Real-Time Closed Loop system controlled by an Artificial Neural Network for Estimation of the Optimal Load Shedding

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Abstract

Electrical Power Systems (EPS) are constantly exposed to various disturbances that can significantly affect their operation. Hence, the load shedding philosophy was proposed in order to relieve the overloaded infrastructure in cases of imbalances between generation and demand. However, conventional methods of shedding are slow and inaccurate. In this context, where shedding processes must be optimized, there is a need to pursue new methods and technologies to provide fast and optimized management. Therefore, this paper proposes an Artificial Neural Network (ANN) to estimate the minimum amount of load to be shed in order to recover load-generation balance. The ANN training and testing data were extracted from an EPS simulated using a Real Time Digital Simulator (RTDS). The best ANN topology, selected through cross-validation technique, was able to estimate the load shedding quantity with high precision. The system was then configured to work in a real-time closed loop so that the efficiency of the ANN was tested. The results demonstrate a good generalization over the presented overload situations. As a contribution, this work presents the dynamic of a load shedding scheme controlled by an ANN in real-time closed loop system performed only in one step offering a fast and effective alternative for restoring the frequency close to its nominal value.

1 Introduction

Over the last few years, large blackouts have occurred around the world as stated in the literature [1, 2, 3]. Overload lines, voltage instability, incorrectly dimensioned protection systems and non-functional load shedding schemes are the main reasons that led to the final stage of system failure, bringing directly or indirectly harmful consequences to the economy and security in the affected area [4, 5].

Therefore, appropriate control, capable of preventing catastrophic conditions such as overload situations, is vital to the operation of the EPS. One of the main underfrequency protection schemes is the load shedding process recommended since the 1965 blackout in the northeast of the United States [6] by providing low cost resources to prevent unwanted interruptions and shutdowns.

Since the frequency is an important indicator of alignment between load and generation, any deviation in its value due to excessive loads or unforeseen incidents, such as faults, equipment defects, generation and lines losses, etc. can lead to a state of emergency [7]. The effects of a drop in frequency can result in cascading failures, causing loss of synchronization and finally the general collapse of the system.

Assuming the existence of spinning reserve, speed regulators can respond quickly to maintain the frequency close to its nominal value, otherwise the load shedding strategy should be adopted [8, 7, 9]. The most appropriate scheme is the one that rejects the fewest number of loads in less time, considering the EPS constraints [10].

A dynamic analysis of an electrical network after a disturbance is a very demanding task [8]. Accordingly, several studies have been proposed to restore the frequency of systems subject to severe situations. Intelligent system techniques have demonstrated a better performance compared to the conventional ones [11]. Some studies have utilized ANN [8, 9, 12, 10], Fuzzy Systems [13], Evolutionary Algorithms [14, 15], among others [16, 17].

Thereby, this paper proposes a system with the ability to quantify the power deficit between power generation and demand and, consequently, show the amount of load to be removed from the system. In order to achieve this, an ANN applied to a Hardware-In-Loop (HIL) system was developed, promoting an effective control and testing platform. Therefore, the task of supervising the EPS is carried out, ensuring better efficiency in decision making schemes of shedding. Furthermore, the load block was handled in one step, bringing significant advantages to current processes which generally rely on multiple steps to obtain frequency balance.

Section 2 of this paper presents the conventional load shedding philosophies listed in the literature. The methodology used to develop this work is presented in Section 3. The results obtained are shown in Section 4, as well as a brief conclusion in Section 5.

2 Load Shedding Philosophy

The load shedding process aims to maintain the frequency stability margin of the EPS close to its nominal level, ultimately avoiding the general collapse of the system [18]. It also prevents an undesired disconnection of important branches, due to overloads, which have social, economic or political relevance. The load shedding needs to be performed when the electricity demand is greater than the supply. This involves cutting the power supply to some electrical circuits, thereby reducing the stress on the system. This cut should be made optimally considering the appropriate priorities and pertinence between loads. The aim is to prevent the decay of frequency and voltage while maintaining the balance between generation and demand.

