

Zonal Partitioning of Deregulated Power Systems Considering Fuzzy-Random Load Model.

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ABSTRACT

Market zonal partitioning is one of the most efficient methods for congestion management which is used in many power markets around the world. To improve the market performance it is very important to recognize the best zones of the system. While congestion is due to deficiencies in transmission network or generation, load pattern of the system is the most important variable which has impact on occurrence of congestion and therefore it has a large influence on zonal partitioning.

This paper uses a fuzzy-random load model to take into account both probabilistic and possibilistic uncertainties of long-term predicted load in market studies. Based on this load model, the proposed approach finds mostly congested transmission lines using Fuzzy Monte Carlo Simulation (FMCS). Finally, using a clustering feature which depends just on the network parameters, Fuzzy C-mean (FCM) clustering algorithm is used to divide the network into the best partitions. Such a partitioning algorithm is useful especially in the stage of transmission expansion planning to study the market with any possible future plan. The work is illustrated using 30-bus IEEE test system.

(Keywords: deregulated power system, fuzzy-random load model, Fuzzy Monte Carlo Simulation, FMCS, zonal partitioning)

INTRODUCTION

Due to the rapid expansion of privatization of the power industry across the world, many topics on different issues of power systems need to be restudied based on new conditions. Both planning and operation of power systems have been influenced by this revolution.

Congestion management is one important issue in operation of new deregulated power systems. One of the most usual methods of congestion management is zonal partitioning of the market. In many actual power markets, such as Norway, Australia, California, ERCOT and PJM in USA, the zonal pricing has been widely accepted [1]. To improve the market performance it is very important to divide the market into the best price based partitions.

While the network zonal partitioning is widely accepted for congestion management between adjacent markets, it is not desirable to divide a market into partitions. Therefore in the stage of transmission expansion planning (TEP) it is very important to determine mostly congested transmission lines and corresponding network partitions for the year of horizon then make the best decisions to reduce the number of partitions or unify the market if it is worth. Although mostly congested lines are usually known for system operators, but in TEP stage it is important to analyze and simulate the condition in the future and make the best decision [2].

To break up the network into suitable zones, the system planner should find mostly congested lines in the year of horizon and estimate all zones and partitions of the system for that year. Although the congestion is due to deficiencies in transmission network or generation, the load pattern of system is one of the most important variables which have impact on the occurrence of congestion. Although forced outage of lines or generators may have a similar impact on the network congestion but they can be referred to network deficiencies. But the load variation is regular and it can change the power flow in the network.

Therefore, forecasted system load for the year of horizon is very important and has a large

influence on suitable zonal partitioning. The most significant problem is the vagueness in the system predicted load with both possibilistic and probabilistic features. Practically, power system planning suffers from vagueness in forecasted network load, budgets, actual finish time of the other planned projects and many other uncertainties [3]. In deregulated environments the existence of private participants makes it more difficult and more important to model these uncertainties.

Reference [4] models the probabilistic uncertainty of the load to find congested transmission lines of the network and divide the power system into price based zones. Reference [5] refers to the uncertain parameters which partly exhibit random properties but may not be modeled as random variables and introduces a fuzzy probability distribution concept. The fuzzy-random variable concept is completely explained in [6] which describes fuzzy probability density function for uncertain variables. In [7] a combined fuzzy and probabilistic model for load is used in network reliability assessment.

This paper proposes a fuzzy-random load model for each load point to consider both aspects of vagueness of predicted load. Then with a Fuzzy Monte Carlo Simulation (FMCS) [8] the fuzzy expected value of congestion ($FE(\text{cong})$) and fuzzy expected value of shadow price ($FE(\gamma)$) are computed for all transmission lines. Mostly congested lines are identified by means of a fuzzy decision making process. The next step is to define a clustering feature for network buses to categorize them in different partitions. Reference [4] proposes the sensitivities of nodal power injections to the power flows in congested lines as a feature of nodal price. Because of its useful properties, this feature has been used as network clustering index. The final stage is clustering the nodes of the network using fuzzy c-means algorithm to achieve an acceptable price based zonal partitioning.

Numerical studies on IEEE 30 bus test system have desirable results.

