Energy Constrained Generation Dispatch based on Price Forecasts Including Expected Values and Risk

Damien. C. Sansom, *Student Member*, and Tapan. K .Saha, Senior *Member*, *IEEE*

Abstract—**A number of price forecasting methods are used to forecast wholesale (spot) electricity prices. The forecasts are evaluated for both accuracy and variation in accuracy (risk). These forecasts are used to balance revenue against forecasting error risk in dispatching constrained generation. The best dispatch method found was based on the half-hours with the maximum demand.**

Index Terms—Electricity market, spot or pool price forecasting

I. Introduction

In Electricity Supply Industry (ESI) the generator companies, independent system operators (ISO), distributors and customers all make organizational decisions that include balancing return against risk. Decision makers benefit from estimations of risk and returns contributions of different factors.

This paper investigates dispatching of energy constrained generation to obtain maximum revenue. In the first group of simulations, only the expected price of the price forecast is used to determine the half-hours of generation. In the second set of simulations, the expected price and variation of the forecasts are considered.

II. Price Forecasts

A. Forecasting Data and Dates

All price forecasting models were trained with 28 days of data and tested by forecasting the next seven days of New South Wales (NSW) regional electricity price. The results were obtained by testing over 25 weeks of data from the 12th of February to the 30th of July 2002. All data was obtained from the National Electricity Market Management Company's (NEMMCO) web site (http://www.nemmco.com.au) [1]. The Australian National Electricity Market (NEM) is a regional (state) pool based open auction style electricity market [2]. The wholesale (spot) pool price of electricity is the same for all market participants. The NEM market user limited locational nodal pricing with only 5 pricing nodes, the five regions.

Note all forecasts are SEVEN days ahead, which are 336 half-hour time steps. The accuracy of the forecasts increases when forecasting 24 hours ahead and especially one half-hour (one time step) into the future. For dispatch planning, it requires a minimum of 48 hours and we found little accuracy difference between forecasting two days or seven days into the future.

The 25 weeks of testing data was divided into two sets. One set, the first 14 weeks for evaluating the accuracy of the forecasts and another set the last 11 weeks (15 to 25) for calculating the revenue of the dispatching methods. Table I displays the inputs presented to the neural network and Support vector Machine price forecasting methods.

TABLE I
IN PUTS TO THE NEURAL NETWORK AND SUPPORT VECTOR MACHINE MODELS

	Inputs to NN & SVM		
Input	Input Name	Half-hour delay. t=0 NOW	Comment
Target	spot price	t=-336	Cents/MW
1	spot price	t=3	1 hour
2	daily half-hour	t=-336	
3	weekly half-hour	t= -336	
4	capacity required	N/a	PASA File at delay t=2 Data read at time delay t=-336
5	reserve required	N/a	
6	reserve surplus	N/a	
7	PASA demand 10%	N/a	
8	PASA demand 50%	N/a	
9	PASA demand 90%	N/a	
10	spot price	48	1 day
11	spot price	96	2 days
12	spot price	144	3 days
13	spot price	336	1 week
14	spot price	672	2 weeks

B. Summary of Price Forecasting Methods

1) Same as Last Week

A very simple forecasting method is to assume that the electricity price this week is the same as last week.

2) Linear regression as sum of sine waves

Linear regression models have been used to forecast loads for many years. The load pattern is modeled by the addition of

The authors are with the School of Information Technology and Electrical Engineering (ITEE) at the University of Queensland (UQ), Australia, D. C. Sansom e-mail: sansom@itee.uq.edu.au T. K. Saha, e-mail: saha@itee.uq.edu.au

a number of sine waves of different frequencies and amplitudes. Visualize that the load pattern is modeled by overlapping a number of sine waves over the load pattern. Sine waves are used with different frequencies and amplitudes. The form of the function is always a sine wave so that the sine wave is called the kernel function. The amplitude and frequency are the parameters of this kernel function (1). The amplitude and frequency are the parameters that are trained (adjusted) through a linear regression algorithm to fit the data with a minimum of error.

$$\text{kernel function } \mathrm{K}(A,\omega) = A\sin(\omega t)$$
$$\text{model } \mathrm{F(t)} = \sum_{\text{all kernals n}} A_n \sin(\omega_n t) \tag{1}$$

We have found that linear regression of sine waves is far less accurate than taking a simple average. The load is more suitable for linear regression [3] as the load pattern follows clear cycles. In the FFT of the demand Fig. 1 the 7 day, 1 day, 0.5 day (12 hour) and 0.33 day (4 hour) cycles can be clearly identified. In the FFT of the price (Fig. 2) only a daily cycle is clear and this indicates correctly that the electricity price pattern is unsuitable for linear regression modeling.

