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Reliability Investigation of Series-Parallel Components of Power System using Grey Fuzzy Theory

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Abstract

Grey Fuzzy set based methods have been proved to be effective in handling many types of uncertainties in different fields, including reliability engineering. This paper presents a new approach on Grey fuzzy reliability.

In the present paper the probabilistic consideration of basic events is replaced by possibilities, thereby leading to fuzzy fault tree analysis. Grey Fuzzy GM (1,1) model are used to represent the failure possibility of basic events. The failure possibility of a basic event will be assigned more than one Grey numbers by different experts under various operating conditions. The proposed techniques are discussed and illustrated by taking an example of a thermal power plant.

Keywords:

Fuzzy reliability of series parallel components; Grey Fuzzy, Fuzzy Fault tree analysis (FTA).

1. Introduction

Fault tree analysis (FTA) seems to be a very effective tool to predict probability of hazard, resulting from sequences and combinations of faults and failure events. A fault tree is a logical and graphical description of various combinations of failure events. To depict a fault tree, first we determine the hazards and then look for the events causing this hazard. In conventional FTA based on a probabilistic approach the basic events are represented by the probabilities (crisp numbers).However for the system like nuclear power plants, space shuttles, clinical appliances etc., wherein available data are insufficient for statistical inference(Jackson et al., 1981), it is often very difficult to estimate precise failure rates of the basic events. For such systems it is therefore unrealistic to assume a crisp number (classical) for different basic events. Zadeh (1965) suggested a paradigm shift from a theory of total denial and affirmation to a theory of grading to give new concept of fuzzy set. Tanaka and Singer (1983, 1990) then usedfuzzy set theory to replace crisp numbers by fuzzy numbers for better estimation of possibility of top event in FTA. (Suresh et al.1996) used a method based on α-cuts to deal with FTA, treating the failure possibility as triangular and trapezoidal fuzzynumbers.

Accurate failure data is a crucial requirement for reliability assessment. In many situations, where human judgment, evaluationand decision-making are important, failure data may not be corrected accurately. It might sometime require linguistic terms toexpress data value (Pandey et al. 2007). But if more than one fuzzy number is assigned to a particular event then randomselection of any of these fuzzy numbers to determine the failure possibility of this event is not realistic. This work proposes amethod to obtain a single fuzzy number having least variance with the fuzzy numbers assigned to that particular event.

In FTA the concept of importance may be used to make some vital modifications in the designing of system. (Furuta et al. 1984) proposed the concept of fuzzy importance using max-min fuzzy operator and fuzzy integral. (Pan et al. 1988)developed a model for computing the importance measure of basic events using variance importance measure. Monte-Carlo simulation is generally used in the determination of variance importance measure even though computing process is time taking in this method. Thus for a very complex system having large number of components, the whole procedure has to be repeated again and again, thus not suitable for the fuzzy approach. (Suresh et al.1996) proposed another method to evaluate an importance measure called fuzzy importance measure (FIM).For effective evaluation of the importance index of each basic events, we have introduced a comparatively easier method to calculate fuzzy importance index (FII), based on ranking of fuzzy numbers and Hamming distance. The proposed methods are demonstrated by taking an example of nuclear power plant.

In real system, the information is inaccuracy and supposed tolinguistic representation, the estimation of precise values of probability becomes verydifficult in many cases. In order to handle the insufficient information, the type-2fuzzy approach is used to evaluate the failure rate status. Singer presented a type-2fuzzy set approach for fault tree and the reliability analysis in which the relative frequencies of the basic events are considered as fuzzy numbers. Pointed out that there are two fundamental assumptions in the conventional reliability theory, i.e.(a)Binary state assumptions: the system is precisely defined as functioning or failing.(b) Probability assumptions: the system behavior is fully characterized in the context of probability measures .However, because of the inaccuracy and uncertainties of data, the estimation of precise values of probability becomes very difficult in many systems. (Cai et al. 1993) presented the following two assumptions:(a) Fuzzy-State assumption: the meaning of the system failure can’t be precisely defined in a reasonable way. At any time the system may be in one of the following two states: fuzzy success state or fuzzy failure state.(b) Possibility assumption: the system behavior can be fully characterized in the context of possibility measures.(Cai et al. 1993) presented the following three forms of “fuzzy reliability theories”. (i) Profust reliability theory, based on the probability assumption and fuzzy-state assumption. (ii)Posbist reliability theory, based on the possibility assumption and binary-state assumption. (iii) Posfust reliability theory, based on the possibility assumption and the fuzzy-state assumption.

