Short Term Power System Forecasting Using an Adaptive Neural-Fuzzy Inference System

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Abstract

This paper presents an application of an Adaptive Neural-Fuzzy Inference System (ANFIS) *to power forecasting problems. The need for accurate forecasts is increasing as power markets are becoming more competitive. This paper gives a brief overview of the issues facing power system forecasting and proposes the use of ANFIS to perform short term scheduling. Finally, it gives a comparison against other techniques that have been previously presented, highlighting ANFIS favourably.*

1. Introduction

The operation of a power system is usually divided into four different categories: long term, medium term, short term and real-time [1]. Long term forecasting is primarily associated with maintenance scheduling and generator lifespan. It considers time frames well over a year in advance. Medium term scheduling is used primarily for fuel planning and ensuring that the system will continue operations between maintenance checks and upgrades. It generally considers time frames from a week to a year ahead. Short term scheduling is the operation of a power system from anywhere between five-minute load schedules to week-ahead planning. It is the operation that ensures that loads are capable of being met and are being met in an efficient manner. Lastly is real-time scheduling, based on the operation of the machines themselves. Real-time scheduling focuses on supplying the energy to meet the goals that are set, while preserving operation limits on the machines.

This paper investigates short-term forecasting for a power system. However it especially centres on a sub-class referred to as *very* short term forecasting. Very short term forecasting is predominantly focussed on predicting the value of the next period of an applicable data set. In this instance, that period will be the operating cycle of the National Electricity Market of Australia.

2. Overview of the National Electricity Market

The National Electricity Market (NEM) is managed by an overseeing body called the National Electricity Market Management Company (NEMMCO). The NEM is a wholesale power pool to which the generators sell the power they produce and the distributors buy the power they need to sell to their clients. This form of power system is known as a "deregulated system". The generators make a bid to supply a certain amount of power at a chosen price and NEMMCO receives the generators' bids, ranks them according to price and accepts enough bids to satisfy the projected demand plus a safety margin. Usually this means that the last bid accepted is accepted as a partial amount. The highest accepted bid price is the price that each supplier receives for the power that they produce in that time period, regardless of their individual bid price. Finally, most generators and distributors have a majority of their power resources set in contracts. These contracts are unaffected by the spot price market so far as the customer is concerned. However, the generators can choose to buy power from the spot price market to fill their contracts if they either cannot make the contract themselves or it would be more economical to do so.

3. General Overview of Power System Operation

Short term scheduling is widely recognised as an essential element of power system operation [2]. It is a complex problem as there is no ideal solution. Certain generators operate better under different operating systems and schemes. Due to high production costs, small increases in efficiency also lead to large savings. This means that utilities are always in pursuit of a more efficient means of short term operation.

When considering short term scheduling and economic dispatch, accurate demand forecasts are essential [3]. The forecasts are used to try to reduce the difference between the power available and the power consumed. The use of forecasting techniques for load forecasting is a topic widely discussed in power engineering. Another less discussed, but no less useful, parameter is that of electricity prices. Traditionally, these "spot prices" have been difficult to predict and when investigated by a human, it is near impossible to discern any pattern in changes of spot price. This paper shows a way to overcome this issue.

4. Power System Specifics

In order to schedule a power system correctly, it is essential to know how that particular system operates and what factors are most important to optimise. Generally, a system can be considered as fossil fuel-based or renewable, but even that distinction is somewhat blurred. However, for the purposes of this paper it will be convenient to use these two titles as all-encompassing categories. The fossil fuel based systems destroy the fuel they use, but can purchase more when needed. The renewable energy systems do not destroy the fuel, but the access to the fuel is limited.

4.1. Fossil Fuel Based Systems

Fuel based systems are diverse and include many variations that can solve most generation issues. Nuclear power has low running costs, but initial expenses are high. Gas power has low initial expenses, but running costs are relatively high. In the middle of these extremes is coal-fired generation. The coal-based and nuclear tend to have slow ramp-rates (rate at which the level of operation can be altered).

For a system that cannot be altered rapidly, once the system is turned on, it is committed to operation for a significant period of time. This means that the cheaper to operate systems, are also less flexible and sometimes even have to incur losses at low spot price periods in order to continue operations. To have a fossil fuel based power system that can rapidly respond to changes in demand, high-cost gas-fired stations must be used. The other alternative is to consider a renewable system.

