ANN Approach for Predicting Economic Trends based on Electric Energy Consumption during Natural Disaster Period

Akanit Kwangkaew
School of ICT, Sirindhorn International Institute of Technology , Thammasat University,
Email: akanitk84@gmail.com

Virach Sornlertlamvanich
School of ICT, Sirindhorn International Institute of Technology, Thammasat University
131 Moo 5, Tiwanont Rd., Bangkadi Muang, Pathum Thani 12000, Thailand
Email: Virach@gmail.com

Itsuo Kumazawa
Tokyo Institute of Technology, Suzukakedai Campus
4266 Nagatsuta-cho, Midori-ku, Yokohama, 226-8503, JAPAN
Email: kumazawa.i.aa@m.titech.ac.jp

Siriya Skolthanarat
National Electronics and Computer Technology Center
112 Thailand Science Park, Phahon Yothin Rd., Klong I, Klong Luang, Pathum Thani 12120, Thailand
Email: siriya.skolthanarat@nectec.or.th

***Abstract*—Economy trend (eco-trend) is the most important factor for developing the country. Unfortunately, various inevitable and unpredictable factor causes an effect on economic trend while the Natural Disaster period happened. The fluctuation of the trend is then occurred and make it more difficult to forecast. According to this research, the analysing method of the eco-trends prediction was represented by stock prices prediction and use the datasets of some industrials sector which mainly uses electricity for production. Then we found that the stock prices can be predicted more precisely after increasing electric energy consumption to be input features taking by using Artificial Neural Network. However, the result of the prediction is precisely in the normal period only. Therefore to analyse the prediction occurring in natural disaster period (the flood of Thailand 2011), the cross-checking method is considered. Finally, For the performance comparison of experiment results, the mean squares error (MSE) and root mean squared error (RMSE) are used. Finally the results of this research, they not only show how power consumption makes the results of stock prediction are more precise, but also provide the time-delay that is the indicator of the economic trends changing and can then explain the behaviour of the industrial segment in the natural disaster period.**

I. INTRODUCTION

Electric energy consumption can be easily converted into other energy types. So it is an important energy factor for developing the country and this is the idea of this research. Moreover, it also can be a perfect factor in predicting the economy trend, especially for industrial segment mainly uses electricity for production. The reason for taking the electric energy consumption for prediction the trends in natural disaster period, it has explained from the related research of relation between electric energy consumption and the eco-trends, which was represented by the trend of stock prices, and about details in Section IV.

Meanwhile, it will be a very useful thing if we can precisely predict the eco-trend in disaster period. In order to analyse the eco-trends in natural disaster period, this period was represented by the flood of Thailand 2011. The reason why the datasets were chosen for doing this experiment is that the industrial sector of Thailand is one of ASEAN's largest production center and being the world's 2nd largest producer as follow [2] and [3]. And the damage of the flood was around 1.44 trillion baht and this is said to be the world's fourth deadliest natural disaster follow as [1]. And the datasets of the industrial sector were used. They are represented by the two examples, i.e. Company A (an automobile parts factory) and Company B (a food processing factory) in Thailand. The detail of the datasets would be explained in Section III.

The prediction algorithm, Artificial Neural Network (ANN) is a famous information processing for many application was used in the experiment. Because of Imitated information processing power of the nervous system in human brain. According to the other researches as [4], [5], [6], [8], [9] and [14], ANN can be used with the power consumption with several kinds of features for finding their result. This is why ANN is a powerful tool for taking implementation of this research

In our content, the literature reviews are described in Section II. Materials and the methodology are described in Section III. The implementation and the results are given in Section V and Section VI respectively. Section VII concludes the resultss.

II. LITERATURE REVIEWS

A. Artificial neural network architecture (ANN)

The ANN used for this paper is trained by passing data to layers named input layer, hidden layer(s). And the output layer gives the result. Each layer consists of nodes containing the weights and bias factors (as shown in Fig.1). And then, the result was computed by adjusting weights and biases for the input and target dataset. This calculation is called Feed Forward Neural Network (FFNN) as in [11], which is the same concept of human brain.

