Artificial Neural Network Based Adaptive Load Shedding for an Industrial Cogeneration Facility

Cheng-Ting Hsu, *Member*, *IEEE*
Department of Electrical Engineering
Southern Taiwan University
Tainan, Taiwan

Hui-Jen Chuang, *Member*, *IEEE*,
Department of Electrical Engineering
Kao-Yuan University
Kaohsiung, Taiwan

Chao-Shun Chen, *Senior Member*, *IEEE*
Department of Electrical Engineering
I-Shou University
Kaohsiung, Taiwan

Abstract—**This paper presents the design of adaptive load-shedding strategy by executing the artificial neural network (ANN) and transient stability analysis for an Industrial cogeneration facility. To prepare the training data set for ANN, the transient stability analysis has been performed to solve the minimum load shedding for various operation scenarios without causing tripping problem of cogeneration units. Various training algorithms have been adopted and incorporated into the back-propagation learning algorithm for the feed-forward neural networks. By selecting the total power generation, total load demand and frequency decay rate as the input neurons of the ANN, the minimum amount of load shedding is determined to maintain the stability of power system. To demonstrate the effectiveness of the ANN minimum load-shedding scheme, the traditional method and the present load shedding schemes of the selected cogeneration system are also applied for comparison and verification of the proposed methodology.**

Keywords- Load shedding, Artificial neural networks, Cogeneration

I. Introduction

To enhance the reliability of electricity power supply, more and more industrial customers have installed cogeneration units to produce electricity as well as steam for manufacturing process. Up to now, the total installation capacity of cogeneration has been increased to 7377 MW in 2007, which contributes 19.7% of the Taiwan Power Company (Taipower) system peak demand. The cogeneration has to be tied together with the bulk utility system for the consideration of power quality. When an external fault contingency occurs, the tie line should be tripped in time according to the protective relay settings. For the isolated cogeneration system, the proper load-shedding scheme has to be designed to disconnect its partial loading from service so that the cogeneration units can remain steady operation and the power system collapse can be prevented.

An effective load-shedding scheme is absolutely important for the cogeneration system to maintain power system stability. Insufficient load shedding will cause serious frequency decay and may result in total system blackout. On the other hand, excessive power outage may be introduced if too much load is tripped. It is a common practice to perform the load shedding by using under-frequency relays to trip the predetermined load with many shedding steps when the frequency drops below the setting values [1]. The load shedding methods based on the power flow from the utility and the instant frequency decay rate after tie line tripping [2] are also implemented in the cogeneration systems. To determine the minimum load shedding required for system contingencies, an adaptive ANN model has been proposed in this paper.

Up to now, ANN has been successfully used to deal with the data by imitating the human neural network. It has been applied in the areas of function approximation and pattern recognition. It is also suitable for multivariable applications because of the capability to easily identify the interaction between the inputs and outputs. In recent years, the ANN has been applied in the load forecasting [3], power estimation [4], harmonic detection [5], power system controllers [6] and fault protection [7]. Because the variation of system frequency is highly dependent on the initial operation condition, the seriousness of fault contingency, the response of governor systems and so on, it becomes more and more difficult to determine the minimum amount of load shedding by the traditional methods for the cogeneration system. By performing the stability analysis for various fault scenarios, the training data set of ANN model can be created. With the ANN model derived, the optimal load shedding at the instant of tie lines tripping is determined according to the input neurons of the neural network.

II. Training Algorithms of the Back-Propagation Artificial Neural Networks

A multi-layer feed-forward network with back-propagation algorithm has often been applied for the ANN training. The data is propagated from the input layer to the hidden layers before reaching the final output layer. The error signals at the output layer are then propagated back to the hidden and input layers. The sum of square error is then minimized by adjusting the synaptic weights and bias in any layers during the training process of ANN models as shown in Fig. 1. For a multi-layer network, the net input $v^{k+1}(i)$ and output $y^{k+1}(i)$ of neuron i in the $k+1$ layer can be expressed as (1) and (2).

$$v^{k+1}(i) = \sum_{j=1}^{Sk} w^{k+1}(i,j) y^k(j) + b^{k+1}(i) \tag{1}$$

$$y^{k+1}(i) = \phi^{k+1}(v^{k+1}(i)) \tag{2}$$

This work is supported by the National Science Council of Taiwan, ROC, under Grant NSC 95-2213-E-218-069.

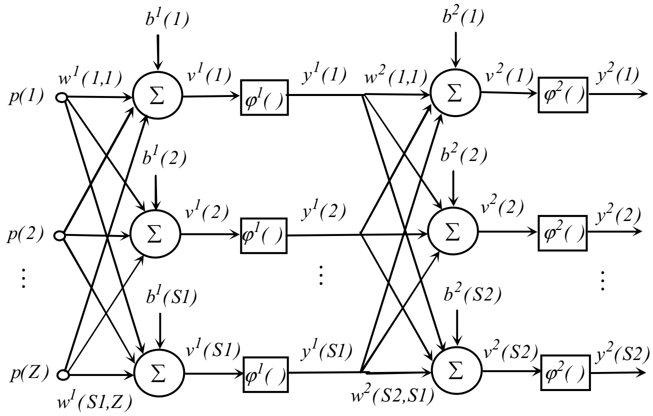

Fig.1 A two-layer feed-forward network

where Sk is the number of outputs in the k layer, $w^{k+1}(i,j)$, $b^{k+1}(i)$ and ϕ^{k+1} represents the synaptic weight, bias and activation function of neuron i in the $k+1$ layer. For an ANN with K layer network, the system equations in matrix form are given as

$$\bar{y}^0 = \bar{p} \tag{3}$$

$$\bar{y}^{k+1} = \bar{\phi}^{k+1}(W^{k+1}\bar{y}^k + \bar{b}^{k+1}) \qquad k = 0,1,\ldots K-1 \tag{4}$$