The principal object of UC in conventional power systems is to schedule the status of generation units in order to serve the load demand at minimum operating cost while meeting all plant and system constraints. While in new power markets the financial aspect is one of the most important objects in power generation scheduling,

the secure operation of the system is essential. Therefore in some competitive electricity markets a centralized Security Constrained Unit Commitment (SCUC) determines the generation schedule. SCUC provides a financially viable unit commitment (UC) that is physically feasible.

The UC problem as a part of SCUC is considered as a large scale nonlinear, nonconvex and mixed integer problem. In order to overcome the complexity of the UC problem, several methods have been proposed to obtain exact optimal solution.

Tabu search [8], simulated annealing [4], priority list based methods [3], simplex method [4], lagrangian relaxation [6], dynamic programming [10], and mixed-integer programming [9] are some techniques have been used to solve UC problem. As it will be discussed in the next section, SCUC is much more complex than UC problem.

Decomposition of the problem is a good simplification technique to divide the main complex problem of SCUC into a master problem (UC) and network security check sub-problems [17, 18]. Reference [12] shows the advantages of benders decomposition technique to solve the SCUC problem in power system. References [5, 11 and 13] use benders decomposition technique to solve SCUC problem in new deregulated power systems. In these works lagrangian relaxation and dynamic programming are used for unit commitment scheduling and linear programming is applied to solve sub-problems.

In [1] the authors developed and implemented an integer coded genetic algorithm (ICGA) to solve the UC problem. ICGA is able to find a better unit commitment schedule in a comparatively lower amount of time because of the power of GA in optimization problem. Therefore this paper presents a method based on ICGA which have improved with perturbation operator. Numerical studies on 6-bus system show the advantages of proposed algorithm. Final schedule have a lower operating cost in comparison with previous mentioned methods.

FUZZY-RANDOM LOAD MODEL

There are many variables and parameters in the world that have both aspects of uncertainty: possibility and randomness. The concept of

fuzzy-random variables is an extension of the axiomatic probability concept to describe this kind of vagueness. Consider a random variable \underline{x} with probability density function of $f(x)$. If the mean value of x be a fuzzy variable with fuzzy membership $\mu(\cdot)$, we can define a fuzzy probability distribution function $\tilde{f}(x)$ which maps the fuzzy-random variable $\underline{\tilde{x}}$ into a fuzzy-random set $\{(\underline{\tilde{x}}, \mu(\underline{x}), p(\underline{\tilde{x}}))\}$.

This is one type of fuzzy-random variables that we are dealing with in this paper. A more complete discussion can be followed in references [6, 5].

Predicted electrical load has both kinds of vagueness. During each period of time, (e.g. the year of horizon) load value of each load point varies in a predictable bound. To model the uncertainties of these bounds, possible load values can be introduced by a fuzzy membership function as in Figure 1.

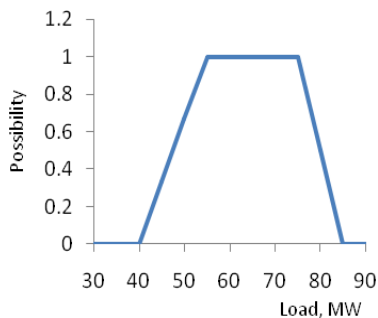


Figure 1: Typical Fuzzy Membership Function for Possible Load Values.

Figure 1 shows the whole interval of possible loads, but usually only in a small portion of this interval the load may contribute in transmission congestion. Therefore, a fuzzy membership function can be introduced to model the possibility that the load of corresponding node contributes in the system congestion.

Figure 2-a shows the membership function of this possibility. The load possibility is depicted with continuous line and the possibility of load contribution in transmission congestion is shown with dashed line. Figure 2-b shows the intersection of these membership functions. It is

the possibility that the possible load contributes in transmission congestion.

