elaborated with respect to others.
7. The weight generation mechanism of the proposed scheme is relatively stabled with respect to noise.
8. The weight generation mechanism of the proposed scheme is organized based on the rapid recursive technique to generate accurate weights in the span of coefficients variation.
9. Realization of the proposed approach is possible, even though the multiple linear models of the system cannot mathematically be identified.
10. The control scheme could be realized by the minimum number of possible models.
11. The control scheme is realized in line with the LGPC approach as the powerful control approach in the LMBPC family.
12. The control scheme could be used in deriving several industrial domains.

Subsequently, the disadvantages of the proposed control schemes are outlined as

1. Realization of the proposed approach is not possible, if the linear model(s) of the system cannot explicitly be identified.
2. Realization of the proposed scheme is elaborated with respect to others.
3. The control scheme is not applicable in the systems with the relatively wide coefficients variation.
4. The control scheme cannot be realized based on the LGPC approach with respect to others.

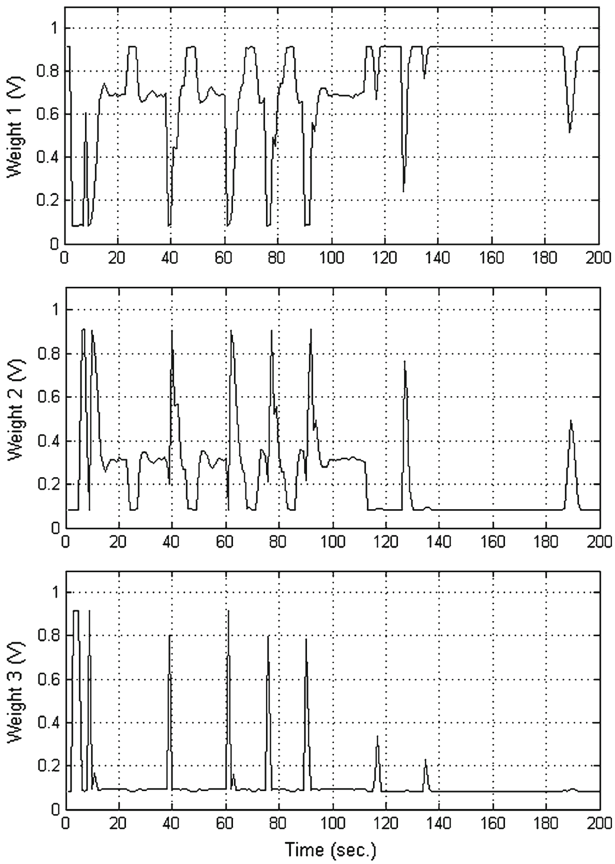


Fig. 28 The weight signals the proposed control scheme 6

5. The margin of the operating environments variation of the system must first be defined.

Regarding the advantages of the control schemes, items 1, 5 and 11 are related to the control scheme 1, while items 2, 6, 7, 10, 11 and 12 are also related to the control scheme 2, respectively. In this case, items 2, 6, 10, 11 and 12 are related to the control scheme 3, while items 2, 5, 10, 11 and 12 are also related to the control scheme 4, respectively. Hereinafter, items 2, 6, 9, 10 and 12 are related to the control scheme 5, while items 3, 7, 10, 11 and 12 are also related to the control scheme 6, respectively. Finally, items 1, 6 and 11 are related to the control scheme 7, while items 4, 7, 8, 10, 11 and 12 are also related to the control scheme 8, respectively. In case of the disadvantages of the control schemes, items 1, 3 and 5 are related to the control scheme 1, while items 1 and 5 are also related to the control schemes 2, 3 and 4, respectively. In line with this case, items 4 and 5 are related to the control scheme 5, while items 1, 2 and 5 are also related to the control scheme 6, respectively. Consequently, items 1, 3 and 5 are related to the control scheme 7, while items 1, 2 and 5 are also related to the control scheme 8, respectively.