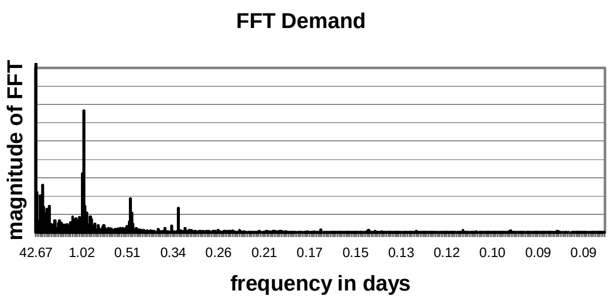

Fig. 1. Fast Fourier Transform of 2048 half-hours (~43 days) of electricity demand.

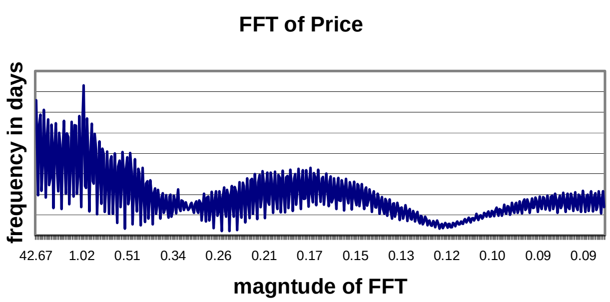

Fig. 2. Fast Fourier Transform of 2048 half-hours (~43 days) of electricity price.

3) Neural Network

A neural network is designed to model a set of data by the sum of non-linear threshold kernel functions (2). This conceptual simple method of reconstructing the data with on/off threshold functions has been found to be a powerful method in many problems in electrical engineering. Most directly relevant to this research is the use of neural networks in load forecasting [4] and price forecasting [5].

In neural networks the parameters are the weights [6]. These weights are trained by an algorithm that adjusts the weights so that the mean squared error between the network output F(x) and the target electricity price is minimized over all input vectors x in the training data [7]. The neural network used for price forecasting in this research was trained using the error back-propagation algorithm.

$$\text{inputs } \tilde{x} \quad \text{weights } W_n$$
$$\text{kernel (neuron) function } \mathrm{K}(\tilde{x}) = \tan sig(w.\tilde{x}) \tag{2}$$
$$\text{model } \mathrm{F}(\tilde{x}) = \sum_{\text{all kernals n}} W_n K(\tilde{x})$$

4) Support Vector Machines

Support Vector Machines (SVM) enables the user to select from a wider range of kernel functions than neural networks. SVMs have been applied to similar problems as neural networks including forecasting in financial problems [8], [9]. The SVM models were trained and simulated using the "mySVM" program [10]. In this research, the price forecasts were done using radial bases functions (circular hills) (3). The radial bases function was found to be the most suitable of a number of kernel functions tested on Australian electricity prices Fig. 3 [11]. A simple visualization is that similar to neural networks, the data is modeled by overlapping many copies of the kernel function (circular hill) in the data space. The SVM is based on quadratic optimization to maximize margins in the weight space (4) [12], [13].

$$\text{inputs } \tilde{x} \quad \text{support vectors } \tilde{s} \quad \text{weights } W_n$$
$$\text{kernel function } \mathrm{K}(\tilde{x},\tilde{s}) = \exp(-\gamma\|\tilde{x}.\tilde{s}\|^2) \tag{3}$$
$$\text{model } \mathrm{F}(\tilde{x}) = \sum_{\text{all kernals n}} W_n K(\tilde{x},\tilde{s})$$

Equations (4) show SVM training for regression problems. C and ξ are constants describing error tolerance. The dot products are performed with the kernel functions K(x,s).