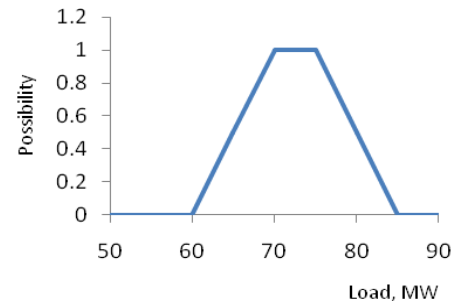
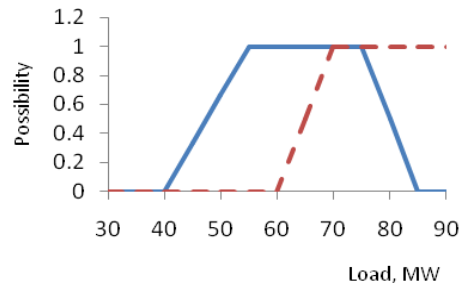


Figure 2: (a) Load Possibility (continuous line) and Possibility that Load Contributes in system Congestion (dashed line) (b) Possibility that Possible Loads Contribute in System.

If we consider similar load models for all load buses we can model all load points with similar fuzzy membership functions but with different values. Figure 3 shows fuzzy membership function for some different load points.

If we divide the support of fuzzy set of possible load values into n divisions, each division determines a simultaneous load pattern for all buses with equivalent possibility.

On the other hand, simultaneous load of buses at each time is not exactly equal to the mentioned possible value but it is probabilistic with a specified distribution function. The mean value of probable load and its possibility are calculated from the corresponding division of trapezoidal membership function. Figure 4 illustrates the concept of fuzzy-random load variables [6].

In the other word, the fuzzy-random load model consists of a probability density function with a fuzzy mean value.

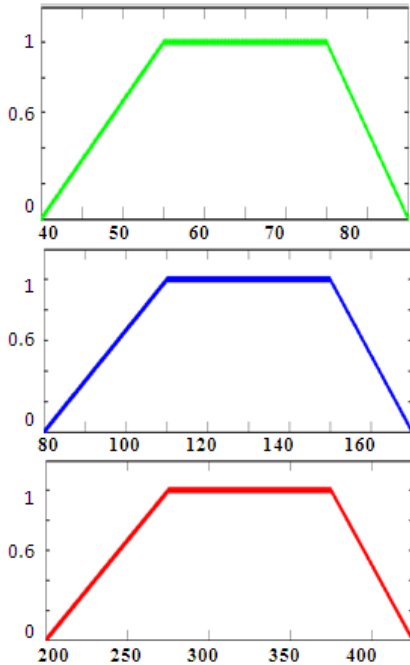


Figure 3: Some Typical Membership Functions for Different Load Points.

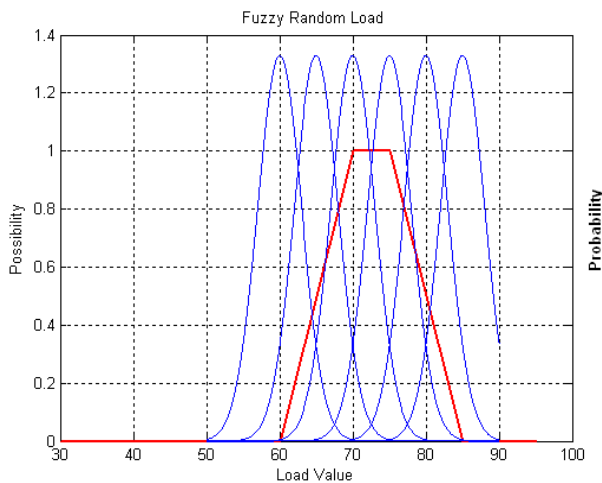


Figure 4: Normal Probability Distribution Functions when Membership Function Traces from 0 to 1.

Figure 4 depicts some normal probability distribution functions (PDF) with different mean values. A trapezoidal membership function determines the possibility of mean values of PDFs. For example the second PDF from left side corresponds to the member (65, 0.5) of fuzzy set of mean values. It means the mean value of 65 MW with fuzzy membership value of 0.5.

According to this curve probability of 70 MW load is 0.0344. Therefore we can write one member of fuzzy-random load set as $(70, 0.625, 0.0344)$. Some other members of this fuzzy-random set are $(70, 0.875, 0.1641)$, $(80, 0.625, 0.1641)$.

FUZZY MONTE CARLO SIMULATION FOR DETERMINING CONGESTED LINES

The proposed method tries to find mostly congested lines of the network. One of the best methods to remove the system congestion is optimal power flow (OPF) with suitable cost function. Therefore OPF can be used to find the mostly irresolvable congested lines of the network.

