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Introduction of a Hybrid Method for Determination of Operating Reserve in the Well-Being Framework

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Abstract: In this study a hybrid method for determining of operating reserve in the well-being framework is introduced. The new framework and optimization method are respectively based on fuzzy and genetic. The probability of being in the risk state and the probability of being in the healthy state constraints are considered as soft limits in the proposed framework. Genetic Algorithm (GA) is used for solving fuzzy well-being Unit Commitment Problem (UCP). Using total operating cost of generating units plus a penalty function which is determined by the fuzzy risk and healthy probabilities, a fitness function is determined. The proposed method has been applied to the IEEE reliability test system to examine its applicability and effectiveness.

Key words: Fuzzy set, genetic algorithm, hybrid method, well-being framework, operating reserve, unit commitment problem, reliability

INTRODUCTION

Operating reserve is used in electric power systems to respond to unforeseen load changes and sudden generation outages and a wide range of techniques have been used to determine operating reserve requirements (Fotuhi-Firuzabad *et al*., 1999b). Usually, operating reserve requirements are determined using deterministic criteria or rule-of-thumb methods. The most common deterministic criterion dictates a reserve margin equal to the size of the largest unit or to some percentage of the peak load (Billinton and Fotuhi-Firuzabad, 1994). For example in Spanish and Ontario power system, reserve is determined equal to some fraction of the peak load and to the largest on line generator, respectively (Bouffard and Galiana, 2004). Due to their simplicity of concept and ease of applying, the deterministic criteria methods have widely used in practice. The basic weakness of the deterministic criteria is that they do not consider the stochastic nature of system behavior and component failures. In the probabilistic techniques, the stochastic nature of system components is incorporated and a comprehensive evaluation of system risk is provided. The first major probabilistic technique for operating reserve assessment, known as the PJM method, was proposed in 1963 (Billinton and Allan, 1996). This method evaluates the probability of the committed generation just satisfy or failing to satisfy the expected demand during a specified time into the future, known as the lead time.

A major task for a power system operator is to make rapid on-line decisions based on the available information. This information should be easy to understand and interpret, because more realistic and understandable information will help the operator make an appropriate decision. On the basis of the PJM method, the system operator can make a decision regarding the required capacity based on the calculated risk, the forecast load and the specified risk criterion. Although, PJM technique considers stochastic nature of the power system, but it has not been employed widely in practice. Difficulty in interpreting the risk index and the lack of system operating information contained in the use of a single risk value are the two most important reasons for this.

A well-being approach is introduced in (Billinton and Fotuhi-Firuzabad, 1994) to overcome these difficulties by incorporating system operating states in operating reserve assessment. Deterministic criteria and probabilistic indices for monitoring system well-being are combined in (Billinton and Fotuhi-Firuzabad, 1994). In the previous treatment of well-being framework probability indices are considered fix (Billinton and Fotuhi-Firuzabad, 1994; Billinton and Fotuhi-Firuzabad, 2000, Fotuhi-Firuzabad *et al*., 1996, 1999; Fotuhi-Firuzabad and Billinton, 1999; Fotuhi-Firuzabad, 1999). This may result in an overestimated solution and consequently higher operating costs. Operating limits, such as system reserve requirement, is often imposed to enhance security and does not represent a physical bound (Mantawy, 2004). In other words,

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reserve requirement and reliability indices constraints are soft constraints. Fuzzy set theory provides a natural platform to model fuzzy relationship such as Very Good, Not Bad and so on. Numbers of application of fuzzy set in power system operation are presented in (Attaviriyanupap *et al.*, 2004; Mantawy, 2004).

In this study a hybrid method is proposed for operating reserve determining in the well-being framework. In the proposed framework the probabilities of being in the risk and healthy states are considered as soft limits. A fuzzy well-being unit commitment is solved using Genetic Algorithm. At first, probabilities of being in the risk and healthy states are fuzzified. Then, fuzzy penalty function corresponding to each chromosome of generation is calculated. Finally, fitness value is determined using total operating cost of generating units plus penalty function. Algorithm is repeated until the stopping criterion is met. The proposed method is applied on IEEE-RTS and test results are also presented. This results show the out-performance of the proposed method with respect to the crisp well-being unit commitment (CWBUC) from the reliability and cost point of view.