Classical methods for frequency control are based on parameters such as:

- The instantaneous frequency of the system, typically set at steps in underfrequency relays;
- The rate of change of frequency $\frac{df}{dt}$, measuring the rate of change of imbalance; and
- The average rate of frequency change $\frac{\Delta f}{\Delta t}$, measuring the variation tendency.

All parameters generally used have advantages and/or disadvantages in their use and, therefore, have to be mutually analysed to obtain better results [19].

Typically, each country sets the appropriate philosophy for each of its regions monitoring the amount of load available for cutting and the requirements of the adequacy of existing schemes [20]. In Brazil, for example, in the South-East and South areas, the instantaneous frequency scheme predominates. The Table 1 specifies the frequency steps for cutting and the percentage of load to be rejected at each step.

	South-East		South	
Step	Setting (Hz)	Load Shedding (%)	Setting (%)	Load Shedding (%)
1^{st}	58.5	7.0	58.5	7.5
2^{nd}	58.2	7.0	58.2	7.5
3^{rd}	57.9	7.0	57.9	10.0
4^{th}	57.7	7.0	57.6	15.0
5^{th}	57.5	7.0	57.3	15.0

Source: [20]

Table 1: Load Shedding schemes in the South and South-East areas of Brazil

For the correct application of the load shedding scheme, continuous monitoring of the frequency should be performed in power substations in order to avoid a general collapse in transmission and distribution grids.

3 Methodology Used

As stated, a system was developed to estimate the minimum amount of load to be shed in order to recover load-generation balance. As an alternative to usual procedures, which usually use multiple cutting steps, an ANN was trained so that only one block was dealt with in one step. Moreover, the ANN was included in an HIL system in order to check its suitability in real dynamic electrical systems.

The simulated EPS used for data gathering for supply ANN training and validation stages is shown in Figure 1. The circuit is an equivalent system in which a power generator of 100 MVA is controlled by a voltage and speed regulator responsible for determining the equilibrium point. The total load is connected via a double circuit transmission line TL1–TL2, representing 80% of the maximum rated load of the generator and distributed in 5 feeders (Bus-3), represented in the high voltage, as shown in Table 2.

Each feeder from 1 to 4 represents a discrete control point for removing a load block. Each load block has a priority that represents their level of importance on the system. The shedding must take into account the priority level of the loads and reject the blocks with lower priority first (corresponding to higher values in the table). As to feeder 5, an auxiliary point was created to set overload conditions. For each case study, the variable power consumption at feeder 5 is set to simulate the entry of large demand blocks and the exceeding request of generation, as shown in Table 3. The power factor of 0.92 was chosen.

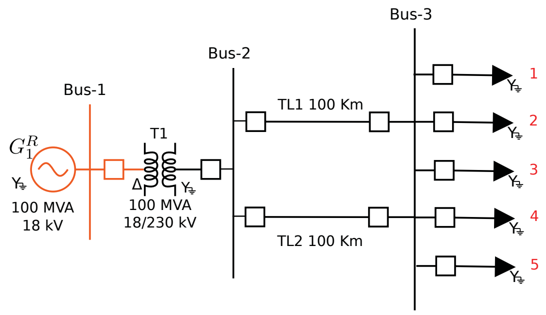

Fig. 1: Electrical system simulated

To better represent the dependence of the frequency of each load block, the exponential model was chosen to simulate the dependence of voltage and frequency of the connected load. Equations 1 and 2 relate the magnitudes of active and reactive power consumed.

$$P = P_0 \left(\frac{V}{V_0}\right)^{K_{pv}} [1.0 + K_{pf}\,(f - f_0)] \quad (1)$$

$$Q = Q_0 \left(\frac{V}{V_0}\right)^{K_{qv}} [1.0 + K_{qf}\,(f - f_0)] \quad (2)$$

where: $K_{pv} = 0.1$ and $K_{qv} = 0.1$ are the parameters of voltage sensitivity for active and reactive power, respectively. $K_{pf} = 1.0$ and $K_{qf} = 1.0$ are the sensitivity parameters of frequency for active and reactive power. $V_0 = 230$ kV and V are the rated and instantaneous voltages at Bus-3, respectively. $f_0 = 60$ Hz and f are the rated and instantaneous frequency at Bus-3, respectively. Finally, the initial active and reactive power depends on Bus-3 loading, but for the initial configuration (80% of total capacity) they are $P_0 = 73.60$ MW and $Q_0 = 31.35$ MVAr.