Equations (1) – (4) model the proposed optimal power flow. The objective function (1) is the total cost of purchasing energy from all running generators which can be deduced from the bidding curve of generators [4]. Dc power flow equations, line flow limits and generation limits are the constraints of this optimization problem. Consider a power system with N_b buses, N_g generators, N_d loads and N_l lines. Optimal power flow is modeled as below:

$$\text{Min } F(\vec{P}_G) = \sum_i (\alpha_i P_{Gi} + \beta_i) \quad (1)$$

$$B \vec{\delta} = \vec{P}_G - \vec{P}_D \quad (2)$$

$$-\vec{P}_l^{\max} \leq H \vec{\delta} \leq \vec{P}_l^{\max} \quad (3)$$

$$\vec{P}_G^{\min} \leq \vec{P}_G \leq \vec{P}_G^{\max} \quad (4)$$

Where,

$F(\vec{P}_G)$ (1x1): Total generation cost in \$/hr

\vec{P}_G ($N_b \times 1$): Vector of active power generations in p.u.

\vec{P}_D ($N_b \times 1$): Vector of fuzzy-random active loads in p.u.

B ($N_b \times N_b$): Node admittance matrix

H ($N_l \times N_b$):
Incidence Matrix of network

$\bar{\delta}$ ($N_b \times 1$):
Vector of voltage angles in radian

$\bar{P}_G^{\min}, \bar{P}_G^{\max}$ ($N_b \times 1$):
Vector of minimum and maximum active power generation limits in p.u.

\bar{P}_L^{\max} ($N_L \times 1$):
Vector of lines limits in p.u.

α_i, β_i :
The bid parameters of the i th power Generation Company.

Using DC load flow the system power loss is ignored in this method.

Proposed Algorithm

In order to solve the mentioned optimal power flow and determine the lines which mostly get congested, a fuzzy Monte Carlo simulation is applied to model the vagueness of system loads. This method will regard both probabilistic and possibilistic features of the forecasted load and covers the useful properties of fuzzy arithmetic and Monte Carlo simulation techniques. The FMCS approach includes two important phases: fuzzy number generation and simulation stages. As previously described, the load value of each load point at any time can be modeled as a probabilistic value with normal probability distribution function.

$$P = f(x|m, \delta) = \frac{1}{\delta\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\delta^2}} \quad (5)$$

The mean value m is a fuzzy variable with membership function $\mu_A(m)$.

$$\tilde{A} = \{m, \mu_A(m) \mid m \in M\} \quad (6)$$

The following steps explain the proposed solution for the described problem:

Break the range of the fuzzy membership function of bus loads into N slices.

Select n th fuzzy pair for each load point i .

Generate a random load value for each load point according to its probability density function.

Solve the OPF problem and determine congested lines.

If the i th line has been congested, $P(\text{Congin})=1$ and $P(\gamma_{in})$ is equal to the corresponding Kuhn-tucker multiplier.

Repeat steps (c) to (e) and complete the Monte Carlo simulation for specified fuzzy pairs.

Calculate the expected value of the shadow price and congestion for each line.

$$E^s(\gamma_i) = \frac{1}{m} \sum_{k=1}^m \gamma_i^k \quad (7)$$

$$E^s(\text{cong}_i) = \frac{1}{m} \sum_{k=1}^m \text{cong}_i^k \quad (8)$$

Go to step (b) and repeat for all of N fuzzy pairs. Compute fuzzy expected congestion (FE(cong)) and fuzzy expected shadow price (FE(γ)) for each transmission line.

$$FE(\gamma_i) = \max_n \{E^s(\gamma_i) \times \mu^s\} \quad (9)$$

Determination of Congested Lines

The fuzzy Monte Carlo simulation will determine the fuzzy expected value of congestion (FE(cong)) and fuzzy expected shadow price (FE(γ)) for each transmission line. Then a fuzzy interference system based on the following rules is used to determine the line is congested or not. If FE(cong) is very large the line is congested.

If FE(cong) is small the line is not congested.

If FE(cong) is large and FE(γ) is large the line is congested.