MATERIALS AND METHODS

The concepts of PJM method for solving unit commitment problem are illustrated by Billinton and Allan (1996). In this probabilistic method, the system performance is identified as being in either the comfort or at the risk domains for a given load and committed units. This is a pure probabilistic method and doesn't give any information about the degree of the system comfort. To solve this problem, a well-being framework as shown in Fig. 1 is introduced by Billinton and Fotuhi-Firuzabad (1994), which includes deterministic considerations into the probabilistic indices for monitoring system well-being. The definitions of these three states are as follows (Billinton and Fotuhi-Firuzabad, 1994):

- **Healthy:** A system operates in the healthy state when it has enough reserve to withstand the deterministic criterion, i.e., any single unit outage
- **Marginal:** A system operates in the marginal state when it does not have sufficient margin for withstanding specified deterministic criterion
- **At risk:** A system operates in the risk state when the system load is greater than or equal to operating capacity

According to the above definitions, the total system state probabilities can be expressed by Eq. 1 as follows:

$$P_H+P_M+P_R = 1 \quad (1)$$

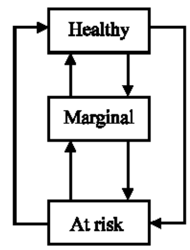

Fig. 1: System well-being states and their interactions in this framework

where, P_H+P_M and P_R are probabilities of the system being in the healthy, marginal and at risk states, respectively. The operating criterion which can be used in the unit commitment, are satisfying an acceptable risk level, satisfying an acceptable healthy level or both. Selecting an operating criterion depends on the required reliability level. If a single criterion is adopted, the goal is to satisfy the following constraint:

$$P_R \leq SRL \quad (2)$$

The above relationship means that, the generating units are committed so that the probability of system risk is not greater than the Specified Risk Level (SRL), which is determined by the system operator. If multiple criteria are adopted, the following constraints should be satisfied:

$$P_R \leq SRL \quad \text{and} \quad P_H \geq SHL \quad (3)$$

The above conditions mean that, generating units should be committed such that, not only the probability of the risk is smaller than SRL, but also, the probability of the healthy state is greater than Specified Healthy Level (SHL). These criteria are determined by the system operator.

Fuzzy well-being framework (proposed framework): In the crisp well-being framework, the minimum value of the probability of being in the healthy state and the maximum value of the probability of being in the risk state are crisp values. In the proposed framework, these constraints and also objective function are considered as fuzzy values. In order for considering the amount of fuzzy constraints satisfaction in the unit commitment problem, a penalty factor function is also introduced. This penalty factor is added to the operating cost, which is an objective function in the unit commitment problem. The value of penalty factor depends on the degree of the satisfaction of fuzzy constraints. The genetic algorithm is used to solve the combinatorial optimization problem of the proposed fuzzy well-being unit commitment problem. The genetic algorithm test allows the acceptance of any solution at the beginning of the search, while only good solutions will have higher probability of acceptance as the generation number increases.

A general fuzzy system has basically five components, fuzzification, application of the fuzzy operator (AND or OR), implication, aggregation and defuzzification. The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The probability of risk and the probability of healthy are input variables for proposed framework that proper membership functions should be defined for them. In the proposed framework AND operator has been chosen as the fuzzy operator. Zero-order Sugeno inference is used for implication. In the Sugeno inference method aggregation and defuzzification is done simultaneously and the final output of the system is the weighted average of all rule output. In our framework, each rule is weighted by its firing strength which has been calculated using product method.

Membership function for probability of risk: The fuzzy set of input for probability of risk is divided into five fuzzy values. These values are: risk is very low (RVL), risk is low (RL), risk is medium (RM), risk is high (RH) and risk is very high (RVH). In Fig. 2 the parameters R_1, R_2, R_3, R_4 and R_5 are determined from the following relationships:

$$\begin{aligned} R_1 &= R_2 - \alpha \\ R_2 &= \text{Required risk} \\ R_3 &= R_2 + \alpha \\ R_4 &= R_2 + 2\alpha \\ R_5 &= R_2 + 3\alpha \end{aligned} \tag{4}$$

where, α is determined by the system operator.