4.2. Renewable Systems

Renewable systems also have diverse potential for generation. Hydro generation has the advantage of quick response, while wind and geothermal energy have the advantage of providing a non-exhaustible (within practical limits) supply of power. Furthermore, the energy sources used to produce the electricity are free. However, these systems do have their own shortcomings.

Renewable systems have a high installation cost and so have been prohibitively expensive to nations with closely limited resources. Wind and geothermal energy are not able to be stored in their own right. Hydro power, which can be stored, is not always available. If there is a drought, or even a period with less rain than forecast, this can cause problems with the operation of a hydro system. However, even with these negative aspects, in developed countries, most locations that could be used to generate renewable power (especially hydro) are being investigated or utilised [1]. Thus, most countries rich enough to afford the initial outlay agree that the advantages of free energy in the long term outweigh the negatives of renewable power – the fact it is environmentally sustainable is becoming more important as well.

5. Necessary Forecast Parameters

To efficiently operate a power system, it is important to have good predictions for the characteristics that determine the system's operation. For instance, unless the wind speed it accurately forecast, it becomes difficult to properly schedule any wind resources. This paper is based on very short term forecasting of demand (or load) and spot price data.

A typical load profile is relatively smooth and responds well to forecasting techniques. However, even the best predictions still tend to have significant errors associated with them.

Load forecasting has been approached in several ways, including weather dependent, weather independent and a combination of the two [3]. While, these have met with comparable levels of success, the weather independent models' main advantage is that there is no need to include another predicted variable (weather). This comes at the slight expense of accuracy. However, some power stations are very dependent upon the weather predictions for other operating parameters and thus the accuracy is more important as the weather predictions are already an integral part of the system.

Load forecasting is extremely important and has been researched quite extensively using traditional methods and in recent years, artificial intelligence techniques have also been applied to this field.

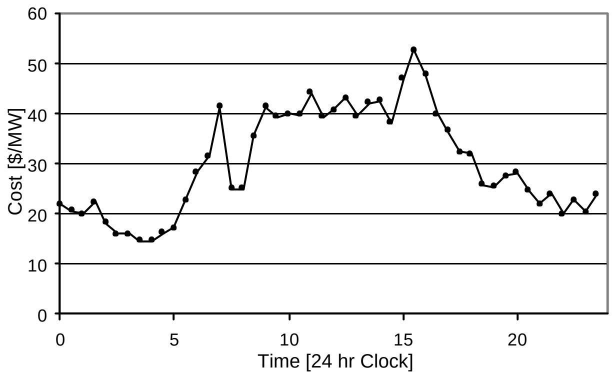

Figure 1: 20 February 2002. Typical summer day for Victoria, Australia. Data derived from NEMMCO site.

Spot price forecasting is a new area of research. Deregulation of power markets is still relatively new (beginning around 10 years ago) and the accurate forecasting of spot price data has had very little written about it. The most likely reason for this is the difficultly in obtaining good results and the limited application of most techniques so far investigated.

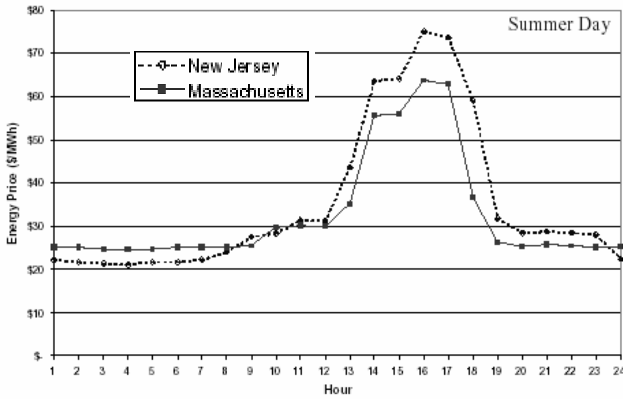

Figure 2: Typical summer day for large American spot price power pools. Tabors Caramanis and Associates developed this figure for a report [4].

Often an application is so site specific that there is no way that it can be used to forecast for another region. Furthermore, the very essence of the spot price data can vary greatly from region to region. Figure 1 shows a typical summer day's data from the Victorian (Australia) spot price energy pool and Figure 2 shows a typical summer day's data from New Jersey and Massachusetts (USA).