(Cheng and Mon 1994) used interval of confidence for analyzing the fuzzy system reliability. (Chen 1994) presented a new method for analyzing the fuzzy system reliability using fuzzy number arithmetic operations and used simplified fuzzy arithmetic operations rather than complicated interval fuzzy arithmetic operations of fuzzy numbers or the complicated extended algebraic fuzzy numbers.(Chen 1994) presented a new method for fuzzy system reliability analysis based on fuzzy time series and the α-cuts arithmetic operations of fuzzy numbers. So far, in the literature, arithmetic operations between same types of vague sets are discussed .Also to analyze the fuzzy system reliability, it is assumed that the reliability of all components of a system follows the same membership functions. However, in practical problems, such type of situations rarely occurs. Therefore, it is need of a method by which we can also find the fuzzy reliability of systems having components following different type of type-2membership functions.

To illustrate the above approach the fuzzy reliability of series, parallel, parallel-series and series-parallel systems all consisting of four components has been evaluated using the proposed algorithm.

3. Grey Fuzzy Theory

3.1 Grey System Modeling

Grey numbers, grey algebraic and differential equations, grey matrices and their operations are used to deal with grey systems. A grey number is such a number whose value is not known exactly but it takes values in a certain range. Grey numbers might have only upper limits, only lower limits or both. Grey algebraic and differential equations, grey matrices all have grey coefficients.

3.2 Generations of Grey Sequences

The main task of grey system theory is to extract realistic governing laws of the system using available data. This process is known as the generation of the grey sequence. It is argued that even though the available data of the system, which are generally white numbers, is too complex or chaotic, they always contain some governing laws. If the randomness of the data obtained from a grey system is somehow smoothed, it is easier to derive the any special characteristics of that system. For instance, the following sequence that represents the speed values of a motor might be given:

X(0) = (200, 300, 400, 500, 600)

It is obvious that the sequence does not have a clear regularity. If accumulating generation is applied to original sequence, X(1) is obtained which has a clear growing tendency.

X(1) = (200, 500, 900, 1400, 2000)

3.3 GM (n,m) Model

In grey systems theory, GM (n, m) denotes a grey model,where n is the order of the difference equation and m is the number of variables. Although various types of grey models can be mentioned, most of the previous researchers have focused their attention on GM (1, 1) model in their predictions because of its computational efficiency. It should be noted that in real time applications, the computational burden is the most important parameter after the performance.

3.4 GM (1,1) Model

GM (1,1) type of grey model is most widely used in the literature, pronounced as "Grey Model First Order One Variable". This model is a time series forecasting model. The differential equations of the GM (1,1) model have time-varying coefficients. In other words, the model is renewed as the new data become available to the prediction model .The GM (1,1) model can only be used in positive data sequences. In this paper, a non-linear liquid level tank is considered. It is obvious that the liquid level in a tank is always positive, so that GM(1,1) model can be used to forecast the liquid level .In order to smooth the randomness, the primitive data obtained from the system to form the GM(1,1) is subjected to an operator, named Accumulating Generation Operation(AGO), described above. The differential equation (i.e.GM (1,1)) thus evolved is solved to obtain the n-step ahead predicted value of the system. Finally, using the predicted value, the inverse accumulating operation (IAGO) is applied to find the predicted values of original data. Consider a single input and single output system. Assume that the time sequence $X^{(0)}$ represents the outputs of thesystem) x.