Feeder	Consumption (%)	Power (MVA)	Power (MW)	Power (MVAr)	Priority
1	8.0	8.0	7.36	3.14	3
2	16.0	16.0	14.72	6.27	2
3	24.0	24.0	22.08	9.41	1
4	32.0	32.0	29.44	12.54	4
5	–	–	–	–	–

Table 2: Load distribution in the feeders

Overload (%)	Overload (MVA)	Overload (MW)	Overload (MVAr)
5	5.0	4.6	1.96
10	10.0	9.2	3.92
15	15.0	13.8	5.88
20	20.0	18.4	7.84
25	25.0	23.0	9.80
30	30.0	27.6	11.76
35	35.0	32.2	13.72
40	40.0	36.8	15.68
45	45.0	41.4	17.64
50	50.0	46.0	19.60

Table 3: Overload at feeder 5

The simulation of the electrical system was performed via RTDS which is a digital test system in real-time to simulate electromagnetic transient phenomena in power systems. The hardware architecture is based on parallel processing of multiple digital signal processors, allowing the representation of large power schemes without affecting the simulation time step [21]. The RTDS was used to collect data to supply ANN training and validation stages, accurately representing the dynamic behavior of the system. Additionally, its hardware provides multiple input and output interfaces to conduct closed loop testing of physical devices, such as protection and control equipment.

3.1 ANN Training

For the development of a new load shedding heuristic, an ANN was built using the frequency of an EPS. The ANN infers the amount of electrical power (load) to be shed in order to return the frequency close to its nominal value. The ANN is a MultiLayer Perceptron (MLP) using the backpropagation algorithm. The Open Source library FANN was used. This library provides a framework in C language to facilitate the creation, training and validation of multilayer ANNs [22].

The choice of the best ANN topology was based on the cross-validation method to obtain the best generalization point. Figure 2 represents the model used in which the input and output patterns are formed from the normalized data obtained from the simulation. The mass of data is then separated and 75% of the cases are used for the training set, while the 25% remaining are reserved for the validation phase. One hidden layers was fixed and the number of its neurons was varied in each cycle as long as the Mean Square Error (MSE) value does not reached the minimum determined value. To define the number of neurons in the hidden layer, 50 tests were performed varying from 1 to 50 neurons, and the ANN with the lowest MSE for the training set was chosen.

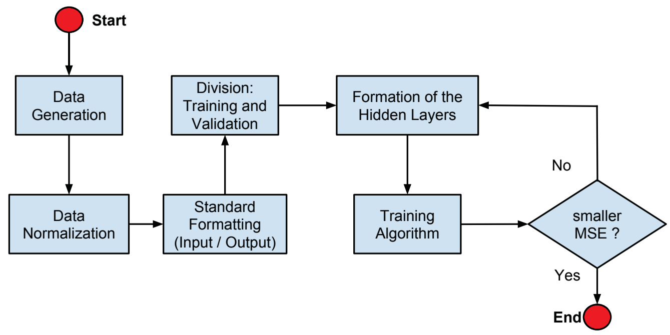

Fig. 2: Flowchart for choosing the best topology for the cross-validation method

Initially, the implementation receives the input values of the application and normalizes them between the values -1 and 1. Afterwards, the training starts using the backpropagation algorithm. The activation function processes the received set of inputs and transforms it into a state of activation, limiting the final output value. The activation function used for the hidden and output layer was the hyperbolic tangent.