The two figures show that the smaller market (Victoria) is far more difficult to predict. A smaller market means load fluctuation has a more pronounced effect. This research applied new techniques to forecast this data.

6. Forecasting Technique

This paper proposes an application of a new forecasting technique that looks very promising. This technique was to use an Adaptive Neural-Fuzzy Inference System (ANFIS).

Traditionally, power systems operators have been focussed on load forecasting and used conventional mathematical procedures to try to predict future load values. There were several separate techniques applied from the mathematical domain [5]. Multiple linear regression (MLR) is used to derive the forecast value from other values that affect it. Stochastic time series (STS) forecasting works by creating a model, which essentially acts as a filter to a white noise input. There are numerous techniques that can be used as part of this encompassing heading. General exponential smoothing (GES) works by developing a fitting function to create a smooth transition from point-to-point (a likely behaviour of load). State space (SS) and Kalman filter is a general forecasting approach that utilises state space mathematics to combine several models to create a better overall system.

Then knowledge-based systems (KBS) started being investigated and were found to work well although were difficult, or even impossible (if there was no available expert), to implement. The next generation of forecasting measures was based on artificial neural networks (ANN). ANNs worked very well, but had the problem of over-fitting or "memorisation". As forecasting can include a very wide range of data with sharp spikes, a large amount of training data is necessary to be able to handle unusual events. Although, if too much information is used to train an ANN, the ANN will adjust to predict the training data very well, but not be able to handle new data.

6.1. The ANFIS model

ANFIS is a hybrid system that combines the low-level computation power of neural networks with the high-level reasoning capability of a fuzzy inference system [6, 7]. This research has been implemented using a version of ANFIS in the "Matlab Fuzzy Toolbox".

The easiest way to understand how the ANFIS model operates is to consider it in two steps. Once trained, the system operates as a fuzzy expert system would. Information is input, fuzzy rules are fired and a corresponding output is achieved. However, the training is more like that of a neural network (although not identical).

As with a supervised-learning neural network, the fuzzy system is trained with a set of data called a training set. This set is represented by several subsets of inputs and one desired output for each subset. Where it differs is in the selection of model parameters.

To use the ANFIS model, the user defines the number of inputs; the number of membership functions (MFs) and their type, and the number of epochs of training. One of the more unusual aspects of the ANFIS model is that changing even one of these parameters be the difference between a system that appears to be not working at all and a system that produces almost perfect results. This is exemplified in the *Results* section of this paper.

The number of inputs for this work was varied between 4 and 6 and it was found that the more inputs that were used, the better the result became. However, this also came at the cost of speed of training. When four inputs were used, it was possible to operate with three MFs, however, with six inputs, the number of MFs was limited to two (within reasonable training times). It was also noticed that in some cases, a system with four inputs and only two MFs outperformed a system with four inputs and three MFs.

This was due to a form of over-memorisation. The rules became too specific and could not handle a wide variety of test cases. Thus, for this example, it was found that six inputs and two MFs were the best combination.

The number of epochs is another factor that is very different from a standard ANN training regime. Generally an ANN will be trained for anywhere up to 1000 epochs (and is some cases even more). However, the ANFIS model trains in such a way that the number of epochs is of far less importance. Each epoch of an ANFIS model can take several minutes (or more) by itself and generally makes very little change after the first epoch, provided the training parameters are well chosen. Thus, the number of epochs for this work has been set to one.

The last of the parameters to be chosen was the type of MF. The type of MF is generally a "bell function", such as the Gaussian distribution function. This is a very good function for precise work and will function better if the system is relatively smooth and trained to cover all likely events. However, it does lack the robustness of some of the simpler membership functions.

6.2. Measures to Ensure Robustness

In the beginning sections of this work, the ANFIS was being trained with the bell function for its MF and was using a linear set of training data. When tested on intermediate sections between the test data, such as system gave almost perfect results. However, the results were less impressive for later test data and unusable for unusual and spikey test data. This showed the need for some added robustness to the ANFIS predictor.

The first step taken was to randomise the training data. For this project, the training set was initially chosen as every day in January 2002. To randomise the data, the training set was still selected in day-sized sections from the January data, however, now the sections began from different times of day and also occurred in a random order.

The next step to ensure robustness was to search the previous year (2001) for unusual events and randomly include these in the training data. This meant that the training set was "seeded" with large spikes so the model could accurately predict such events.

