Electricity Consumption in Industrial Segment on Time Series Analysis

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***Abstract*—The economic growth in each country mostly depends on their industrial sector which always require an electrical energy. Therefore, power consumption should have some relations with changing of the economic trends that are represented by trends of the stock price in each an industrial sector for this paper. The relations also depend on each period and place. To prove the relations, our experiments are represented by two example companies in the difference industry sector, i.e. Company A (an automobile part factory) and Company B (a food processing factory), and consist of two phases using Artificial Neural Network(ANN). In Phase-I, monthly unit stock prices are predicted in the normal period by using 2 feature inputs of data sets. The first input is the history of their stock prices from Bloomberg website in the past 5 years. And another is their power consumption in the past 5 years and collected by PEA (Provincial Electricity Authority) of Thailand government enterprise in the utility sector. In Phase-II, we estimate the same thing in Phase-I but focus on Thailand flood 2011 period or hazardous period. And then we conduct cross-checking between the two examples with a Disaster Signal (DS). Finally, the performance showed up to 37.25% and 64.55% in Phase-I and Phase-II respectively. So our experiment can completely prove the relations that mentioned over the period.**

I. Introduction

Electrical energy is an important power factor is an important factor in country development, and it can be easily converted into other energy types. In the industrial sector which affects to economic of the country required the electrical energy. Therefore, our assumption is the power consumption should have some relations with the changing of the economic section. It is represented by the monthly stock price of the samples. To prove the relations, the set of stock prices are predicted by the input features consist of datasets of the power consumption and the stock price from the two example companies as mentioned. The details of the experiment are described in Phase-I (in Section IV).

Natural disasters are an extreme adverse event which utterly devastates human lives and human build environment. From a review in [4], Approximately 12.8 million of people were severely affected due to the tremendous flood in Thailand occurred in 2011 causing thousands of deaths and vast property damage. According to the world bank records, the damage was estimated at 1.44 trillion baht and this is said to be the world's fourth deadliest natural disaster as detail in [4]. The damage has directly effect to the industrial sector behaviour. To analyse this case, we considered the damage of due to the flood to create the (DS) by employed as a feature in order to represent the impact of the flood effect to the economic trends in the country. The details are described in Phase-II (in Section IV).

To deal with the difficult forecasting such the stock prediction from many features of input is same as [1], ANN is quite common use. The ANN uses gradient descent method learn weights and bias follow from the datasets and the algorithm is known as backpropagation(BP) which used in conjunction with an optimisation method which was used in the experiment [3]. The optimisation method as mention in BP is Levenberg-Marquardt(LM) Algorithm which is the most widely used optimisation algorithm as in [11] and [9]. To re-arrange our inputs, we used the sliding window method as [2], and the number of them affects the performance of the prediction. Finally, the performance was evaluated by mean square error (MSE) and root mean square error (RMSE) to analyse the data by comparison. However, ANN is a popular tool used to predict the arbitrary value, especially the stock price as reported in [1], [2] and [3].

In our content, the literature reviews are described in Section II. The related datasets and methods are described in Section III. The implementation and the results were given in Section IV and Section V respectively. Section VI emphasises the conclusion.

II. Algorithms

This section provides some the brief of the algorithms and methods using which related to our experiment as follow.

A. Artificial neural network architecture (ANN)

The ANN used for this paper are described, the data will be trained by passing an input layer, hidden layer(s) and feed the target data into output layer. In each layer consists of nodes which will be contained the weights and bias inside (as shown in Fig. 1). And then, it will be calculated by adjusting weight and bias follow the input and target dataset to created the model for prediction. The calculating is the manner of Feed Forward Neural Network (FFNN) as in [9], which is the same concept of how working in the human brain.

