Neuro-Fuzzy Development Model to Calculate LOLE and Capacity Margin Probabilities

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Abstract: Any power system needs a comprehensive study. One point is a required for any power system is the reliability of that system, where in the present study the Loss of Load Expectation (LOLE) is the required term. The advanced Adaptive Neuro-Fuzzy Inference System (ANFIS) approach used to estimate the LOLE and the Capacity Margin Probabilities (CMP). The main target of the present study is to avoid the blackout of the system, which is the novelty of the study for the considered power system, which helps for a high reliable system also. The developed model is helping for different sectors through required period. The obtained results for any country will help in reducing the capital investment that help in limiting the installed equipment and the load expectation. Finally, the Neuro-Fuzzy applied in the planning and development of electric power systems.

Keywords: CMP, LOLE, EF, NFuzzy.

1. Introduction

To control the electric power flow and make it balance, it needs to have a smart grid for generation and distribution. The smart grid helps to find any fault occurrence. The smart grid enhances, as well, for a high energy efficiency. To satisfy the energy efficiency produced using a new generating unit, design of these units is a must to satisfy the required loads. This target will help to raise the required production capacity for a full power system load. The terms LOLP and LOLE are two terms of reliability which assist in the design, operation, and maintenance of power systems.

The term LOLE which is known as the expected number of days annually and defined in Qamber [1] as one of the power system reliability indices. This definition can be defined, as well, in another word that the capacity available is not sufficient to satisfy the required load. Through the load observation, the determination of the number of hours expectation is insufficient under available capacity. In addition, the Reserve Margin is defined as mentioned in the given reference [1], where it is defined as a percentage of any extra installed capacity through the period of considered peak load. Qamber in reference [1] discussed examples of reserve margin probabilities and the loss of load expectation.

Moghaddam et al [2] in their study discussed the hybrid systems. The discussion is taken from the energy management side of you and from the optimal design. The authors applied their model to minimize the total cost, where they considered two terms known as the loss of energy expected and LOLE.

In a study carried out by Almousawi et al [3], a PV-battery energy storage system was used. The study takes into consideration a losses factor to be minimized in the study. To preserve a balanced power and charge/discharge of the battery storage is taken into consideration. The purpose of that is to support the PV panel. The present study implements the fuzzy logic to control the LOLE, where the implementation of the control system in Almousawi et al [3] is taken in mind for the design, validation, and analysis of the hybrid system results.

The term LOLE is discussed in Čepin [4] which restoring gradually energy sources such as nuclear and wind power plants. One out of the power system plants is the nuclear power plant, where the rest are wind power plant. In the coming future, the nuclear power plant will be replaced by three wind power plant. This action will help to produce a total of five times the present capacity power plant capacity.

Reference [5] authored by Qamber deals with the two power reliability indices called LOLP and LOLE. Both terms deal with the electric power load lost. These two indices define the exceeding generated power capacity.

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Heather et al [6] and reference [7] deal with the Value of Loss Load (VOLL) against Average Net hourly Wage ($). This term VOLL is helping to assess the electric power system from the reliability point of view. The main objective of finding the VOLL is to find the most efficient adequacy of the required value VOLL.

Two systems were compared by controlling the strategies using the Simulink/Matlab in the study carried out by Pidikiti et al [8]. The vector control strategy is used for both systems. In their study, the authors [8] explain the control of a grid-tied wind energy conversion system following a Doubly Fed Induction Generator with partial scale converter and Permanent Magnet Synchronous Generator. This was carried out with full-scale converter. The study applied to the wind energy generation system, where the present study used the fuzzy system to control the LOLE.

The study of Kumar et al [9] highlights the use of Renewable Energy Sources. Enhancing the Power Quality in Photovoltaic systems is used to reach a novel technique in their study. The authors used in their study a combination of Fuzzy Logic Controller and Adaptive Cuckoo Search Algorithm. The Adaptive Cuckoo Search Algorithm is applied to monitor the power obtained. The combination of both Fuzzy Logic Controller and Adaptive Cuckoo Search Algorithm increased the performance of Maximum Power Point Tracking and minimize the total harmonic distortion. The Fuzzy Logic is applied in the present study which helps in controlling the LOLE. At the same time, the calculation of LOLE is carried out.