The data were organized into patterns with 2 inputs (representing the instantaneous and the average rate of change of the system frequency, respectively) and a single output (representing the amount of load to be shed according to the active power deficit of the system). The weights were randomly generated as defined by the layers of ANN. For the learning process, the application required a learning rate of 0.01. The *momentum*, which accelerates the convergence of the ANN, was set to 0.1. The desired error was set to 10^{-4}, and the maximum number of epochs, if the network does not converge, was 100,000. After convergence, the matrix of fixed weights is stored for its subsequent use in the validation phase.

3.2 Real-Time Closed Loop

The neural network was embedded in a real-time platform consisting of specific software and hardware. The operating system chosen was the Real-Time Application Interface (RTAI) [23] which is an extension of Linux Kernel that lets users write applications with strict timing constraints for Linux. A hardware platform, consisting of a PC104 [24], capable of performing control and supervision algorithms with low latency was set as a validation base in closed loop. The PC104 is intended for applications of embedded computing where it depends on a reliable data acquisition in extreme environments.

Thereby, the impact of the performance of the ANN on the electrical system can be observed in real time. Figure 3 illustrates the schematic simulation in closed loop. The RTDS, which simulates the electrical circuit of Figure 1, sends electrical signals of $\pm 10\ V$ to its analogic outputs, representing the voltage for each phase of Bus-3. The ANN, embedded in the PC104 platform, analyzes the behavior of the voltage curves, by calculating the instantaneous frequency and its average rate of change. If the behavior of frequency is distorted, indicating a possible overload situation, the digital signals for opening the breakers should be sent back to RTDS.

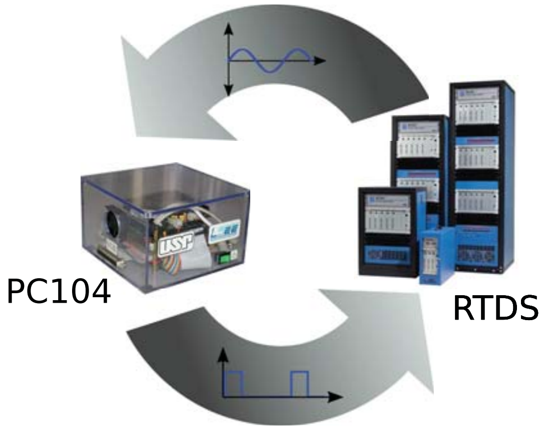

Fig. 3: Illustration of the testing scheme in closed loop
Adapted from [25]

Accordingly, the electrical system simulation were done in real-time closed loop, that is, the data collected from the EPS was fed to ANN inputs which process them and estimate the amount of load to be shed. The ANN output was fed back to RTDS which disconnects the load blocks according to their priority order.

4 Analysis of the Results

The simulation cases of overloading described in Table 3 were performed in the system of Figure 1, incrementing the power consumption in 5% steps of the initial generator capacity.

The behavior of the frequency variation can be observed in Figure 4. For the sake of clarity, and without loss of generality, only 7 curves are shown in this graph (from a total of 11 cases). The system can recover from overloads of up to 25%, keeping the frequency close to its nominal value. In these cases, no corrective action should be done, providing selectivity to the system.

For the cases above 30%, the same is not true. The system does not have enough spinning reserve to meet the excess demand and, as a result, the frequency tends to stabilize at new levels below the nominal value. In cases of extreme overload, the system as a whole collapses.

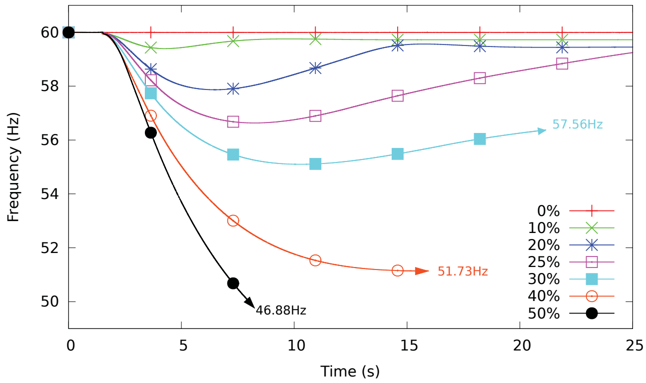

Fig. 4: Subfrequency curves

The dataset generated by the simulation had a very small integration step. In most cases, the transitions between samples did not represent significant variations. Therefore, it was decided to re-sample the generated signal. In order to achieve this, the time corresponding to a variation of 0.1 Hz for the first frequency decay curve for the 50% overload case was adopted. Thus, the interval between samples for all cases was 26 ms.

