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ORIGINAL ARTICLE

Performance of optimal hierarchical type 2 fuzzy controller for load–frequency system with production rate limitation and governor dead band

Mohsen Ebrahimian Baydokhty [a], **Assef Zare** [b], **Saeed Balochian** [b,*]

[a] *Young Researchers Club, Gonabad Branch, Islamic Azad University, Gonabad, Iran*
[b] *Department of Electrical and Electronics Engineering, Islamic Azad University, Gonabad Branch, Gonabad, Iran*

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Fuzzy Mamdani;
Cuckoo Optimization Algorithm (COA);
Non-linear system

Abstract Controlling load–frequency is regarded as one of the most important control-related issues in design and exploitation of power systems. Permanent frequency deviation from nominal value directly affects exploitation and reliability of power system. Too much frequency deviation may cause damage to equipment, reduction of network loads efficiency, creation of overload on communication lines and stimulation of network protection tools, and in some unfavorable circumstances, may cause the network collapse. So, it is of great importance to maintain the frequency at its nominal value.

It would be useful to make use of the type 2 fuzzy in modeling of uncertainties in systems which are uncertain. In the present article, first, the simplified 4-block type-2 fuzzy has been used for modeling the fuzzy system. Then, fuzzy system regulations are reduced by 33% with the help of hierarchy fuzzy structure. The simplified type-2 fuzzy controller is optimized using the Cuckoo algorithm. Eventually, the performance of the proposed controller is compared to the Mamdani fuzzy controller in terms of the ISE, ITSE, and RMS criteria.

1. Introduction

Maintaining system frequency within a nominal range as load vacillates up and down has long been considered as a crucial task for system operators. This issue is of even greater significance today, taking into account radical growth in size and complexity of present power systems.

Any imbalance in generation and consumption of electrical energy in power system causes the system to deviate and thus the rate of the programmed exchange power changes [1]. Responding to lack of balance in actual power of power systems is known as load frequency control (LFC) [2].

A well-designed power system is generally represented by high power quality standards, nearly-fixed and stable frequency as well as wisely-regulated voltage [36]. As such, small breeze in active power (demand) will nonlinearly spur the frequency of the system while its voltage may be perturbed if the

* Corresponding author.
E-mail addresses: ebrahimian.mo@gmail.com (M.E. Baydokhty), assefzare@gmail.com (A. Zare), saeed.balochian@gmail.com (S. Balochian).
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Nomenclature

Tt_i	time constant of turbine
Tp_i	time constant of power system
Kp_i	efficiency of power system model
Tg_i	time constant of governor
R_i	multiple of regulation of area i
ΔF_i	frequency deviation of area i
ISE	Integral Square Error
ITSE	Integral Time Square Error
RMSE	Root Mean Square Error
T2FH	Type-2 Fuzzy Hierarchical
T2FHC	Simplified 4 Blocks Optimal Type-2 TSK Fuzzy Hierarchical Controller
OHTSKF	Optimal Hierarchical TSK Fuzzy

reactive power (VAR) absorption keeps changing in the grid. To curb the frequency oscillations, Load Frequency Control (LFC) loop was developed in interlocking the power and frequency to the nominal values subject to time variation instances in operation. Given a number of interconnections among neighboring utilities, controlling load frequency required paying a great deal of attention.

Minimal deviations in the real power are tantamount to Rotor Angle (δ) variation, which is technically construed as frequency deviation in system. On the other hand, any change in active power will vibrate system frequency and re-shape the main parameters of the system performance. Therefore, an additional controller is needed to regulate the frequency of system instantaneously along with tighter accuracy.

To design a real-time load frequency controller, deviations in Rotor Angle ($\Delta\delta$) must be monitored. In other words, frequency and real power variations can be recorded so that error signals Δf, and ΔP_{tie} are established which are then consolidated to cast real power ΔP_v variable. Such power is in turn fed into primary stimulator to increase the input Torque. Hence, primary stimulator changes generator output as much as ΔP_g, and accordingly adjusts the amount of Δf and ΔP_{tie} on a predefined basis.

Following are three major purposes of load frequency control system:

(1) Keeping frequency within the permissible and acceptable level.
(2) Distribution of load among generators.
(3) Controlling load transmission in the tie-line.

In Refs. [1–19], several methods for frequency load control have been presented. Among these, PI and PID classic controllers, which have attracted more attention in the industry, use optimization algorithms to obtain the optimized values of classic controllers in nominal conditions. Although they are optimized methods, they have some deficiencies. This makes an actual power network to obtain some types of uncertainties causing the system parameters to be changed and modeling faults to occur. In addition, work point of the power system is changed during the day. So, a LFC optimized based on the nominal parameter of the system is not appropriate for the issue of frequency load control, and implementation of this frequency adjuster is deemed to be inadequate to reach the target performance.

Among other disadvantages of classical controllers are having large fluctuation and being robust against nonlinear factors cited as governor dead band.

In most studies carried out so far on the issue of frequency load control, centralized control approach has been most widely used. The most important limitation on centralized control is the fact that it is needed to transfer data between several areas which cover a wide range of geographical area. This may lead to increase in data information and their process volume, causing a decrease in the reliability [1]. In order to overcome these problems, use of decentralized control is recommended. Because of this, the system under control is divided into some control areas.

Linear optimal control [10] is a technique proposed with smooth controlling outfit. Though it is still constrained for further application due to its impracticality and lack of complete system information, yet the linearity characteristics of the controller itself may procure inaccurate and faulty control actions [10]. Ref. [11] shows a hierarchical optimal robust controller implementation in power system LFC model. However, simulations were carried out in two hierarchical levels (one follows another consecutively) consisting of system optimization and control system robustness verification levels.

Due to the increase in complexity of modern power systems, some advanced control systems have been recommended to be used in this regard. For instance, it is possible to use self-adjusting and adaptive control [3], predictive model-based controls [4,5], and smart controls [6,7]. Using advanced control method makes it possible to improve the efficiency rate. For this purpose, it is needed to have information on network status as well as an online effective identifier which makes their implementation hard.

According to technical literature, most of the proposed techniques have merely introduced controlling load frequency in a system with an unclear picture on how to determine system stability in practice. Since power systems commonly experience perceptible and large number of fluctuation and disturbance during operation, therefore, most of the studied literature has not provided adequate tools that maintain system stability measures within numerically cumbersome and technically arduous senses.

In load–frequency system, there is always disturbance. Thus, the final control chosen for system must be robust against disturbances. On the other hand, type 2 fuzzy controllers are inherently robust and contain all the properties of type 1 fuzzy controllers. Also, they are based on real world modeling. Therefore, for this paper, type 2 fuzzy controller has been used [43–45].

In this paper, a LFC controller is developed by means of fuzzy controller. Fuzzy controller can be utilized to overcome the plants with unexpected complex dynamics and external disturbances [18,31–33]. Moreover, LFC controller mathematically embellishes the control model via assigning a wider range for system deviations, considering nonlinear utilization in LFC model is reasonably justifiable.

In power systems, the computational time performance is of significant importance and requires close and cautious attention, especially when augmenting the dynamic model for load–frequency vacillations. However, in some extreme cases this may even lead to an interminable executional process that might promote an unreliable solution. The use of Fuzzy controller in classical and traditional forms was limited by two major drawbacks:

(1) An excessive and explosive number of rules defined in the algorithm [30].
(2) A numerically unstable computational performance especially in LFC which inherently possesses a tremendous number of control parameters involved.

In the proposed fuzzy based control systems the prime aim is to design a system that offers congruous control actions with the least number of rules in a tractable computing time frame. In this paper, a hierarchical fuzzy control system is proposed and implemented in order to effectively control nonlinear load–frequency power system phenomena. The proposed hierarchical fuzzy control can reduce both the number of rules and complexity of control system. Further, the Cuckoo Optimization Algorithm (COA) was employed to further enhance the developed hierarchical fuzzy model in this work.

Generally, the salient features of the proposed model can be listed as follows:

(1) A nonlinear model turbine and governor in simulation are applied.
(2) A robust controller against load instability is designed.
(3) Simplified 4 Blocks Type-2 Fuzzy system for robustness against load disturbance has been used.
(4) The level of frequency and Tie-line deviations is squeezed.
(5) The measurement error of three criteria Integral Square Error (ISE), Integral Time Square Error (ITSE), and Root Mean Square Error (RMSE) is reduced.
(6) A hierarchical fuzzy system is used and the hierarchical TSK fuzzy is implemented.
(7) The number of fuzzy rules is moderated.
(8) Using COA, The Simplified 4 Blocks Optimal Type-2 TSK Fuzzy Hierarchical Controller design has been improved.

2. Tie-line bias control

In load frequency control systems with a primary control loop, power deviations in the first area (area 1) are caused by ramping up/down generation within areas 1 and 2. However, this has been done by means of a change in currently transferring power in tie-line bias and a reduction in system frequency. Commonly, several steps are taken to perform load frequency in a traditional fashion including: (A) retaining system frequency close to its nominal value, (B) governing undergoing power in tie-line within a predefined range and (C) controlling load variations between heterogeneous areas and within each homogenous area.

The ordinary load frequency system control based on tie-line bias control means a tendency in each area to reduce control error (ACE (as close as zero. The control error signal in each area is a combination of frequency error and power deviation in tie-line bias which can be cast as

$$ACE_i = \sum_{j=1}^{n} \Delta P_{ij} \tag{1}$$

Area constant K_i determines the amount of mutual effect between neighboring areas while there is an error. Generally, satisfactory control action can take place when constant K_i is set to the constant frequency of the given area, that is, $B_i = \frac{1}{R_i} + D_i$. Hence, area control errors for a two-area system can be stated as

$$ACE_1 = \sum_{j=1}^{n} \Delta P_{12} + B_1 \Delta\omega_1 \tag{2}$$

$$ACE_2 = \sum_{j=1}^{n} \Delta P_{21} + B_2 \Delta\omega_2 \tag{3}$$

ΔP_{12} and ΔP_{21} are the difference between amount of scheduled power and current power flows in tie-line. Area error signals serve to form an appropriate power regulation in reference system. In a stable condition, ΔP_{12} and $\Delta\omega$ become infinitesimal amounts nearby zero. In this sense, the integral constant should be so small to prevent the area from galling into tracking mode.

3. Explaining the two-area power system in this paper

In most systems a number of generators are closely related to each other and each generator's deviation affects others. Besides, generator turbines have a tendency for similar responses. Such generators are called identical generators, which often create multiple areas in systems.

A very important physical constraint is limitation of the generation rate of the units which is caused by mechanical and thermal limitations which practically limit the frequency load control. So, it should be noted that in frequency load control, it is impossible to change signals fast, and performance of the frequency load loop controller highly depends upon the limitation of the units' generation rate [1].

Governor dead area is another important issue in system performance. With change in the signal input to governor, it may not respond until the input signal reaches a certain level. Governor dead band is of much importance in the issue of the system's response to disturbances. In this paper, the nonlinear model for steam turbine without reheater estimated with a time constant has been used.

In most of the load frequency simulations, two area nonlinear turbine power systems with governor that possesses a saturation surface of [−0.2 to 0.2] are considered. Fig. 1 indicates a nonlinear turbine and governor and Fig. 2 shows an equivalent simulated system in MATLAB Simulink.