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots \dots x^{(0)}(n)\right), n \geq 4 \qquad \dots\dots\dots\dots\dots(1)$$

Where X(0) is a non-negative sequence and n is the sample size of the data. When this sequence is subjected to the Accumulating Generation Operation (AGO), the following sequence X(1) is obtained. It is obvious that X(1) is monotonei$^{0)}$(n)) , n ≥ 4

$$X^{(1)} = \left(\left(x^{(1)}(1), x^{(1)}(2), \dots \dots x^{(1)}n\right)\right), n \geq 4 \dots \qquad \dots\dots\dots (2)$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,3, \dots\dots n \qquad \dots\dots\dots\dots(3)$$

The generated mean sequence Z(1) of X(1) is defined

$$z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \dots \dots z^{(1)}(n)\right) \qquad \dots\dots\dots\dots\dots(4)$$

Where z(1)(k) is the mean value of adjacent data, i.e.

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), k = 2,3, \dots\dots n \qquad \dots\dots\dots\dots (5)$$

The least square estimate sequence of the grey difference quation of GM (1,1) is defined as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b \qquad \dots\dots\dots\dots\dots(6)$$

The whitening equation is therefore as follows:

$$\frac{dx^1(t)}{dt} + ax^1(t) = b \qquad \ldots\ldots\ldots\ldots\ldots(7)$$

In above, $[a,b]^T$ is a sequence of parameters that can be foundas follows:

$$[a,b]^T = (B^TB)^{-1}B^TY \qquad \ldots\ldots\ldots\ldots\ldots..(8)$$

Where

$$Y = \left[x^{(0)}(2), x^{(0)}(3), \cdots\cdots\cdots, x^{(0)}(n)\right]^T \qquad \ldots\ldots\ldots\ldots(9).$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(2) & 1 \\ . & \\ . & \\ . & \\ -z^{(1)}(n) & 1 \end{bmatrix} \qquad \ldots\ldots\ldots\ (10)$$

According to equation (6.8), the solution of x(1)(t) at time k:

$$x_p{}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \qquad \ldots\ldots\ldots\ldots\ldots\ (11)$$

To obtain the predicted value of the primitive data at time (k+1), the IAGO is used to establish the following grey model.

$$x_p{}^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1 - e^a) \qquad \ldots\ldots\ldots\ldots\ldots(12)$$

And the predicted value of the primitive data at time (k+H):

$$x_p{}^{(0)}(k+H) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k+H-1)}(1 - e^a) \qquad \ldots\ldots..(13)$$

The parameter (a) in the GM (1,1) model is called "development coefficient" which reflects the development states of X(1)p and X(0)p . The parameter b is called "grey action quantity" which reflects changes contained in the data because of being derived from the background values.

3. Fuzzy importance

In FTA we have observed that each basic event play different role in the occurrence of top event, which infers that the basicevents are of different importance. Thus a critical analysis of the importance of different basic events may help in making a propersequence of their importance. On improving the reliability of the event having greater importance, one can improve the reliabilityof the system. The fuzzy importance of any event is always calculated in the form of fuzzy importance index (FII). This FII maybe evaluated by ranking fuzzy numbers (P_T –P_{Ti})for *i=1,2,3…n.* Here $P_T$and P_{Ti}denote the possibility of absolute occurrence oftop event and the possibility of occurrence of top event in absence of basic event *i* respectively. In our analysis we have used lesscomplicated and very significant method for ranking of fuzzy numbers. To rank the fuzzy numbers (P_T –P_{Ti})*'s* for *i=1, 2,...n,* firstof all we have to find MAX (P_T –P_{Ti})*i=1,2…n,* where the MAX operator on fuzzy numbers is defined as below.

$$MAX(A_1, A_1, A_1, \ldots . A_n)(z) = sup \min_{z=max(x_1, x_2, ---x_n)} [A_1(x_1), A_2(x_2), \ldots . A_n(x_n)]$$

Where A_1, A_2, A_3 …An *are* different fuzzy numbers.

Taking the MAX of given fuzzy numbers, we try to get the distance of all these fuzzy numbers from their MAX with the helpof Hamming distance formula[0,1]

$d_H(A, B) = \int |A(x) - B(x)|\, dx$Between two fuzzy numbers A and B.