Membership function for probability of healthy: The fuzzy set of input for the probability of healthy is divided into five fuzzy values. These values are: healthy is very low (HVL), healthy is low (HL), healthy is medium (HM), healthy is high (HH) and healthy is very high (HVH). In Fig. 2 the parameters H_1, H_2, H_3, H_4 and H_5 are determined from the following relationships:

$$\begin{aligned} H_1 &= H_4 - 3\beta \\ H_2 &= H_4 - 2\beta \\ H_3 &= H_4 - \beta \\ H_4 &= \text{Required healthy} \\ H_5 &= H_4 + \beta \end{aligned} \tag{5}$$

where, β is determined by the system operator.

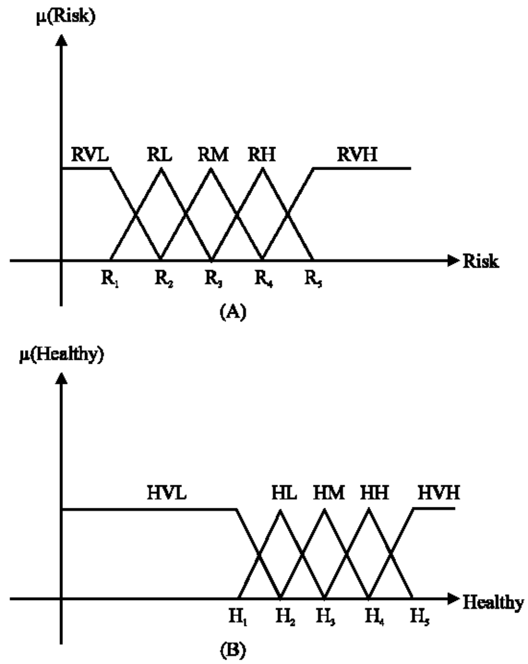

Fig. 2: (A) Membership function of the probability of risk, (B) Membership function of probability of healthy

Penalty factor: Penalty factor is used to guide the solving of the fuzzy well-being optimization problem. Membership function of the probability of healthy and membership function of the probability of risk are used to calculate the fuzzy penalty factor. For this purpose zero-order Sugeno implication has been implemented based on the decision matrix of Table 1 and according to Table 2. The final output of system which is the so-called penalty factor is then calculated as the weighted average of the fired rules outputs. In this stage, each rule is weighted in accordance with the production of the membership value of its inputs (product method). Finally, using the following equation, total cost of the committed units is computed.

Total cost = (1+ Penalty factor)×(Operating cost of committed units) (6)

Applying genetic algorithm: Genetic algorithms are widely used in science, business and engineering (Belkadi *et al*., 2006; Borji, 2008; Farshadnia, 2001; Hashemi *et al*., 2008; Kangrang and Chleeraktrakoon, 2008; Rabi, 2006; Reyes-Garcia *et al*., 2008; Tlelo-Cuautle and Duarta, 2008; Ustun, 2007). Coding of chromosomes, fitness function, selection, crossover, mutation (Haupt and Haupt, 2004) and stopping criteria are the main steps of genetic algorithm. These steps have been applied for present optimization problem via following steps:

Table 1: Decision matrix of fuzzy rules

Fuzzy value of probability of healthy	Fuzzy value of probability of risk				
	VL	L	M	H	VH
VL	VL	VL	VVL	VVL	VVL
L	L	L	VL	VVL	VVL
M	G	L	L	VL	VVL
H	VG	G	L	VL	VVL
VH	VVG	VG	G	L	VL

V: Very; H: High; L: Low; M: Medium; G: Good

Table 2: Output membership function values

Fuzzy output	VVL	VL	L	G	VG	VVG
Output value	1	0.6	0.3	0.1	0.05	0.0

- **Coding of chromosomes:** A chromosome should contain information about the solution that it represents. The most common way for coding is a binary string, which is used in this study. The solution in well-being framework is represented by a vector of N dimension. Each column of the vector determines the ON or OFF status of each generating unit
- **Fitness function:** The fitness function, which is used in this study, is the summation of total operating cost plus production of the total operating cost and penalty factor which is determined by fuzzy risk membership function and fuzzy healthy membership function
- **Selection:** In this study a roulette wheel selection method is used for selecting parents to produce the next generation. The size of the section in the roulette wheel is proportional to the value of the fitness function of each chromosome
- **Crossover:** Two points crossover is used for creating new generation from the selected parents. Two crossover sites are produced randomly and the data of the two parents between these sites are swapped
- **Mutation:** In this study a uniform method is used for mutation. Uniform mutation is a two-step process. First, the algorithm selects a fraction of the vector entries of an individual for mutation, where each entry has a probability rate of being mutated. In the second step, if the produced probability corresponding to each gene is smaller than the mutation rate then this gene is mutated
- **Stopping criteria:** The algorithm stops when the number of generation reaches the value of generations or if there is no improvement in the objective function for a sequence of consecutive generations of length stall generations