Another step that was taken was to change the input configuration. The inputs used were derived from previous data points, however, rather than simply taking the six points previous to the forecast point, it was found that taking a wider set of inputs improved the results. The final outcome was using the last, second last, third last, fifth last, seventh last and ninth last points gave the best results.

Even with these additions, it was found that the results were yet to reach an acceptable level on a consistent basis. Investigation showed that the ANFIS model was having difficulty in predicting the next point due to the coarse nature of the data. Figure 1 shows an example of spot price data and note the drop from 07:00 to 07:30.

With such rapid changes between data points, a successful forecast was almost impossible. Thus some attempt had to be made at bridging the gap between points. The first inclination is to use spline interpolation. However, interpolation is not possible between a known point and an unknown point (the point to be forecast). Thus, interpolation was used where possible in order to obtain input data, but another technique had to be used to obtain other the intermediary points leading to the desired forecast point. This was essentially a forecast to predict each intermediary point, which was in turn was used to predict the next point and so on, until the wanted prediction was reached. At that stage, the latest point was known again and interpolation was used to replace all the predicted intermediary points with real interpolated data. The actual time step that was used created 10 sub steps between each data point.

The last measure to ensure robustness was to try changing the MF type. Until this stage, large events still caused massive overshoot and undershoot as even with the seeded training set, the fuzzy rules were incapable of being trained to account for very rapid rises. This repetition of error lead to experimentation with other MFs. It was found that the more basic the MF was, the more robust the system was. However, the robustness did come at a slight cost of accuracy during the rest of the test data (see Table 4).

6.3. Predicting Difference to Improve Short Term Accuracy

One of the key features of the technique and results presented in this paper is using ANFIS to predict difference between points instead of raw data points themselves. The prediction of difference instead of the data points themselves presented some interesting problems. Difference data tends to be even more unpredictable than the data it is derived from. Thus, it is difficult to tune an ANFIS to predict the difference data correctly. However, when the difference data is properly predicted, the end results are improved and so is the robustness. During this work, difference data prediction was used and compared to similar systems that did not use difference prediction and those using the difference method were found to perform better. The reason for this is that while the difference data itself is more difficult to predict accurately, the prediction will be of smaller numbers, resulting in smaller total errors in the true prediction data. Unfortunately, this technique is limited to very short term (or possibly short term) forecasting as the errors have a greater tendency to compound than with the more traditional techniques.

7. Results

Forecasts often have different time spans and can be performed on very different data, making good comparisons difficult to obtain. However, while it is difficult to objectively compare forecasting results, it is clear that the results obtained in this research were exemplary.

For the purposes of this paper, three papers were chosen as comparison cases. All three papers focussed on very short term forecasting. This means that the forecast values are likely to have similar errors. Reference [5] was chosen as it presented a good selection of techniques against which this paper can be compared. It was published in 1989 and is verging on being out of date, however, in order to compare artificial intelligence results with conventional techniques, it is necessary to go back that far. The other two references, [8, 9], were both published in 1999, both using ANNs. However Drezga and Rahman [8] looked at load forecasting and Szkuta, Sanabria and Dillon [9] looked at price forecasting. The price forecasting paper also used Australian market data, which limits another variable.

Moghram and Rahman [5] used conventional techniques and a knowledge-based technique to look at very short-term load forecasting (one hour ahead). They split the test values into summer and winter and achieved the results shown in Table 1.

Table 1: Absolute mean percentage errors from [5]

Algorithm	MLR	STS1	STS2	GES	SS	KBS
Summer %	2.78	0.54	0.51	2.12	1.57	1.22
Winter %	3.76	2.17	2.70	1.79	1.71	1.29
Total %	3.27	1.36	1.61	1.94	1.64	1.26

Drezga and Rahman [8] looked at several lead times and their results showed only a small difference in the errors, however, for the purposes of this paper, it is more appropriate to only look at the one hour ahead forecast. The results they obtained are shown in Table 2.

Table 2: Absolute mean percentage errors from [8]

Utility	Utility A				Utility B			
Month	Jan	Apr	Jul	Oct	Jan	Apr	Jul	Oct
Error	1.15	1.01	.8	1.04	1.59	1.23	.88	.99
Total	1.00				1.17			

Szkuta, Sanabria and Dillon [9] also were trying to predict the next data point (half hour values in this case) and reported their findings as a week worth of predictions and associated errors. The results are presented in Table 3. It also pays to note that the days used to test the ANN in this paper did not including the large spikes that can occur in the spot price market such as those included in Table 5.

