UTILISING LOAD FORECASTING FOR ENERGY MANAGEMENT IN A HIGH VOLTAGE SYSTEM

C. S. Carlson[1*], W. A. Cronjé[1] and M. A. van Wyk[1]
[1]School of Electrical and Information Engineering, University of the Witwatersrand,
Private Bag 3, 2050, Johannesburg, South Africa
*Email: Craig.Carlson@students.wits.ac.za

Abstract: This paper presents a unique modelling approach to perform load forecasting, which ultimately aids energy management. An algorithm was implemented using fuzzy logic systems and parameterised using a genetic algorithm. Following algorithm characterisation, comparative tests were performed on two high voltage systems within South Africa. Forecasting on the 11 kV system yielded an average peak error of 2.01 % and an average total energy error of 0.33 % over a week. Forecasts on the 88 kV system, tested using data from each of the four seasons, yielded an average peak energy error of 2.45 % and an average total energy error of 0.30 %. It is observed that the algorithm is susceptible to fluctuations in the load, thus future work was proposed to minimise the effect.

1 INTRODUCTION

Currently there is a significantly reduced margin of reserve power in the South African power distribution system [1]. This issue can be addressed by enhancing the existing architecture or by raising user awareness in order to reduce the power usage. This is referred to as energy management.

Energy management is an important factor in the world today since it focuses on increasing efficiency of most energy consuming equipment and processes [2]. Thus energy management can be used to monitor and control the efficiency of the usage and distribution of power.

This process can be aided by implementing an algorithm that can perform load forecasting using measured power usage data, capable of accurately determining the peak daily usage and the total energy required during one day. Load forecasting is the prediction of power usage for a specific time and power system. Several modelling approaches have been implemented in the past using techniques such as statistical models [3, 4] and computational intelligence models [5, 6, 7]. Each modelling approach performs the desired function, but varies in accuracy.

This paper presents a unique modelling approach, combining fuzzy logic systems and genetic algorithms to perform load forecasting for energy management. Preliminary tests are performed to determine the system requirements and performance. Comparative tests are then performed on two high voltage systems (at 11 kV and at 88 kV) within South Africa. Future work is proposed to enhance the algorithm.

2 DEVELOPMENT OF THE ALGORITHM

The model developed uses two different fuzzy logic systems to represent weekdays (Monday to Friday) and weekend days (Saturday and Sunday). This is due to the observed differences in the load profiles, discussed in Section 3.2. Public holidays have not been modelled as yet so they have been excluded from the test data.

Two *errors* were defined to evaluate the performance of the algorithm. They were:

1. the difference in the forecast peak load and the measured peak load (PkE) in (1) and
2. the difference in the total energy required in a 24 hour period between the forecast load and the measured load (EnE) in (2).

$$PkE = \frac{|max(P_{forecast}) - max(P_{measure})|}{max(P_{measure})} \times 100 \qquad (1)$$

$$EnE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|P_{forecast}(i) - P_{measure}(i)|}{P_{measure}(i)}\right) \times 100 \quad (2)$$

where: $P_{forecast}$ = forecast power usage,
$P_{measure}$ = measured power usage,
N = maximum terms in the forecast.

The algorithm used historic power usage data, and the time of day for reference, to forecast the load profile for the following week. The historic data was measured half hourly, therefore the algorithm was configured to accommodate this. Historic input power usage data was normalised on 0 - 12 kWh to allow for the algorithm to forecast loads of all magnitudes.

A genetic algorithm was implemented to accurately parameterise the fuzzy logic system parameters to minimise the two defined errors. An overview of this system is depicted in Figure 1.

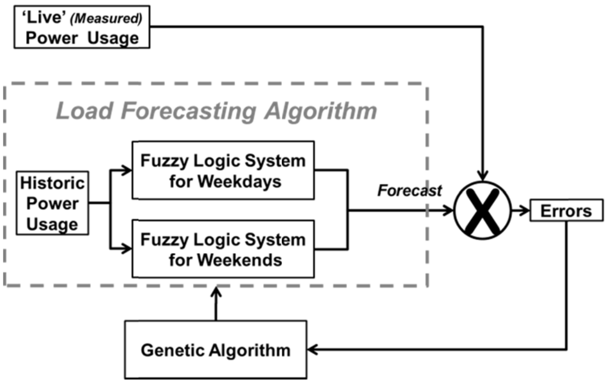


Figure 1: Overview of the algorithm, showing the load forecasting process, error calculation and genetic algorithm parameterisation.

3 PRELIMINARY TESTING

To characterise the algorithm the desired quantity of input data was to be determined. Once the required input data was known, a preliminary test on a 380 V system was used to verify the load forecasting ability of the developed algorithm.

3.1 Characterising the algorithm

To determine the input data to yield the best results, three cases were considered. Load profile data from a varying number of weeks was used as the input to the algorithm and the results observed. These results are shown in Table 1.