where the input signal vector $\bar{p}$ with Z variables is expressed as $[p(1), p(2), \ldots, p(Z)]^T$. The input/output vector pairs $\{(\bar{p}_1, \bar{q}_1), (\bar{p}_2, \bar{q}_2), \ldots, (\bar{p}_R, \bar{q}_R)\}$, which are generated by performing the transient stability analysis, will be used as the training data set of ANN. By representing the sum of the output square error as the performance index for the ANN, the error function is given by

$$E = \frac{1}{2}\sum_{r=1}^{R}(\bar{q}_r - \bar{y}_r^K)^T(\bar{q}_r - \bar{y}_r^K) = \frac{1}{2}\sum_{r=1}^{R}(\bar{e}_r)^T\bar{e}_r \tag{5}$$

where, $\bar{e}_r = \bar{q}_r - \bar{y}_r^K$ is the output error and $\bar{y}_r^K$ is the final output of the rth input. To minimize the mean square error function $E(\bar{x})$ in (6) with respect to vector $\bar{x}$, the Newton's method is given by (7)

$$E(\bar{x}) = \frac{\sum_{i=1}^{N} e_i^2(\bar{x})}{N} \tag{6}$$

$$\Delta\bar{x} = -\left[\nabla^2 E(\bar{x})\right]^{-1}\nabla E(\bar{x}) \tag{7}$$

where

$$\bar{x} = \left[w^1(1,1)w^1(1,2)\ldots w^1(S1,Z)b^1(1)\ldots b^1(S1)w^2(1,1)\ldots b^K(SK)\right]^T \tag{8}$$

$$\nabla E(\bar{x}) = J^T(\bar{x})\bar{e}(\bar{x}) \tag{9}$$

$$\nabla^2 E(\bar{x}) = J^T(\bar{x})J(\bar{x}) + S(\bar{x}) \tag{10}$$

and

$$J(\bar{x}) = \begin{bmatrix} \frac{\partial e_1(\bar{x})}{\partial x_1} & \frac{\partial e_1(\bar{x})}{\partial x_2} & \cdots & \frac{\partial e_1(\bar{x})}{\partial x_m} \\ \frac{\partial e_2(\bar{x})}{\partial x_1} & \frac{\partial e_2(\bar{x})}{\partial x_2} & \cdots & \frac{\partial e_2(\bar{x})}{\partial x_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_N(\bar{x})}{\partial x_1} & \frac{\partial e_N(\bar{x})}{\partial x_2} & \cdots & \frac{\partial e_N(\bar{x})}{\partial x_m} \end{bmatrix} \tag{11}$$

$$S(\bar{x}) = \sum_{i=1}^{N}\bar{e}_i(\bar{x})\nabla^2\bar{e}_i(\bar{x}) \tag{12}$$

where $N = R \times SK$. The Newton's method assumes $S(\bar{x}) = 0$ to update (7) by

$$\Delta\bar{x} = -\left[J^T(\bar{x})J(\bar{x})\right]^{-1}J^T(\bar{x})\bar{e}(\bar{x}) \tag{13}$$

Many back-propagation learning algorithms, which are available in the MATLAB Neural Networks Toolbox, will be discussed in this section.

2.1 Levenberg-Marquardt Back-Propagation (LMBP)

The Levenberg-Marquardt algorithm [8,9] modifies the Newton's method as

$$\Delta\bar{x} = -\left[J^T(\bar{x})J(\bar{x}) + \mu I\right]^{-1}J^T(\bar{x})\bar{e}(\bar{x}) \tag{14}$$

where the parameter μ will be updated according to the change of the performance index at each iteration of the training process and I is the identity matrix. It can be found that the performace index in (5) is equivalent to (6). For the LMBP algorithm, all the R input/output vector pairs are given to the network first, and the corresponding outputs and errors are computed by using (3), (4) and (6). The Jacobian matrix $J(\bar{x})$ in (11) and the incremental change $\Delta\bar{x}$ in (14) are calculated and the performance index is recalculated by $E(\bar{x})$ with $\bar{x} + \Delta\bar{x}$. The ANN becomes converged if the performance index is less than the specified tolerance. Otherwise, the parameter μ is modified to repeat the training process of the neural network.

2.2 Variable Learning Rate Back-Propagation (VLRBP)[9,10]

This is a steepest descent algorithm with an adaptive learning rate to modify the incremental change during the training process. One-iteration of the algorithm can be written as

$$(\Delta\bar{x})_k = (\bar{x})_{k+1} - (\bar{x})_k = -\alpha_k \nabla E(\bar{x})_k \tag{15}$$

where α_k and $\nabla E(\bar{x})_k$ are the learning rate and the gradient of the performance index function at the k-th iteration respectively.

2.3 Resilient Back-Propagation (RBP) [9,11]

This is also a steep descent algorithm by considering the sign of the derivative as the direction to update the weighting factors. Each weighting and bias is increased by a factor whenever the derivative of the performance index function has the same sign for two successive iterations. On the other hand, each weighting and bias is decreased by a factor with the change of derivative sign from the previous iterations.

2.4 Fletcher-Reeves Conjugate Gradient Back-Propagation (FRCGBP) [10,12]

All of the conjugate gradient algorithms start out by searching in the steepest descent direction on the first iteration. Then the next search direction is determined so that it is conjugate to the previous search direction. One-iteration of the algorithm can be expressed as

$$(\Delta \bar{x})_k = (\bar{x})_{k+1} - (\bar{x})_k = \alpha_k \bar{h}_k \tag{16}$$

where

$$\bar{h}_k = -\nabla E(\bar{x})_k + \beta_k \bar{h}_{k-1} \tag{17}$$

The various versions of conjugate gradient algorithms calculate the constant β_k by different methods. For the Fletcher-Reeves algorithm, the constant is obtained as

$$\beta_k = \frac{(\nabla E(\bar{x})_k)^T \nabla E(\bar{x})_k}{(\nabla E(\bar{x})_{k-1})^T \nabla E(\bar{x})_{k-1}} \tag{18}$$

2.5 Polak-Ribiere Conjugate Gradient Back-Propagation (PRCGBP)[10,12]

For the Polak-Ribiere algorithm, the constant β_k is calculated by

$$\beta_k = \frac{\Delta(\nabla E(\bar{x})_{k-1})^T \nabla E(\bar{x})_k}{(\nabla E(\bar{x})_{k-1})^T \nabla E(\bar{x})_{k-1}} \tag{19}$$

It is the inner product of the previous gradient change with the current gradient divided by the norm square of the previous gradient.