The state-space of the system in Fig. 2 is defined as follows:

$$\dot{X}(t) = F(X(t), U(t), D(t)) \tag{4}$$

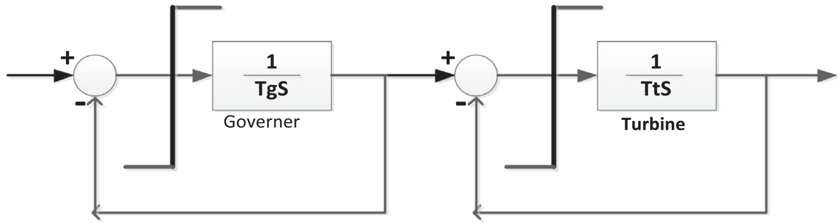

Figure 1 Nonlinear model of the turbine and governor.

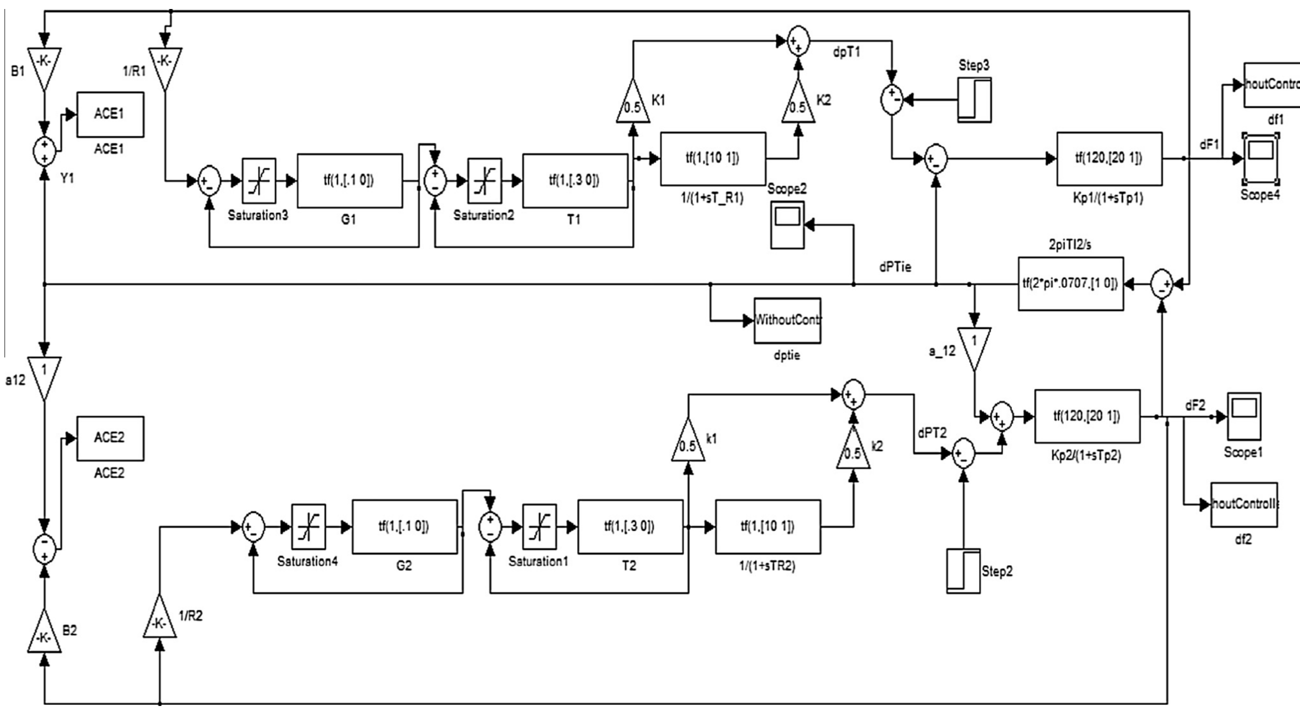

Figure 2 Two area power system model.

$$Y(t) = F(X(t)) \tag{5}$$

$$X = [\Delta P_{C1}\ \Delta X_{G1}\ \Delta P_{T1}\ \Delta F_1\ \Delta P_{tie}\ \Delta P_{C2}\ \Delta X_{G2}\ \Delta P_{T2}\ \Delta F_2]^T \tag{6}$$

$$U = [\Delta P_{C1}\ \Delta P_{C2}]^T \tag{7}$$

$$Y = [ACE_1\ ACE_2]^T \tag{8}$$

$$ACE_i = \Delta P_{tie} + B_i \Delta F_i \tag{9}$$

where $X(t)$, $U(t)$ and $D(t)$ are the state vector and control and disturbance respectively.

Generally, load–frequency system is stable system [41,42]. Load–frequency system contains integral controller. Considering the importance of this system, attempts have been made in the real world to improve the performance of the system.

As the range of entrance into saturation considered for governor increase, controlling system becomes easier and as it decreases, controlling system becomes harder. After all, simulation is possible but the amount considered [−0.2, 0.2] is a common amount [40].

4. Simplified 4-block type 2 fuzzy

The concept of type-2 fuzzy sets (FST2s) was proposed by Zadeh as an extension of the ordinary type-1 fuzzy set (FST1). Unlike the FST1s, the FST2s is such that its fuzzy set is defined by a typical fuzzy membership function. This means that the membership degree for each element is a fuzzy set in [0, 1], where the membership grade of FST1 is a crisp number in [0, 1]. Therefore, type-2 fuzzy techniques with uncertainties in the antecedent and the consequent MFs have attracted a considerable interest.

Control level in type-2 fuzzy system is smoother than in type-1 fuzzy systems. As a result, the effect of noise in areas with stable state is reduced [34]. Given the degree of freedom created by the uncertainty of type-2 fuzzy systems, modeling of uncertainty in such systems is done better than in type-1 fuzzy systems. The important point in type-2 fuzzy systems is their usage in control of systems, considering their large volume of calculation. Like type-1, type-2 fuzzy systems have fuzzifier, rule base, fuzzy inference engine and defuzzifier. The difference is that they need the type reducer before defuzzifier process. The process of reducing the order is done in order to transform type-1 into type-2 fuzzy systems. Finally, a crisp output is obtained through the defuzzifier process.

4.1. Proposing a simple structure for type-2 fuzzy systems

An interval type-2 fuzzy set can be considered as a collection of a large number of type-1 fuzzy set. The union and intersection of all type-1 fuzzy sets with the corresponding embedded membership functions being their membership functions are found. With the information represented by the union and intersection combined, a type-1 membership function is retrieved and an interval type-2 fuzzy set is reduced to a type-1 fuzzy set [31].

There have been several methods proposed for reaching a crisp output in type-2 fuzzy systems [35,37].

Using the method proposed here, the number of difficult calculations existing in type-2 fuzzy systems is decreased. The method being a combination of four type-1 fuzzy systems presents a new flexibility and strength. This may be used as follows:

(A) Nonlinear control of multivariable systems, with several types of uncertainty such as type-2 fuzzy systems (T2FS) in industrial applications.
(B) Effective learning in using T2FS4 inference systems.

Compared to other complex methods for order-reducing, the method is very simple and only requires some knowledge of type-1 fuzzy systems.

An interval type-2 fuzzy set $\widetilde{A}$ is characterized by its MF $\mu_{\widetilde{A}}(x,u)$ as

$$\widetilde{A} = \int_{x\,\in\,\widetilde{D}} \int_{u=\in J_x \subseteq [0,1]} \mu_{\widetilde{A}}(x,u)/(x,u) \tag{10}$$

where $x \in D_{\widetilde{A}}$ is the primary variable in domain, $D_{\widetilde{A}}$, $u \in J_x$ is the secondary variable, J_x is called the primary membership of x and the amplitude of $\mu_{\widetilde{A}}$ is the secondary grades of $\widetilde{A}$. In interval type-2 fuzzy sets, the secondary grades of $\widetilde{A}$ are all equal to one $\forall x \in D_{\widetilde{A}}$ and $\forall u \in J_x \subseteq [0,1]$. The uncertainty of MF of $\widetilde{A}$ can be described by the union of all the primary memberships which is called the footprint of uncertainty (FOU) of $\widetilde{A}$:

$$FOU(\widetilde{A}) = \bigcup_{x\in D_{\widetilde{A}}} J_x = \{(x,u) : u \in [\underline{\mu}_{\widetilde{A}}(x), \overline{\mu}_{\widetilde{A}}(x)]\} \tag{11}$$

where $\underline{\mu}_{\widetilde{A}}(x)$ is the lower membership function (LMF) and $\overline{\mu}_{\widetilde{A}}(x)$ is the upper membership function (UMF).

An example of interval type-2 fuzzy sets is illustrated in Fig. 3. Observe that an interval type-2 fuzzy set is bounded by two fuzzy set type-1, $\overline{A}$ and $\underline{A}$. The area between $\overline{A}$ and $\underline{A}$ is the footprint of uncertainty.

As shown in Fig. 4, each type-2 MF can represent two type-1 MFs, upper MF and lower MF. Therefore, each one of two neighbor type-2 MFs intersects the other in four points and object to get four MFs, upper MF, lower MF, left MF and right MF shown in Fig. 5.

Thus, four T1 TSK Fuzzy controllers supplanted are used discretely. The MFs in each controller are supplanted by upper MF, lower MF, left MF and right MF, which will create upper fuzzy controller (UFC), lower fuzzy controller (LFC), left fuzzy controller (LEFTFC) and right fuzzy controller (RFC) respectively.

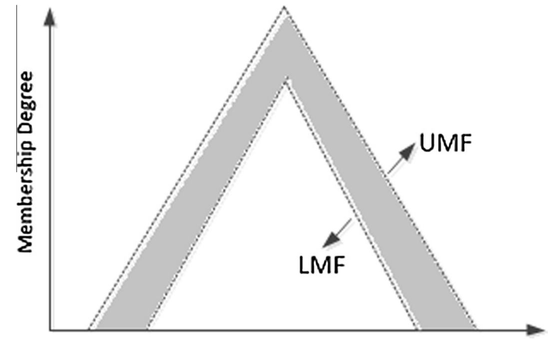

Figure 3 The type-2 MF.

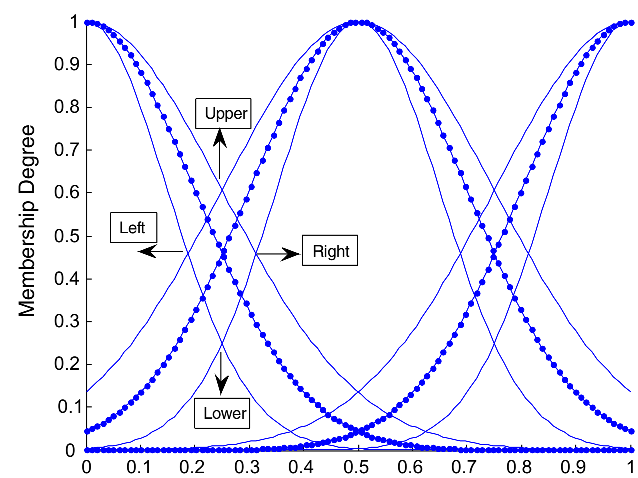

Figure 4 Illustration of decomposing type-2 MFs into 4 type-1 MFs.

The defuzzified output of the type-2 fuzzy system is then obtained by averaging the defuzzified outputs of the resultant four embedded type-1 fuzzy systems, as shown in Fig. 6.

$$Y(x) = \frac{1}{2}y_{Upper} + \frac{1}{2}y_{Lower} + \frac{1}{2}y_{Left} + \frac{1}{2}y_{Right} \tag{12}$$

Generally, type 2 fuzzy contains some calculation complexities. In this paper, simplified type 2 fuzzy has been used that contains 4 type 1 fuzzy blocks. This approach is parallel with type 2 fuzzy in terms of efficiency and parallel with type 1 fuzzy in terms of calculations. Therefore, there won't be any problems in terms of online control because there are 4 parallel type 1 fuzzy blocks.