The distance of these fuzzy numbers ($P_T - P_{Ti}$)for *i =1, 2 …n* from their MAX decides the rank of fuzzy numbers($P_T - P_{Ti}$).Smaller the distance of fuzzy number ($P_T - P_{Ti}$)from MAX ($P_T - P_{Ti}$) ,*i=1,2…n*, in comparison to distance of $PT\ PT2 -$ from MAX($P_T - P_{Ti}$)implies that fuzzy number ($P_T - P_{Ti}$)is greater than ($P_T - P_{Ti}$). It concludes that the fuzzy importance index (FII) may bedefined in form of distance of $P_T$from P_{Ti} i.e.

$$FII(i) = \frac{1}{1 + Distance\ of\ fuzzy\ number\ (P_T - P_{T_i})\ from\ their\ MAX}$$

4. Reliability Analysis of Series and Parallel Components

In this section, taking the reliability of each component to be a triangular interval type-2 fuzzy setwe have evolved a fuzzy reliability evaluation technique for series and parallel systems.Let us consider a system consisting of *n* components, the interval type-2 fuzzy $\tilde{R}_j^i$sets j=*1,2,3…….n*, are taken to represent the reliability of each component. If the components areconnected as a series system as shown in Fig.3, the reliability$\tilde{R}_s^i$ of the series system isdefined as follows:

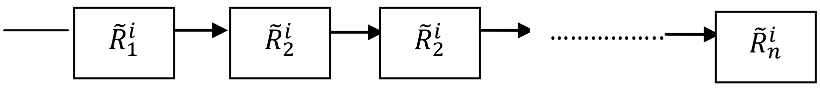

Fig.3Systems in Series

$$\tilde{R}_s^i = \otimes_{j=1}^n \tilde{R}_j^i =$$

$$< \left[\left(\prod_{j=1}^n a_{1j}, \prod_{j=1}^n a_{2j}, \prod_{j=1}^n a_{3j} \right) : \min_{j=1\ldots n} \mu_{\tilde{A}_j}(x) \right], \left[\left(\prod_{j=1}^n a_{1j}, \prod_{j=1}^n a_{2j}, \prod_{j=1}^n a_{3j} \right) : \max_{j=1\ldots n} \nu_{\tilde{A}_j}(x) \right] >$$

If the components are supposed to be in parallel as shown in Fig.4, the reliability$\tilde{R}_p^i$of theparallel system can be defined by using the expression

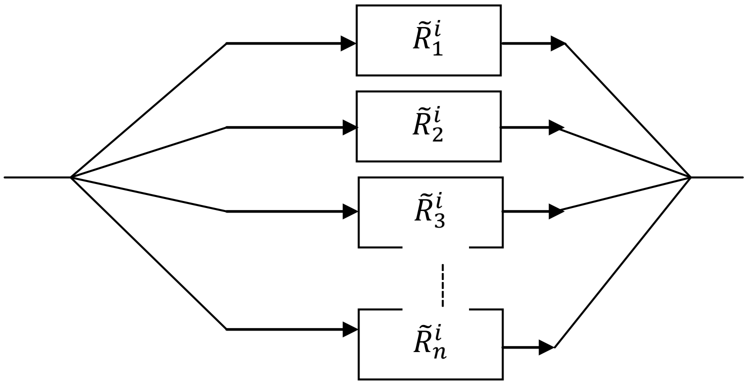

Fig. 4 Parallel System

$$\tilde{R}_p^i = 1 - \prod_{i=1}^{n}(1 - \tilde{R}_1^i) =$$

$$< \left[\left(1 - \prod_{i=1}^{n}(1 - a_{1i}), 1 - \prod_{i=1}^{n}(1 - a_{2i}), 1 - \prod_{i=1}^{n}(1 - a_{3i})\right) : \min_{j=1\ldots n} \mu_{\tilde{A}_j}(x)\right], \left[\left(1 - \prod_{i=1}^{n}(1 - a_{1i}), 1 - \prod_{i=1}^{n}(1 - a_{2i}), 1 - \prod_{i=1}^{n}(1 - a_{3i})\right) : \max_{j=1\ldots n} v_{\tilde{A}_j}(x)\right] >$$