Since the present study as mentioned earlier is applied to control the value of LOLE, a salp swarm algorithm is applied in the study of Malik and Suhag [10] to mitigate frequency deviations under different operating conditions in a hybrid power system, where a fine-tuned segmented proportional integral derivative control scheme was designed and implemented. The salp swarm algorithm is used for optimal tuning of the controller. The evaluation of the control study is applied to two cases. Those cases are with and without different energy storage systems, in addition, the diesel engine generator besides parametric variations of one of the energy storage systems.

Ben Ali et al [11] in their study they make two curricular energy management strategies were investigated the hybrid electric vehicles using fuzzy logic and Boolean logic. The internal combustion engine is used as a backup system. The main purpose of the study is the management of the energy flow between two sources. The investigation of two different fuzzy logic scenarios is considered which are the main purpose of their study. The present study used fuzzy logic to control the LOLE.

2. NEURO-FUZZY MODEL

Any system information might be combined with the advantages of Neural Networks to permit and reach both of interaction between human operators and the considered information system under study. Later, ANFIS is trained a data contains both Generation and Load Models to reach the targeted results.

The input data are a fuzzy value, and the output results is the LOLE of the power system. Therefore, the input data which are fuzzy trained using the Neuro-Fuzzy, where the trained data are the predicted values. The predicted values are based on the relationship of the predicted values with the time. As a conclusion and by using ANFIS, the developed model obtained is reasonable output of LOLE values.

A multi-layer utilized as a rule-based of Neural Network. Furthermore, by minimization of the Neuro-Fuzzy weight the firing strength vector [12-14] is up-dated:

$$v^x = \frac{v_r}{\sum_{i=0}^{m} v_i} \quad (1)$$

The cost function $J_N(v)$ is used through its minimum. The firing strengths of the Fuzzy rules is v^x. This considered as a step value and weight space to get Newton Algorithm. The cost function might be approximated by the quadratic function using Taylor's expansion:

$$J_N(v+\Delta v) = J_N(v) + \Delta v \frac{dJ_N(v)}{dv} + \frac{1}{2}\Delta v^T \frac{d^2J_N(v)}{dv^2}\Delta v \quad (2)$$

As a definition, the updated weight vector Δv is defined as the weight vector v and T defined as the transpose. Finding the differentiation and minimization of equation (2) and setting the equation equal to zero, where the results become:

$$\frac{dJ_N(v)}{dv} = \frac{d^2J_N(v)}{dv^2} \Delta v \quad (3)$$

$$g = -H \,.\, \Delta v \quad (4)$$

where:

g is the gradient of $J_N(v_k)$, and

H is the Hessian of $J_N(v_k)$

Using the Newton's equation to find the solution to the equation which is a combination of a gradient algorithm. Hence, the algorithm is defined as:

i) k = zero

ii) v_k. is called the starting value of weight vector.

iii) $g(v_k)$ and $H(v_k)$ are the gradient and Hessian functions of the weight, respectively.

iv) Applying the rule of ending the $\|g(v_k)\|$ through the condition, it will be less than $\in$

v) As a case of $\| v_{k+1}\| \leq D_k$, the $H(v_k)\,\Delta v_k + g(v_k)$ is solved using a conjugate gradient.

vi) Starting with λ_k=1and under circumstances $v_{k+1} = v_k + \lambda_k \Delta v_k$., we can calculate λ_k

The (D_{k+1}) is adjusted with the following:

$$D_{k+1} = \begin{cases} 2D_k & if \quad \lambda_k \geq 1 \\ \frac{D_k}{3} & if \quad \lambda_k < 1 \end{cases} \tag{5}$$

vii) Back to step (iv).