Summary of the proposed algorithm: In summary, the proposed fuzzy genetic well-being unit commitment algorithm can be implemented through the following steps:

Step 1: Determine the required risk level, required healthy level, α and β

Step 2: Construct membership functions of the probability of being at the risk state and the probability of being at the healthy state using Fig. 2

Step 3: Create an initial population of genetic algorithm randomly

Step 4: Calculate the operating cost corresponding to each member in the population

Step 5: Calculate the probability of being at the risk state and the probability of being at the healthy state for each member in the population

Step 6: Calculate fuzzy penalty factor for each member;

Step 7: Determine fitness function for each member in the population using operating cost and penalty factor

Step 8: Sort the population members according to their fitness functions

Step 9: Check stopping criteria. If satisfied stop, otherwise go to the step 10

Step 10: Generate next generation using genetic algorithm operators (elitism, crossover and mutation)

Step 11: Go to step 4

RESULTS AND DISCUSSION

The IEEE-RTS (Billinton and Allan, 1996) has been used as our benchmark to examine the applicability of the proposed method. The total system generation is 3405 MW and the system annual peak load is 2850 MW. It is assumed that the system lead time is 4 h.

Performance analysis: Table 3 shows system operating state probabilities with the Crisp Well-Being Unit Commitment (CWBUC) framework and when the system is required to satisfy both a specified risk and a specified healthy probability. Experience of the operator and conditions under which the system is being operated are used for determining risk and healthy probabilities. Table 4 shows system operating state probabilities with the fuzzy genetic well-being unit commitment (FGWBUC) framework and with $H_4 = 0.9$, $R_2 = 0.01$, $\alpha = 0.005$ and $\beta = 0.05$. From the Table 3 and 4 the out-performance of the FGWBUC method with respect to the CWBUC is obvious from the reliability point of view. Using the proposed method, not only the risk value is smaller than which is obtained via the CWBUC method but also the obtained healthy probability is greater than which is obtained by the CWBUC method. This is one of the most important features of the proposed method.

Table 3: Unit commitment with the CWBUC method and a specified risk of 0.01 and a desired healthy state probability of 0.9

Load level (MW)	Probability of Health	Margin	Risk
1140	0.97719573	0.02266299	0.00014127
1425	0.97684725	0.02298005	0.00017271
1710	0.96871937	0.03104789	0.00023273
1995	0.95691649	0.04272104	0.00036247
2280	0.95424218	0.04536093	0.00039689
2565	0.93958229	0.05987774	0.00053997
2850	0.91916923	0.08011214	0.00071863

Table 4: Unit commitment using the FGWBUC method and with $H_4 = 0.9$, $R_2 = 0.01$, $\alpha = 00.005$ and $\beta = 0.05$

Load level (MW)	Probability of Health	Margin	Risk
1140	0.98508513	0.014831379	8.34894269e-005
1425	0.96725946	0.032512302	2.28237113e-004
1710	0.98889220	0.011066117	4.16788954e-005
1995	0.95373073	0.045888520	3.80744729e-004
2280	0.96460205	0.035092379	3.05564124e-004
2565	0.91923013	0.080090550	6.79309626e-004
2850	0.91355203	0.085697613	7.50350439e-004

Table 5: Comparison of the operating cost for CWBUC and FGWBUC methods

Load level (MW)	Operating cost CWBUC ($)	FGWBUC ($)	Saving (%)
1140	8770.4	7783.6	11.3
1425	13644.0	10170.0	25.5
1710	16953.0	13540.0	20.2
1995	20192.0	17839.0	11.7
2280	24578.0	21975.0	10.6
v2565	33477.0	26830.0	20.0
2850	34611.0	32511.0	6.1

Table 5 shows the total operating cost with the Crisp Well-Being Unit Commitment (CWBUC) and the Fuzzy Genetic Well-Being Unit Commitment (FGWBUC) methods. It is obvious that the FGWBUC is superior to the CWBUC from the operating cost point of view. The saving of the total operating cost is varied from 6.1 to 25.5%. The average of saving in the total operating cost for these ranges of load is 15.8%. This is the other good feature of the proposed method.