Parallel-series system

Consider a parallel-series system consistingof 'm' branches connected in parallel andeach branch contains 'n' components asshown in Fig.5. The fuzzy reliability$\tilde{R}_{PS}$= 1 $\Theta\otimes_{k=1}^{m}(1\Theta \otimes_{i=1}^{n} \tilde{R}_{ki})$)of the parallel-series system shown in Fig.5 can beevaluated using the algorithm proposed insection 3 for multiplication and subtraction.where $\tilde{R}_{ki}$ represents the reliability of the ithcomponent at kth branch.

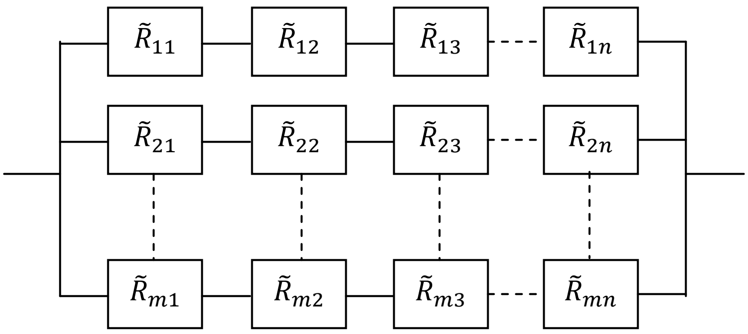

Fig.5.Parallel-series system

Series-parallel system

Consider a series-parallel system consistingof 'n' stages connected in series and eachstage contains 'm' components as shown inFig.6. The fuzzy reliability$\tilde{R}_{SP}$= $\otimes_{k=1}^{n}$ (1 $\Theta\otimes_{i=1}^{m}(1\Theta\ \tilde{R}_{ik})$)of the series-parallelsystem shown in Fig.6 can be evaluatedusing the algorithm proposed in section 3 formultiplication and subtraction.where $\tilde{R}_{ik}$represents the reliability of the ithcomponent at kth stage.

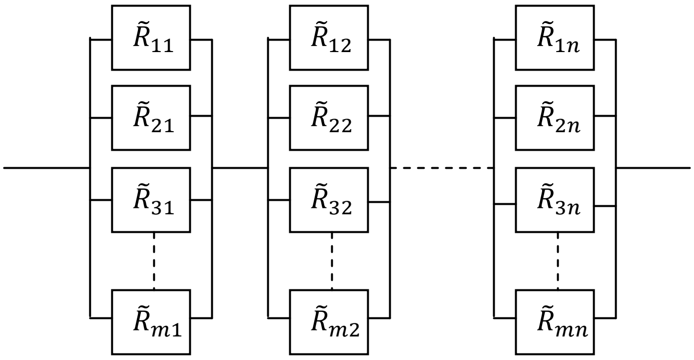

Fig.6Series-parallel system

5. Fuzzy Fault tree of Therma

A Thermal power plant model is considered. Develop a fault tree for the desired event (*i.e.* top event): Each fault event in the fault tree diagram isconsidered as Triangular Interval Type-2 Fuzzy Number (TIT2FN)&Trapezoidal Interval Type-2 Fuzzy Number (TrIT2FN).Using series parallel components formula and fuzzy fault tree Fig.7,the reliability of thermal power plant can be investigated as below.