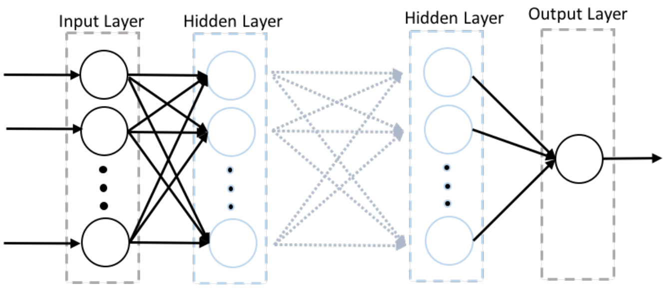

Figure 1. Artificial neural network architecture

In our experiment, the datasets are fed into the model. The difference between predicted value and a target value (or observation value) is called Cost function or Error function. It will be minimised using gradient descent method to train until getting the minimum error according to the error value setting. And the Backpropagation is the popular algorithm that tackles the calculation in the ANN model. When this concept is implemented. It then has some problem which takes a long time in a computer process. And the LM algorithm is used to make the computer run faster by cutting some numerical term in the process off and it still gets the valid results. And the LM′s details is shortly described later.

B. Backprobagation algorithm (BP)

Recently, the BP is the most widely applied neural network architecture covering the area of architectural design, performance measurement, function approximation capability, and learning as follow [10]. In ANN, Gradient Descent method is used to calculate the weight function in each node of NN as shown Fig.1 and the computing direction start from the output layer to input layer. And then the predicted error value and observed value must be decreased to minimise by backwards computing. In order to reduce the error, the weight of each node is decreased.

C. Levenverg-Marquardt (LM)

Follow as [15], LM is a blend of gradient descent and Gauss-Newton and it was taken into the function in this paper which is called Nonlinear Least Squares Minimization. The reason of using LM is to deal with the problems from using gradient descent method. Some of the problem and solutions will be explained in this section. Using gradient descent method is still has some restricted issue to implement. It always takes a long time when it is implemented in a real world and sometimes the calculating machine has a limited capability to run it on a computer. How to deal with the problem, we need to explain a little deep in the mathematic in our function. The double derivative of matrix is called Hessian $\nabla^2 f(x)$ (assume that $f(x)$ is a cost-function). To make it faster, the small term in Hessian has been cut off by approximate, but the result is still acceptable.

III. Materials and the Methodolog

A. The Datasets used

In this paper, the two example companies are considered, i.e. Company A (an automobile parts factory) and Company B (a food processing factory) in Thailand. And each of company contains of two datasets. The first data set is the monthly electrical power consumption of two companies during the flood , collected by utility sector of PEA (Provincial Electricity Authority). And the second data set is the monthly average stock prices from Bloomberg website. The two datasets of each company were collected during 2011 to 2015 in flooding period.

B. Generating the Disaster Signal (DS)

DS is the indicator of the damage due to the flood during the Thailand flood in 2011. We tried to define the as an additional feature for training model in ANN. The definition of DS is mapped from the flood map of each province as [7]. The annotated DS level in training data set of Company A and Company B is used to retrain the model. Company A is in Pathum Thani province and Company B is in Nakhon Pathom province. To figure out the DS features, it consists of 5 levels of damage as shown in Table I:

Table I
Definition of the Disaster Signal(DS)

Damage Level	definition	% flood area
level 1	no flood	0%
level 2	know to be the flood (but no flood)	0%
level 3	some area has the flood	less than 30%
level 4	half area	30 - 60 %
level 5	full area	more than 60 %

C. The Performance Indicator

In our experiment, ANN is a supervised neural network (NN). The most NN's use MSE as shown in equation(1) to show the performance of the NN model. The MSE is a one of robust method to evaluate NN's performance because MSE can deal with both positive and negative values[12]. In the past, it is commonly known as the least mean squares (LMS) which can be used well and feasible when no computer was available. Nevertheless, it is still a common method for NN in the present. The root mean squared error (RMSE) which follows as an equation(2) can also evaluate the permanence of the NN as well. Because it is a large digit number so that we can easily observe the result.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2 \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - t_i)^2}{n}} \quad (2)$$

Where t is the target value and y is the predicted value.