Both $g(v_k)$ and $H(v_k)$ are required to $J_N\,(v_k)$. Later, consider v and the derivatives of $J_N\,(v)$, where we can find the following:

$$\frac{\partial J_N(v)}{\partial v_p} = \frac{1}{N}\sum_{k=1}^{N} 2\,\frac{\partial \hat{y}(v(k),v)}{\partial v_p}\,[y(k) - \hat{y}(v(k),v)] \tag{6}$$

$$\frac{\partial^2 J_N(v)}{\partial v_p \partial v_q} = \frac{1}{N}\sum_{k=1}^{N}\left[2\,\frac{\partial^2 \hat{y}(y(k),v)}{\partial v_p \partial v_q}\,y(k) - \hat{y}(v(k),v) + 2\,\frac{\partial \hat{y}(v(k),v)}{\partial v_p}\,\frac{\partial \hat{y}(v(k),v)}{\partial v_q}\right] \tag{7}$$

Finally, finding:

$$\frac{\partial \hat{y}(x,v)}{\partial v_p} = \begin{cases} \mu^u_{A^i} \\ \left[\prod_{u=1,u\neq k}^{U} \sum_{i=1}^{P_u} \mu^u_{A^i} v_i^u\right] \mu^k_{A^j} \end{cases} \tag{8}$$

Firing strengths v_i^u, where the ith is the weight and uth is the tensor model.

$$\frac{\partial^2 \hat{y}(x,v)}{\partial v_p \partial v_q} = \begin{cases} \left[\prod_{u=1,u\neq m\neq k}^{U} \sum_{i=1}^{P_u} \mu^u_{A^i} v_i^u\right] \mu^k_{A^j} \mu^m_{A^l} \\ 0 \end{cases} \tag{9}$$

3. DEVELOPMENT OF NEURO FUZZY

The ability of exchange between the main grid system and microgrids might be defined as a concept of the smart grid infrastructure of the microgrids. The applied method helps in the study as a tool to find the system's performance over time or after an improvement has been made if it is operating or failing. In addition, the index term LOLE is a power system reliability well-known index. Furthermore, this index is helping in the reliability analysis of the power system.

Following ANFIS and applying the Artificial Neural Network (ANN). ANFIS model developed, illustrated, and represented by Fig. (1).

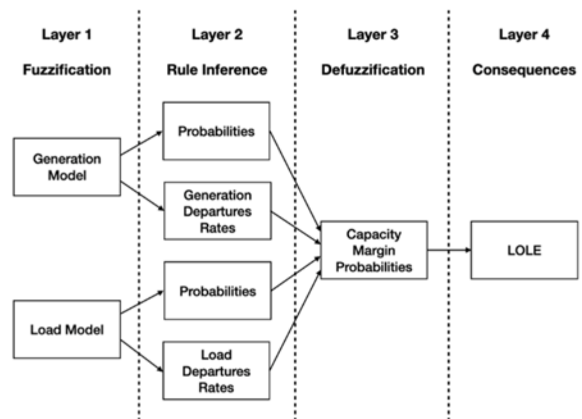

Fig. (1) N-Fuzzy Development Model

The FIS controlling the term LOLE. Through Layer (1) two inputs, which defined as generation and load, are cleared. Then, Layer (2) helps in conversion of fuzzy output set. After that Layer (3) is representing the results of the Capacity Margin Probabilities. Finally, the LOLE is calculated and represented by Layer (4).

Three generating units are represented as shown in Fig. (2). Each generating-unit has 200MW capacity, where the repair rate and failure rate are 0.45 repair per year and 0.05 failure rate, respectively. Fig. (3) shows four cases of load with average maximum electric loads. These loads are 0.45GW, 0.3GW, 0.15GW, and 0GW. The number of occurrences of each average peak load are 3, 5, 7, and 0, respectively. As a definition of Exposure Factor (EF, e) it is defined as the power loss of system, and it is the ratio of two values. These values are the Single Loss Expectancy (SLE) and Asset Value (AV). The model exposure factor € is 0.5. Therefore, the Exposure Factor formulae is:

$$EF = e = \frac{SLE}{AV} \tag{10}$$

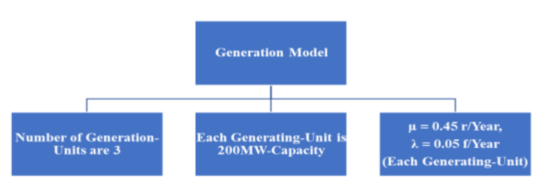

Fig. (2) Generating-Units Model Representation

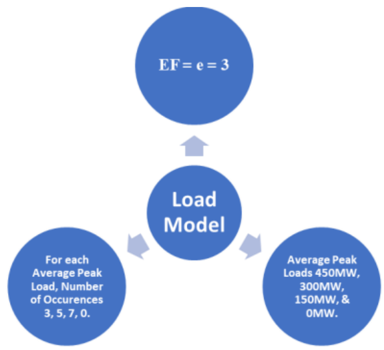

Fig. (3) Load Representation Model

Both of Fig. (4) and Table I represent the four-state model.