After applying the cross validation method, the configuration shown in Figure 5 was obtained, using 2 inputs, 11 neurons in the hidden layer and 1 neuron in the output layer.

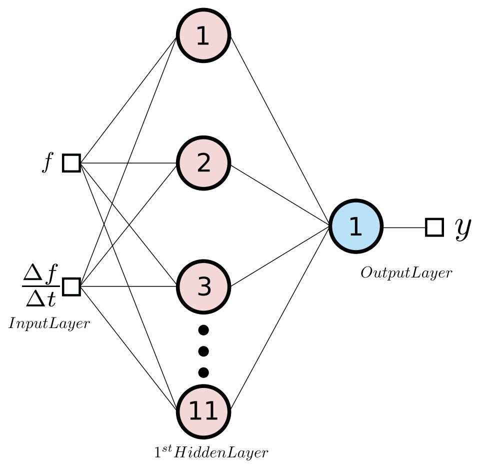

Fig. 5: Best ANN topology

For the validation set, the Figure 6 shows that almost all of the absolute errors are very close to the zero value with few exceptions, concentrated mostly on minor deviations less than 2.76. The absolute mean error presented was 9×10^{-05}.

As for the test set, representing the 45% overload case, two load blocks are required for relief of the system, as shown by Figure 7. As seen in Tables 2 e 3, for shedding 41.4 MW it is necessary to cut two blocks of lower priorities: the 29.44 MW block (priority 4) and the 7.36 MW block (priority 3). After the shedding, with the ANN response, the frequency was stabilized close to 60 Hz.

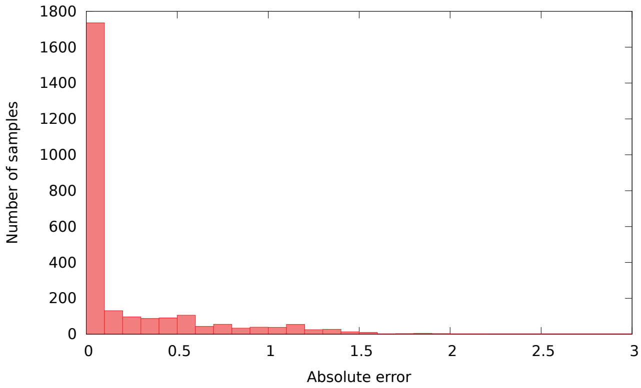

Fig. 6: Bar Chart of errors

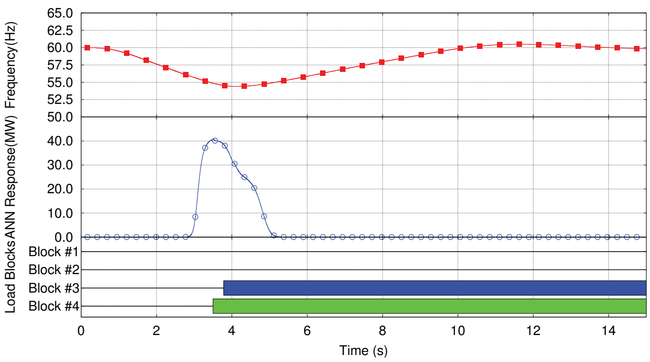

Fig. 7: Closed-Loop response for the 45% overload case

Figure 8 shows the dynamic ANN response to the 45% overload case. It can be verified that, from the expected value (32.2 MW), the error margin defines a precision envelope of 5% of the expected value. From the foregoing, the good behavior of the solution is verified, showing its applicability across the system dynamics.