For each set of results a different quantity of data was presented to the algorithm. It was observed that using data from one week prior to the test yielded the best results. This result was more accurate by factors of 2.5 and 4.0 when compared to the results achieved when using averaged data from the two weeks prior and averaged data from the three weeks prior to the test respectively. Thus load profile data from one week prior to the test was used as the input to the algorithm.

3.2 380 V system

Using data from an office building the performance of the load forecasting algorithm was determined. The results for a full week prediction are shown in Table 2 with a sample of the load profile shown in Figure 2.

Table 1: Results of varying the amount of load profile data presented to the algorithm.

Input Data (weeks)	Peak Error (%)	Total Energy Error (%)	Average Errors (%)
1	0.18	3.11	1.65
2	4.55	3.68	4.12
3	6.18	7.17	6.68

Table 2: Results of the 380 V system load forecast for a week.

Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	0.18	0.64
Tuesday	0.18	0.18
Wednesday	0.18	0.02
Thursday	0.18	0.37
Friday	0.20	0.56
Saturday	1.00	0.20
Sunday	1.00	0.00
Average	**0.42**	**0.28**

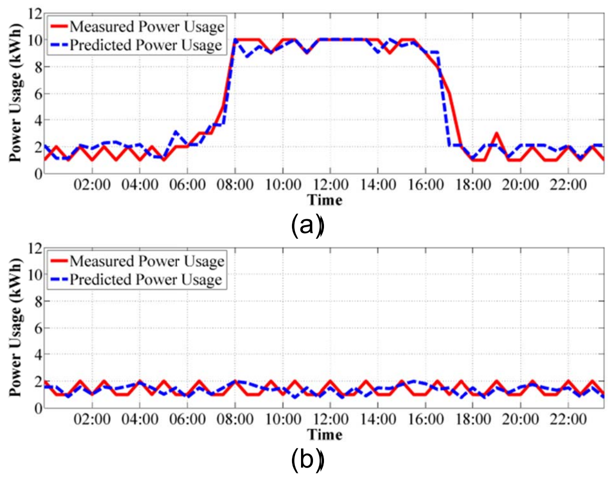


Figure 2: Normalised load profile and the predicted power usage of a 380 V fed office building for: (a) weekdays and (b) weekend days.

The results of the forecast for a week show that the average peak error over the period of a week is 0.42 % and the average total energy error is 0.28 %. These results verify the load forecasting ability of the algorithm.

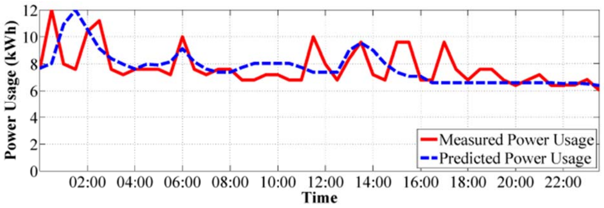
The load profiles in Figure 2 clearly indicate the need to differentiate between week and weekends for load forecasting purposes. The predicted power usage does not correlate perfectly with the measured power usage. However this does not impact the results since the defined performance of the algorithm does not consider the difference between the measured and forecast loads at each sample point.

4 LOAD FORECASTING ON HIGH VOLTAGE SYSTEMS

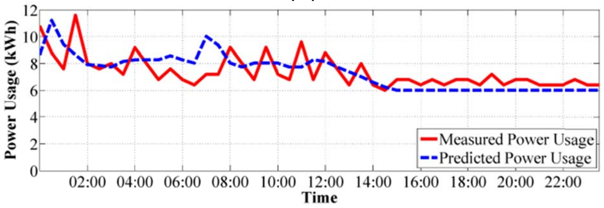
Two high voltage loads were used to evaluate the performance of the load forecasting algorithm on high voltage systems.

Table 3: Results of the 11 kV system load forecast for a week.

Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	0.00	0.01
Tuesday	0.34	0.01
Wednesday	9.00	0.00
Thursday	1.11	2.25
Friday	0.18	0.00
Saturday	3.28	0.00
Sunday	0.18	0.01
Average	**2.01**	**0.33**



(a)



(b)

Figure 3: Normalised load profile and the predicted power usage for the 11 kV system for: (a) weekdays and (b) weekend days.

4.1 11 kV system

Data was acquired from the 11 kV ring feed for one of the university campuses. The results of the test are shown in Table 3 and the campus load profile is shown in Figure 3.

The results from the load forecasting algorithm indicate that the average peak error over the period of a week is 2.01 % and the average total energy error is 0.33 %. The peak errors fluctuate greatly when there is a noticeably higher peak during the test week when compared to the input data to the algorithm. This is particularly evident in the Wednesday peak prediction.