5. Hierarchical fuzzy systems

The design of a fuzzy system is subject to a number of rules in the system which may enlarge exponentially as the number of inputs in the system outgrows. Basically, imagine (n) inputs for a system and (m) fuzzy rules defined for each input. Therefore, there will be as formidable as m^n fuzzy system rules. In

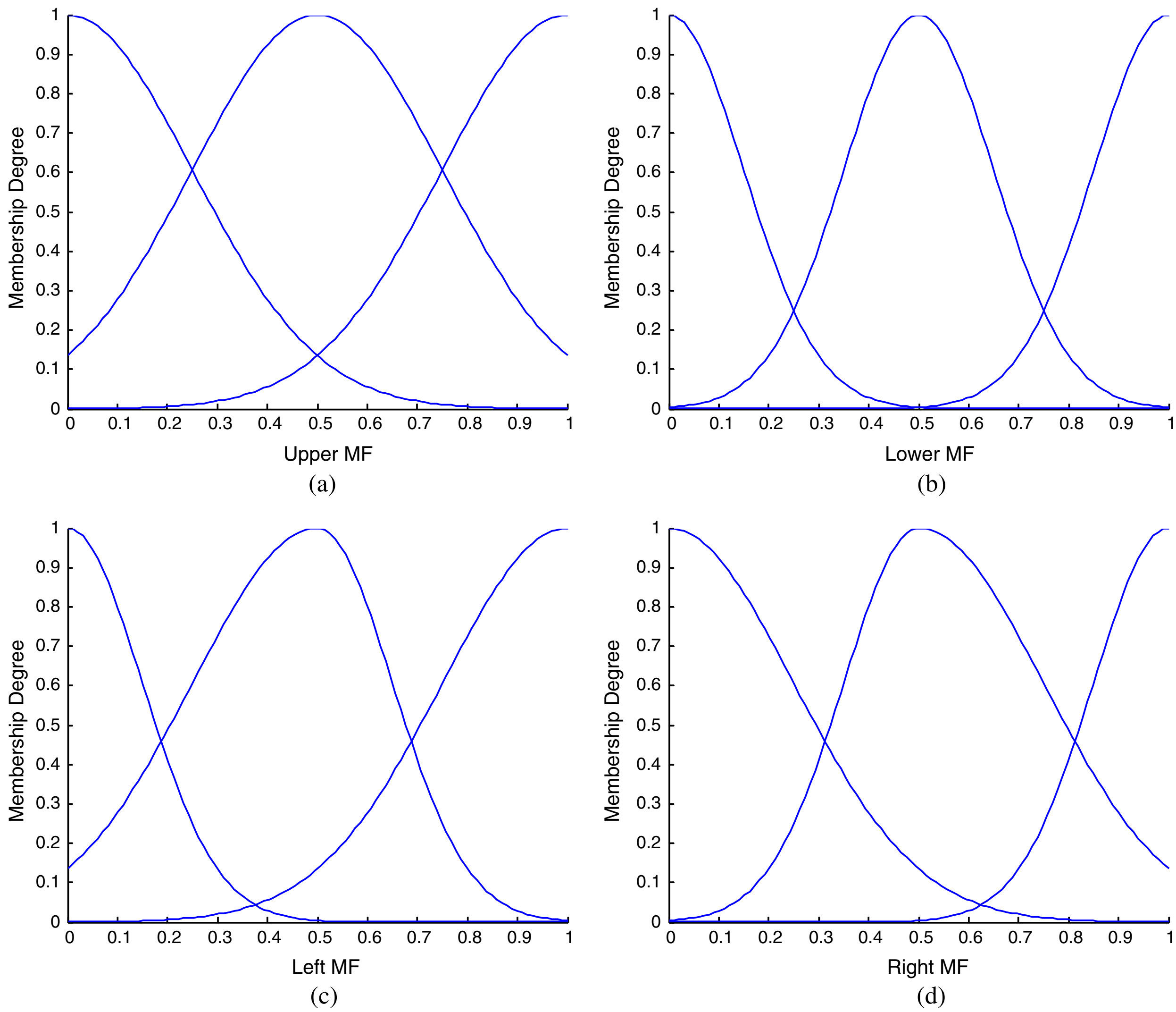

Figure 5 (a) Membership functions of upper intersection points. (b) Membership functions of lower intersection points. (c) Membership functions of right intersection points, and (d) membership functions of left intersection points.

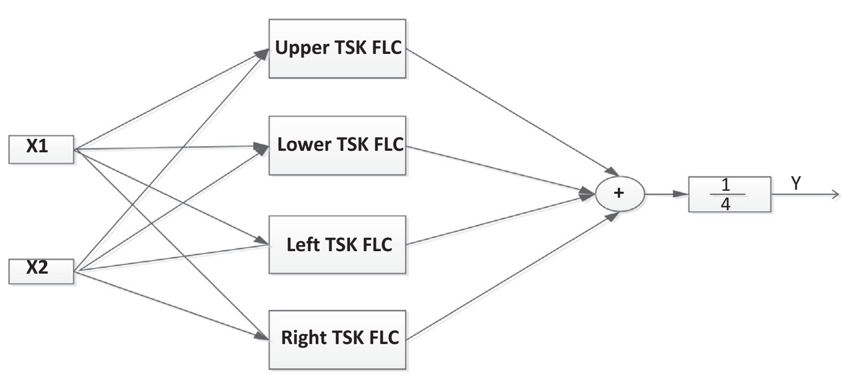

Figure 6 Systems simplified 4-block type 2 fuzzy (S4BT2F (Simplified 4 Blocks Type-2 Fuzzy)).

practice, however, executing a fuzzy system with thousands of rules will be impossible. As an alternative, hierarchical fuzzy system will improve the algorithm via truncating a number of superfluous rules.

5.1. Designing hierarchical fuzzy system

The hierarchical fuzzy system is designed so that input variables, instead of being fed into a fuzzy system with high dimensions, which is a common practice, will be spread over several homogenous fuzzy systems with denser dimension. As a result, each individual fuzzy system with a moderate dimension forms a surface in overall hierarchical fuzzy system.

Assuming that there are n input variables say $x_1, \ldots, x_n$, therefore:

(A) The first surface will be a fuzzy system with n_1 variables say $x_1, \ldots, x_n$, with following rules defined:

$$\text{If } x_1 \text{ is } A_1^L, \ldots, x_n \, is \, A_n^L \text{ then } y_1 \text{ is } B_1^L \quad 2 \text{ £} n_1 < n, \\ L = 1, 2, 3, \ldots M_1 \tag{13}$$

(B) i_{th} surface ($i > 1$) in a fuzzy system with $(n_i \geqslant 1), n_i + 1$ is an input variable with the following rules:

$$\text{If } x_{N_i+1} \text{ is } A_{N_i+1}^L, \ldots, x_{N_i+n} \text{ is } A_{N_i+n_1}^L, \; y_{i-1} \text{ is } C_{i-1}^L \\ \text{then } y_i \text{ is } B_i^L \quad N_i = \sum_{j=1}^{i-1} n_j, \; L = 1, 2, 3, \ldots M_i \tag{14}$$

(C) Construction of various surfaces continues until $i = L$ such that $\sum_{j=1}^{L} n_j = n$, when all input variables are placed in a surface.

As it can be seen, the first surface n_1 maps variable $x_1, \ldots, x_n$ into variable Y_1 which are then sent to the second surface. In the second surface, n_2, another variable of $x_{n_1+1}, \ldots, x_{n_1+n_2}$ and variable Y_1, are combined and generate another variable called Y_2. Later, it also passes to the upper surface. The process repeats until all the variables $x_1, \ldots, x_n$ were used up.

In Fig. 7, one of the common structures of hierarchical fuzzy systems is depicted.

Assuming that the fuzzy system contains n inputs and each input contains m members while c is the number of inputs in each surface of a fuzzy system, then one can write

$$M = \frac{m^c}{(c-1)(n-1)} \tag{15}$$

Since $\frac{m^c}{(c-1)}$ is a constant, it can be seen in Eq. (15) that the number of hierarchical fuzzy system rules can be increased as the number of input variables enlarges. Also, it can be easily inferred from the above equation that the fuzzy system contains minimal rules when $c = 2$ [19–24].

The hierarchical fuzzy systems have been used in various disciplines, including: Multi-objective genetic learning for large-scale problems [39], astronomical telescope tracking [36], Control Nonlinear Swing Up and Stabilizing of Inverted Pendulum [25] and controlling flexible link robot arm performing in constrained motion tasks [12].

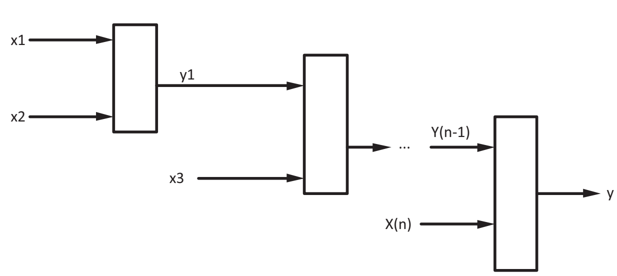

Figure 7 A fuzzy hierarchical structure [23].

6. Cuckoo Optimization Algorithm

Cuckoo Optimization Algorithm (COA) was introduced by offering a global optimal solution for nonlinear systems. COA is one of the latest and most powerful meta-heuristic optimization methods. Previously, in the same family, Genetic Algorithm (GA) and Simulated Annealing (SA) have long been employed, which were later competed by other optimization techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Fish Swarm (AFS). There are a number of evidences for the use of such methods in engineering and complicated scientific optimization problems.

Cuckoo Optimization Algorithm, an imitation of the life of a bird called Cuckoo, was developed in 2011 by Yang, X.S and Deb, S. Later, Ramin Rajabyoon tested Cuckoo Optimization Algorithm into more details. Eventually, adapted version of program by Humar Kahramanli appeared in 2012 [27,28]. Cuckoo Optimization Algorithm is shown in Fig. 8.

The claim that one optimization algorithm is the best method for solving optimization problems is not correct. New algorithms are created each year that obviate the limitations of old algorithms. GA and PSO were once considered best algorithms in their own type. Although these algorithms are still common in some scientific papers, these new approaches are often used as criterions for comparing functions in new methods.

Some researchers believe that there is no reason to claim that one optimization method is superior to another method since each method is able to find appropriate answer because of the existence of supplement. The point here is that like their real models, evolution in some of these approaches is incredibly slow. For example, like real genes, evolution in genetic method is incredibly time-consuming. This might be the reason why GA requires more repetitions for finding the answer than other types. Conversely, PSO as inspired by birds searching for food acts incredibly faster than GA in problem solving. Whatever the reason, what is seen is that some algorithms are inherently faster than others, leading to more popularity among researchers. This is true about Cuckoo Optimization Algorithm. In experiments performed on this algorithm so far, it can be seen that it acts much faster than other algorithms. This is a good reason why COA is appropriate in solving problems with higher difficulty and complexity.

In [27], Cuckoo Optimization Algorithm has been used for optimization of a problem with 1000 variables. Next, a comparison has been made between the performance of COA with GA and PSO. The results of simulations indicate the superiority of COA over other algorithms.

The main reason why Cuckoo Optimization Algorithm works more efficiently than other similar algorithms lies in the fact that COA has a multiple function, such as egg laying and migration. In other types of evolutionary algorithms one can find that functions contain only one particular purpose. In COA, however, defined parameters follow several functions simultaneously.