IV. The Relation of Electric Energy Consumption and Stock Price

The explanation of the relation between electric energy consumption and eco-trends are shown in this section. This experiment was conducted in normal period without any disaster. And the result shows that the power consumption can improve stock prediction efficiently in each sector especially for the industrial segment as follows.

1) Experiment of Electric Energy Consumption and Stock Price: As mentioned, the eco-trends were represented by the trend of stock prices for this experiment. They are predicted by using the two datasets of each example industrial factories (Company A and Company B). The datasets of this experiment are taken in the normal period. In the prediction, the monthly stock price (UNT: unit stock price) of the examples are predicted by using input two features of their monthly and separate to 2 cases. And the relation between electric energy consumption and the trend of stock price is examined using the observations of the procedures and the results.

First case, the input is only monthly stock price (UNT : Unit Stock Price). And the second case, UNT and monthly electric energy consumption (kWh: kilo-Watt hour). Each case, the prediction model will be used the inputs for the training set. And, compare the two cases. Next, in the same experiment, Company B is predicted in the same method. Then the error from the experiment is recorded using mean square error (MSE) and root mean square error (RMSE).

2) Summary of Electric Energy Consumption and Stock Price: After doing the experiment, the performance results are shown by MSE and RMSE using Company A's datasets are tabulated in TABLE II and illustrated in Fig.2. The error 3 of 5 cases can be reduced (up to 3.51%) after adding the electric energy consumption to predict.

Table II
PERFORMANCE OF COMPANY A'S STOCK PREDICTION

Sliding window(n month)	Input Feature			
	UNT		UNT and kWh	
	MSE	RMSE	MSE	RMSE
n=2	0.8725	0.93409	0.89068	0.94376
n=3	0.8683	0.93187	0.83892	0.91593
n=4	0.86699	0.93112	0.8617	0.92828
n=5	0.89069	0.94377	0.87342	0.93457
n=6	0.78826	0.88784	0.8016	0.89532

And the results of an experiment using Company B's datasets shown in TABLE III and Fig.3. The error 5 of 5 cases can be reduced (up to 37.25%) after adding the electric energy consumption to predict.

According to the results, it was shown the electric energy consumption data can improve the performance of stock prediction of industrial segment. That is the reason of this research analyse the eco-trend by electric energy consumption.

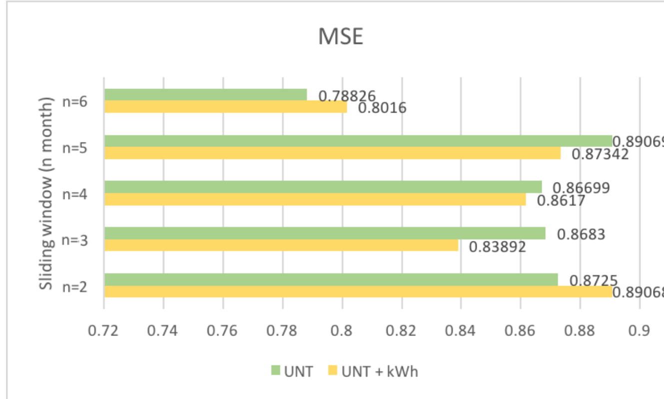

Figure 2. Comparing the Performance of Company A's stock prediction

Table III
PERFORMANCE OF COMPANY B'S STOCK PREDICTION

Sliding window (n month)	Input Feature			
	UNT		UNT and kWh	
	MSE	RMSE	MSE	RMSE
n=2	0.89124	0.94405	0.65877	0.81165
n=3	0.97703	0.98845	0.74423	0.86269
n=4	0.80969	0.89983	0.65938	0.81202
n=5	0.71537	0.8458	0.52119	0.72193
n=6	0.79383	0.89097	0.66516	0.81558