2.6 Powell-Beale Conjugate Gradient Back-Propagation (PBCGBP)[9,13]

For all the conjugate gradient algorithms, the search direction is periodically reset to the negative of the gradient. In general, the reset ponit occurs as the number of the iterations is equal to the number of the weights and biases. For the Powell-Beale conjugat gradient algorithm, the search direction is reset to the negative of the gradient if the following inequality can be satisfied.

$$\left|(\nabla E(\bar{x})_{k-1})^T \nabla E(\bar{x})_k\right| \geq 0.2\left\|\nabla E(\bar{x})_k\right\|^2 \tag{20}$$

2.7 Scaled Conjugate Gradient Back-Propagation (SCGBP)[9,14]

The conjugate gradient algorithms described above require a line search for each iteration. The scaled conjugate gradient algorithm can avoid the time-consuming line search by using the model-trust region and the conjugate gradient approach.

2.8 Quasi-Newton Back-Propagation (QNBP)[9,15]

The basic Newton's method given by (7) is complex and expensive to compute the second derivatives matrix of $\nabla^2 E(\bar{x})$ of the performance index function. However, the quasi-Newton method updates the matrix with an approximation of function gradient instead of computing the second derivatives of the $\nabla^2 E(\bar{x})$ matrix.

III. DESIGN OF ADAPTIVE MINIMUM LOAD SHEDDING

This section presents the process to determine the amount of load shedding for power systems by using the ANN with various training algorithms according to the transient stability analysis. Fig. 2 shows the flowchart of the proposed adaptive minimum load shedding. It can be divided into five steps as follows:

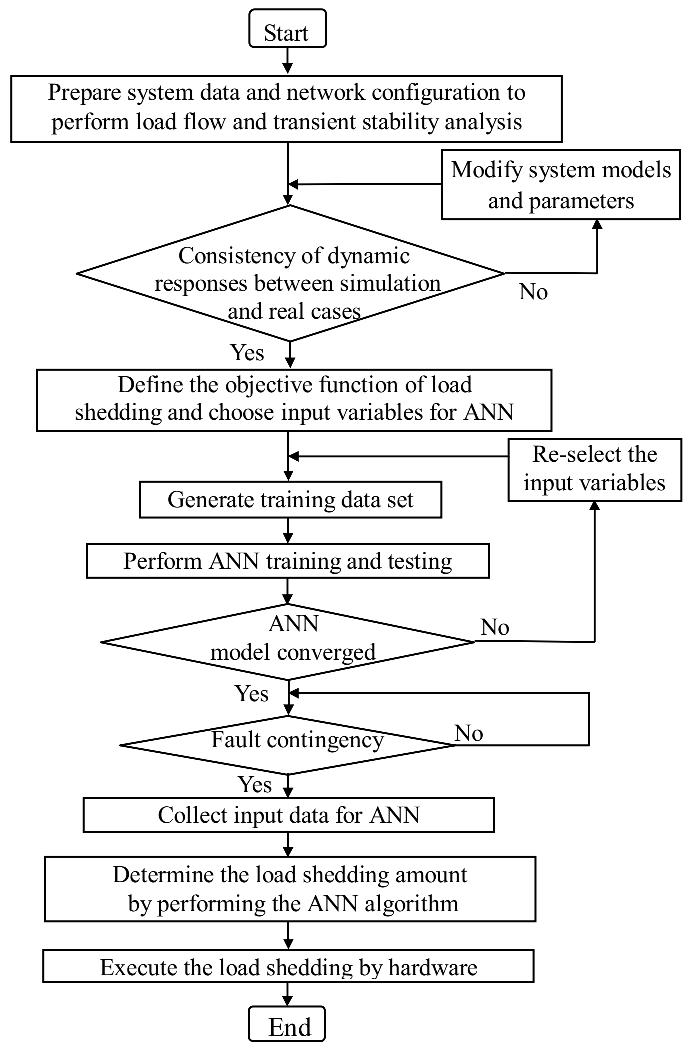

Fig. 2 The flowchart of ANN based adaptive minimum load shedding

Step 1: Identify the network configuration and prepare the data for the power system to be studied. It includes the branch and bus data for load flow analysis and the mathematical models with corresponding parameters of generators, excitation systems, governor systems and loads for transient stability analysis. Also, the protective relays settings and the actual system responses captured by recorder should be collected.

Step 2: To verify the accuracy of the mathematical models, computer simulation of the actual contingency cases is performed by the transient stability analysis. The models and parameters of the power systems are modified accordingly.

Step 3: For system contingency, the dynamic frequency response of the power system is highly dependent on the amount of load to be shed. The objective function of the ANN model is to derive the optimal amount of load shedding so that the stable operation of power system can be maintained and the economic loss can be minimized. Choose the input variables, which are highly correlated to the frequency deviation as the training data of ANN models.

Step 4: To prepare the input data for the ANN, the transient stability analysis of power system for many operation conditions and fault contingencies have to be executed. The data of the selected input variables and the corresponding output are then divided into two data sets for training and testing respectively. Before the training and testing process, all the data sets should be normalized to the same range of values. Training and testing of ANN models are executed by using the feed-forward ANN with various back-propagate algorithms as described previously until the performance index is less than the specified error tolerance. Redefine the input variables if the convergence of ANN models can not be obtained.

Step 5: When a fault occurs, the proposed ANN controller will determine the minimum amount of load shedding quickly according to the input data captured by the SCADA system in real time. Finally, the hardware of the load-shedding scheme will trip the predetermined load to restore the system frequency.

IV. CASE STUDY

To demonstrate the effectiveness of the ANN method to determine the minimum amount of load to be disconnected from service for system fault contingency, a large cogeneration system is selected for computer simulation. The traditional and the present load-shedding schemes are also introduced for comparison and verification of the proposed methodology.