$$\begin{aligned} &\text{minimise} \quad F(W) = \frac{1}{2}(W \bullet W^T) + C\sum_k \xi_k \\ &\text{subject to} \quad y_k(W \bullet X_k + b) - 1 + \xi_k \geq 0 \\ &\quad \text{for data points} \quad k = 1,\ldots,l \\ &\text{where} \quad y_k \quad \text{is price of data point } k \end{aligned} \tag{4}$$

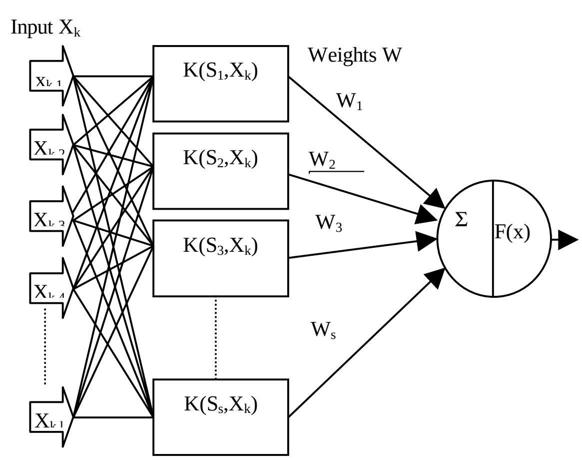

Fig. 3. Structure of SVM Implementation.

III. Price Forecasting Results

A. Accuracy Measures

The forecasting results are measured by the Mean Absolute Error (MAE) (5).

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\frac{actual_n - forecast_n}{actual_n} \tag{5}$$

This measure distorts the importance of error because when the actual price is small, the MAE is larger and when the actual price is larger, the MAE is smaller. In the market, the most important times are when the price is high. To overcome this distortion we use the MAE average based (6), where the actual price denominator is replaced with the daily average price. The squared error measure often used will emphases larger errors. However, the denominator distortion is still a problem.

$$\begin{aligned} MAE &= \frac{1}{N}\sum_{n=1}^{N}\frac{actual_n - forecast_n}{day(n)} \\ where \quad day(n) &= \frac{1}{48}\sum_{h=n'}^{n'+48} actual_h \end{aligned} \tag{6}$$

Where n' is start of the day containing half-hour n.

B. Same as Last Week

The same as last week forecasting model forecasted the electricity price over the 25 weeks with an MAE of 33.5% and an MAE average based of 45.2%.

C. Neural Network Price Forecast

The neural network forecasting model forecasted the electricity price over the 25 weeks with an MAE of 28.3% and an MAE average based of 37.4% [14].

D. Support Vector Machine Price Forecast

The SVM forecasting model forecasted the electricity price over the 25 weeks with an MAE of 27.8% and an MAE average based of 36.3% fig. 4 [15].

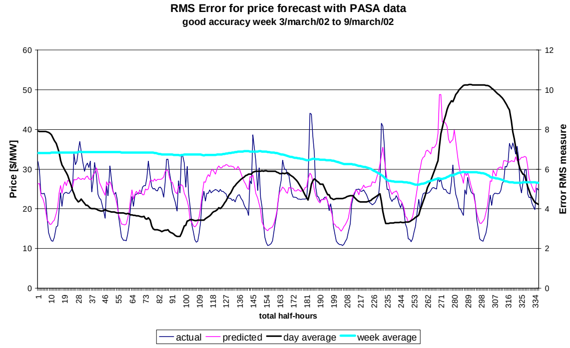

Fig. 4. Sample week of SVM price forecast.

IV. Generator Dispatch Results

In the simulation of dispatching an energy constrained generator, the total daily energy was fixed at 20MWhours with a maximum power output of 5MW. This output is equivalent to 4 hours (8 half-hours) of continuous power output. The situation can be visualized as a small (micro) hydro generator with limited temporary storage and river flow requirement or a bio-generation plant that must use all of the fuel (farm or factory waste) over a 24 hour day.

A. Dispatch Based on Price Only

The simplest dispatch method is to select the 8 highest priced half-hours (4 hours) of the day and run at the full 50MW. The dispatch based on price only is applied on the actual price (perfect knowledge) to calculate the maximum possible return that can be obtained from 8 half-hours of generation. Then the price based dispatch is applied to each of the price forecasts by selecting the 8 half-hours of each day based on the highest forecasted price and outputting the maximum 50 MW of power for that half-hour.

The revenue is calculated by multiplying the actual electricity price of the 8 half-hours selected by 50MW and summing the results.