Steam pressure release (low) is assumed to be a hazard and treated as the top event in fault tree analysis. The Steam pressure release may becaused due to the occurrence of some events, and these events may again occur due to some other events as shown in Fig.7

The interval type-2 set operations corresponding to this Fuzzy fault tree is given below:

$SP = X \cup Y,$

$X = A \cup B,$

$Y = C \cap D \cap E_0,$

$A = F \cup G_0,$

$F = P_0 \cap Q_0,$

$B = H_0 \cap I_0,$

$C = J_0 \cup K_0,$

$D = I_0 \cup L_0,$

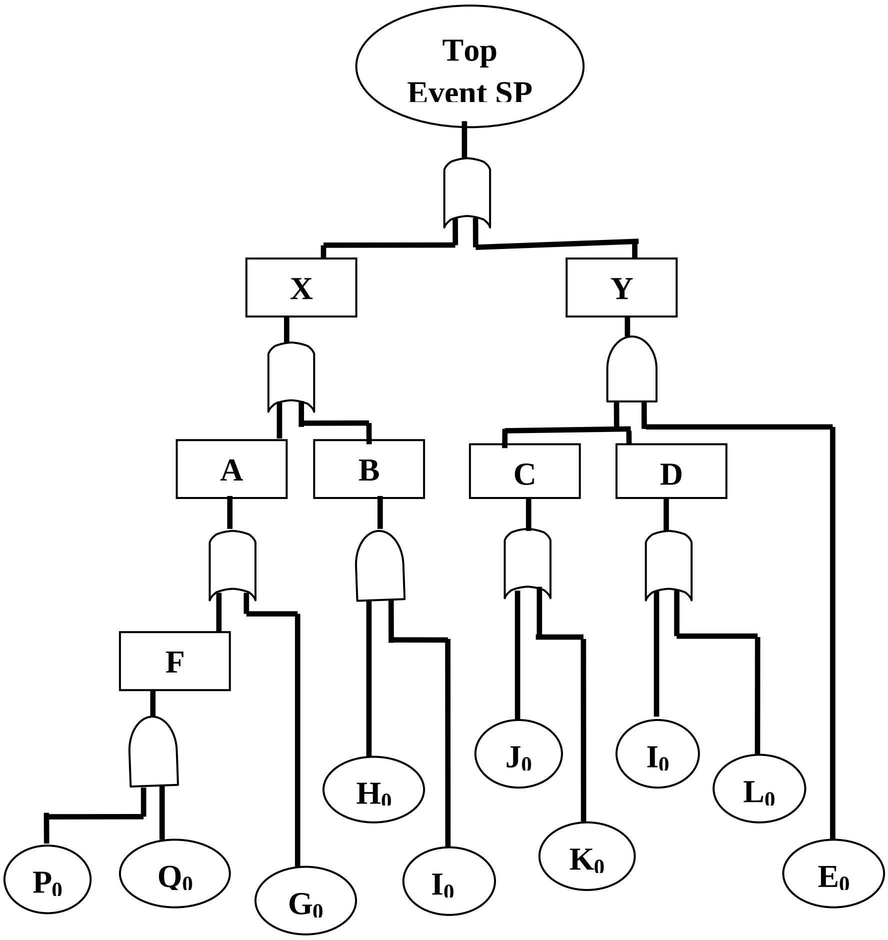

Fig.7 Fault tree of Nuclear Power Plant

Where

*SP*denotes Steam Pressure Lowin turbine,

X = formation of corrosion product due to turbine blade corrosion,

Y = unwanted shaft vibration,

A= physical damage to the rotor,

B = thermaldamage to the rotor,

C = alarm system fails,

D = stress present,

E_0= breach of physical boundary,

F=mechanical damage to theturbine,

G_0= explosive damage to the boiler,

P_0= safety signal fails,

Q_0=power fails,

H_0=insufficient thermal generation,

I_0= Safety Valve not working,

J_0=control circuit of alarm system fails,

K_0= sensor fails and

L_0= high premise temperature.

On replacing the Boolean operators with fuzzy logicoperators *FNOT*, *ORF* and *ANF*, we get the possibility of the top event in form of a fuzzy number. It is also assumed that eachbasic event is fuzzzified by assigning three fuzzy numbers to each basic event following the decision of three experts. TheTriangularand trapezoidal fuzzy numbers assigned to these basic events are listed in Table 1 and Table 2.