As an example, clustering in COA helps cuckoos divide their surrounding region into several sub-regions and compute the best region. This region probably has the general optimization point where in the next stage all cuckoos move toward and search that region. Cuckoos can search more comfortably,

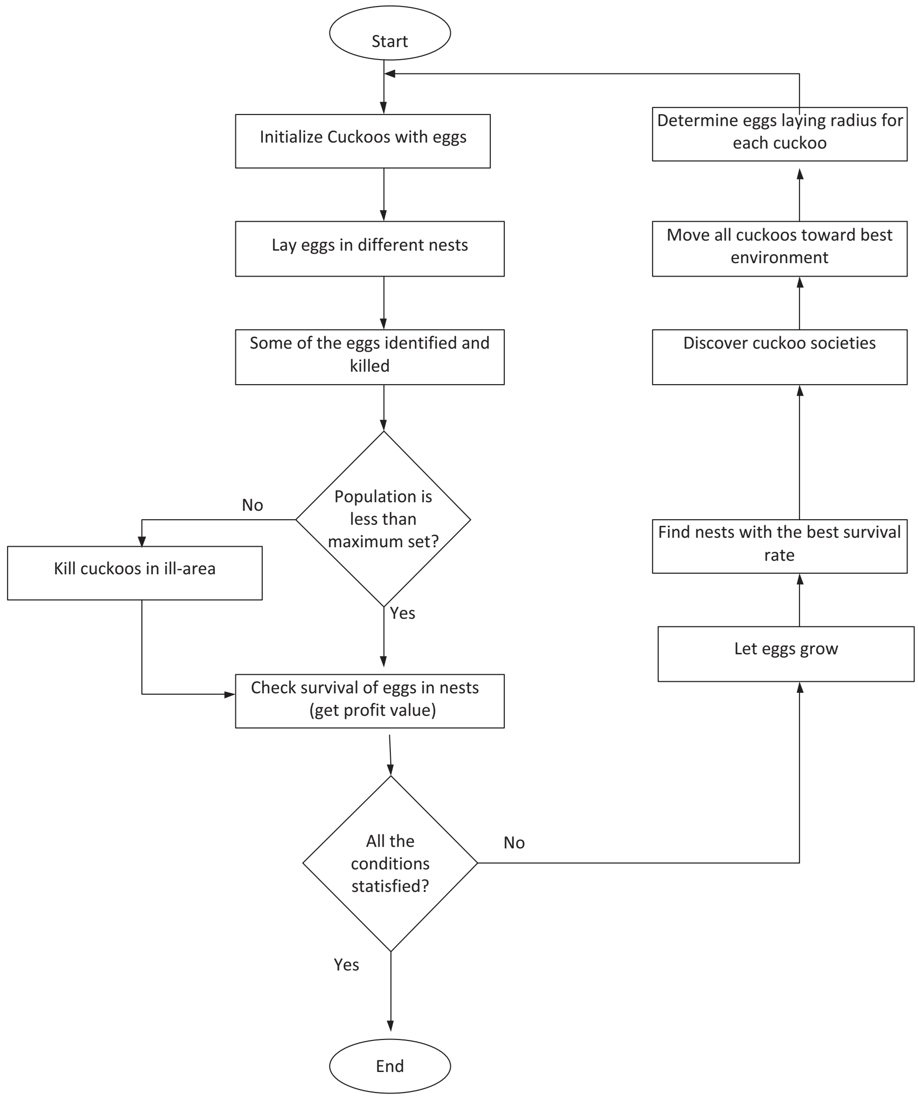

Figure 8 Flowchart COA.

which will, in turn, lead to increased convergence among Cuckoo algorithm. Unlike other algorithms, in COA, cuckoos put eggs in various locations. These special egg laying techniques play two critical roles in the algorithm: (1) distribution of eggs around the current optimization point helps COA avoid from getting stuck in local optimization; and (2) Egg laying process, by its very nature, is a local search process. Other optimization algorithms, however, lack such key function, thus need to be combined with such algorithms such as Tabu Search (TS). As a consequence, in COA, convergence occurs at a much faster rate [27–30].

Taking into account various functions and characteristics of COA, as indicated in Refs. [27–30], it can be contended that COA has the following advantages over similar algorithms:

1. Faster convergence.
2. Higher speed.
3. Much higher precision.
4. Capability to perform local as well as global searching.
5. Much lower chance of being stuck in local optimization points.
6. Searching with various population.
7. Population movement toward more favorable locations as inappropriate answers are removed.
8. High capability to solve multidimensional optimization problems.

7. Comparison of Fuzzy controllers

In control systems, the purpose is to provide a number of features based on quantifiable figures which determine the general function and performance of system. A number of such parameters determine system performance, such as (M_p, t_s, t_r, and t_p,) and others determine steady-state error (e_{ss}), which must be dissolved concomitantly. In practice, however, using such functions requires trial and error.

If a defined function can act as a criterion for determining whether a system is performing properly, then we can design system more easily and logically. Performance index is generally a component of system variables; therefore, to obtain appropriate results, it is necessary to select an appropriate performance index. Some of the most famous performance indices are ISE, ITSE, IAE, ITAE and RMSE.

Among the four performance indices mentioned above, the use of ISE is more common, since (1) it functions as a criterion for control energy, (2) it is easier to perform mathematical functions with this criterion and (3) error of root square increases the amount of function [26,27].

Eqs. (16)–(18) represent criterions ISE, ITSE and RMS:

$$\text{ISE} = \int_0^{30} (ACE_1(t)^2 + ACE_2(t)^2)dt \tag{16}$$

$$\text{ITSE} = \int_0^{30} t \times (ACE_1(t)^2 + ACE_2(t)^2)dt \tag{17}$$

$$\text{RMSE} = \sqrt{(ACE_1(t)^2 + ACE_1(t)^2)/N} \tag{18}$$

To compare the function of controller, three criterions ISE, ITSE and RMS were chosen.

8. Simulation results

In this section, two-area system with nonlinear characteristics is simulated. Table 1 lists the parameters involved at each area.

In Table 1 T_r and B_i are constants of reheat turbine and frequency is bias coefficient of ith area respectively.

8.1. Designing Fuzzy Mamdani controller

In this paper all the fuzzy controllers embrace three factors of ACE, ΔACE, and $\int ACE$ which are input controller gains proportional, derivative, and integral respectively. Each input falls in the range of $[-2, 2]$. "trimf" membership function is selected throughout this work. To design TSK controller, the output parameters are both set to fix the linear values. Each control input has three membership functions which, on the other hand, becomes $27 = 3^3$. In Figs. 9 and 10, input and output membership functions are shown and the relevant fuzzy rules are described in Table 2.

8.2. Designing an optimized simplified type-2 TSK hierarchy fuzzy controller

In designing a hierarchy fuzzy system, level 1 has two inputs ACE and ΔACE, with an output which, along with the input

Table 1 Information of systems.

Parameters	Area 1	Area 2
Tg	0.1	0.1
Tt	0.3	0.3
Tr	10	10
Tp	20	20
Kp	120	120
K_1	0.5	0.5
K_2	0.5	0.5
B	0.425	0.425
R	2.4	2.4

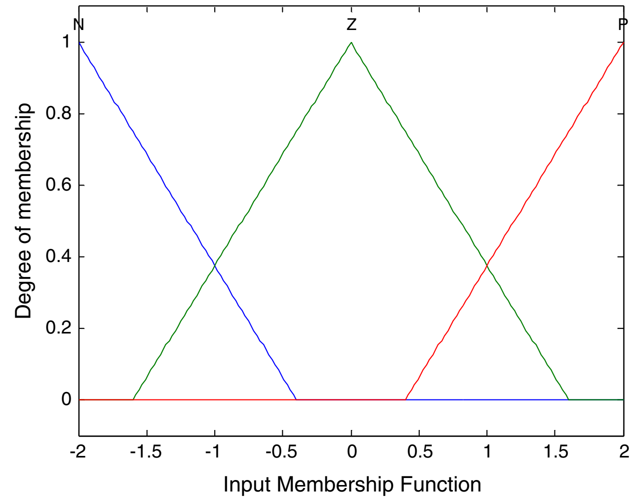

Figure 9 Input membership function.

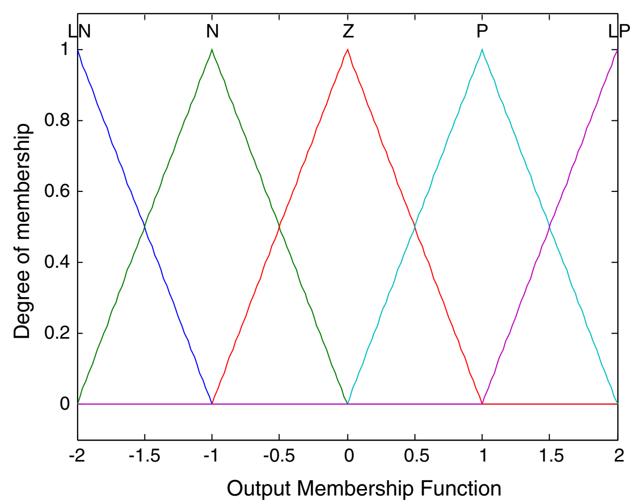

Figure 10 Output membership function.

$\int ACE$, is applied to the second fuzzy system as the level-2 inputs. Each fuzzy system has nine principles, so there are totally eighteen principles. As a result, it is possible to reduce the number of principles from 27 to 18 by using the hierarchy controller. In other words, number of principles has been reduced by 33 percent.

As four type-1 fuzzy systems have been used instead of one type-2 fuzzy system, the output of the type-1 fuzzy sum-operator should be multiplied by the coefficient $\frac{1}{4}$. It is also possible to move the coefficient $\frac{1}{4}$ to a place before the sum-operator, multiply the output of each fuzzy system by this coefficient, and finally add all the results together.

Then, the coefficient may be optimized using optimization algorithm so that dimension coefficient of each fuzzy system can be introduced in the form of α_i with $i = 1, 2, 3, 4$ and if $\sum_{i=1}^{4}\alpha_i = 1$. Optimizing the α_i coefficients causes the type-1 fuzzy systems to have weight.

In this paper, uncertainty of upper and lower member functions is shown as β_i and α_i, respectively, where i indicates the

Table 2 Basic rules to controllers TSK and Fuzzy Mamdani.

**	ACE	ΔACE	∫ACE	OUT
1	N	N	N	PL
2	N	N	Z	P
3	N	N	P	P
4	N	Z	N	P
5	N	Z	Z	P
6	N	Z	P	Z
7	N	P	N	P
8	N	P	Z	Z
9	N	P	P	N
10	N	N	N	P
11	Z	N	Z	P
12	Z	N	P	Z
13	Z	Z	N	P
14	Z	Z	Z	Z
15	Z	Z	P	N
16	Z	P	N	Z
17	Z	P	Z	N
18	Z	P	P	N
19	P	N	N	P
20	P	N	Z	Z
21	P	N	P	N
22	P	Z	N	Z
23	P	Z	Z	N
24	P	Z	P	N
25	P	P	N	N
26	P	P	Z	N
27	P	P	P	NL

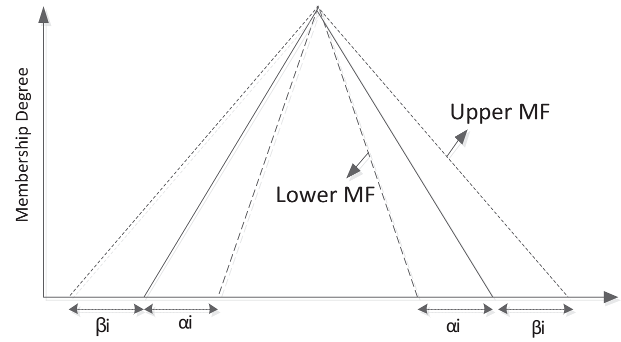

Figure 12 Type 2 fuzzy uncertainty.