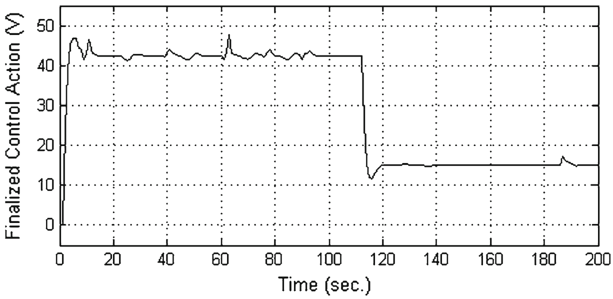


Fig. 29 The finalized control action of the proposed control scheme 6

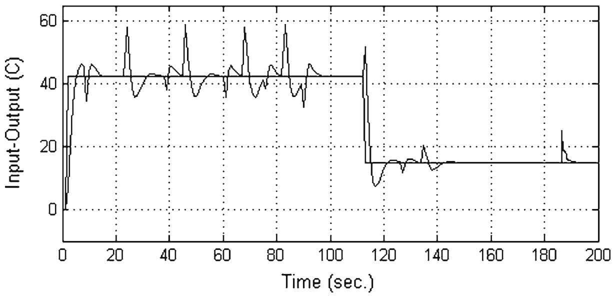


Fig. 30 The tracking performance of the proposed control scheme 7

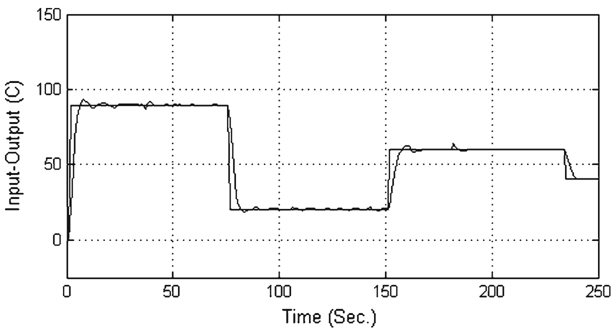


Fig. 31 The tracking performance of the proposed control scheme 8

As a consequence, we are not just able to propose one of the PCSs as the chosen control scheme with respect to others, due to the fact that each one of them has the advantages and the disadvantages over the system presented. Here, it seems that the control scheme has to be identified based on the corresponding situation. In case of this matter, the chosen control schemes with respect to the following situation could now be analyzed, i.e.,

The proposed control scheme 1 could be identified as the chosen scheme, provided that we have the following

- The system which has the fixed coefficients is used to control.
- The simplicity of the control scheme is recommended.

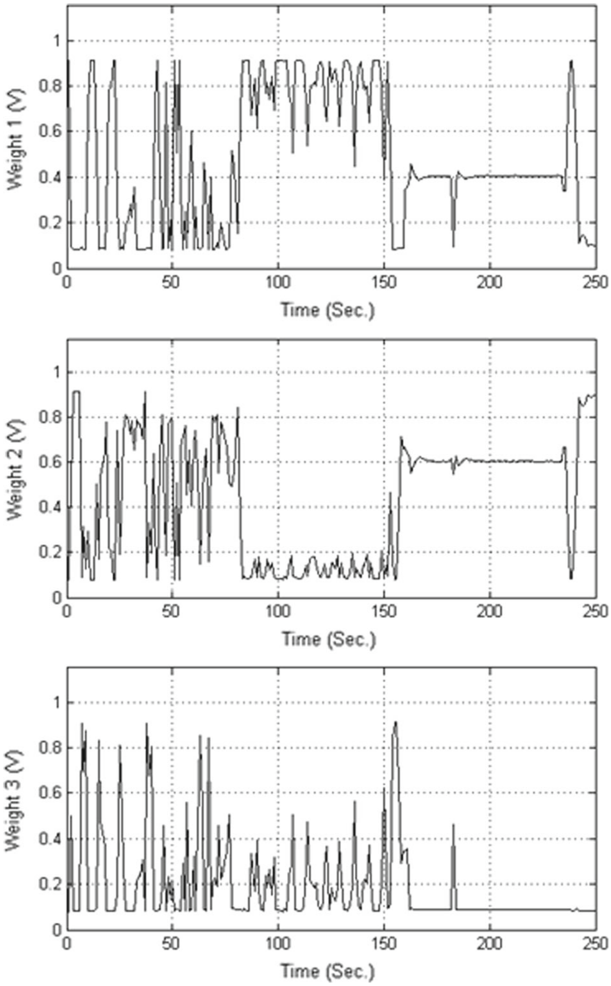


Fig. 32 The weight signals the proposed control scheme 8

The proposed control schemes 2 and 5 could be identified as the chosen scheme, provided that we have the following

- The system which has the mediocre coefficients variation is used to control.
- The simplicity of the control scheme is relatively recommended.

The proposed control schemes 3 and 4 could be identified as the chosen scheme, provided that we have the following

- The system which has the mediocre coefficients variation is used to control.
- The simplicity of the control scheme is recommended.