The load profile for a university campus clearly has less variance than a single office building (see Section 3.2). Thus there is also less variance between week and weekend predictions, which is depicted in Figure 3. There is still a noticeable difference between the week prediction and the weekend prediction, due to the quantity of persons on campus.

Table 4: Results of the 88 kV system load forecast for a week, using autumn data.

Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	0.10	0.06
Tuesday	0.44	1.74
Wednesday	0.28	0.54
Thursday	0.09	0.41
Friday	14.00	0.02
Saturday	0.39	0.00
Sunday	0.24	0.00
Average	**2.22**	**0.40**

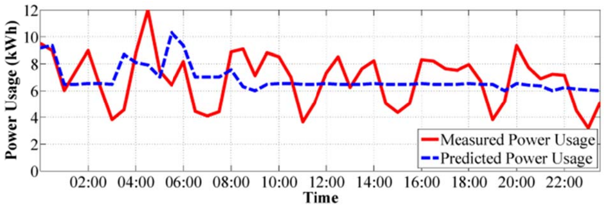


Figure 4: Normalised load profile and the predicted power usage for the 88 kV system during autumn for a Friday.

4.2 88 kV system

Four separate tests were performed on the 88 kV system load data, acquired from the South African power utility. A week from each season in 2010, based on the South African weather patterns, was selected to evaluate the load forecasting algorithm for eventual all-year-round forecasting.

The load profiles observed showed that the week and weekend loads follow the same trend. Thus no discernable difference between the two could be established.

3.2.1 Autumn test Results shown in Table 4 are for the autumn season of the 88 kV system tests. The power usage data used was for the month of March. The typical daily autumn load profile is shown in Figure 4.

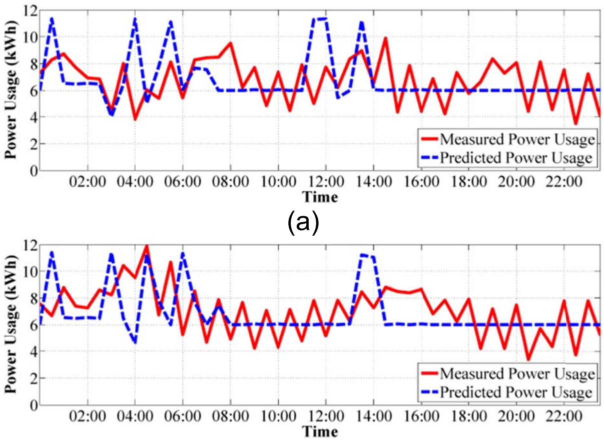
The results of the week long forecast indicate that the average peak error over the period of a week is 2.22 % and the average total energy error is 0.40 %. The increased total energy error on Tuesday is due to an overestimation of the required energy by the load forecasting algorithm. The significantly increased peak error on Friday was due to a substantial underestimate by the algorithm, as shown by the comparison of the measured and predicted power usage in Figure 4. The peak fluctuation drastically reduces the peak forecasting accuracy.

Table 5: Results of the 88 kV system load forecast for a week, using winter data.

Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	0.03	0.11
Tuesday	2.20	0.01
Wednesday	0.50	0.01
Thursday	14.74	0.00
Friday	4.06	3.21
Saturday	0.19	0.01
Sunday	0.03	0.00
Average	**3.01**	**0.48**

Table 6: Results of the 88 kV system load forecast for a week, using spring data.

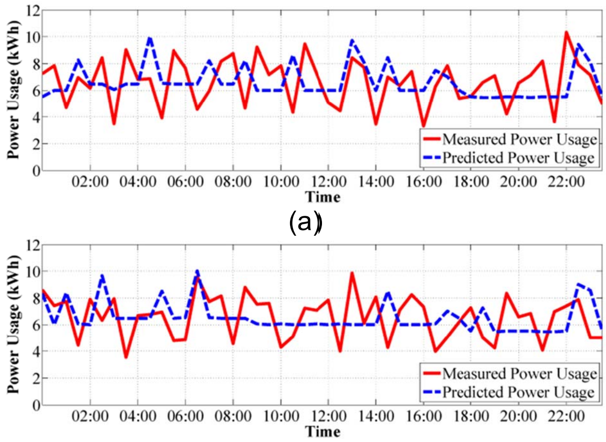
Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	0.28	0.01
Tuesday	2.94	0.00
Wednesday	0.68	0.50
Thursday	1.66	0.01
Friday	0.16	0.01
Saturday	0.50	0.01
Sunday	0.07	0.00
Average	**0.90**	**0.08**



(a)

(b)

Figure 5: Normalised load profile and the predicted power usage for the 88 kV system during winter for a: (a) Thursday and (b) Friday.



(a)

(b)

Figure 6: Normalised load profile and the predicted power usage for the 88 kV system during spring for a: (a) Tuesday and (b) Thursday.