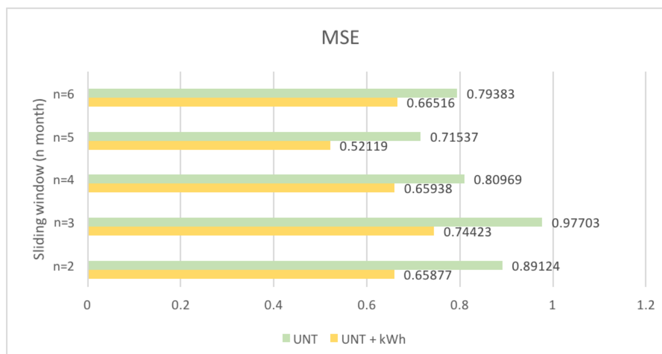

Figure 3. Comparing the Performance of Company B's stock prediction

V. Implementation

This section has the same concept explained in previous section. Eco-trends are also represented by the trend of stock prices in the example. Then, the analysing process for this section is designed to analyse the trend with the electrical energy consumption because the previous section has shown that they have a relation to each other. And the special thing in this paper is the feature inputs of the cross-checking prediction model is the difference field.

The stock prices are also predicted from observation their history of stock prices and electric energy consumption in order to observe the result and find the Time-delay. The input selection chooses the sliding window method follow as [13] which is quite common use in the time series with the prediction by using ANN. Then, the experiments are classified to be 2 tasks (Task I and Task II) of the experiment.

NN models for predicting the eco-trend are used in the MATLAB with using the Levenberg-Marquardt backpropagation algorithm. The setting parameter, consists of one input and one output layer. Neurons in the input layer depend on the number of windows sliding and neurone in the output layer. The other settings values are used in the same in every process. Because of our experiment need to compare the result of each model which focus the effect of input features as follow the assumption. Therefore, the number in hidden layer was set to 20, the learning was the rate set to 0.05, the maximum of the each approach was set to 1000 and the goal performance was set at 0.001. All conditions were set to the same values. For the datasets, approximately 70% was used for training, 20% for validation and 10% for testing.

A. *Task I: Cross Checking*

Cross-checking of the stock prediction is proposed in this task. The stock prices of Company A are predicted on ANN model having the training datasets of the Company B datasets (monthly electric energy consumption and stock price). And then, get the result of Company A′s stock prices. Next step, they are cross check by predicting the Company B′s stock prices from NN model having the training datasets of the Company A datasets in the same method. Finally, the performance in each process are shown in Table IV. And the number of sliding window in the best case of performance, it is the time-delay.

B. *Task II: Cross Checking with DS*

This topic is the same concept of Task I, but the damage level of the flood (DS) is added to the predicting model to point the damage in each place. And evaluating the result is the same concept of Task I. Finally, the number of sliding window of the best case, it is the Time-delay follow Table V.

VI. Result

From the experiment, it shows the performance of each issue from cross checking which can figure out the behaviour of each industrial segment correspond the 2 example companies. According to our result, see in TABLE II and TABLE III.

Table IV
Performance of Task I

Sliding Window (n month)	Error of Predicted value (Without DS)			
	Company A		Company B	
	MSE	RMSE	MSE	RMSE
n=2	0.57455	0.75799	0.7052	0.83976
n=3	1.1487	1.0718	1.2861	1.1341
n=4	0.49617	0.70439	0.4949	0.7035
n=5	0.73923	0.85979	0.5984	0.7736

Before the DS adding to be a feature in ANN, two companies have the pattern of charts (see Fig. 2 and Fig. 3). And they have the same best value is 4 month of both. But after adding the DS, the error of predicted values was decreased from Task I to Task II up to 24.76 % for Company A and 45.31% for Company B. And the same best values have changed the Time-delay to 2 months for Company A and 4 months for Company B.