Table 3 Characteristics of Cuckoo algorithms.

**	Object	Value
1	numCuckooS	5
2	minNumberOfEggs	2
3	maxNumberOfEggs	4
4	maxIter	100
5	knnClusterNum	1
6	motionCoeff	2
7	Accuracy	0
8	maxNumOfCuckoos	10
9	radiusCoeff	5
10	cuckooPopVariance	1e−13

number of dependency function. The uncertainty considered is equal to [0, 0.25] (see Fig. 11).

The Simplified 4 Blocks Optimal Type-2 TSK Fuzzy Hierarchical Controller (T2FHC) has been designed in three different modes as follows:

(1) Upper and lower uncertainties are equal to each other, that is to say, there is only one uncertainty that is ($\beta_1 = \beta_2 = \ldots = \beta_i = \alpha_1 = \alpha_2 = \ldots = \alpha_i \in [0, 0.25]$) (T2FHC1).
(2) Upper uncertainties are equal to each other, and lower uncertainties are equal to each other too, meaning that there are two uncertainties that are ($\alpha_1 = \alpha_2 = \ldots = \alpha_i \in [0, 0.25]$) and ($\beta_1 = \beta_2 = \ldots = \beta_i \in [0, 0.25]$) (T2FH C2).
(3) Each dependency function has its own uncertainty, that is to say, there are multiple uncertainties that are $\alpha_1 \neq \alpha_2 \neq \ldots \neq \alpha_i \in [0, 0.25]$, ($\beta_1 \neq \beta_2 \neq \ldots \neq \beta_i \in [0, 0.25]$) (T2FHC3). To further understand, see Fig. 12.

Table 3 summarizes the COA processing characteristics. The objective function is to minimize the ISE drawn in Fig. 13 as a way to optimize the rate of changes given in Tables 4 and 5.

8.3. Controller's performance comparisons

In order for the performance of controllers to be determined, the following conditions have been considered for the simulation processes:

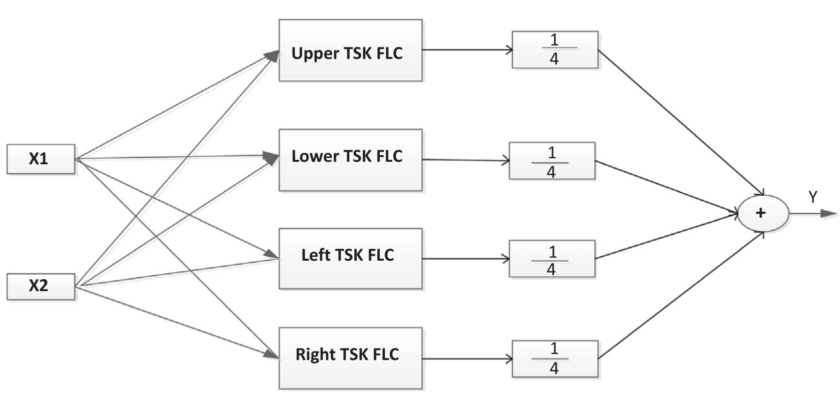

Figure 11 Controller S4BT2F.

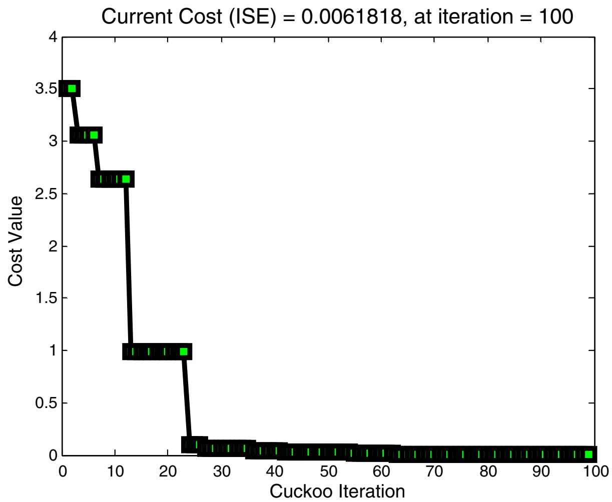

Figure 13 Diagram of the cost function reduction.

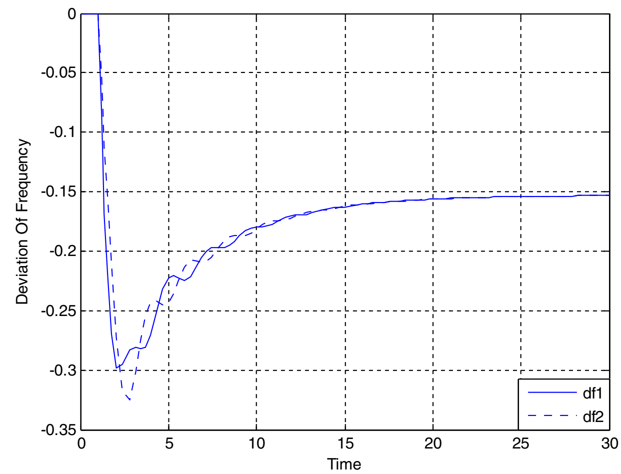

Figure 14 Changes in the ΔF_1 and ΔF_2 without control systems in scenario (a).

Table 4 Basic rules for the first level of the hierarchical controller.

**	ACE	ΔACE	OUT1
1	N	N	P
2	N	Z	P
3	N	P	Z
4	Z	N	P
5	Z	Z	Z
6	Z	P	N
7	P	N	Z
8	P	Z	N
9	P	P	N

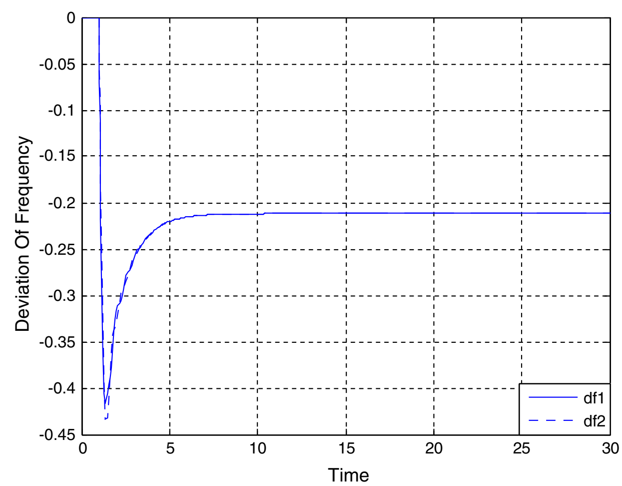

Figure 15 Changes in the ΔF_1 and ΔF_2 without control systems in scenario (b).

Table 5 Basic rules for the second level of the hierarchical controller.

**	OUT1	ACE$\int$	OUT
1	N	N	LP
2	N	Z	P
3	N	P	Z
4	Z	N	P
5	Z	Z	Z
6	Z	P	N
7	P	N	Z
8	P	Z	N
9	P	P	LN

(a) 8 and 5 percent load disturbances for the areas 1 and 2 in the 1st second of the simulation process.
(b) 25 percent reduction in the nominal values, and 10 and 8 percent load disturbances for the areas 1 and 2 in the 1st second of the simulation process.
(c) 8 and 5 percent load disturbances for the areas 1 and 2 in the 1st second of the simulation process following the 3 and 6 percent load disturbances for area 1 in the 15th

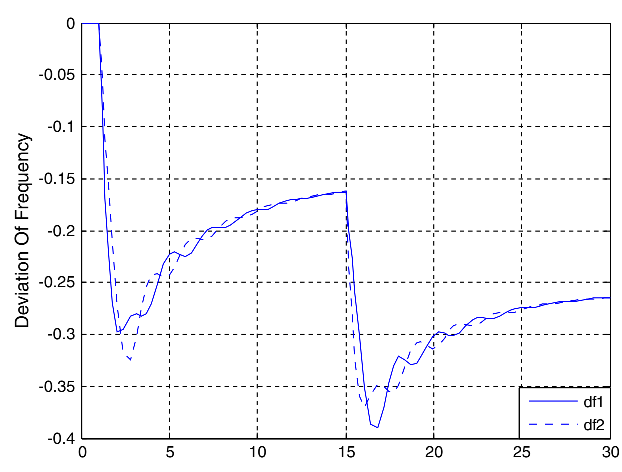

Figure 16 Changes in the ΔF_1 and ΔF_2 without control systems in scenario (c).

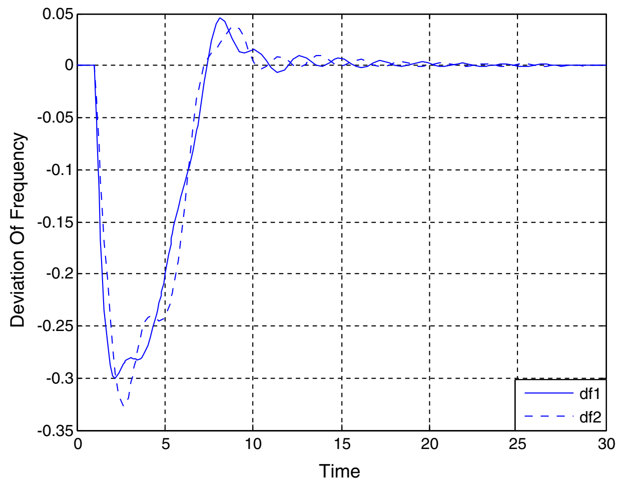

Figure 17 Changes in the ΔF_1 and ΔF_2 with fuzzy controller in scenario (a).

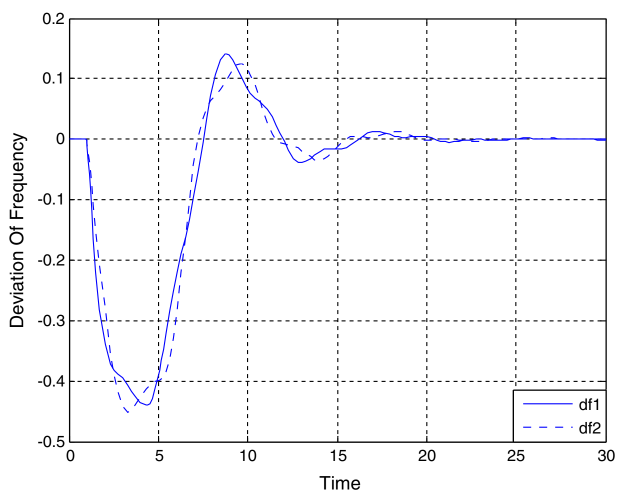

Figure 18 Changes in the ΔF_1 and ΔF_2 with fuzzy controller in scenario (b).

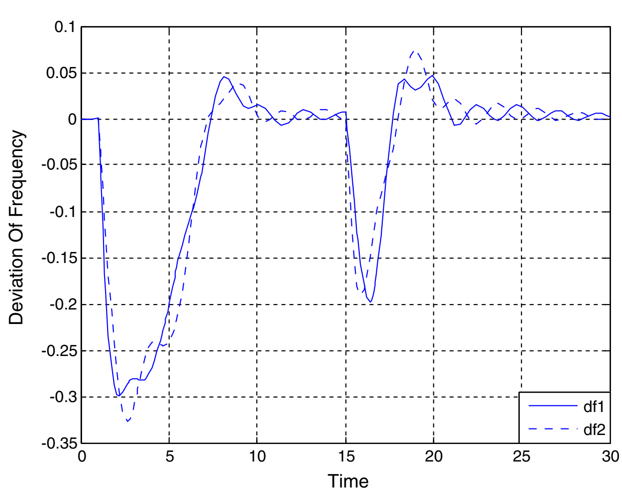

Figure 19 Changes in the ΔF_1 and ΔF_2 with fuzzy controller in scenario (c).

