IMPACT OF POWER CONSUMPTION ON STOCK PRICE PREDICTION IN MANUFACTURING SECTOR BY ANN APPROACH

BY

AKANIT KWANGKAEW

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (INFORMATION AND COMMUNICATION TECHNOLOGY FOR EMBEDDED SYSTEMS)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
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A Thesis Presented

By

AKANIT KWANGKAEW

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Abstract

IMPACT OF POWER CONSUMPTION ON STOCK PRICE PREDICTION IN MANUFACTURING SECTOR BY ANN APPROACH

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Economy growth system in each manufacturing country mostly depends on the manufacturing sector which uses electric energy to produce their products. Electric energy consumption (EPC), which can be easily converted into other energy types, plays an important role in producing the products in the manufacturing sectors. In this research, stock price (SP), reflexing the economic trends, are predicted by adding an EPC input feature in particular manufacturing sector. It improves the performance of the prediction to prove the relationship between EPC and SP.

To tackle the restriction of quantity of type of data sets, Cross Domain Checking (XDC) method is proposed for the prediction to eliminate the issue. According to an experiment, it was found that two data sets, automobile part and food processing factory, which is the different domain, can be crossed domain to predict SP by techniques in this research. This is a concept of XDC which a prediction uses data to be a training set from the different factories in manufacturing sector. This is useful for a lacking data set problem.

The XDC method was also used to approximately predict the trend of SPs in disaster period(Flooding in 2011 of Thailand). It is helpful to predict the trend of SPs even in an unexpected situation by using small data set. According to observations, in the disaster period, EPC dramatically decreased at the beginning. After that, the trend of SPs fluctuates and takes small rest period which is called “time-delay” that can be

measured by Monthly Time-Delayed Consequence (MTDC) Detection proposed method.

Keywords: Artificial Neural Network, Electric Power Consumption, Stock Prediction, Cross Prediction, Time lag, Time Delayed Consequence, Monthly Time-Delayed Consequence Detection

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Chapter1
Introduction

1.1 Statement of problems

- The trend of EPC is a possible cause for changing the trend of SP in an individual factory producing their product for selling. Therefore, the relationship between the trend of EPC and the trend of SP in an individual factory should be useful for analyzing processes.
- The relation between EPC and SP is significant for the manufacturing sector. To predict SP using EPC and SP inputs using artificial techniques. But, unprepared and lacking data set problems occur in natural disaster period. To tackle the problems, the training process prediction is modified by input data set to train from another manufacturing sector data set which is a different type and place but mainly consume electric energy.
- In a natural disaster period, the relationship between the trend of EPC and SP, they are thought to have significantly more than in the normal period. Because any manufacturing factories mostly consume the electric energy, therefore lacking of energy should induce the relation clearly.

When EPC is dramatically decreased at the beginning of the disaster period, it creates some small rest period in the trend of SP after fluctuating of the trend of EPC in the individual factory. This generates a small rest period which is called “time delay” that should be measured by mathematical method.

1.2 Significance

This research has speculated using EPC which affect to SP. EPC feature involved with SP prediction is studied with experiments aiming to use EPC feature to improve performance of the SP prediction and tackle the unprepared and lacking data problems in natural disaster period. Therefore, the relation of EPC and SP in manufacturing sector is highly significant in this research.

1.3 Objectives

- Prove that an EPC input feature has significant effect to SP prediction in normal period (without natural disaster period).
- Propose artificial intelligence (AI) method to improve performance of SP prediction with an EPC input feature.
- Propose method to tackle the unprepared and lacking data set problem of the SP prediction during natural disaster period.
- Propose method to find the time delay between the trend of EPC and SP of factories in manufacturing section.

Chapter 2
Literature Review

Economic growth in each country mostly which reflexes the trend of SP of individual factory depends on their manufacturing sector consuming an electrical energy. Besides electric energy is consumed by the engines in the factory in manufacturing sector to produce their products for selling. Therefore, in manufacturing sector, consuming electric energy is expected to have influence with their business which is reflexing by SP. Because Electric Power Consumption (EPC) though to have been indicating some energy consumption behaviors in individual the sector. The SP prediction is the importance method for doing experiment to figure out the relation between EPC and SP. This is why this research takes an EPC to be considered as another input feature for SP prediction.