In our experiment, the datasets will be fed into the model. The difference between predicted value and target value (sometimes call "observation value")are call Cost function or Error function. The Cost function will be minimised using gradient descent method to train until getting the minimum

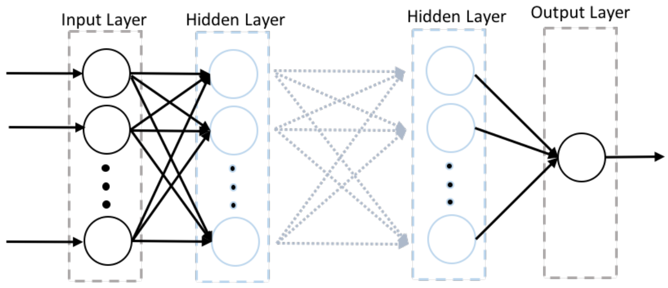

Fig. 1. Artificial neural network architecture

error according to the error value setting. The BP is the popular algorithm that tackles the calculation in the ANN model. When this concept is implemented. It has some problem which takes a long time in a computer process. So, 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.

1) Gradient Descent (GD): In the experiment using mathematically derivative techniques, the result must be calculated from the function which is our data fitting to find one minimum value of hypothesis. But the function will get an unexpected curve and several local optimum values. So, it has many unexpected hypotheses and it does not have any local optima except for the experiment. So that to get the one of the optimum value, the solution is called a convex function. It will turn out the unexpected shape (minimum values) of cost-function is to be the bow shape (has only one optimum value).

2) Levenverg-Marquardt (LM): Follow as [11],[9], 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.

3) Newton's method: Another issue of the problem, the gradient descent suffers from various convergence problems. In the calculation, we need to take the steps down the gradient to find the minimum value. But it is controlled by setting the learning rate variable. It is large the gradient will rattle out of the minimum value and can not get the result as well. And the curvature of error function may not we the same directions. To tackle the problem the Newton's method is the importance role of editing the problem as [11].

III. Materials and Methods

A. The Datasets used

Before the analysing procedure, we classified the experiment to be two phases (Phase-I and Phase-II). Both phases used two datasets of the two examples but in the different period. The two examples are considered, i.e. Company A (an automobile parts factory) and Company B (a food processing factory) in Thailand.

In details of the two datasets, the first data set is the monthly electrical power consumption (kilowatt hour: kWh) of the two companies in the past 5 years (September 2011 - November 2015), collected by PEA (Provincial Electricity Authority) of Thailand government enterprise in the utility sector. And the second data set is the monthly average stock prices (unit stock price : UNT) from Bloomberg website for the past 5 years. The two datasets of each company during 2011 to 2015 of the two companies are gathered which covers the big flooding period in Thailand.

B. Generating the Disaster Signal (DS)

To analyse the economic during the Thailand flood in 2011 in Phase II, we try to define the DS in order to include the damage factor which is the additional feature for training model in ANN. The definition of DS is mapped from the flood map of each province as [5]. The annotated DS level in training data set of Company A and Company B is used to retrain the model. Company A is located Pathum Thani province and Company B has located Nakhon Pathom province. Because of both provinces are in the seriously damaged areas in the flood of Thailand. The DS consists of 5 levels of damage as shown in Table II:

C. The Performance Indicator

In our experiment, using ANN is a supervised neural network (NN's). The most NN's use MSE which follows as an equation (1) to show the performance of the NN model. And the research in [10] said it is a one of robust error for measure NN's. Because of the error value always has positive and negative value, MSE can deal with that reason as well. However, it is a common method in NN. 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. The root mean squared error (RMSE) which follows as an equation(2). It can also show the permanence of the NN as well. Because it is a large digit number so we can easily observe the result.

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

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

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

IV. IMPLEMENTATION

In this section, we will prove of the relation as mentioned by observing the result of stock prediction in each process.

ANN are used in the MATLAB with using BP algorithm. The setting parameter, it consists of one input and one output layer. Only the number neurones in the input layer depend on the number of window sliding and one neurone in the output layer. But 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 epoch was set to 1000 and the goal performance was set at 0.001. All conditions were set the same value. For the datasets, approximately 70% was used for training, 20% for validation and 10% for testing.

For our implementing, we classified the process of the experiment to be two phases (Phase-I and Phase-II). In Phase-I, we design the model to analyse the power consumption (kWh) of each company which demonstrates their unit stock price (UNT) in the stock market and simultaneously analyses the economy in the future. The prediction UNT with the history of UNT along with the history kWh. We input the feature into the ANN model by sliding window which is the representing method in both phases. In Phase-II, we design the two model to analyse the economic fluctuation during the disaster time (the hazardous period). Both models have added the disaster signal (DS) to point out the two facts.