The proposed control scheme 6 could be identified as the chosen scheme, provided that we have the following

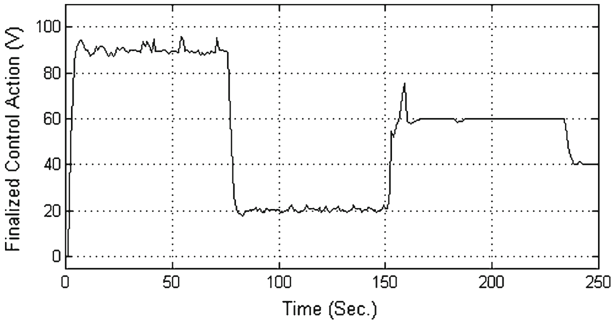


Fig. 33 The finalized control action of the proposed control scheme 8

Table 4 The comparative results of the proposed control schemes

	mo_{scv} (%)	ts_{scv} (s)	ess_{scv}(v)	mo_{dspv} (%)	tr_{dspv} (s)	ts_{dspv}	ess_{scv}(v)	WPCSR	CSCV
$PCS_{\#1}$	51.35	14.31	4.15×10^{-3}	8.78	3.97	12.13	4.06×10^{-3}	35	25
$PCS_{\#2}$	2.09	15.86	2.34×10^{-4}	6.43	3.13	11.25	1.12×10^{-4}	60	75
$PCS_{\#3}$	2.63	13.60	3.84×10^{-3}	6.24	3.72	10.12	2.22×10^{-3}	50	70
$PCS_{\#4}$	2.64	14.47	3.13×10^{-3}	7.36	2.93	11.92	2.79×10^{-3}	50	70
$PCS_{\#5}$	2.86	15.43	3.19×10^{-4}	8.89	3.29	12.02	2.94×10^{-4}	60	75
$PCS_{\#e}$	2.90	13.12	2.17×10^{-4}	7.28	3.07	11.11	2.01×10^{-4}	80	80
$PCS_{\#7}$	31.94	13.56	4.07×10^{-4}	9.68	3.19	12.09	3.98×10^{-4}	60	40
$PCS_{\#8}$	2.35	12.72	1.17×10^{-5}	5.47	2.98	10.31	1.06×10^{-5}	100	100

- The system which has the wide coefficients variation is used to control.
- The simplicity of the control scheme is not relatively recommended.

The proposed control scheme 7 could be identified as the chosen scheme, provided that we have the following

- The system which has the fixed coefficients is used to control.
- The simplicity of the control scheme is relatively recommended.

The proposed control scheme 8 could be identified as the chosen scheme, provided that we have the following

- The system which has the wide and the fast coefficients variation is used to control.
- The simplicity of the control scheme is not recommended.

5 Conclusion

A comparative study on a number of proposed control schemes are considered, in the present research. Based on the results investigated here, each one of the control schemes is fully surveyed based on the system tracking performance, while the system coefficients and the desired set points are abruptly varied, as well, at each instant of time. As it can be seen from the results, all the proposed control schemes are able to control a class of industrial complicated systems such as the tubular heat exchanger system under varying coefficients in the span of time. Hereinafter, the weight of the realization of the control schemes in addition to the cover of the system coefficients variations with respect to each other are fully investigated, in this study. In conclusion, we can propose each one of the schemes as the chosen control scheme, when the corresponding situation is given. With this purpose, the control scheme 1 is implemented on the system with the fixed coefficients, while the simplicity of the control scheme is strongly recommended. The control schemes 2 and 5 are implemented on the system with the mediocre coefficients variation, while the simplicity of the control scheme is relatively recommended. Hereinafter, the proposed control schemes 3 and 4 are implemented on the system with the mediocre coefficients variation, while the simplicity of the control scheme is recommended. Besides, the proposed control scheme 6 is implemented on the system with the wide coefficients variation, while the simplicity of the control scheme is not relatively recommended. Also the proposed control scheme 7 is implemented on the system with the fixed coefficients, while the simplicity of the control scheme is relatively recommended. At last, the control scheme 8 is implemented on the system with the wide and the fast coefficients variation, while the simplicity of the control scheme is not recommended. As a matter of fact, we present some appropriate control schemes, when the system is realized in the corresponding situation. It means that all the control schemes could be identified as the chosen scheme, while they are used in the corresponding situations.

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