4.1 System Description of the Cogeneration System

To determine the ANN based adaptive load shedding for industrial customers with cogeneration facility, a large petroleum company with three cogeneration units has been selected for the case study as shown in Fig. 3. The dotted boundary represents the power system of the cogeneration facility, which is connected to Ding-HuE substation of Taipower system by double 161kV circuits. To simplify the simulation, the rest of Taipower system is represented as the equivalent generation unit G_{eq} at Ding-Hu 345kV EHV substation. Two autotransformers are used to step-down the voltage level to Ding-HuW and Ding-HuE 161kV buses. For the cogeneration system, there are two 50MVA on load tap changer transformers to step down the voltage level from 161kV to 69kV to serve the loads at A, B, C, D, E and F buses. The cogeneration units G1 and G2 with backpressure type turbine have the rated capacity 10MW each and the cogeneration unit G3 with condensing type turbine has the rated capacity 40MW.

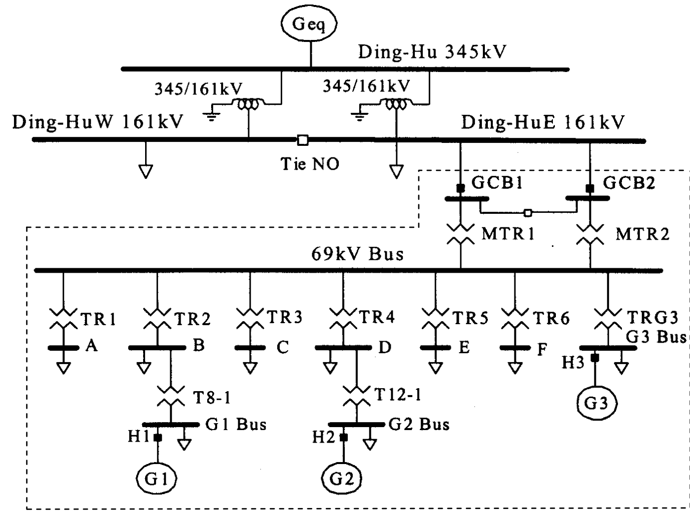

Fig. 3 One-line diagram of the cogeneration system

To perform the transient stability analysis of the isolated cogeneration system, all the generators, excitation systems and governor systems have to be represented by the mathematical models so that the response of the cogeneration units to the system disturbances can be simulated accurately. All the generators in this study system are represented by detailed model with transient and sub-transient circuits on both the direct and quadrate axes [16]. The IEEE Type 1 excitation model [17] is considered for the G1 and G2 cogeneration units. For the cogeneration unit G3, the control block diagram of its excitation system is shown in Fig. 4. The simplified governor model [18] as shown in Fig. 5 is used for all the cogeneration units. Parameters of the generators, excitation systems and governor systems are listed in Appendix.

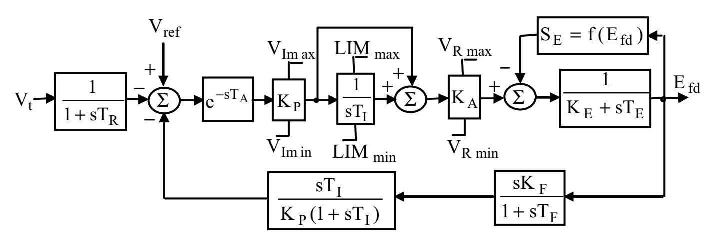

Fig. 4 Excitation control block diagram of G3 unit

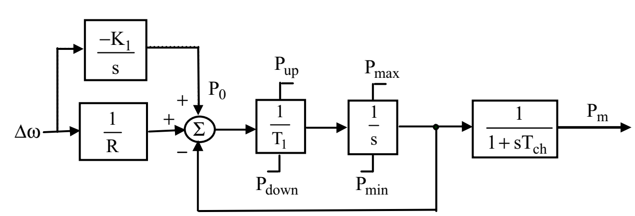

Fig. 5 Governor control block diagram of the cogeneration units

4.2 Verification of the Cogeneration Units Modeling

It is important to guarantee the accuracy of the proposed cogeneration unit models. One of the verification cases of G3 to execute the load rejection test is presented in this paper. Before the test, G3 is operated with constant power output 31MW and power factor 0.875. The power demand of the generator auxiliary loads is 2.23MW and the rest power of 28.77MW is delivered to the load center via transformer TRG3. During the load rejection test, the circuit breaker between the load center and TRG3 is opened and the connected loads are reduced from 31 MW to 2.23 MW instantaneously. Fig. 6 shows the actual frequency response recorded during the test. It is found that the frequency rises to 62 Hz in a short time period. The governor system with constant frequency control is activated and the frequency is restored to 60 Hz after 10 seconds. Fig. 7 shows the frequency response solved by the stability analysis. By comparing the two figures, it is found that very consistent result has been obtained by computer simulation with the proposed governor model and parameters.

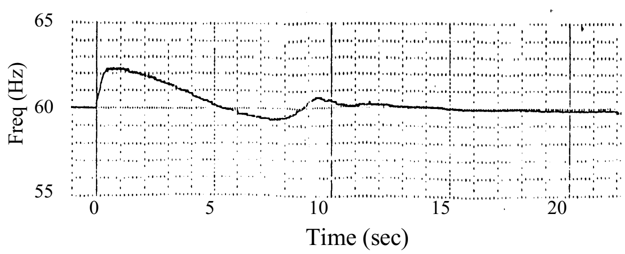

Fig. 6 Actual frequency response of load rejection test.

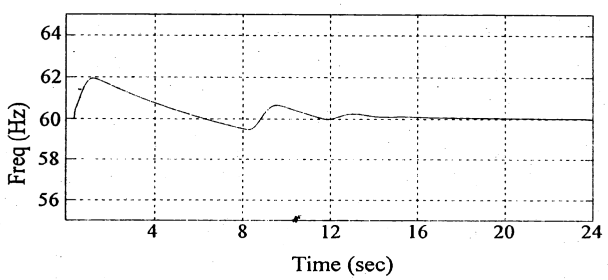

Fig. 7 Frequency response of load rejection test by computer simulation.