The maximum possible revenue obtained from the actual price was $660233 ($8574 per day). The average spot price over the 11 weeks for the 8 highest priced half-hours each day was $214/MW compared to an average of $59/MW for all half-hours Table II.

Using the SVM with Projected Assessment of System Adequacy (PASA) price forecast, the revenue was $587674 ($7632 per day). If this forecast was used then the total revenue would be $75744 less than the maximum possible with perfect knowledge. When this forecast was used, an average of 4.1 out of the 8 highest priced half-hours was selected correctly. This is shown in the reduction in the average highest 8 half-hour price from $214/MW (perfect knowledge) to $191/MW.

Our neural network forecast has been found to be very similar to the SVM forecast but was less stable during repeated training. Basing the dispatch on the neural network forecast, the revenue was $568564 ($7384 per day). An average of 4.15 out of 8 of the highest priced 8 half-hours of each day was correctly identified by the neural network forecast.

If the 8 highest priced half-hours are assumed to be the same as last week then the revenue was $651491 ($8461 per day). Assuming same as last week correctly identified 4.16 out of 8 of the highest priced half-hours.

Basing the dispatch on another set of perfect knowledge the actual demand was more successful giving a revenue of $655363 ($8515 per day). Using the 8 half-hours of the day with the greatest demand correctly identified an average of 5.35 out of the 8 highest priced half-hours.

Actual demand is not available but NEMMCO makes publicly available a demand forecast in the PASA data. Selecting the 8 highest demand forecasts from the 10% POE (probability of exceeding) demand forecast gave a revenue of $652626 ($8476 per day). This method correctly identified an average of 4.52 out of 8 of the highest priced half-hours over the 77 days (11 weeks).

TABLE II
RESULTS OF EIGHT 50 MW DISPATCH BASED ON DIFFERENT PRICE FORECASTS

Forecast	Revenue	MAE	MAE average based	Average correct out of 8	Average top 8 price
Actual price	660233	n/a		8	214.4
Actual demand	655363	n/a		6.68	212.8
10% POE demand	652626	n/a		6.26	211.9
Same as last week	651491	33.5 %	45.2%	6.08	211.5
Neural Network	568564	28.3 %	37.4%	5.96	189.3
SVM	587674	27.8 %	36.3%	6.04	191.1

B. Dispatch Based on Price and Risk

One of the original goals of this research was to examine if the dispatch could be improved by including both the price and the risk. Thus, treating the dispatch as a portfolio [16], [17] of half-hourly generations, the revenue risk balance was modeled by a utility equation (8) with the forecast price multiplied by the 50MW output as the return and the variation of the error as the risk. The risk tolerance T is a constant chosen to model the user's attitude to risk.

$$\text{Utility} = \Sigma(T.\text{return} - \text{risk}) \qquad (8)$$

In the dispatch problem studied, the risk was the variation in forecast error and not the variation in price. The highest prices were the most poorly forecasted and so had the greatest variation in error. If risk of error was reduced then the highest priced half-hours would be selected less often and the revenue would be greatly reduced. However, after more investigation, it became clear that the risk in price forecasting error was not the relevant risk to select dispatch times for the generator.

The best dispatch solution was to select the 8 highest priced half-hours so more specifically, the risk was in not selecting the correct eight highest priced half-hours. The magnitude of the price forecast for each half-hour was not important for the dispatch problem. The important factor was correctly forecasting the order of half-hours through-out the day from the highest priced to the lowest priced half-hours. So the risk was the probability that the order would be inaccurate.

Except in the extreme case where the risk tolerance was set so that all half-hours were dispatched evenly, (that is 8.3MW (400/48) for all 48 half-hours of the day) the results including the risk were the same as for price based only results. That is, the highest 8 priced half-hours of the day were selected.

V. DISCUSSION

The important risk in the dispatch is the risk of missing a high priced half-hour. This proved to be of limited importance as all the 8 highest priced half-hour selection methods were good at selecting the two or three very high priced half-hours of each day. After the top two or three highest priced half-hours, the price dropped and remained similar between the 4th to 12th highest priced half-hours. Correctly identifying the top three half-hours was important in selecting the very high prices. In contrast, correctly identifying the other 5 half-hours in the top 8 priced half-hours was not as important. The highest priced half-hour of each day had an average price of $800/MW the second highest half-hour $400/MW the third $170/MW all other half-hours had averages of less than $50 as shown in Fig. 5.