Firstly, it shows that how the disaster effects to the economic behaviour and secondly how DS feature improves the accuracy of the prediction. Finally, the goal is to deal with unseen damages and making accurate predictions in the future. In order to figure out of using the data sets in each phase, they are shown in Table I:

TABLE I
USING THE DATASETS

Phase	Company A		Company B		DS	Period
	kWh	UNT	kWh	UNT		
I	(T)	T, P	-	-	-	N
I	-	-	(T)	T, P	-	N
II (Model 1)	-	P	T	T	T	H
II (Model 2)	T	T	-	P	T	H

T : use for training, P : is predicted, N : non-hazardous period, H : hazardous period, () : use and do not use

A. Phase-I : Power consumption and Economy

As mentioned, in this phase, we use kWh to prove the relation by feed in the stock prediction, the datasets from each the company in the non-hazardous period. Then, we examine the current economic condition using the observations of the procedures and the prediction of the stock price as the inputs to the UNT. The monthly UNT of Company A are predicted by using input two features of their monthly by separate to be two patterns. First use only UNT, and second use both UNT and kWh, to be the training set. And, compare the two patterns. Next, the monthly UNT of Company B is predicted in the same method. Finally, to get the result, the error from the experiment are recorded using mean square error (MSE) and root mean square error (RMSE) in the next section.

TABLE II
DEFINITION OF 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 %

B. Phase-II, Power consumption and Economy in the flood

In this case, we analyse the economic behaviour during the flood disaster by using the UNT prediction and observe their fluctuation. The DS is taken into account in this phase to understand the factor of the flood. The method is devised into two models, which are model 1 and model 2. In the model 1 uses the monthly kWh and UNT data from Company B as the training data sets to create the model and then predict the UNT of Company A. The effect of the flood with DS and without DS are investigated. And in the model 2, we conducted cross checking to predict the UNT of Company B from the data set of Company A in order to find the same of power consumption behaviour from both companies. Using the data can easily see in Table I. Finally, the experiment results show the performance by using MSE and RMSE in the next section.

V. RESULT

A. The result of Phase-I

The result of Phase-I shows the performance by MSE and RMSE. The performance of Company A shown in TABLE III. 80% of the error of the prediction result is reduced after adding the kWh feature to be input. Moreover, the result shows that Company A has the best number of the sliding window (previous number of input) is 3 months. And the performance of Company B is shown in TABLE IV. 100% of the error of the prediction result is reduced after adding the kWh feature. And the best number of sliding window is 5 months. Table III and IV show the error results of Company A and Company B in the experiment in Phase-I. The performance of Company A, in 3 of 5 cases, the MSE are reduced (up to 3.51%) after adding the kWh feature (as shown in Fig. 2). The performance of Company B, in all cases, the MSE are reduced (up to 37.25%) after adding the kWh feature (as shown in Fig. 3).

In this section, the performance of the two models of Phase-II is discussed. The performance of Model 1 and Model 2 are recorded in Table V and Table VI respectively. To analyse the economic impact of flooding, we observe the error (MSE) as shown in Fig. 4 and Fig. 5. In Phase-II, the error is decreased up to 54.67% and 64.55% in Model 1 and Model 2 respectively after adding the DS in the input feature of ANN in Phase-II.

TABLE III
PERFORMANCE OF COMPANY A'S STOCK PREDICTION, PHASE-I

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

TABLE IV
PERFORMANCE OF COMPANY B'S STOCK PREDICTION, PHASE-I

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

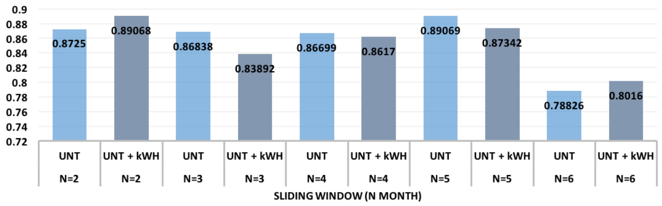

Fig. 2. MSE of Company A's stock prediction, Phase-I
3 of 5 cases, the MSE were reduced (up to 3.51%).