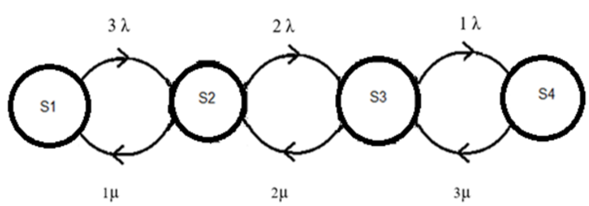

Fig. (4) Four States Model

TABLE I. SYSTEM OF FOUR-STATE

Transition Rates	***From (S1)***	***From (S2)***	***From (S3)***	***From (S4)***
To (S1)	-85E-02	45E-02	0	0
To (S2)	15E-02	-45E-02	9E-01	0
To (S3)	0	1E-01	-5E-02	135E-02
To (S4)	0	0	5E-02	-35E-02

Applying the binomial distribution, where the available generators are 3 generating-units, p = 0.9 and q = 0.1:

$$P(No.of\ Success) = \frac{n!}{r!\ (n-r)!}\, p^r\, q^{(n-r)} \qquad (11)$$

Table II shows the output results.

TABLE II. THREE GENERATING-UNITS RESULTS

(r!)	(p^r)	($q^{(n-r)}$)	Individual Prob	Cumulative Prob.
6	0.729	1	0.729	1
2	0.81	0.1	0.243	0.271
1	0.9	0.01	0.027	0.028
1	1	0.001	0.001	0.001

Table III represents the generating-units, where Table IV represents the average maximum loads.

The generation model results are represented by Fig. (5a) as a Pie-shape, where the slices represent the results. The individual probabilities represent the Capacity IN (MW) of generation. The highest value of the probability result (72.9%) belongs to the 600MW-Capacity which represents three generating units are under success operation. Furthermore, the probability becomes 24.3% for the case of success becomes 2 generators. The same model is illustrated as a Radar-Shape and illustrated in Fig. (5b). Fig. (5c) shows the four-states model with 3, 2, 1, and 0 as the generating-units number of success. The quality control tool is illustrated through Fig. (5c) represented by a histogram that display graphically a data set. Also, the same results are formed as a cumulative probability. With reference to the results, the model became 99.9% reliable. This is clear based on this results that the system is highly reliable.