4.3 Load Shedding Schemes of the Cogeneration System

For the industrial customer, the power shortage has to be imported from Taipower because the total power generation is not enough to cover the load demand. The present load-shedding scheme is designed to trip the load in one step according to the tie line power flow when the frequency drops to 58.4Hz. The criterion of the load to be shed is given by

$$0 \le P_s - P_{tie} \le 3.5MW \tag{21}$$

where P_s is the amount of load to be shed and P_{tie} is the power purchased from the utility.

A traditional load-shedding scheme with the maximum anticipated overload value of 40MW with three shedding steps [2] are also considered for the cogeneration system. The amounts of load to be shed are 10MW, 15MW and 15MW for each step when the frequency drops to the values of 58.4Hz, 58Hz and 57.4Hz respectively.

4.4 ANN Based Adaptive Load Shedding

To protect the industrial power system for an external fault contingency in Taipower, the under frequency relay will be activated to trip the tie lines by opening circuit breakers GCB1 and GCB2 in Fig. 3 when the frequency declines to 58.4Hz. To maintain the stable operation of the isolated cogeneration system, the proper load-shedding scheme has to be executed immediately if the generation power is less than the power demand in the plant. The frequency goes to an unacceptable value when the load-shedding scheme is failed. To protect the cogeneration units from damage, the circuit breakers at H1, H2 and H3 will be tripped if the frequency drops to 57Hz for 1.1 second.

The stability margin has been included during the ANN training process to circumvent system uncertainty. It is therefore to define the objective function of the ANN based adaptive load shedding as "tripping the load at the instant of tie line tripping in one step to avoid the system frequency drop below 57Hz with one second time delay", which implies that a 0.1 second time margin has been considered. The total power generation of cogeneration units (P_G), total load demand (P_L), the frequency decay rate before tie line tripping (df_1/dt) and the frequency decay rate at the instant of tie line tripping (df_2/dt) are considered as the input variables of the ANN model, while the output neuron is defined as the minimum amount of load shedding ($P_{S\,min}$). The training data set of input/output pairs are given as

$$\{\bar{p}, \bar{q}\} = \left\{ \left[P_G \quad P_L \quad \frac{df_1}{dt} \quad \frac{df_2}{dt} \right]^T, [P_{S\,min}] \right\} \tag{22}$$

According to the definition described above, load flow analyses with 17 different scenarios of generation and load conditions have been executed. For these study cases, the values of P_G and P_L are varied between 30~50MW and 50~70MW respectively. Transient stability analysis is then executed for external fault contingencies by controlling the df_1/dt between 0.2~3.9Hz/sec. The frequency decay rates after tie line tripping, df_2/dt are solved with values between 0.6~5.3Hz/sec by computer simulation. The combination of load flow scenarios and fault cases generates 99 input pairs as the training data set. The minimum amounts of load to be shed ($P_{S\,min}$) for these study cases are solved by transient stability analysis and represented as P_{sim} in Fig. 8. It is found that the minimum load shedding required to maintain the system stability for all scenarios will be varied between 0.2~25.4MW.

By taking the P_G, P_L, df_1/dt and df_2/dt as the values of neurons in the input layer and P_{sim} as the coressponding value of neuron in the output layer for ANN training process, various training algorithms are applied to solve the ANN model with the performance index of 10^{-6} as the mean square error. P_{ANN} in Fig. 8 represents the amount of load shedding solved by using the LMBP algorithm. Fig. 9 shows the error percentage of the ouput values after the ANN training is converaged. It is found that load shedding obtained by the proposed ANN methodology is very consistent to the values solved by the transient stability analysis. The maximum forecasting error is 0.23MW, which is about 0.33% and appears at the 58th data sequence. All the ouput error percentage will be limited to the range of ± 0.33%.

To achieve better convergence during training process, different ANN models have to be designed for different network structures. To compare the effectiveness of various training algorithms, ten different cases were executed for each training algorithm on a Pentium III PC and the average training time and epoch required are shown in Table I. It is found that the LMBP algorithm is most effective because of the smallest training time and the least epochs. Therefore, the LMBP algorithm is selected in the paper for the training of the cogeneration ANN based load shedding.

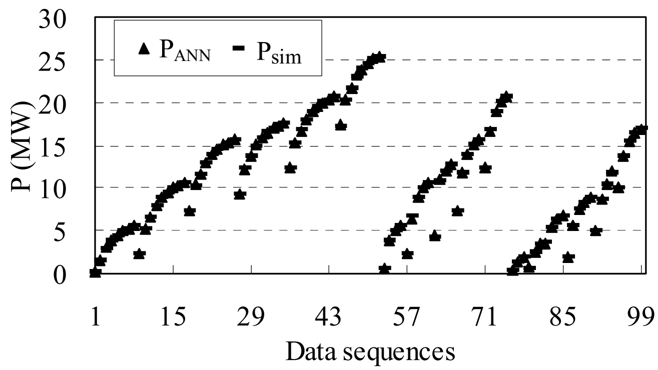

Fig. 8 Amount of load shedding by transient stability analysis and ANN model

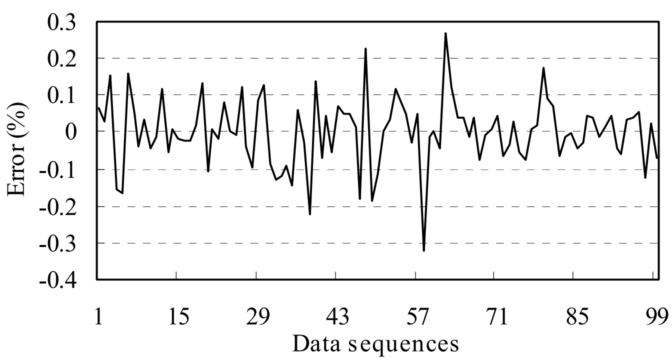

Fig. 9 Output error of the ANN training process for the cogeneration system

TABLE I. CONVERGENCE TIME AND EPOCHS FOR VARIOUS ANN TRAINING ALGORITHMS

Algorithms	Time (sec)	Epochs
LMBP	1.58	11
VLRBP	155.55	13777
RBP	11.95	1014
FRCGBP	9.53	381
PRCGBP	9.04	359
PBCGBP	8.19	309
SCGBP	6.82	307
QNBP	8.23	209