Table 1.Triangular Interval Type-2Fuzzy Numbers (Basic Events)

Event E_0			
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
1	0.006,0.008	0.009,0.01	0.014,0.016
2	0.024,0.026	0.028,0.03	0.032,0.036
3	0.018,0.02	0.024,0.026	0.028,0.032
Event G_0			
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
1	0.030,0.033	0.040,0.043	0.051,0.54
2	0.042,0.045	0.051,0.055	0.052,0.056
3	0.032,0.035	0.041,0.046	0.042,0.046
Event P_0			
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
1	0.071,0.076	0.076,0.008	0.078,0.082
2	0.042,0.046	0.051,0.055	0.051,0.056
3	0.061,0.066	0.071,0.076	0.072,0.078
Event J_0			
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
1	0.042,0.046	0.052,0.056	0.054,0.06
2	0.055,0.059	0.061,0.065	0.063,0.067
3	0.036,0.04	0.044,0.048	0.052,0.056
Event L_0			
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
1	0.041,0.045	0.12,0.15	0.14,0.18
2	0.15,0.19	0.24,0.28	0.32,0.36
3	0.16,0.21	0.21,0.25	0.22,0.26

Table 2.Trapezoidal Fuzzy Number (Basic Events)

Event Q_0				
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$	$a_{4(UMF,LMF)}$
1	0.070,0.074	0.078,0.082	0.084,0.088	0.091,0.095
2	0.053,0.057	0.061,0.065	0.072,0.077	0.074,0.078
3	0.044,0.047	0.051,0.055	0.054,0.057	0.062,0.068
Event H_0				
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$	$a_{4(UMF,LMF)}$
1	0.011,0.015	0.021,0.026	0.023,0.027	0.031,0.035
2	0.021,0.025	0.031,0.035	0.035,0.038	0.044,0.048
3	0.034,0.038	0.04,0.044	0.042,0.046	0.046,0.052
Event I_0				
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$	$a_{4(UMF,LMF)}$
1	0.068,0.072	0.12,0.016	0.14,0.018	0.15,0.019
2	0.17,0.021	0.22,0.026	0.21,0.025	0.23,0.027
3	0.23,0.027	0.24,0.028	0.26,0.032	0.28,0.034
Event K_0				
Expert	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$	$a_{4(UMF,LMF)}$
1	0.12,0.16	0.14,0.18	0.16,0.20	0.18,0.22
2	0.15,0.19	0.21,0.25	0.22,0.27	0.25,0.29
3	0.28,0.32	0.3,0.34	0.33,0.37	0.35,0.39

Using the approximation method discussed earlier, a single fuzzy number is obtained by which suits with all the three experts'decision for each basic event. Thetriangular fuzzy numbers thus obtained for each basic event are listed in Table 3.

Table 3.Approximated Triangular Fuzzy Numbers (Basic Events)

Basic Event	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$
E_0	.0162,.0166	.02,.024	.0234,.0238
G_0	.0378,.0382	.044,.048	.0520,.056
P_0	.0702,.0708	.074,.078	.0796,.080
J_0	.044,.048	.052,.056	.058,.062
L_0	.110,.114	.174,.178	.238,.242

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Table 4. Approximated Trapezoidal Fuzzy Numbers (Basic Events)

Basic Event	$a_{1(UMF,LMF)}$	$a_{2(UMF,LMF)}$	$a_{3(UMF,LMF)}$	$a_{4(UMF,LMF)}$
Q_0	.058,.062	.064,.068	.068,.072	.074,.078
H_0	.022,.026	.030,.034	.033,.037	.041,.045
I_0	.152,.156	.174,.178	.194,.198	.216,.220
K_0	.192,.196	.224,.228	.244.248	.274,.278

FII of basic events in Thermal Power Plant

The fuzzy importance of each basic event can be obtained in the form of fuzzy importance index (FII) for all basic events. Wecalculate the possibility of top event RR using fuzzy operators and possibilities of basic events. The possibility of top event isresulted as trapezoidal fuzzy number ([.044,.048], [.054,.058], [.056,.060, [.064,.068]) given by the following expression.