If FE(cong) is large and FE(γ) is small the line is not congested.

Feature Extraction For Partitioning

In new competitive power systems, network partitioning is one of the most efficient methods for congestion management. After partitioning the network, system operator may run market pricing process for each partition separately. To have the most efficient network partitions, network buses should be categorized based on suitable indices. Because we want to have price based zones it seems that nodal price is a good clustering feature but the worst disadvantage of nodal price is its dependency on the time varying load values and operating conditions. Time variable index can lead to time varying partitions which are not suitable.

Reference [4] suggests a clustering feature which is based on nodal price but it is not time variant. Equation (11) is the Lagrangian function of optimal power flow which is formulated by (1) through (4).

$$L = F(\vec{P}_G) - \lambda^T (B\vec{\delta} - \vec{P}_G + \vec{P}_D) + \gamma_{\max}^T (H\vec{\delta} - P_L^{\max}) - \eta_{\max}^T (\vec{P}_G - \vec{P}_G^{\max}) - \eta_{\min}^T (\vec{P}_G - \vec{P}_G^{\min}) \quad (11)$$

The nodal prices are calculated by differentiating the Lagrangian function (11) with respect to the

$$\frac{\partial L}{\partial \delta} = 0$$

voltage phase angle, δ :

$$\rho_N = \lambda_N \quad (12)$$

$$\rho = \hat{\lambda} = \lambda_N e + (\hat{H}\hat{B}^{-1})^T \gamma \quad (13)$$

ρ_N : nodal price in reference node N

ρ : the vector of nodal prices of other nodes

e : unit vector

$\hat{\lambda}, \hat{B}, \hat{H}$ are matrices λ, B, H excluding the term corresponding to the reference node N.

Equation (14) is the sensitivity of the nodal power injection to line power flows, and depends only to the admittance matrix (B) and the incidence matrix (H).

$$S = (\hat{H}\hat{B}^{-1})^T \quad (14)$$

According to (13) and (14), nodal price of any node consists of nodal price of reference node

and the sensitivity of the nodal power injection to line power flows. While nodal price depends on variable load, matrix S depends only on network configuration and is constant. Equation (13) shows that matrix S can be used instead of nodal price to categorize nodes of system. Because of multiplication of S with shadow price of mostly congested lines, the main features to partition the network are the corresponding columns of S matrix named X.

$$X = (x_i \in R^d : i = 1, \dots, d) \quad (15)$$

Where

$x_i = (G_{i1}, \dots, G_{id})^T ; i = 1, \dots, N$: is the sensitivities of the power injections at node i to power flows on line l.

d: is the total number of congested lines.

Node Clustering Fuzzy C-mean Algorithm

Extracting the clustering features, the fuzzy c-mean clustering algorithm is used to achieve accurate zonal partitioning. It is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. This technique provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. References [4, 7] are useful to understand the theory and algorithm of this technique.

CASE STUDY

The 30-node IEEE Test System is used to illustrate the algorithm. Table 1 shows the line flow limits. Trapezoidal fuzzy membership function parameters are written in Table 2. The congestion condition of the transmission network is analyzed by using fuzzy Monte Carlo simulation method. Fuzzy inference system is used to determine mostly congested line. Table 3 includes parameters of trapezoidal membership functions used for two input variables.

Table 4 shows final results of fuzzy Monte Carlo simulation for four mostly congested lines. It can be seen from this table that congestion definitely occurs on lines 6-8, 23-24 and 24-25 while the

TABLE 1
LINE FLOW LIMITS

Line	1-2 1-3 6-7	2-4,5-7 2-5,21-22 2-6,22-24 4-12	3-4 4-6 6-8	others
Line Flow Limits (MW)	125	50	100	30

TABLE 2
FUZZY LOAD MODEL

bus No.	a	b	c	d	sigma
1	0	0	0	0	0
2	0	0	0	0	0
3	85	90	97	110	5
4	0	0	0	0	0
5	60	64	68	77	5
6	0	0	0	0	0
7	35	40	48	55	5
8	13	15	17	21	3
9	0	0	0	0	0
10	35	40	48	55	5
11	0	0	0	0	0
12	22	25	28	31	2
13	10	12	14	16	2
14	35	40	48	55	5
15	22	25	28	31	3
16	2	3	4	6	1
17	0	0	0	0	0
18	22	25	28	31	2
19	5	6	8	11	2
20	27	29	32	36	3
21	13	15	17	21	2
22	0	0	0	0	0
23	35	40	48	55	5
24	2	3	4	6	1
25	5	6	8	11	2
26	5	6	8	11	2
27	35	40	48	55	5
28	0	0	0	0	0
29	13	15	17	21	3
30	0	0	0	0	0