V. CONTINGENCY SIMULATION FOR COGENERATION SYSTEM

To demonstrate the effectiveness of the proposed methodology to determine the minimum load shedding, five study cases have been selected for the transient stability analysis to investigate the dynamic response of the isolated cogeneration system. The load shedding schemes by using the present method in the cogeneration system, traditional method and the proposed ANN based model with LMBP algorithm are considered in the transient stability analysis.

5.1 Case A

For the industrial system in the Fig. 3, an external fault is assumed to occur at 0.167 second with the frequency decay rate of 0.97Hz/sec. The under frequency relays are activated to trip circuit breakers GCB1 and GCB2 when the frequency drops to 58.4Hz at 1.83 second. The original power generation and load demand of the cogeneration facility are 35MW and 55MW respectively while the Taipower has provided 20.2MW electric power to the cogeneration facility before the fault occurs.

Fig. 10 shows the frequency response of the industrial power system and Fig. 11 illustrates the mechanical input power of cogeneration unit G3. According to the present load-shedding scheme, 23MW load will be tripped at the instant of tie line tripping. Due to the governor action, the mechanical input power increases from 25MW to 31.5MW. After the load has been tripped, the frequency of the isolated system reaches the maximum value of 60.44Hz and the mechanical input power of G3 has reduced to 21.7MW and then increased to 23.1MW after the frequency has been restored to 60Hz. By the traditional load shedding, step 1 is initiated at the same time as tie lines tripping to trip 10MW load. One step load shedding is enough to recover the system frequency. The mechanical input power of G3 is increased from 25MW to 36.5MW and then reduced to 31.8MW after the frequency has been restored to 60Hz. By the proposed ANN methodology, the minimum amount of load shedding is solved as 2.3MW with one step at the instant of tie line tripping. The frequency keeps declining and reaches the minimum value of 56.9Hz at 3.65 second. After that, the frequency begins to rise and reaches the maximum value of 60.6Hz at 8.17 second. The mechanical input power of G3 has been increased to the maximum value of 40MW at 6.15 second and then reduced to 37.5MW after the frequency has been restored to 60 Hz. It is also found that the system stability of the isolated cogeneration system can be obtained because the time duration for the frequency below 57Hz is less than one second.

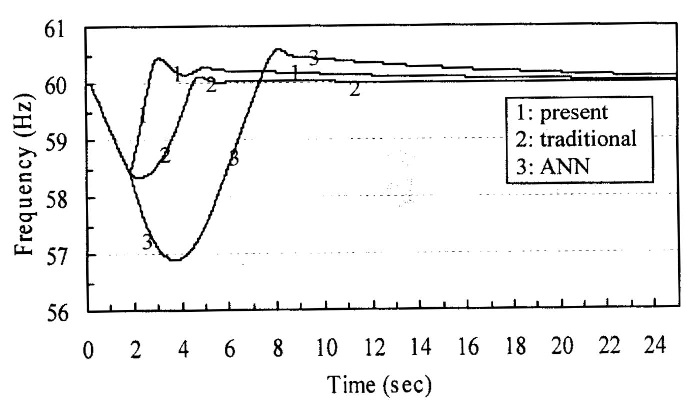

Fig. 10 Frequency response of cogeneration system for case A

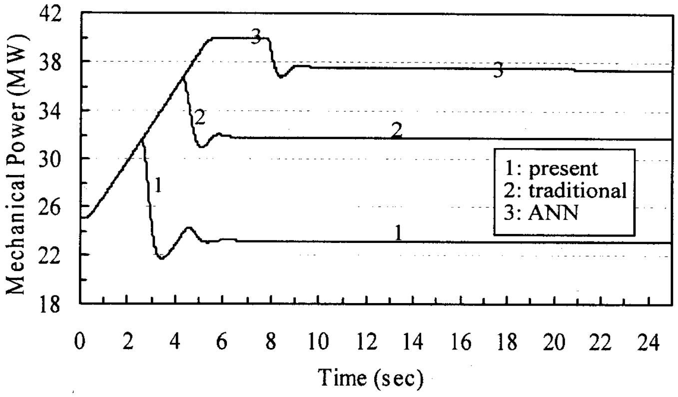

Fig. 11 Mechanical input power response of cogeneration unit G3 for case A

5.2 Case B

For the study case B, an external fault with the frequency decay rate of 2.1Hz/sec has resulted in the tripping of circuit breakers GCB1 and GCB2 at 0.95 second. Taipower has provided 40.2MW power to the cogeneration before the fault occurred while the initial in plant power generation and load demand are 30MW and 70MW respectively.

Fig. 12 shows the frequency response of the industrial power system and Fig. 13 illustrates the mechanical input power of cogeneration unit G3. The present load-shedding scheme will trip 40.2MW load at the instant of tie line tripping. Due to the governor action, the mechanical input power increases from 20MW to 25.7MW. After the load has been tripped, the frequency reaches the maximum value of 60.25Hz and the mechanical input power of G3 has reduced to 19.2MW and then increased to 20.2MW after the frequency has been restored to 60Hz. By the traditional load shedding, step 1 is initiated at the same time as tie lines tripping while step 2 and step 3 are executed at 1.08 and 1.42 second respectively. Three shedding steps with a total amount of 40MW load are required to recover the system frequency. After the load shedding, the frequency of the isolated system will reach the maximum value of 60.5Hz and the mechanical input power of G3 is reduced to 18.9MW at first and then increased to 20.2MW after the frequency has been restored to 60Hz. By the proposed ANN methodology, the minimum amount of load shedding is solved as 25.8MW. The frequency keeps declining and reaches the minimum value of 56.9Hz at 2.8 second. After that, the frequency begins to rise and reaches the maximum value of 60.7Hz at 6.58 second. The mechanical input power of G3 has been increased to 36.9MW at 6.1 second and then reduced to 29.5MW after the frequency has been restored to 60 Hz.