Table V
Performance of Task II

Sliding Window (n month)	Error of Predicted value (With DS)			
	Company A		Company B	
	MSE	RMSE	MSE	RMSE
n=2	0.37331	0.61099	0.37285	0.61061
n=3	0.52069	0.72159	0.27506	0.52446
n=4	0.53683	0.73269	0.27066	0.52025
n=5	0.16296	0.4036	0.21213	0.46057

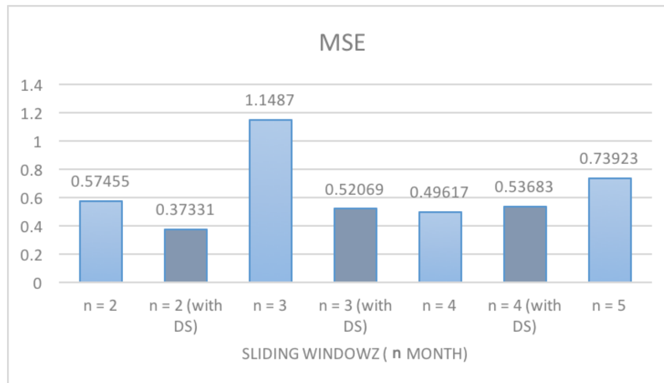

Figure 4. The performance of Company′s A Predicted Value

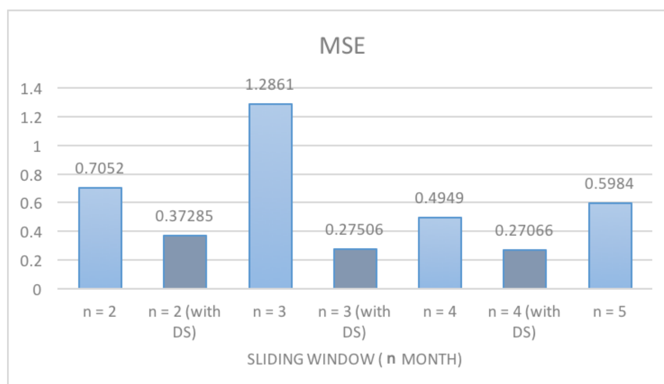

Figure 5. The performance of Company′s B Predicted Value

VII. Conclusion

Not only taking electric energy consumption can improve the the performance of stock prediction in normal period, but also it can improve the performance in the natural disaster period by using DS and cross checking method. According to the results, two issues will be described. The first issue, in Task I, although the two example companies are difference type of industrial type, but the results show the same pattern when the examples are observed by their history of power consumption and stock prices. In this case, we can found the same behaviour of company or industrial in the period but more errors. For the second issue in Task II, after adding the DS which is the flood indicator into our model, it makes deceasing in the resulting error the performance of the prediction model. So, it has improved. According to the number of time series, the predicted value being most accurate is the time-delay which is the importance indicator for planing the eco-trend. And to deal with the natural disaster period. As the experiment, the time-delay is 2 month for Company A and 4 months for Company B.

ACKNOWLEDGEMENT

This research is financially supported by Thailand Advanced Institute of Science and Technology (TAIST), National Science and Technology Development Agency (NSTDA), Tokyo Institute of Technology, Sirindhorn International Institute of Technology (SIIT), Thammasat University (TU) under the TAIST Tokyo Tech Program. Also thanks to support from Provincial Electricity Authority (PEA).