The setting of the risk tolerance T was very sensitive to switching from dispatching the generation totally based on forecasted price to totally on forecasted risk over a very small range. This range was found by trial and error, which would be impractical is real situations.

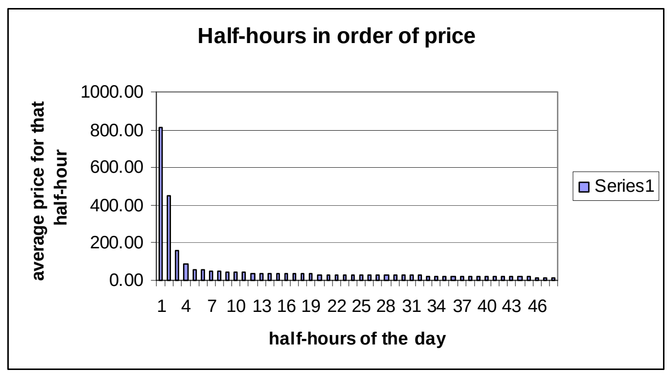

Fig.5. Average Price of half-hours of the day in order of price.

An Investigation of the influence of the risk in forecasting the price order would be interesting if the generator could only be run at maximum output for one half-hour. Diversifying the risk, that is spreading the generation over a number of half-hours could provide benefits over choosing only one half-hour. The choice of one half-hour increases the risk of missing the one or two high priced half-hours of the day. So in case II only one half-hour is required.

VI. GENERATOR DISPATCH RESULTS CASE II

In case II the total daily energy was still fixed at 20MWhours but with an increased maximum power output of 40MW. The whole of the 20MWhours daily energy output could be dispatched in one half-hour.

A. Dispatch Based on Price Only

The single half-hour is selected based on the half-hour with the greatest forecasted price or demand. The revenue is calculated by multiplying the actual price of the selected half-hour by the generator output of 40MW as shown in Table III. The column, in top 2, represents the percentage that the selected half-hour was the highest or second highest half-hour of the day in order of actual price. That is the percentage of selected half-hours that were the highest or second highest actual priced half-hour of that day.

TABLE III
RESULTS OF EIGHT 50 MW DISPATCH BASED ON DIFFERENT PRICE FORECASTS

Forecast	Revenue [$]	In top 2 [%]	In top 3 [%]	Average correct out of 1	Average top 1 price [$
Actual price	2497732	100	100	1.0	811.02
Actual demand	2062620	95	98	0.78	669.68
10% POE demand	1915615	96	99	0.66	621.95
Same as last week	1991184	95	98	0.75	646.48
SVM	1980940	86	91	0.52	643.16

On 29th of June 2002 at 18:00 the price spiked to $8047.61/MW. This is over twice the price of all other half-hours over the period tested. The SVM was the only forecasting model to correctly select this half-hour as the highest priced half-hour of that day. To see the difference the price spike made, the revenue from 29th June was removed from the result.

TABLE IV
RESULTS OF EIGHT 50 MW DISPATCH BASED ON DIFFERENT PRICE FORECASTS

Forecast	Revenue [$]
Actual price	2175827
Actual demand	1972424
10% POE demand	1825419
Same as last week	1900988
SVM	1659039

B. Dispatch Based on Price and Risk

The selection of dispatch was based on the probability that the price of the half-hour would be greater than the highest forecasted price for that day {max$(d)}.

The risk of each forecast used was the standard deviation of the error for that half-hour of the week. Each week contains 336 half-hours.

Risk(n) = standard deviation(over first 14 weeks of data |actual – forecast|) for all n=1,2,…,336

The distribution of the error was approximately normal so the probability was calculated using a normal distribution. The probability of the price of the half-hour being greater than the max$(d) is 1 minus the cumulative probability at the max$(d) (9). The forecast price {for$(h)} was used as the mean of the normal distribution and the risk(n) as the standard deviation. "norm_dist(a,b,c)" is a function that gives the cumulative probability of a normal distribution at the value (a) given the mean (b) and standard deviation (c) of the normal distribution.

Each half-hour of the day was dispatched by the probability that the price would be greater than the max$(d) with all half-hours normalized so the total energy for the day was 40MWhours (10).