According to the computer simulation of the above two study cases, the present, traditional and proposed ANN load-shedding schemes have tripped 23MW, 10MW and 2.3MW loads respectively for case A. For study case B, 40.2MW, 40MW and 25.8MW loads have been shed for the present, traditional and proposed ANN load-shedding schemes respectively. It is found that excessive load shedding has been performed by the present and traditional shedding scheme, although better dynamic responses can be obtained. To better illustrate the effectiveness of the proposed neural oriented load shedding scheme, test cases C, D, and E are included in Table II, which give more simulation results for various load shedding schemes. According to these case studies to determine the proper load shedding with the ANN models proposed, it is concluded that the minimum amount of load to be disconnected can be determined very quickly and the transient stability of the isolated cogeneration system can therefore be maintained by minimizing the economic loss due to overload shedding.

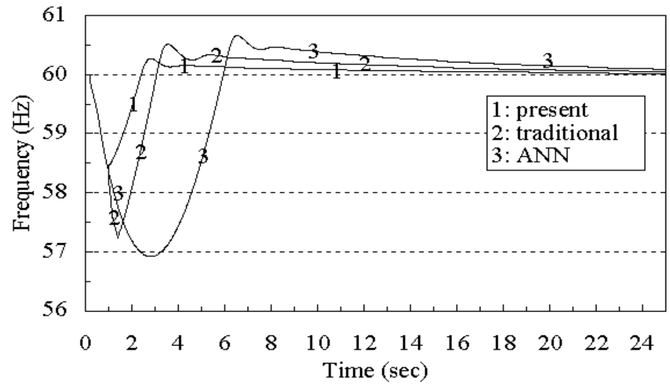

Fig. 12 Frequency response of cogeneration system for case B

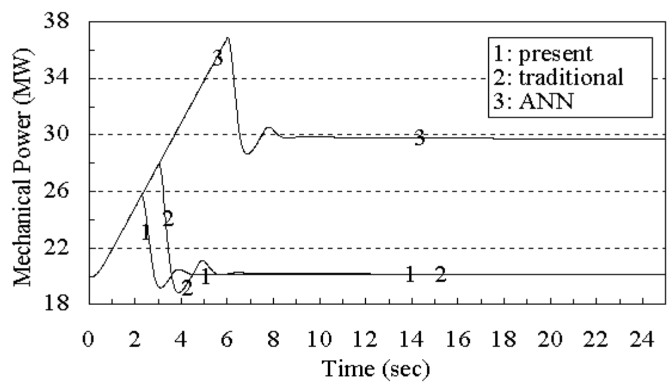

Fig. 13 Mechanical input power response of cogeneration unit G3 for case B

TABLE II. AMOUNT OF LOAD SHEDDING FOR VARIOUS TEST CASES AND PROTECTION SCHEMES

Test Cases	P_G (MW)	P_L (MW)	df_1/dt (Hz/s)	df_2/dt (Hz/s)	ANN (MW)	traditional (MW)	present (MW)
A	35	55	0.97	1.50	2.3	10	23.0
B	30	70	2.10	5.27	25.8	40	40.2
C	40	65	1.70	2.80	11.4	25	28.5
D	30	60	1.05	3.02	11.2	25	32.5
E	40	70	0.70	2.70	10.3	25	32.5

VI. CONCLUSIONS

This paper has developed an adaptive minimum load-shedding scheme by the ANN model for a cogeneration system. By executing the transient stability analysis for various operation scenarios of the industrial power system, the training data set of ANN model, which consists of total system power generation, total load demand, frequency decay rate and the minimum amount of load-shedding has been created. Various training algorithms have been applied and incorporated into the back-propagation learning process for the feed-forward neural networks. With the smallest training time and the least epochs, the LMBP algorithm is verified to be most effective and has been selected in the paper to derive the ANN model of minimum load shedding for the cogeneration facility.

To verify the effectiveness of the proposed ANN model for load shedding with system fault contingency, the present and the traditional load-shedding schemes are applied in the computer simulation to investigate the dynamic response of system frequency and mechanical input power of generators. It is found that the proposed ANN model requires only 2.3MW and 25.8MW load shedding for the study cases A and B, which implies that fewer loads will be affected by the fault contingency than the other two methods. It is concluded that the proposed ANN based methodology with LMBP algorithm can achieve more effective load shedding to maintain system stability and to prevent the excessive power outage of the cogeneration system.

VII. REFERENCES

[1] C. T. Hsu, C. S. Chen and J. K. Chen, “The Load-Shedding Scheme Design for an Integrated Steelmaking Cogeneration Facility”, IEEE Trans. on Industry Applications, vol. 33, no. 3, 1997, pp. 586-592.

[2] C. S. Pierre, “Microprocessor-Based Load Shedding Keeps Industrial Systems in Balance”, IEEE Computer Applications in Power, 1992, pp. 21-24.

[3] K. Methaprayoon, W. J. Lee, S. Rasmiddatta, J. R. Liao and R. J. Rose, “Multistage Artificial Neural Network Short-Term Load Forecasting Engine With Front-End Weather Forecast”, IEEE Trans. on Industry Applications, vol. 43, no. 6, Nov./Dec. 2007, pp.1410-1416.

[4] K. Methaprayoon, C. Yingvivatanapong, W. J. Lee and J. R. Liao, ”An Integration of ANN Wind Power Estimation Into Unit Commitment Considering the Forecasting Uncertainty”, IEEE Trans. on Industry Applications, vol. 43, no. 6, Nov./Dec. 2007, pp.1441-1448.

[5] H. C. Lin “Intelligent Neural Network-Based Fast Power System Harmonic Detection”, IEEE Trans. on Industrial Electronics, vol. 54, no. 1, Feb. 2007, pp. 43-52.