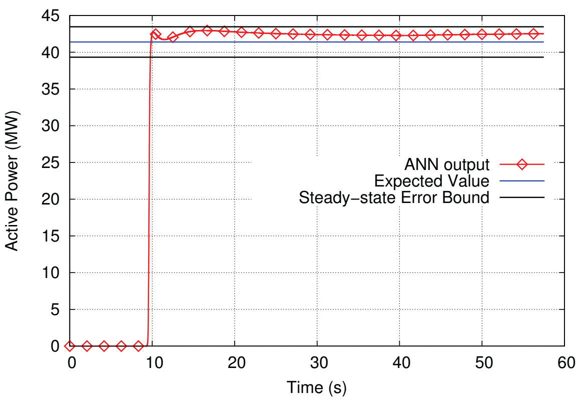

Fig. 8: ANN dynamic response for the 45% overload case

5 Conclusions

The overloading phenomena results in considerable damage both for the utilities and their customers that range from residential to large corporations. Load shedding procedures should be performed in order to preserve the overall balance of the system, ultimately avoiding its collapse. Thus, it is plausible to disconnect a minimum amount of load blocks to maintain the level of frequency around its nominal value.

With this in mind, this work proposes the use of an ANN to calculate the optimal amount of load to be shed aiming to assist the process of maintaining balance in the EPS. The best topology chosen was obtained by the cross-validation statistical tool applied to the measures of frequency and its average rate of change obtained from the simulation of an equivalent electrical circuit modeled via RTDS equipment. The same EPS was simulated in a real-time HIL test to verify the adequacy of the proposed ANN, according to the real dynamics of the electrical system.

The results demonstrate the approximation capability of ANN in load shedding schemes. Therefore the applicability of the developed system has shown to be promising and appropriate. The shedding is performed only in one step offering a fast and effective alternative for restoring frequency, unlike the usual schemes that use up to 5 stages for its restoration. As a contribution, this work presents the dynamic of a load shedding scheme controlled by an ANN in a real-time closed loop system.

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References

[1] G. Andersson, P. Donalek, R. Farmer, N. Hatziargyriou, I. Kamwa, P. Kundur, N. Martins, J. Paserba, P. Pourbeik, J. Sanchez-Gasca, R. Schulz, A. Stankovic, C. Taylor, and V. Vittal, "Causes of the 2003 major grid blackouts in North America and Europe, and recommended means to improve system dynamic performance," *Power Systems, IEEE Transactions on*, vol. 20, no. 4, pp. 1922 – 1928, Nov. 2005.

[2] S. Corsi and C. Sabelli, "General blackout in Italy Sunday September 28, 2003, h. 03:28:00," in *Power Engineering Society General Meeting, 2004. IEEE*, June 2004, pp. 1691 –1702 Vol.2.

[3] X. Chen, C. Deng, Y. Chen, and C. Li, "Blackout prevention: Anatomy of the blackout in Europe," in *Power*

Engineering Conference, 2007. IPEC 2007. International, Dec. 2007, pp. 928 –932.

[4] H. Seyedi and M. Sanaye-Pasand, "New centralised adaptive load-shedding algorithms to mitigate power system blackouts," *Generation, Transmission Distribution, IET*, vol. 3, no. 1, pp. 99 –114, January 2009.

[5] K. Yamashita, J. Li, P. Zhang, and C.-C. Liu, "Analysis and control of major blackout events," in *Power Systems Conference and Exposition, 2009. PSCE '09. IEEE/PES*, March 2009, pp. 1 –4.

[6] C. Taylor, "Concepts of undervoltage load shedding for voltage stability," *Power Delivery, IEEE Transactions on*, vol. 7, no. 2, pp. 480 –488, Apr 1992.

[7] B. Rad and M. Abedi, "An optimal load-shedding scheme during contingency situations using meta-heuristics algorithms with application of AHP method," in *11th International Conference on Optimization of Electrical and Electronic Equipment, 2008. OPTIM 2008.*, 2008, pp. 167–173.

[8] M. Mitchell, J. Peas Lopes, J. N. Fidalgo, and J. McCalley, "Using a neural network to predict the dynamic frequency response of a power system to an under-frequency load shedding scenario," in *Power Engineering Society Summer Meeting, 2000. IEEE*, vol. 1, 2000, pp. 346–351 vol. 1.