TABLE 3

TRAPEZOIDAL FUZZY MEMBERSHIP FUNCTION PARAMETERS FOR FUZZY DECISION VARIABLES

		a	B	c	d
Fuzzy Expected Shadow Price	Small	0	0	10	15
	Large	10	20	∞	∞
Fuzzy Expected Congestion	Small	0	0	0.2	0.4
	Large	0.2	0.5	0.7	0.8
	Very Large	0.7	0.8	1	1

TABLE 4

CONGESTED LINES

Source	Sink	Line Flow Limits (MW)	Fuzzy Expected Congestion	Fuzzy Expected Shadow Price
6	8	30	1	8.751
18	19	20	0.456	97.16
23	24	20	1	9.244
24	25	20	0.85	21.656

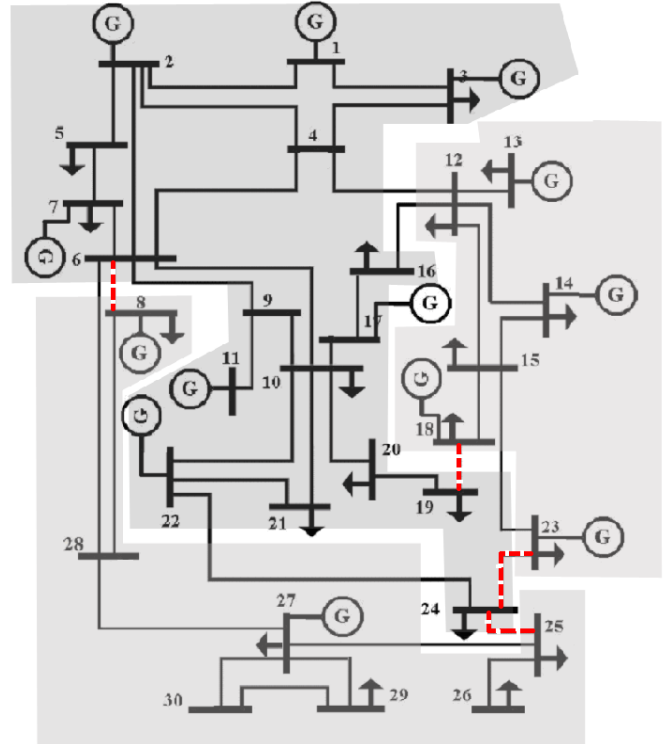


Figure 5: Zonal Partitions of IEEE 30 Bus Test System (the dashed lines are those that mostly get congested).

TABLE 5

CLUSTERS OF NODES

Cluster	Nodes in cluster
1	8,25,26,27,28,29,30
2	12,13,14,15,18,23
3	1-7,9-11,16,17,19-22,24

fuzzy expected value of congestion on lines 18-19 is not very large but because fuzzy expected value of shadow price is large the line is detected as a mostly congested line. Therefore, in partitioning the system or detecting the best price

zones, these lines are regarded as congested lines.

CONCLUSION

Congestion management is one important issue in restructured power systems, and zonal partitioning is one usual solution for this problem. Not only in market operation but also in the stage of transmission expansion planning congestion management is so important. While usually system expansion planning is based on predicted load, the predicted load for the future has a large amount of uncertainty with both possibilistic and probabilistic uncertainties.

In this paper, first, a fuzzy-random load model is proposed to take into account both of mentioned aspects of uncertainties. Then, a fuzzy Monte Carlo simulation is performed and after calculating some indices, mostly congested lines of the network are determined based on a fuzzy rule base. Finally, fuzzy C-Mean clustering is utilized to partition the network into different zones. Numerical examples on 30-bus IEEE test system, show satisfactory results without any intra-zonal congestion.

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