Prob(h) is the probability for half-hour h of the day d.

Prob(h) = 1 − norm_dist(max$(d),for$(h),risk(h)) (9)

Dispatch for half-hour h is G(h)

$$G(h) = 40 * \frac{\Pr ob(h)}{\sum_{h=1}^{48} \Pr ob(h)} \tag{10}$$

Using this probability based dispatch on the demand 10% POE forecast, the revenue reduced from $1915615 to $1040598. Applying the probability to the SVM price forecast method, the revenue reduced from $1980940 to $1345531. The aim of reducing the risk is to decrease the chance of a bad revenue day and to even out the revenue variation from day to day. The variation of revenue was not reduced compared to the price only revenue when using the risk.

VII. Discussion

Based on only price, the best selection method was to assume that the highest priced half-hour selected today would be the same half hour selected the previous week - same as last week method. Based on the selection of the highest POE demand, forecast still functioned well. The SVM method gave a revenue almost as great as the same as last week method. However, this was due to the SVM method correctly selecting one very high priced half-hour. When the day containing this very high priced half-hour was removed from the study, the SVM method performed poorly compared to same as last week and demand methods. More data and testing is required to investigate if the SVM method was 'lucky' or is suitable for forecasting very high price spikes. From our other studies with SVM for price forecasting, we would propose that the SVM was 'lucky'.

Only selecting one instead of 8 half-hours increases the chance of missing the one or two highest priced half-hours of each day. However, all the selection methods were accurate enough to significantly increase the revenue compared to the 8 half-hour case I. The selected highest priced half-hour was outside the three actual top prices only once for the POE demand, twice for actual demand and same as last week and for 7 half-hours when using the SVM forecast. The forecasting methods on almost every day selected contained one of the top three priced half-hours of the day. Recall the three highest priced half-hours were much higher in price than the other half-hours. This explains why the 40MW one half-hour selection gives an average revenue that is approximately three times that obtained by selecting 5MW for the top 8 priced half-hours.

Basing the selection on the average error did not represent the useful error, which is selecting the half-hours in the incorrect order. The useful error (risk) was small. Based on the 10% POE demand forecast, 33% of highest priced half-hours were missed. However, 4% of the selected highest priced half-hour was not the first or second actual highest priced half-hours. Only 1% of the selected half-hours were not in the actual top three priced half-hours. The 1% is only one half-hour event. Therefore, this useful error is too small to be considered in this study.

VIII. Conclusions

A simple solution that works well is usually better than a complex solution that functions ‘optimally’. In this research, the simple solution is also the solution that works best. The best solution was dispatching the generator during the 8 half-hours of the day (mid-night to mid-night) with the highest forecast of demand. The demand forecast is publicly supplied by NEMMCO, the operator of the Australian National Electricity Market. The next best solution was to assume that the 8 highest priced half-hours would be the same as the same day last week. Both these dispatch strategies lost approximately 1.2% of revenue when compared to the maximum possible revenue that could be obtained with perfect knowledge of future prices.

In the selection of only one half-hour a day to dispatch the generator, the same as last week method performed the best, followed by the demand method.

The consideration of risk in the dispatch problem was not beneficial as only one or two very high priced half-hours needed to be identified correctly to obtain the majority of the available revenue.

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X. Biographies

Damien Sansom (M’94) grew up in Northern Australia completing a Degree of Electrical and Electronic engineering at the James Cook University of North Queensland in 1995. Damien finished his Masters of Electrical Engineering at the University of Queensland in 2000 and is currently pursuing a PhD at the University of Queensland concentrating on developing tools for electricity markets. Damien’s research interests include the operation and needs of electrical energy markets, intelligent machine theory applications and optimization methods.

Tapan Kumar Saha (M’93–SM’97) was born in Bangladesh and came to Australia in 1989. Dr Saha is an Associate Professor in the School of Information Technology and Electrical Engineering, University of Queensland, Australia. Before joining the University of Queensland he taught at the Bangladesh University of Engineering and Technology, Dhaka, Bangladesh for three and a half years and at James Cook University, Townsville, Australia for two and a half years. He is a Fellow of the Institution of Engineers, Australia. His research interests include power systems, power quality, and condition monitoring of electrical plants.