[9] E. Thalassinakis, E. Dialynas, and D. Agoris, "Method Combining ANNs and Monte Carlo Simulation for the Selection of the Load Shedding Protection Strategies in Autonomous Power Systems," *Power Systems, IEEE Transactions on*, vol. 21, no. 4, pp. 1574–1582, 2006.

[10] R. Hooshmand and M. Moazzami, "Optimal design of adaptive under frequency load shedding using artificial neural networks in isolated power system," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 220 – 228, 2012.

[11] C. Concordia, L. Fink, and G. Poullikkas, "Load shedding on an isolated system," *IEEE Transactions on Power Systems*, vol. 10, no. 3, pp. 1467–1472, 1995.

[12] C.-T. Hsu, H.-J. Chuang, and C.-S. Chen, "Artificial neural network based adaptive load shedding for an industrial cogeneration facility," in *IEEE Industry Applications Society Annual Meeting, 2008. IAS '08.*, Oct. 2008, pp. 1 –8.

[13] A. Sallam and A. Khafaga, "Fuzzy expert system using load shedding for voltage instability control," in *Conference on Power Engineering 2002 Large Engineering Systems, LESCOPE 02*, 2002, pp. 125 – 132.

[14] T. Amraee, A. Ranjbar, B. Mozafari, and N. Sadati, "An enhanced under-voltage load-shedding scheme to provide voltage stability," *Electric Power Systems Research*, vol. 77, no. 8, pp. 1038 – 1046, 2007.

[15] T. Amraee, B. Mozafari, and A. Ranjbar, "An improved model for optimal under voltage load shedding: particle swarm approach," in *IEEE Power India Conference, 2006*, 2006, p. 6.

[16] F. Shokooh, J. Dai, S. Shokooh, J. Taster, H. Castro, T. Khandelwal, and G. Donner, "An intelligent load shedding (ILS) system application in a large industrial facility," in *Industry Applications Conference, 2005. Fourtieth IAS Annual Meeting. Conference Record of the 2005*, vol. 1, oct. 2005, pp. 417 – 425 Vol. 1.

[17] M. Parniani and A. Nasri, "Scada based under frequency load shedding integrated with rate of frequency decline," in *Power Engineering Society General Meeting, 2006. IEEE*, 0-0 2006, p. 6 pp.

[18] W. Pimjaipong, T. Junrussameevilai, and N. Maneerat, "Blackout prevention plan; the stability, reliability and security enhancement in thailand power grid," in *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, 2005, pp. 1 –6.

[19] P. Committee, "IEEE Guide for the Application of Protective Relays Used for Abnormal Frequency Load Shedding and Restoration," *IEEE Std C37.117-2007*, pp. c1 –43, 24 2007.

[20] ONS, "Monitoring of the regional load shedding scheme - Brazil," vol. 104, no. RE-3/101/2005, p. 21, 12 2004.

[21] R. Kuffel, J. Giesbrecht, T. Maguire, R. Wierckx, and P. McLaren, "RTDS-a fully digital power system simulator operating in real time," in *WESCANEX 95. Communications, Power, and Computing. Conference Proceedings. IEEE*, vol. 2, May 1995, pp. 300 –305 vol.2.

[22] S. Nissen, "Implementation of a Fast Artificial Neural Network Library (FANN)," Department of Computer Science University of Copenhagen (DIKU), Tech. Rep., 2003, http://fann.sf.net.

[23] RTAI, "Realtime application interface for linux from diapm," Available in: <https://www.rtai.org/>. January the 15th 2014., January 2014.

[24] PC104 Consortium, "PC104 Embedded Consortium," Available in: <http://www.pc104.org>. January the 15th 2014., January 2014.

[25] R. M. Monaro, "Fuzzy logic applied in synchronous generators digital protection improvement," Ph.D. dissertation, São Carlos School of Engineering, University of São Paulo (Brazil), 2013.