[6] G. V. Schoor, J. D. V. Wyk, and I. S. Shaw, “Optimal Control of a Hybrid Power Compensator Using an Artificial Neural Network Controller”, IEEE Trans. on Industry Applications, vol. 38, no. 2, 2002, pp. 467-475.

[7] E. J. Thalassinakis, E. N. Dialynas and D. Agoris, “Method Combining ANNs and Monte Carlo Simulation for the Selection of the Load Shedding Protection Strategies in Autonomous Power Systems”, IEEE Trans. on Power Systems, vol. 16, no. 4, Nov. 2006, pp. 1574-1582.

[8] M. T. Hagan and M. B. Menhaj, “Training Feedforward Networks with the Marquardt Algorithm”, IEEE Trans. on Neural Networks, vol. 5, no. 6, Nov. 1994, pp. 989-993.

[9] H. B. Demuth and M. H. Beale, Neural Network Toolbox User’s Guide, The MathWorks Inc., 5th Printing, Version 3, 1998.

[10] M. T. Hagan, H. B. Demuth and M. H. Beale, Neural Network Design, Boston, MA: PWS Publishing, 1996.

[11] M. Riedmiller and H. Braun, “A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm”, Proceedings of the IEEE International Conference on Neural Networks, 1993.

[12] R. Fletcher and C. M. Reeves, “Function Minimization by Conjugate Gradients”, Computer Journal, vol. 7, 1964, pp.149-154.

[13] M. J. D. Powell, “Restart Procedures for the Conjugate Gradient Method”, Mathematical Programming, vol. 12, 1977, pp. 241-254.

[14] M. F. Moller, “A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning”, IEEE Trans. on Neural Networks, vol. 6, 1993, pp. 525-533.

[15] J. E. Dennis and R. B. Schnabel, Numerical Methods for Unconstrained Optimization and Nonlinear Equations, Englewood Cliffs, NJ: Prentice-Hall, 1983.

[16] P. M. Anderson and A. A. Fouad, Power System Control and Stability, New York: IEEE Press, 1993.

[17] IEEE Recommended Practice for Excitation System Models for Power System Stability Studies, IEEE Standard 421.5, 1992.

[18] IEEE Working Group Report, "Hydraulic Turbine and Turbine Control Models for System Dynamic Studies", IEEE Trans. on Power Systems, vol. 7, 1992, pp.167-179.

VIII. BIOGRAPHIES

Cheng-Ting Hsu (M’98) was born in Taiwan in 1963. He received the B.S., M.S, and Ph.D. degrees in electrical engineering from the National Sun Yat-Sen University, Taiwan in 1986, 1988, and 1995, respectively.

From 1990 to 1992, he was with Phoenixtec Power Company Limited as a power electronics engineer, developing UPS equipment. He is currently a Professor of Electrical Engineering, Southern Taiwan University of Technology, Tainan, Taiwan. His research interests include the cogeneration system design, distributed generation, power quality, and stability analysis.

Hui-Jen Chuang (S’99- M’02) received the B.S. and M.S. degree in Electrical Engineering from National Taiwan University of Science and Technology in 1990 and 1992 respectively, and Ph. D. degree in Electrical Engineering from National Sun Yat-Sen University in 2002.

He is presently an Associate Professor at Kao Yuan University, Lu Chu, Taiwan. His research interest is in the area of load flow and power system analysis of mass rapid system.

Chao-Shun Chen (SM’07) received the B.S. degree from National Taiwan University, Taiwan, Taiwan, R.O.C., in 1976 and the M.S. and Ph.D. degrees from the University of Texas at Arlington in 1981 and 1984, respectively, all in electrical engineering.

From 1984 to 1994, he was with National Sun Yat-Sen University as a professor. From 1993 to 1997, he was with the Kaohsiung Mass Rapid Transit Department as the Deputy Director to be in charge of electrical and mechanical system planning. He is currently a full professor with the Electrical Engineering Department at the I-Shou University and a joint professor at National Sun Yat-Sen University, both in Kaohsiung, Taiwan. His research interests include the distribution automation, cogeneration systems, electrical, and mechanical system of mass rapid transit networks. Dr. Chen is a registered professional engineer in Taiwan.

APPENDIX

PARAMETERS OF THE COGENERATION UNITS

Gen.	kV	MVA	H	X_d	X_q	X_l	X'_d	X'_q	τ'_{do}	τ'_{q0}	X''_d	X''_q	τ''_{do}	τ''_{qo}	$S_{G1.2}$	$S_{G1.0}$
G1	3.45	12.5	3.00	2.12	1.50	.134	0.46	.715	1.25	1.5	0.20	.120	0.06	0.21	0.886	0.279
G2	4.16	12.5	3.00	1.72	1.60	.134	0.16	.715	4.20	1.5	0.10	.120	0.06	0.21	0.886	0.279
G3	13.8	50	2.10	1.98	1.75	.108	0.21	.850	5.89	1.5	0.16	.116	0.04	0.01	0.724	0.207

PARAMETERS OF THE EXCITATION SYSTEMS

Gen.	T_R	T_A	K_A	K_F	T_F	K_E	T_E	T_I	K_P	V_{Imax}	V_{Imin}	LIM_{max}	LIM_{min}	V_{Rmax}	V_{Rmin}	SE_{max}	$SE_{.75}$
G1, G2	0.0	0.02	35	0.1	0.35	1.0	0.39	-	-	-	-	-	-	7.2	-5.1	0.48	0.12
G3	0.005	0.02	2	2	0.23	2.0	0.75	2.5	20	10	-10	4	-1	12	-12	0.68	0.65

PARAMETERS OF THE GOVERNOR SYSTEMS

Gen.	R	T_1	K_1	P_{max}	P_{min}	P_{up}	P_{down}	T_{ch}
G1, G2	0.05	0.15	-	0.76	0.0	0.03	-0.03	0.3
G3	0.05	0.01	2	0.80	0.0	0.06	-1.0	0.2