Moreover, Authors would like to express our gratitude and thank you to our colleagues, Phat Jotikabukkana and Panuwat Assawinjaipetch for the guideline in many other methodologies, S.M. Isuru Niroshana and Goragod Pongthanisorn for their help in implementing the software code. Finally, Authors most gratefully acknowledge my teacher and my friends for support throughout the period of this research.

REFERENCES

[1] S. Koontanakulvong and P. Santitamnanon, "Lesson Learned And Information Technology Roles In Thailand Floods 2011," in *IIEEE Region 10 Humanitarian Technology Conference,*Sendai, Japan, August 26-29, 2013, pp.298-302.

[2] Tennesee Valley Authority, "Energy Vision 2020," in *tegrated Resource Plan/Environmental Impact Statement*,Chapter 6, December, 1995.

[3] Thailand Remains World-Class Production Base for Hard Drives. [Online]. Available: http://www.boi.go.th/tir/issue/201202_22_2/42.htm. Accessed Accessed Aug. 13, 2016.

[4] S. Rajab, and V. Sharma, "Performance Evaluation of ANN and Neuro Fuzzy System in Business Forecasting," in *IEEE Inter Conf. Computing for Sustaunable Global Development (INDIAcom),*2^{nd}, India, 2015, pp. 749-754.

[5] W. Mai, C. Y. Chung, T Wu, and H. Huang, "Electric Load Forecasting for Large Office Building Based on Radial Basis Function Neural Network," in *2014 IEEE PES General Meeting — Conference & Exposition*, USA, July 27-31, 2014, pp.1-5.

[6] N. Amjady, F. Keynia, and H. Zareipour, "Short-Term Load Forecast of Microgrids by a New Bilevel Prediction Strategy," in *IEEE Transactions on Smart Grid*, vol. 1, Dec. 2010, pp. 286 - 294.

[7] GISTDA, jun 201. in *[Thailand Flood Monitoring System].* Available at: http://flood.gistda.or.th/. [Accessed 1 May 2016].

[8] T. Kato, H. Horibe, N. Hayakawa, Y. Suzuoki and Y. Kaya, "Economic Evaluation of Independent Power Producers (IPP's) Viewed from Total Generating Costs of Electric Power Systems," in *IEEE Inter Conf. Energy Management and Power Delivery*, Mar. 1998, pp. 229-234.

[9] J.C. Sousa, L.P. Neves and H.M. Jorg, "Load Forecasting based on Neural Networks and Load Profiling" in *IEEE Inter Conf. Bucharest Power Tech Conference,*2^{rd}, Bucharest, Romania, June 28th - July 2nd, 2009, pp. 1-8.

[10] R. Hecht-Nielsen, "Theory of the Backpropagation Neural Network," in *I2001 IEEE International Joint Conference on Neural Networks (IJCNN 1989),* vol. 1, 1989, pp. 593-605.

[11] M. T. Hagan and M. B. Menhaj,"Training Feedforward Networks with Marquardt Algorithm," in *IEEE Trans. Neural networks,*44^{th},vol. 5, no. 6, nov 1994, pp.989-993.

[12] K. Liano,"Robust Error Measure for Supervised Neural Network Learning with Outliners," in *IEEE Trans. Neural networks,*vol. 7,1996, pp.246-250.

[13] J. K. Ting, Michael K. Ng, H. Rong and J. Z. Huang, I. S. Jacobs and C. P. Bean, "Statistical Models for Time Sequences Data Mining," in *IEEE Inter Conf. Computational Intelligence for Financial Engineering Proceedings*, 3^{rd}, Hong Kong, China, 2003, pp. 347-354.

[14] G. Dong, K. Fataliyev and L. Wang,"One-Step and Multi-Step Ahead Stock Prediction Using Backpropagation Neural Networks, in "*IEEE Inter Conf. International Conference on Information and Communication Systems,*4^{th},Irbid, Jordan, April 23-25, 2013.

[15] A. Ranganthan,"The Levenberg-Marquardt Algorithm," June, 8^{th}, 2004.