$$\underline{P}_T = \begin{cases} \frac{x-.044}{.01} & \text{if } .044 \le x \le .054 \\ 1 & \text{if } .054 \le x \le .056 \\ \frac{.064-x}{.012} & \text{if } .056 \le x \le .064 \end{cases}$$

$$\overline{P}_T = \quad 1 \begin{cases} \frac{x-.048}{.01} & \text{if } .048 \le x \le .058 \\ & \text{if } .058 \le x \le .060 \\ \frac{.068-x}{.012} & \text{if } .060 \le x \le .068 \end{cases}$$

Here P_{Ti}'s for different events i= *E0, G0, P0, J0, L0, Q0, H0, I0* and *K0* obtained as triangular and trapezoidal fuzzy numbers are listedin Table 5.

Table 5.Possibility of Top Event in absence of different basic events

Event (*i*)	Possibility of top event in absence of event i,(P_{Ti}) (UMF,LMF)
E_0	([.044,.046], [.052,.056], [.054,.060], [.064,.068])
G_0	([.006,.008], [.012,.016], .014,.018], [.016,020])
P_0	([.042,.046], [.052,.056], [.053,.057],[.062,.066])
J_0	([.044,.048], [.054,.058], [.056,.06],[.068,.072])
L_0	([.045,.049], [.055,.059], [.057,.061],[.069,.073])
Q_0	([.040,.044],[.052,.056], [.054,.058],[.063,.067])
H_0	([.042,.046], [.052,.056],[.060,.064])
I_0	([.043,.047], [.053,.057],[.061,.065])
K_0	([.046,.050], [.056,.060], [.058,.062],[.070,.074])

First we evaluate$\overline{PT - PTi}$, $\underline{PT - PTi}$and then MAX of these fuzzy events for *i=1,2…n*,. The distance of the fuzzy numbers $\overline{PT - PTi}$, $\underline{PT - PTi}$fromtheir MAX is obtained by using Hamming distance formula. Fuzzy importance index (FII) is thus obtained by the followingexpression.

P_T-P_{Ti} = $[\overline{(PT - PTi\ )} + (\underline{PT - PTi})]/2$

$$FII(i) = \frac{1}{1 + Distance\ of\ fuzzy\ number\ (P_T - P_{T_i})\ from\ their\ MAX}$$

Table 6.Fuzzy Importance Index of basic events

Event (*i*)	G_0	I_0	E_0	Q_0	P_0	L_0	K_0	H_0	J_0
FII (*i*)	.9989	.9756	9638	.9628	.9626	.9621	.9618.	.9618	.9617

6. Discussion

The techniques developed in this paper are demonstrated by taking the example of a Thermal power plant, and the following results are drawn:

*Applying the method developed in our study for the importance of basic events, the fuzzy importance index (FII) of basic events is calculated. The basic events are listed in Table 6, in accordance with the descending order of their FII. It is observed that the basic event *Go* is of higher sensitivity (greater importance) in comparison to other succeeding events.

*Taking note of FII of basic events listed in Table 6, it is concluded that we should emphasize on basic event G_o rather than other succeeding events I_o, E_o etc. to improve the reliability of the Thermal power plant.

7. Conclussion

This paper presents reliability investigation of Series-Parallel and Components of thermal power plant using Grey Fuzzy Set Theory. Applying the method developed in our study for the importance of basic events, the fuzzy importance index (FII) of basic events is calculated. The basic events are listed in Table 6, in accordance with the descending order of their FII. It is observed that the basic event *Go* is of higher sensitivity (greater importance) in comparison to other succeeding events. Taking note of FII of basic events listed in Table 6, it is concluded that we should emphasize on basic event G_o rather than other succeeding events I_o, E_o etc. to improve the reliability of the Thermal power plant. Also arithmetic operation of proposed TIT2FN/TrIT2FNis evaluated. Here, a method to analyze system reliability which is based on Grey fuzzy set theory has been presented, where the components of the system are represented by TIT2FN/TrIT2FN fuzzy number. By performing the techniques developed here early in design phase of various complex systems like nuclear power plant, potential deficiencies can be identified and averted to precipitate the occurrence of various basic events causing the happening of top event.

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