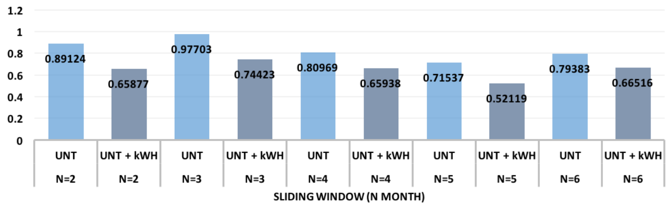

Fig. 3. MSE of Company B's stock prediction, Phase-I
All cases, the MSE were reduced (up to 37.25%).

B. The result of Phase-II

In this section has shown the performance the 2 models of Phase-II. The performance of Model 1 and Model 2 are recorded in Table IV and Table V respectively.

TABLE V
PERFORMANCE OF MODEL 1, PHASE-II

Sliding window (n month)	Input Feature			
	UNT + kWH		UNT+kWH+DS	
	MSE	RMSE	MSE	RMSE
n=2	0.57455	0.75799	0.37331	0.61099
n=3	1.1487	1.0718	0.52069	0.72159
n=4	0.49617	0.70439	0.53683	0.73269
n=5	0.73923	0.85979	0.16296	0.4036

TABLE VI
PERFORMANCE OF MODEL 2, PHASE-II

Sliding window (n month)	Input Feature			
	UNT + kWH		UNT+kWH+DS	
	MSE	RMSE	MSE	RMSE
n=2	0.7052	0.83976	0.37285	0.61061
n=3	1.2861	1.1341	0.27506	0.52446
n=4	0.4949	0.7035	0.27066	0.52025
n=5	0.5984	0.7736	0.21213	0.46057

To analyse the economic impacts of flooding, we can see the error (MSE), is necessary to take and consider the model of the experiment. To figure out the changing of the error (shown in fig.3 and fig.4.). In Phase-II, the error was decreased up to 54.67% and 64.55% in model 1 and model 2 respectively after adding the DS in the input feature of ANN in Phase-II.

VI. CONCLUSION

The results of Phase-I can prove that the power consumption is a factor which makes the stock prediction more precisely in the industrial sector and we can know the trend of the economy in the part by using their power consumption to be more precise. Therefore, the relations are proved follow our assumption. However, the performance of prediction still depends on the selection input or the best number of sliding window in ANN model and the characteristic of each industrial types.

Another case, in the non-hazardous or the flood period, it can be used to forecast the direction of the economy as well. As Phase-II, after the cross check let we know that the power consumption behaviour from both companies when they got the flood are similar. And it proved how the flood absolutely has the impact with the economic behaviour. According to the result of Phase-II , the performance can be increased up to 54.67% and 64.55% and depend on the disaster area and the close one.

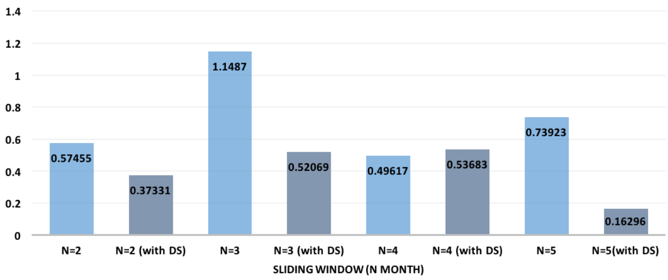

Fig. 4. MSE of model 1, Phase-II

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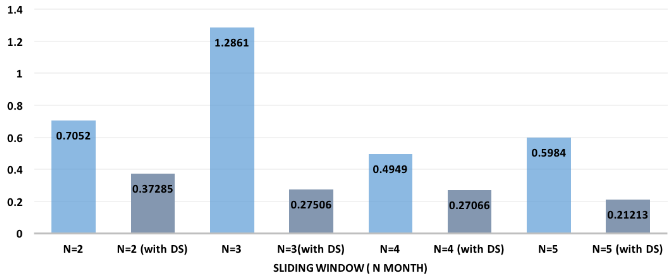

Fig. 5. MSE of model 2, Phase-II

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