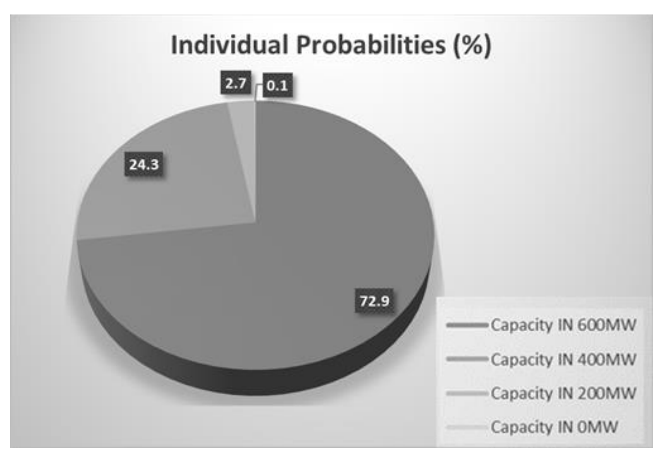

Fig. (5 a) Generation Model Results

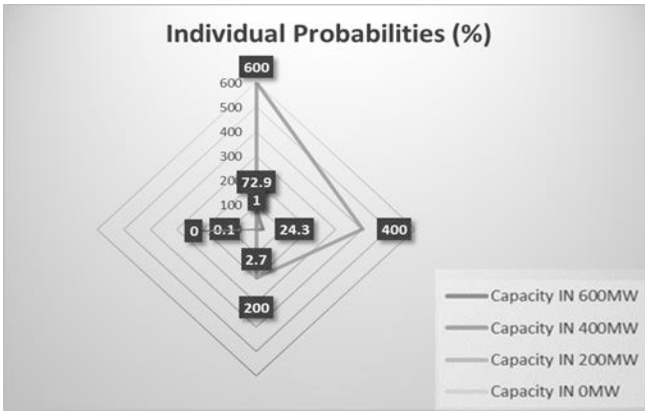

Fig. (5 b) Radar, Generation Results

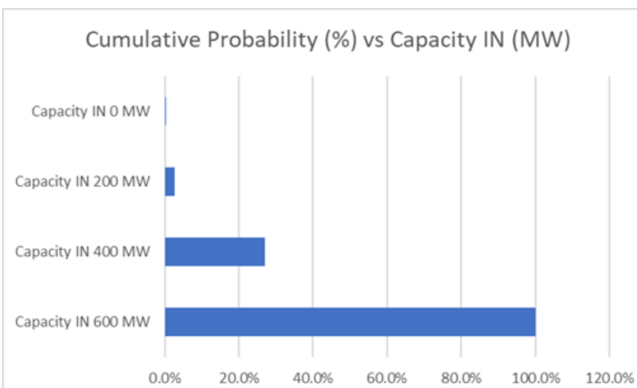

Fig. (5 c) Generation Model, Cumulative Probabilities vs Capacity IN (MW)

The variation of the average maximum load against the percentage number of load occurrences are illustrated and represented by Fig. (6). The 450MW as a highest load value has 46.67% number of occurrences, where 300MW has 33.33%, and the lowest load has 20%.

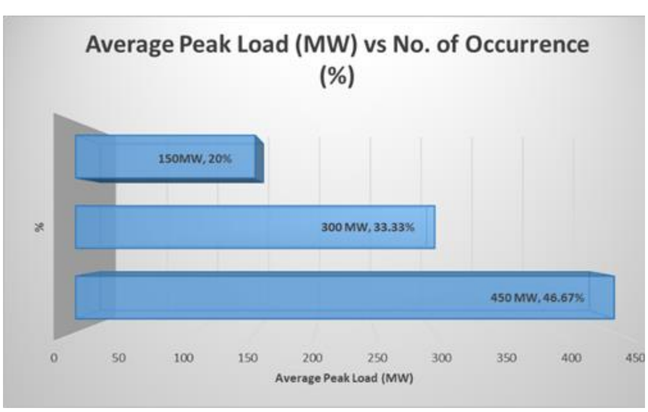

Fig. (6) Load Results of the considered Model

The reserve margin is defined as capacity margin [1]. The CMP results stored in Table V. Fig. (7) illustrates the variation of annual probability with capacity margin. The difference between the availability of capacity minus the load system is called the margin which means that the answer is positive or negative. When the obtained answer becomes negative, it means that the load exceeds the capacity available. In addition, it shows the failure of the system. Both of Table (V) and Fig. (7) show the transition from one margin to another. Furthermore, Fig. (7) illustrates the annual probability against the Capacity IN (MW) of the system which became as a linear relationship.

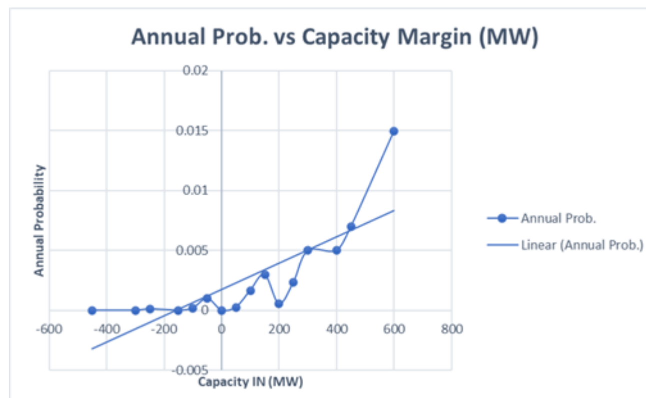

Fig. (7) Annual Prob. vs Capacity Margin

The equation of Reserve Margin is:

$$Reserve\ Margin = \frac{Capacity - Demand}{Demand} \tag{12}$$

The Capacity Margin can be obtained by a combination of the available capacity and load (mk). The relationships between both of available capacity and load are as follows:

$$m_k = P_c - L_i \tag{13}$$

$$P_k = P_c * P_i \tag{14}$$

$$\lambda_{+m} = \lambda_{+n} + \lambda_{-L} \tag{15}$$

$$\lambda_{-m} = \lambda_{-n} + \lambda_{+L} \tag{16}$$

In annual basis, the CMP and LOLE are determined. Table VI summarized the integration of both generation and load models. Therefore, the LOLE is calculated:

$$LOLE = \begin{pmatrix} Cumulative\ Probability\ of \\ the\ first\ negative\ Margin \end{pmatrix} \text{ x } \frac{365}{e} \tag{17}$$

As a relationship of both LOLE and LOLP is:

$$LOLE = LOLP \text{ x } 8760 \quad (18)$$

The results of generation probabilities annually summarized in Table VII. Therefore, as a sample of the results, the LOLE value is 26x10^{-3} days per annual. This result is worth to 622x10^{-3} hours per annual.

The present study developed model is applied using the Neuro-Fuzzy, where the lowest value of LOLE is targeted and obtained. The simple definition of emergency margin is calculated and defined in [1, 14], where three generators and average loads were used to calculate the LOLE in [1] by Qamber.

In a target to calculate the power system reliability, Qamber [1] discussed and explained the way of calculating the power margin. Furthermore, a comparison is made between two references Qamber [1] and Čepin [4] obtained and calculate the LOLE. Čepin [4] at the same time analyzes the nuclear and wind power plants by comparing them under different scenarios.

Two hybrid systems and optimal energy design were examined by Moghaddam et al [2] in their study, where the photovoltaic panels considered. In addition, the wind turbines with a fuel cell discussed. The index LOLE was considered with the expected energy loss expectation. Therefore, to assess the reliability of electric power system [6,7] the loss value needs to be calculated.

The criteria of calculating the LOLE normally expressed as the amount of days/year, where it is a complex metric that might account for the dynamic power system. This means that the generation resources become insufficient to reach the required load demand. In addition, the Criteria forms a good target, but at the same time might create lousy planning/compliance measure. In the present study, the obtained value of LOLE is 26x10^{-3} days per annual which is equivalent to 622x10^{-3} hours per year. This value is considered an accepted value. In case that the daily peak demand exceeds the available generating capacity, the LOLE is required to be calculated. Therefore, the LOLE is defined as the ability of a system's resources to cover a required load demand. The planning reserve margin is simple and static at the same time. Furthermore, the planning reserve margin is easy to be considered and used as a benchmark for planning and compliance. The planning reserve margin is known as a probabilistic measure.

4. CONCLUSION

A developed Neuro-Fuzzy model is investigated and obtained which help to reduce the load shedding and black-out cases. The developed model is found as suitable model that helps to find reliable values, which deals to calculate the LOLE targeted values. The LOLE value calculated is low which is equal to 0.622356164 hours per year. The study helps to avoid the black-out as well as load shedding for the countries and different sectors. In addition, the study is helping to use the developed Neuro-Fuzzy model for the country's economic development.