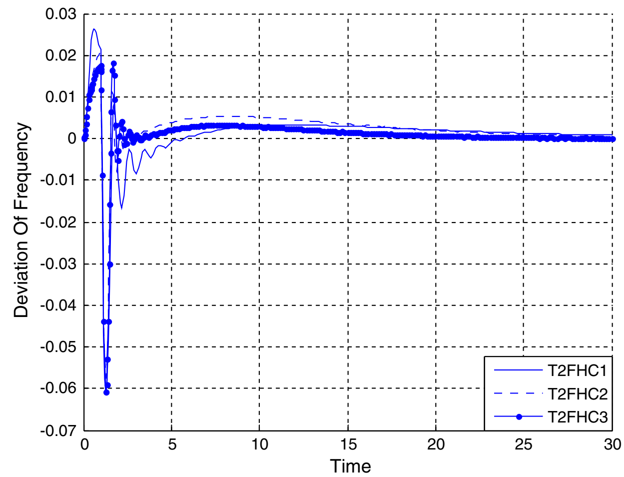

Figure 20 Changes in the ΔF_1 with T2FHCS in scenario (a).

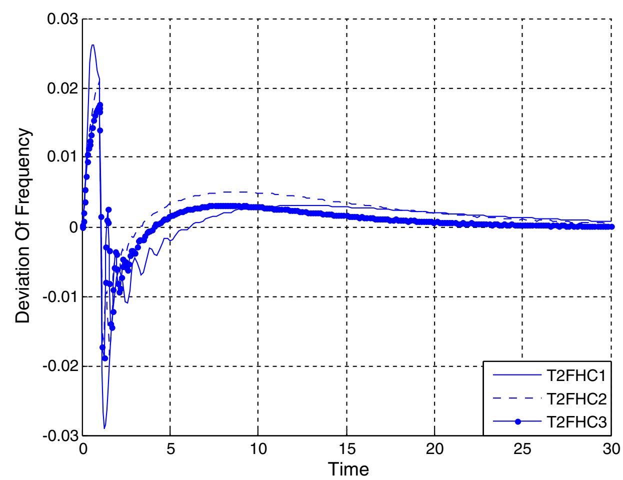

Figure 21 Changes in the ΔF_2 with T2FHCS in scenario (a).

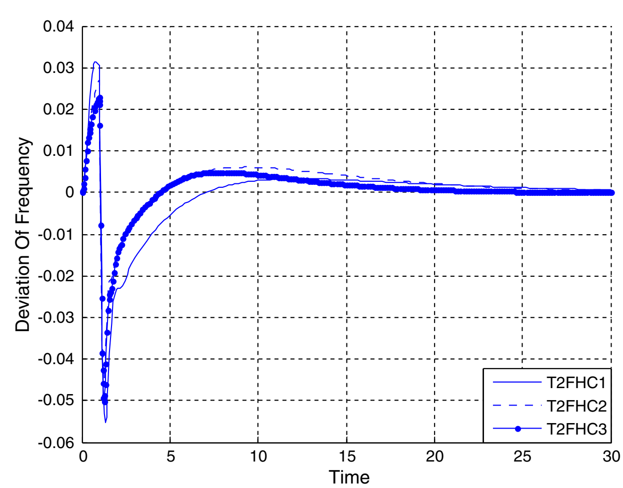

Figure 22 Changes in the ΔF_1 with T2FHCS in scenario (b).

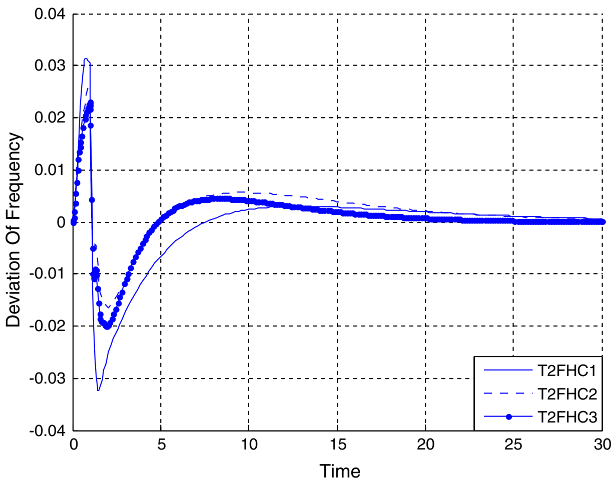

Figure 23 Changes in the ΔF_2 with T2FHCS in scenario (b).

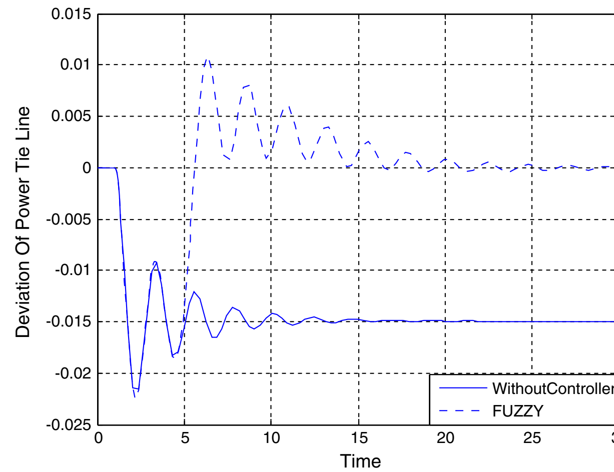

Figure 26 Changes in the ΔP_{tie} with fuzzy controller and without controller in scenario (a).

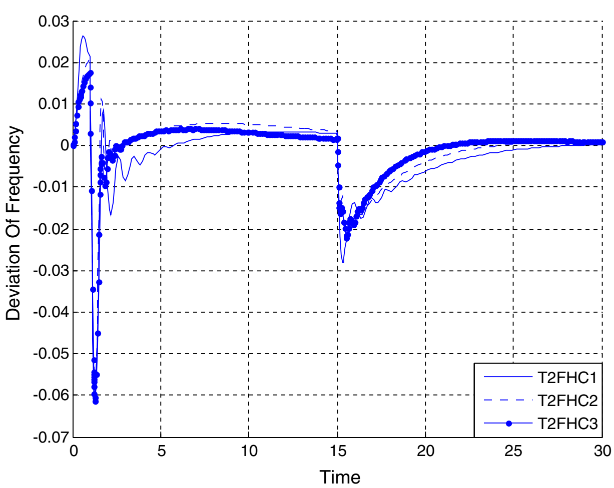

Figure 24 Changes in the ΔF_1 with T2FHCS in scenario (c).

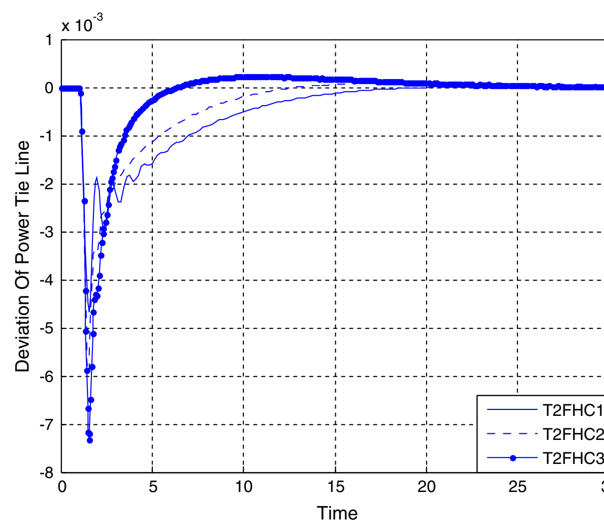

Figure 27 Changes in the ΔP_{tie} with T2FHCS in scenario (a).

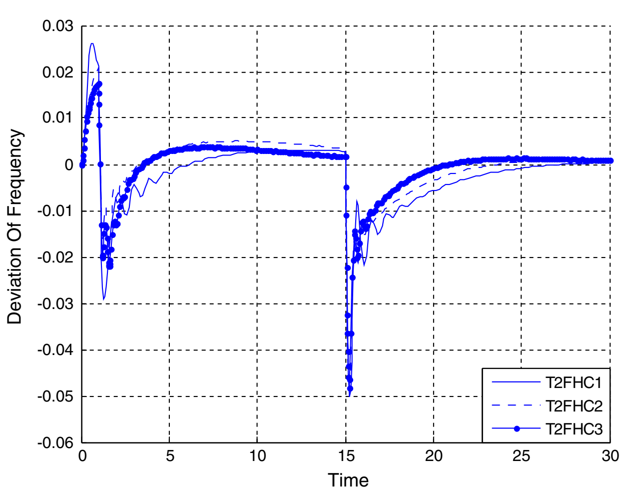

Figure 25 Changes in the ΔF_2 with T2FHCS in scenario (c).

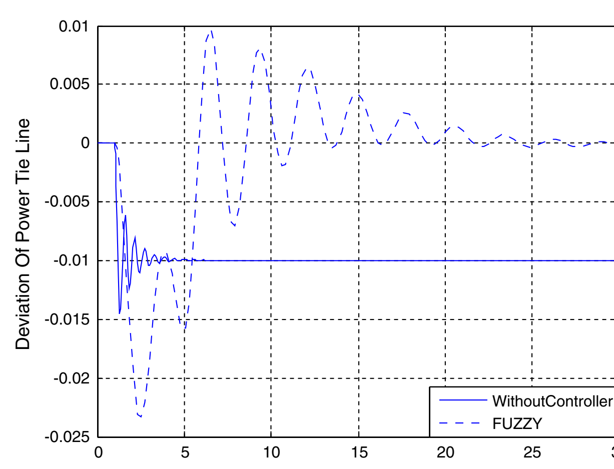

Figure 28 Changes in the ΔP_{tie} with fuzzy controller and without controller in scenario (b).

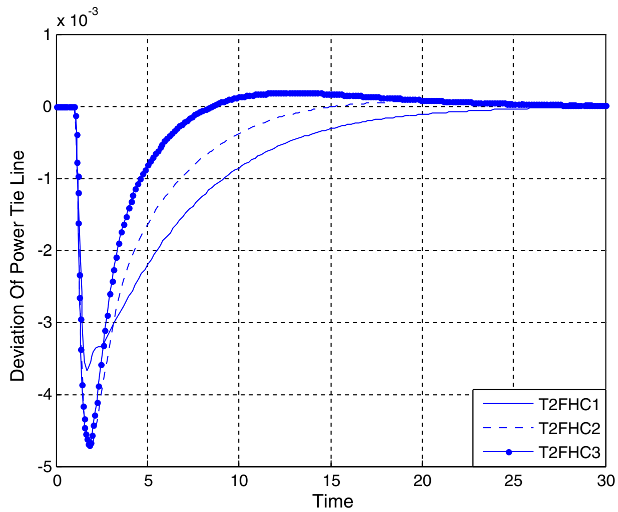

Figure 29 Changes in the ΔP_{tie} with T2FHCS in scenario (b).