Sensitivity analysis: The probabilities associated with the system health and margin depends on many factors such as system lead time, system load and generating unit failure rates. The effects of the variations in lead time and generating unit failure rates on the system operating state probabilities and total operating cost are considered and also the performance of the CWBUC and the FGWBUC under such situations are compared.

The effect of lead time variation: Here, it is assumed that each generation can be represented by a two-state model which includes up and down states. In this case, the probability of the unit failing during a short interval of time T can be modeled as:

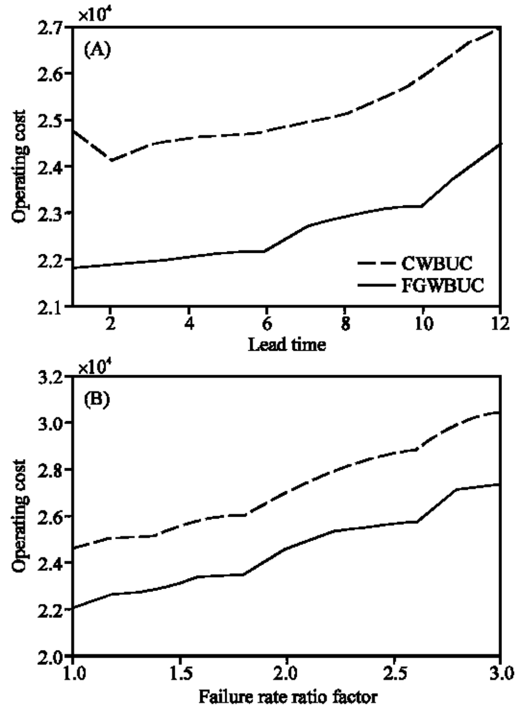

Fig. 3: (A)The effect of lead time on the operating cost using CWBUC and FGWBUC, (B) The effect of failure rate ratio factor on the operating cost using CWBUC and FGWBUC

$$P(\text{down}) = 1 e^{-\lambda T} \quad (7)$$

where, λ is failure rate. If repairing process is neglected and $\lambda T << 1$, then the above equation can be simplified as (Billinton and Allan, 1996):

$$P(\text{down}) \approx \lambda T = \text{ORR (Outage and Replacement rate)} \quad (8)$$

For showing the effect of the lead time on the operating cost, the lead time is varied from 1 to 12 h. The operating cost associated with the CWBUC and the FGWBUC methods for load level of 2280 are shown in Fig. 3A. It can be seen that the operating cost increases as the lead time increases. It is obvious that in this case operating cost using FGWBUC is so much smaller than CWBUC.

The effect of generating unit failure rates variation: The effect of generating unit failure rates on the operating cost, generating failure rates of each generation is varied from 100 to 300% of their nominal values and for the load level of 2280 MW. The effect of the generating failure rate variation on the total operating cost is given in Fig. 3B. As seen, as the failure rate ratio factor (failure rate/nominal failure rate) is increased, the operating cost associated with both CWBUC and FGWBUC are increased, but the amount of the increment for the FGWBUC method is very smaller than the CWBUC.

In this research for showing the effect of generating failure rate variation and lead time on the total operating cost, sensitivity analysis was done. The results showed that the FGWBUC gives smaller operating cost versus CWBUC in all cases.

CONCLUSION

In this study a hybrid method for determining operating reserve in the well-being framework is presented. The proposed method is based on the fuzzy genetic well-being framework. In the proposed method, the probabilities of being in the healthy and risk states are considered as soft limits. Probability of being in the healthy and probability of being in the risk are represented by fuzzy set. A penalty factor for computing the degree of the satisfaction of reliability constraints is introduced in this study. For solving the fuzzy well-being unit commitment problem, a genetic algorithm is used. Fuzzy genetic well-being unit commitment (FGWBUC) method is compared with the crisp well-being unit commitment (CWBUC) method with two different aspects. These aspects are reliability and operating cost. Using the FGWBUC not only the obtained risk is smaller than which is obtained from the CWBUC, but also the obtained healthy probability is greater than which is obtained form the CWBUC. It is shown that the FGWBUC is superior to the CWBUC from the operating cost of view point. Finally, for doing sensitivity analysis the effect of lead time and also the effect of failure rate of generation on the operating cost are considered. Out-performance of the proposed method for wide ranges of variations of these parameters is noticeable again.

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