3.2.2 Winter test Results shown in Table 5 are for the winter season of the 88 kV system tests. The power usage data was for the month of June. The typical daily winter load profile is shown in Figure 5.

The results indicate that the average peak error over the period of a week is 3.01 % and the average total energy error is 0.48 %. The peak error on Thursday was due to an overestimation in prediction, shown in Figure 5 (a). This, in turn, was due to the peak from the week prior to the test being higher than the test week. The total energy error on Friday was due to the prediction being lower than expected, shown in Figure 5 (b). The magnitude of the load was observed to be the smallest of the test cases.

3.2.3 Spring test Data from September was used to perform the 88 kV system test for spring. The results are shown in Table 6. The typical daily load profile for this season can be seen in Figure 6.

The average peak error over the period of a week was 0.90 % and the average total energy error was 0.08 % for the forecast load. The increased peak error on Tuesday was due to a higher measured peak power usage, shown in Figure 6 (a), and the increased peak error on Thursday was due to an overestimate in prediction, shown in Figure 6 (b).

3.2.4 Summer test December power usage data was used to obtain the results shown in Table 7. The typical daily summer load profile is shown in Figure 7.

The results of the forecast indicate that the average peak error of a summer week is 3.65 % and the average total energy error is 0.23 %. The peak error is more significant than for the spring tests due to the greater variance in the load as would be expected during the summer months. The total energy error on Monday was increased since the prediction was consistently lower than the measured power usage, as shown in Figure 7. The magnitude of the load was observed to be the highest of the test cases.

Table 7: Results of the 88 kV system load forecast for a week, using summer data.

Day of Week	Peak Error (%)	Total Energy Error (%)
Monday	2.00	1.57
Tuesday	3.35	0.01
Wednesday	3.59	0.00
Thursday	8.64	0.03
Friday	7.62	0.01
Saturday	0.18	0.00
Sunday	0.14	0.00
Average	**3.65**	**0.23**

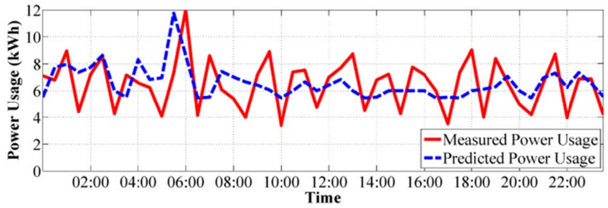


Figure 7: Normalised load profile and the predicted power usage for the 88 kV system during summer for a Monday.

4.3 Analysis of results

Observations were made regarding the measured data used in the described tests. The magnitude of the load varied throughout the year, however the maximum demand occurred during the summer test and the minimum demand occurred during the winter test. This is not intuitive since it is generally assumed that most power is used during the winter months.

Based on the results achieved the following trends were observed regarding the load profile and corresponding errors:

- Week and weekend loads have similar profiles on the 88 kV system.
- The algorithm is highly susceptible to fluctuations in the load profile.
- Both defined errors were increased when significant differences were observed between the test week and algorithm input data.
- The peak error was influenced more by fluctuations in the power usage data than the total energy error.

Despite the errors varying substantially, the load forecasting algorithm was found to function satisfactorily based on the defined performance criteria. The average peak error for the four tests was 2.45 % and the average total energy error was 0.30 %.

5 FUTURE WORK

In order to reduce the errors several enhancements are recommended as future work. Some of these include reducing the dependency of the algorithm on the load profile fluctuations, as well as incorporating a list of South African public holidays. Additional inputs are required for the fuzzy logic systems to reduce the dependency on the load profile fluctuations. The additional inputs would be weather data (such as temperature and precipitation) since there is a strong correlation between weather and power usage [6]. A list of South African public holidays would also be necessary such that all days in the year can be modelled. This would allow for the load forecasting algorithm to be used at any time.

6 CONCLUSION

A novel modelling approach to perform load forecasting to aid energy management has been presented. The algorithm uses two fuzzy logic systems for load forecasting, and a genetic algorithm to parameterise the system parameters. The most accurate results were achieved when data from one week prior to the test was used, by factors of 2.5 and 4.0 when compared to using two and three weeks' data respectively. Preliminary tests on a 380 V system indicated the distinct difference in week and weekend load profiles and confirmed the forecasting ability of the algorithm.

Extending the study, two high voltage systems were tested using the load forecasting algorithm. The 11 kV system yielded an average peak error of 2.01 % and an average total error of 0.33 % over a week. The 88 kV system was tested for each of the four seasons, yielding an average peak error of 2.45 % and a total energy error of 0.30 %. Several trends were observed in the results such as the week and weekend loads having similar profiles (in the 88 KV system) and the susceptibility of the algorithm the fluctuations in the load profile.

Future work, such as incorporating weather data and a list of South African public holidays, was proposed. These additions would potentially increase the performance of the algorithm further.

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