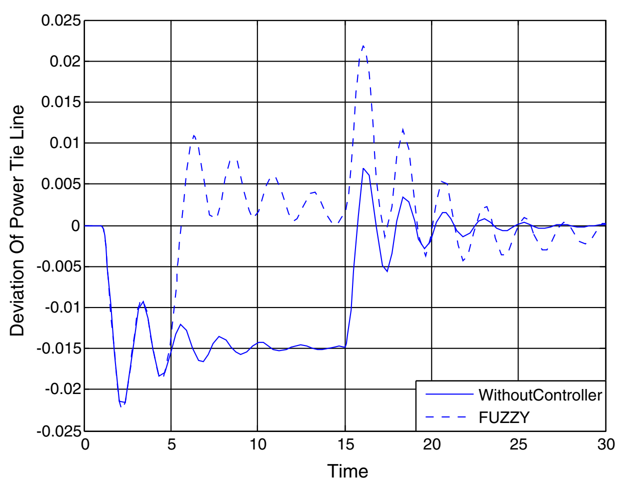

Figure 30 Changes in the ΔP_{tie} with fuzzy controller and without controller in scenario (c).

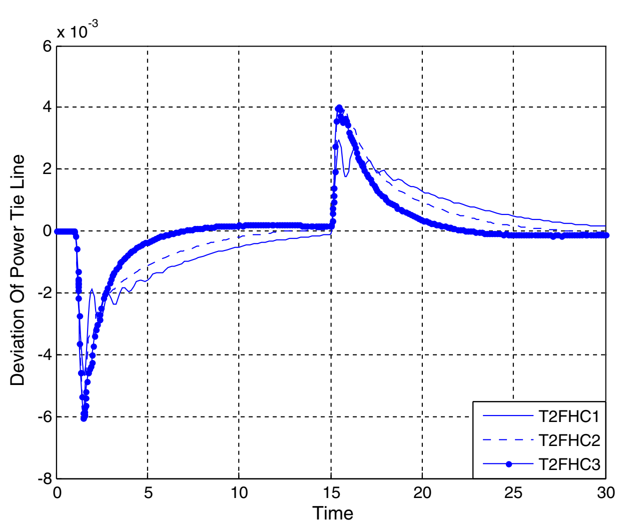

Figure 31 Changes in the ΔP_{tie} with T2FHCS in scenario (c).

second of the simulation (during the simulation process, each area has two different disturbances in two different times).

Figs. 14–16 show the frequency deviations in areas 1 and 2 following the situations in states a, b and c when no controller resides in the model. Both ΔF_1 and ΔF_2 represent almost an identical behavior subject to the conditions set at both scenarios a and b. Although with deep overshoot, the system error in frequencies between interconnected areas was finally stabilized.

Figs. 17–19 show frequency deviation in areas 1 and 2, with fuzzy controller in three states a, b and c. Fig. 20 shows frequency deviation of area 1 with T2FHCS and Fig. 21 shows frequency deviation of area 2 with T2FHCS in state a.

Figs. 22 and 24 show frequency deviation of area 1 with T2FHCS in states b and c respectively. Also Figs. 23 and 25 show frequency deviation of area 2 with T2FHCS in states b and c respectively (see Figs. 26–31).

The following figures of distortion Tie-Line in three different states of simulation show that the proposed controllers have better performance than other controllers and T2FHCS are clearly visible.

In [38], there is a table entitled quality parameters of 50 Hz frequency generalizing which makes it possible to transform this table to Table 6 for 60 Hz frequency.

In the table just mentioned, if the nominal frequency of the network is assumed to be 60 Hz, the standard range of frequency changes will be equal to ±240 mHZ, that is to say, in normal conditions, the network may have changes equal to ±240 mHZ. If an error occurs in the network, the allowable frequency changing for the transient error is equal to

Table 6 Quality parameters 60 Hz [38].

	GB Synchronous Area
Nominal frequency	60 Hz
Standard frequency range	± 240 mHZ
Maximum instantaneous frequency deviation	960 mHZ
Maximum steady-state frequency deviation	600 mHz
Time to recover frequency	1 min
Frequency range within time to recover frequency	± 600 mHz
Time to restore frequency	10 min
Frequency range within time to restore frequency	± 240 mHZ

Table 7 Comparison of ISE, ITSE and RMS criteria in scenario (a).

Controller	Criterion ISE	Criterion ITSE	Criterion RMSE
Without controller	1.6148	14.8362	0.1492
Fuzzy	1.1751	5.5494	0.1398
T2FHC1	0.0084	0.0132	0.0087
T2FHC2	0.0076	0.0159	0.0067
T2FHC3	0.0062	0.0094	0.0053

Table 8 Comparison of ISE, ITSE and RMS criteria in scenario (b).

Controller	Criterion ISE	Criterion ITSE	Criterion RMSE
Without Controller	6.7155	95.2263	0.1876
Fuzzy	0.7443	3.1821	0.1030
T2FHC1	0.0077	0.0135	0.0083
T2FHC2	0.0062	0.0130	0.0060
T2FHC3	0.0061	0.0102	0.0060

Table 9 Comparison of ISE, ITSE and RMS criteria in scenario (c).

Controller	Criterion ISE	Criterion ITSE	Criterion RMSE
Without controller	2.3153	38.9342	0.2074
Fuzzy	1.8349	9.1554	0.1371
T2FHC1	0.0135	0.0961	0.0105
T2FHC2	0.0131	0.1035	0.0084
T2FHC3	0.0113	0.0903	0.0073

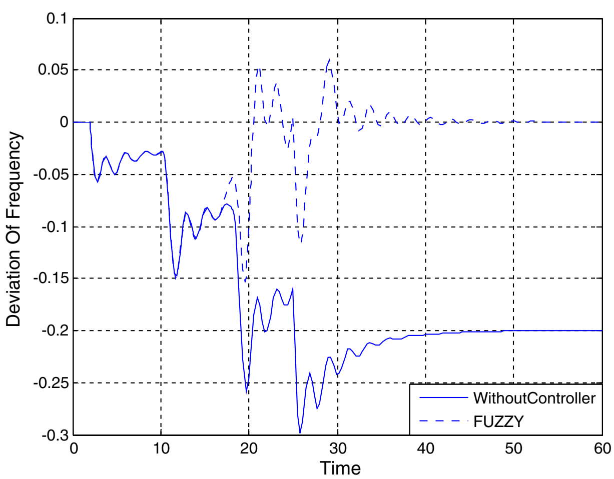

Figure 32 Changes in the ΔF_1 with fuzzy controller and without Controller.

960 mHZ. So, controllers should take action to control the deviation, and in stable conditions, make the frequency change reach 600 mHZ. The amount of time they have for controlling the frequency changes in the error occurred is equal to 1 min, so the frequency changes of ± 600 mHZ are now assumed to be the allowable frequency change in the network. After the first stage of control is done in the presence of an error and frequency changes decreased from 960 to ± 600 mHZ in 1 min, the second stage starts in a way that the frequency changes should be decreased from ± 600 to ± 240 mHZ in 10 min, the same range as nominal frequency changes.

Considering the load disturbances in the simulation processes so far, the system, according to standards, may have frequency changes up to 960 mHZ. Changes should also be

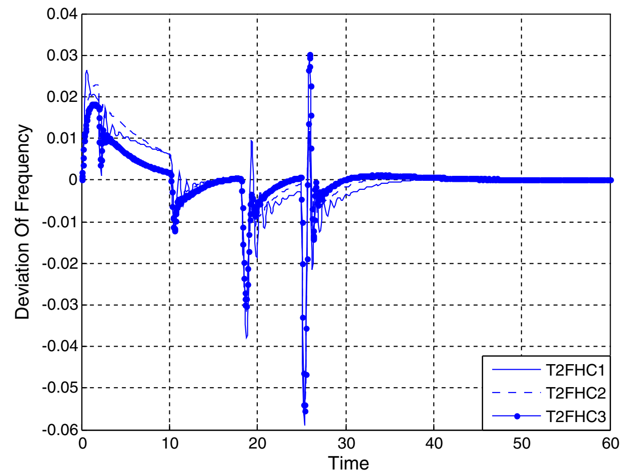

Figure 33 Changes in the ΔF_1 with T2FHCS.

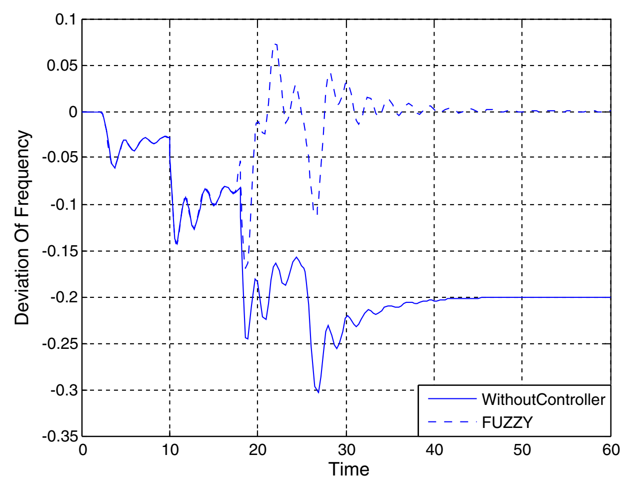

Figure 34 Changes in the ΔF_2 with fuzzy controller and without Controller.

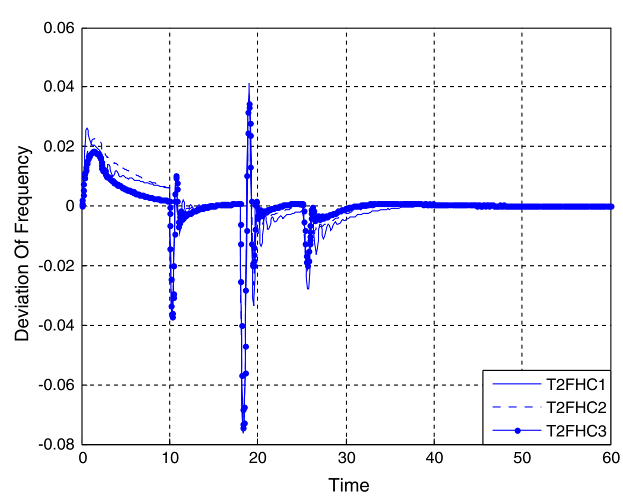

Figure 35 Changes in the ΔF_2 with T2FHCS.

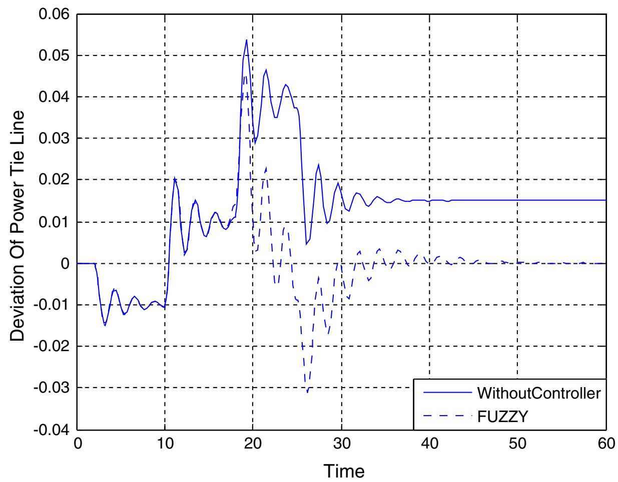

Figure 36 Changes in the ΔP_{tie} with fuzzy controller and without controller.