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TABLE III. GENERATION MODEL RESULTS

S(x)	Cap. IN (GW)	Cap. OUT (GW)	Individ Prob (%)	Depart. λ_{+n}	Rate λ_{-n}	Freq. (%)	Prob (%) (Annual)	Cum Prob (%) (Annual)	Cum Freq (%)
First	6E-01	0	7.29E+1	0	0.15	10.935	3	4	0
Second	0.4	0.2	24.3	0.45	0.1	13.365	0.99863014	1.11369863	10.935
Third	0.2	0.4	2.7	0.9	0.05	2.565	0.1109589	0.115068493	2.43
Fourth	0	0.6	0.1	1.35	0	0.135	0.00410959	0.004109589	0.135

TABLE IV. AVERAGE PEAK LOAD RESULTS

State	Average Peak Load	Occurrence	Probability, P	Annual P =	Departure	Rate
	L_i (GW)	n_i	$= \frac{ni\ e}{D}$	$P\left(\frac{10}{365}\right)$	λ_{+L}	λ_{-L} =1/e
First	0.45	3	1E-01	4.10959E-03	0	2
Second	0.3	5	0.166666667	0.006849315	0	2
Third	0.15	7	0.233333333	0.009589041	0	2
		Σ	1-e	Σ	$\frac{1}{1-e} =$	
0	0	15	0.5	0.020547945	2	0

TABLE V. ANNUAL PROBABILITY OF CM

Margin (in GW)	Annual Probability	
0.6	14.97E-03	
0.45	6.99E-03	
0.4	4.991E-03	
0.3	4.99E-03	
0.25	2.33E-03	
0.2	0.55E-03	7.878E-03
0.15	2.99E-03	
0.1	1.66E-03	
0.05	0.25E-03	
0.0	0.21E-04	
-0.05	0.99E03	First Negative Margin Value
-0.1	0.18E-03	
-0.15	0.95E-05	
-0.25	0.11E-03	
-0.3	0.68E-05	
-0.45	0.41E-05	6.25E-03

TABLE VI. GENERATION-LOAD COMBINATION

	Electric Load	1	2	3	0
	L_i (GW)	0.45	0.3	0.15	0.0
	P_i (%)	0.4109589	0.6849315	0.9589041	2.0547945
	(λ_{+L})	0E01	0E01	0E01	20E-01
	(λ_{-L})	20E-01	20E-01	20E-01	0E01
	Gen. Power				
n = 1, Capacity (GW) =	**0.6**	0.15	0.3	0.45	0.6
P_1 (%) =	**72.9**	0.299589	0.4993151	0.6990411	1.4979452
(λ_{+n}) =	**0E01**	20E-01	20E-01	20E-01	0E01
(λ_{-n}) =	**1.5E-01**	1.5E-01	1.5E-01	1.5E-01	215E-02
n = 2, Capacity (GW) =	**0.4**	-0.05	0.1	0.25	0.4
P_2 (%) =	**24.3**	0.099863	0.1664384	0.2330137	0.4993151
(λ_{+n}) =	**45E-02**	245E-02	245E-02	245E-02	45E-02
(λ_{-n}) =	**10E-02**	10E-02	10E-02	10E-02	210E-02
n = 3, Capacity (GW) =	**0.2**	-0.25	-0.1	0.05	0.2
P_3 (%) =	**2.7**	0.0110959	0.0184932	0.0258904	0.0554795
(λ_{+n}) =	**90E-02**	290E-02	290E-02	290E-02	90E-02
(λ_{-n}) =	**5E-02**	5E-02	5E-02	5E-02	205E-02
n = 4, Capacity (GW) =	**0E01**	-45E-02	-30E-02	-0.15	0E01
P_4 (%) =	**0.1**	0.0	68.49E-05	95.89E-05	60
(λ_{+n}) =	**135E-02**	335E-02	335E-02	335E-02	135E-02
(λ_{-n}) =	**0E01**	0E01	0E01	0E01	20E-01

TABLE VII. PROBABILITIES OF GENERATION PER YEAR

Cap. IN (GW)	*Cap. OUT (GW)*	*Indiv. Prob (%)*	*Cumm. Prob (%)*	*Annual Probab. (%)*	*Ann. Cumulative Prob (%)*
ON ON ON					
0.6	0E01	72.9	100	2.99589	4.109589
OFF ON ON					
ON ON OFF					
ON OFF ON					
0.4	0.2	24.3	27.1	0.99863	1.1136986
OFF OFF ON					
ON OFF OFF					
OFF ON OFF					
0.2	0.4	2.7	2.8	0.11095	0.1150685
OFF OFF OFF					
0.0	0.6	0.1	0.1	4.1095E-03	4.10959E-03

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