Table 3: Absolute mean percentage errors from [9]

Date	14/5	15/5	16/5	17/5	18/5	19/5	20/5
Error	4.16	11.09	2.18	10.61	4.88	3.27	4.17
Total	5.77						

The results shown in Tables 1-3 demonstrate that ANNs represent a superior forecasting technique to the conventional techniques and that spot price data is much more difficult to forecast than load data.

The ANFIS model was trained on seeded January 2002 data and tested on February 2002 (summer) spot price data, June 2002 (winter) spot price data and retrained and tested for March 2002 demand data. Each of the test data sets was trained and tested for many combinations of parameters to ensure that near best results were being achieved and for this paper a comparison of results have been reported.

The data for February was the main thrust of this paper and received the most attention in ensuring good results. It was also much easier to get good results for the summer data than for the winter data as it did not have any large spikes. The results are shown in Table 4.

Table 4: Absolute mean percentage errors for spot price data during February 2002

MF	Bell Function MF		Triangular MF	
Data	Partial	Full	Partial	Full
Error %	0.43	2.30	0.75	0.73

The results show that the bell MF is superior to the triangular MF when given selected data from the seeded training set. If given the full seeded data set, it does not respond so well since it places too much emphasis on the spikes added to allow for unusual results. The bell function with the partial data set will work well for most months of the year, but will return large errors if used to try to predict the winter spikes. This is shown in Table 5. The triangular membership function did not respond quite so well, but was far more reliable at handling unusual events. This makes the triangular membership functions a safer option.

Table 5: Absolute mean percentage errors for spot price data during June 2002

MF	Bell Function MF		Triangular MF	
Data	Partial	Full	Partial	Full
Error %	1.72E09	1.27E07	35.23	10.73

The results shown in Table 5 seem alarmingly high, especially for the bell function. However, upon investigation it was clear that most points were very well predicted and the true data line was followed closely. However, when the data spiked upwards suddenly, the prediction completely overshot the result as it went to the full extent of the MF curve. For a bell function this is a very large number and so the errors were correspondingly large. To give an insight to the suddenness of a spike, in one period between predictions, the price rose from 235.79 to 3839.60. This kind of change is very difficult to properly predict.

The demand data test set was mainly done in order to compare the ANFIS system against a wider range of competition. Due to the vast differences in demand depending upon weather, season and day of the week, the training data was only used for weekdays. With more time spent on finetuning, the demand data could return even better results by using different inputs (such as using one input for weather values and one for day of the week). Even so, the results obtained clearly showed that ANFIS techniques are the best available. The results are presented in Table 6.

Table 6: Absolute mean percentage errors for demand data during Mar 2002

MF	Bell Function MF	Trapezoidal MF
Error %	925.52	0.084

As the training data set was not carefully selected, randomised and seeded, the bell function gave large errors at some stages as the ANFIS was not well trained to handle those particular values. However, by using the more robust trapezoidal MF an excellent result was obtained.

8. Further Research

One of the great advantages of a neuro-fuzzy system is that the operations of the system can be directly affected. This means that the rules can be altered manually to improve the results. The standing problem with this system is still founded in the spot price forecasting of large data spikes. Even with all the measures to improve robustness, the spikes still tend to be overshot by significant amounts. This could be corrected by adjusting the rules to create a cut-off. When the predicted difference might be clearly beyond reasonable expectations, the rules would limit the difference to some upper bound. This would need to be fine-tuned, but would stop the large overshoot and undershoot errors that are presently causing difficulties on the most severe days.

More work could also be done to improve the training set used for the demand data and with the better training set, longer forecasts are a strong possibility for this technique. Both load forecasting and price forecasting could be extended out to a six-hour forecast and maybe beyond.

9. Conclusion

The research shows that ANFIS is an excellent technique for power forecasting and is likely to work very well for other forecasting applications as well. In both instances (spot price and demand) the results obtained using ANFIS are approximately ten times better than the other research that was available. Especially impressive is the 10.73% error achieved for the spot price data of June. This data is almost impossible to predict and an error of around 10% is incredibly accurate.

10. Acknowledgments

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