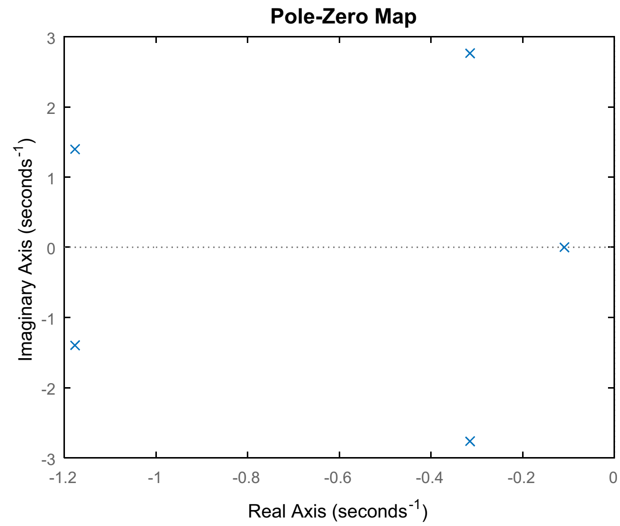

Figure 38 Eigenvalues without controller.

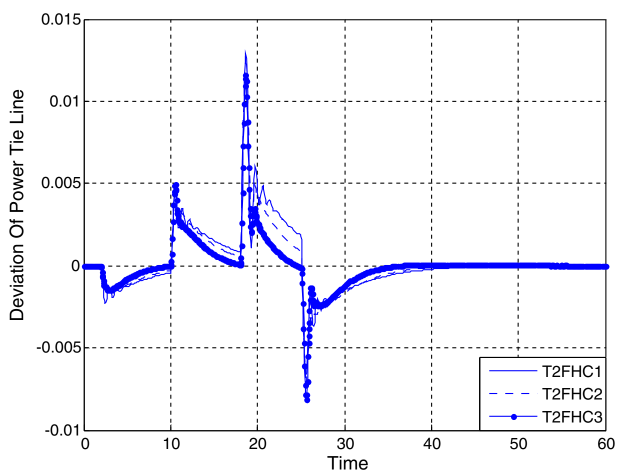

Figure 37 Changes in the ΔP_{tie} with T2FHCS.

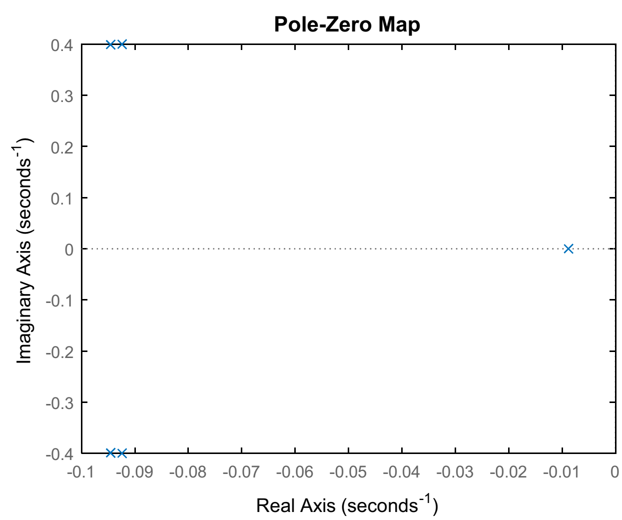

Figure 39 Eigenvalues with T2FHC3.

decreased to the band ± 600 mHz in less than 1 min, and to ± 240 mHZ in less than 10 min. The fuzzy controller has acted in a way that it has managed to reduce the frequency changes to ± 320 mHZ in the state a, and to ± 430 mHZ in the state (b) (final state). The mentioned controllers have reduced the frequency changes to the allowable value of ± 240 mHZ in less than four seconds in the state (a) and in less than six seconds in the state (b), whereas the noted standard allows the frequency changes, in spite of disturbances, to reach 960 mHZ. According to this standard, the frequency changes should reach the band ± 240 mHZ in ten minutes.

Another controller designed has had better performance so that it has managed to act, despite the existing disturbances, in a way that the frequency changes have not exceeded the band ± 240 mHZ at all, indicating that the proposed controller is an optimal one with better performance than fuzzy controller because of the fuzzy characteristics of the type-2, while the fuzzy controller has had an excellent and acceptable performance in controlling the frequency changes.

Table 10 Comparison of ISE, ITSE and RMS criteria.

Controller	Criterion ISE	Criterion ITSE	Criterion RMSE
Without controller	2.4219	87.8080	0.1472
Fuzzy	0.6719	13.4234	0.0535
T2FHC1	0.0266	0.4223	0.0083
T2FHC2	0.0250	0.4116	0.0079
T2FHC3	0.0194	0.2679	0.0066

The simulations for the state (c) also truly show that the performance of the T2FH controller has been improved compared to that of the fuzzy controller.

In the following, performances of the controllers are compared in terms of the criteria ISE, ITSE, and RMS, as shown in Tables 7–9.

As shown in the tables, the T2FHC system has had better performance than the fuzzy controller, while the fuzzy controller has had an acceptable performance and managed to obviate the frequency change problem well and change the errors for the frequency stable conditions and the power transferred between the lines to reach zero.

The system having type-2 hierarchical optimal fuzzy controller has similar performances in all three states. Only T2FHC3 has had better performance than the two other controllers as it has further parameters for optimization process. This is true also for T2FHC2 compared to T2FHC1.

The ISE criterion pays more attention toward the system's response in transient state, and the results obtained in all the states imply the more desirable performance of the proposed controller. For instance, in state (a), T2FHC3 has been reduced by 99.47% compared to the fuzzy controller, and the system having fuzzy controller has been decreased by 27.22% compared to the system without controller. While the ITSE criterion more discusses the error of stable state and given state (b), T2FHC3 has been decreased by 99.18% compared to the fuzzy controller, and the system having fuzzy controller has been reduced by 88.91% compared to the system without controller. Also, given the RMS criterion, in the state (c), T2FHC3 has been decreased by 99.38% compared to the fuzzy controller, and the system having fuzzy controller has been decreased by 20.74% compared to the system without controller.

Three stimulations above clearly indicate the performance of proposed controller according to the considered conditions. In this part, a new simulation with different conditions has been done. The difference is that in this stage, the time and amount of performed disturbances are selected randomly. Also, the considered saturation has been less so that the amount of frequency deviations in the time of disturbances will be higher.

In the simulation below disturbance application and the amount of disturbance have been randomly selected in which for area 1, second 2, 2% and second 25, 5% have occurred while in area 2, seconds 10 and 18 have shown 4% and 6% respectively. Also, the amount of production limitation and governor's steam outputs have reduced from [−0.2, 0.2] to [−0.1, 0.1], which increases the amount of variation in frequency. Fig. 32 indicates frequency deviations in area 1 in system without controller and with fuzzy type 1 controller. Fig. 33 indicates frequency deviations in area 1 with T2FHC controllers. Figs. 34 and 35 show frequency deviations in area 2. Also, Figs. 36 and 37 indicate deviations power tie lines.

As it can be seen in Figs. 32, 34 and 36, system without controller (naturally, systems contain integral controller) in 60 s simulation process cannot reduce frequency deviations and transmission power to zero. However, fuzzy controller can reach these deviations to zero in 45 s.

Figs. 33, 35 and 37 indicate that although frequency deviations and transmission power between lines in T2FHCS have significantly reduced and have been even lower than determined band, but, the deviations have reduced to zero in less than 30 s.

Stimulations in all cases clearly indicate that the proposed controller is able to turn deviations into zero despite existence of difficult conditions or even when conditions have been worsened. Like previous three conditions, the performance of controller has been investigated considering three criterions of ISE, ITSE and RMSE. Results have been shown in Table 10.

9. Stability analysis of fuzzy controller on linearized model

In this section, an analysis of stability of controlled system and an investigation of type 2 fuzzy controlling effect on the location of eigenvalues of linearized system of load frequency have been examined. Because of complications of linear model equivalent with load frequency system, it can be expressed with a linear high order model. Yet, using appropriate approximation according to relations of special amounts by Henkel model with order five can be used for systems without controller and T2FHC3.

$$G_{\text{Without Controller}}\ (s) = \begin{bmatrix} \frac{-2.2227*S^4+3.138S^3+4.779*S^2+20.29*S+2.842}{S^5+3.093*S^4+12.89*S^3+21.7*S^2+28.05*S+2.825} & \frac{-0.04135*S^4+0.1527*S^3-3.663*S^2+6.299*S+0.05816}{S^5+3.093*S^4+12.89*S^3+21.7*S^2+28.05*S+2.825} \\ \frac{0.04135*S^4+0.1527*S^3-3.663*S^2+6.299*S+0.05816}{S^5+3.093*S^4+12.89*S^3+21.7*S^2+28.05*S+2.825} & \frac{-0.2227*S^4+3.138*S^3+4.779*S^2+20.29*S+2.842}{S^5+3.093*S^4+12.89*S^3+21.7*S^2+28.05*S+2.825} \end{bmatrix} \tag{19}$$

$$G_{\text{T2FHC3}}(s) = \begin{bmatrix} \frac{0.1639*S^4+0.01662*S^3+0.02504*S^2-0.002346*S+1.262e-05}{S^5+0.3828*S^4+0.3749*S^3+0.06624*S^2+0.02889*S+0.0002503} & \frac{0.001183*S^4-0.0004611*S^3-3.018e-05*S^2-9.736e-05*S-3.615e-05}{S^5+0.3828*S^4+0.3749*S^3+0.06624*S^2+0.02889*S+0.0002503} \\ \frac{0.001183*S^4-0.0004611*S^3-3.018e-05*S^2-9.736e-05*S-3.615e-05}{S^5+0.3828*S^4+0.3749*S^3+0.06624*S^2+0.02889*S+0.0002503} & \frac{0.1639*S^4+0.01662*S^3+0.02504*S^2-0.002346*S+1.262e-05}{S^5+0.3828*S^4+0.3749*S^3+0.06624*S^2+0.02889*S+0.0002503} \end{bmatrix} \tag{20}$$

Figs. 38 and 39 indicate system eigenvalues without controller and with T2FHC3.

10. Conclusion

In this article, it is recommended that frequency load must be controlled by using the T2FH controller. Performances of the proposed controllers have been compared in terms of the ISE, ITSE, and RMS criteria. According to the results obtained from the simulation processes, the T2FH controller is more efficient than others in all the states.

In addition to having better performance, the T2FH controller has managed to decrease the design principles by 33 percent due to its hierarchical characteristics. On the other hand, it has managed to face uncertainties existing in the system better, and improve the overall performance of the system because of the type-2 fuzzy characteristics.

In this paper an optimal model for Load–Frequency Control loop in power system operation is proposed. Since the power system is mainly subject to the nonlinear load disturbance, the classical PID controllers disqualified tackling the transient nonlinear turbulence in a gigantic electric power system. As an alternative, Fuzzy Mamadani and TSKF are embedded into the classical LFC model. This may result in a satisfactory response for nonlinear disturbances, but the approach is technically expensive in taking smooth control action or curbing oscillations. Therefore, OHTSKF was proposed to improve the Fuzzy Mamdani and TSKF control performances. OHTSKF breaks down the Fuzzy Mamadani systems into several sub-systems and then rule pruning process was applied on each sub-system in a hierarchal ordering classification. This, however, led to an economical number of fuzzy rules which extremely speeded up the computational performance. After that, Cuckoo Optimization Algorithm (COA) was encompassed into the model to further alleviate response errors for the resultant hierarchal fuzzy system. In this case, the addition of COA into hierarchal TSKF made up the OHTSKF controller which outperforms other Fuzzy Mamadani and TSKF controllers in every aspect of ISE, ITSE, and RMS standard criteria as well as the transient response quality in the presence of nonlinear load disturbances. The simulation results indicated that the developed OHTSKF controller is highly efficient as compared with other controllers and can be substituted by current Fuzzy Mamdani and TSKF controllers in LFC loops of every electric utility.

Proposed approach can be used for all power generation such as thermal, hydro, wind and diesel generating units because only the model of turbine changes and the general principles of the recommended method remain unchanged.

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