The concept of the prediction which uses multiple inputs by AI technique. Like a decision circumstance of human thinking and selecting decision by previous data. They are surely deciding any circumstance when they have many data. And, the decision is more surely and precisely if the difference data and types are relevant to the story. From this concept, NN, which think like human brain, is used in the SP prediction models in this research. Multi feature types are taking into the models, i.e. EPC and Disaster Signal (DS). EPC is an indicator representing consuming energy behavior in an manufacturing sector. And, DS is an indicator that represents the damage from natural disaster in the considerable area.

It is impossible for ignoring natural disaster period that affects the financial system especially in manufacturing sector. Therefore, the period is also considered in the predicting model. To consider the period, it was separate to normal period and abnormal (natural disaster period) period which are represented by flooding. Moreover, the damage, of the period is representing by a Disaster Signal (DS) which is the damage level for flooding affecting to the manufacturing sector.

Multi-variables and multi-types in prediction model, as [2], they propose two methods, i.e. ANN and Adaptive Neural Fuzzy Inference System (ANFIS) with using two different data sets for predicting and comparing the results. The first data set is the sales forecasting of cold drinks and temperature which is a kind of different field of feature inputs. The second data set is the stock price from the daily stock market data of BSE obtained from Yahoo Finance. It is kind of unique field of feature input. As their result, ANN is good for the first data set (different type data set) and ANFIS is good for the second data set (same type data set). The algorithms are also work widely in other research. Therefore this research, we choose these algorithms to implement with the data set and compare the performance to choose a suitable algorithm. The comparison is done experiment and descripted in Chapter 5.

As the mention, the reason of using ANN algorithm in this research. Because it has been used vastly in the EPC because can compute about a nonlinear relationship between inputs and outputs abide by the nonlinear characteristics the trends of EPC and the SP as in [1]. Anyway, in the monitoring and assessing stability and security in power system infrastructure as in [17] – [21], ANN is highly recommended.

For prediction relevant to a field of financial in time series such as a SP prediction, ANN model has also been used widely as a core function of SP prediction as in [3], [4], [5], and [6] for normal period. And for abnormal period, in the same way as business failure prediction, ANN can be used as in [7] - [16]. Even though there are no research works which predict by using EPC and SP trends together, but many researchers still uses in predicting in widely application. Also, ANN is suitability modified and highly enough to figure out the result in this research.

According to this research experiments, the input features need to be ordered and arranged by sliding windows to create patterns. This is an important idea in predicting method that is not only learnt (inputting) a previous data but a sliding window reflexing data pattern. The results are clearly shown as in the Chapter 5. As a result, the relation between EPC and SP has significance with each other at the same and different place. In side of ANN model, the setting values are chosen by experiment in chapter 5. And, the results are chosen following the number of window sliding to fine the suitable value.

Chapter3
Algorithms

3.1 Artificial neural network (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 data set. This calculation is called Feed Forward Neural Network (FFNN) which is the same concept of human thinking.

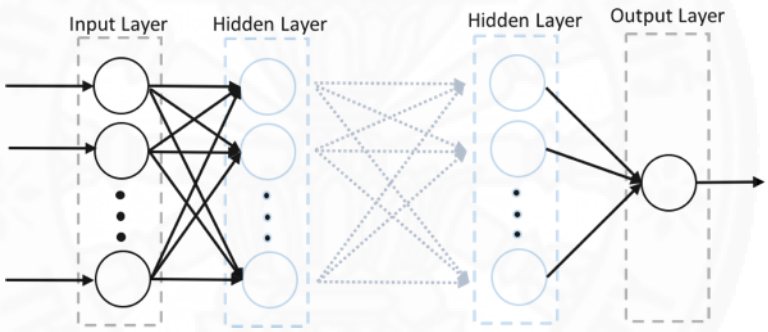


Figure 1 Artificial neural network architecture

3.2 Backpropagation (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 [22]. In ANN, Gradient Descent method is used to calculate the weight function in each node of NN as shown Figure 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 minimize by backwards computing. In order to reduce the error, the weight of each node is decreased.

3.3 Levenberg-Marquardt (LM)

As [23] and [24], 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 having 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.

3.4 Adaptive Neural Fuzzy Inference System (ANFIS)

ANFIS stands for Adaptive Neural Fuzzy Inference System. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows the fuzzy systems to learn from the data into the model as shown in Figure 2.

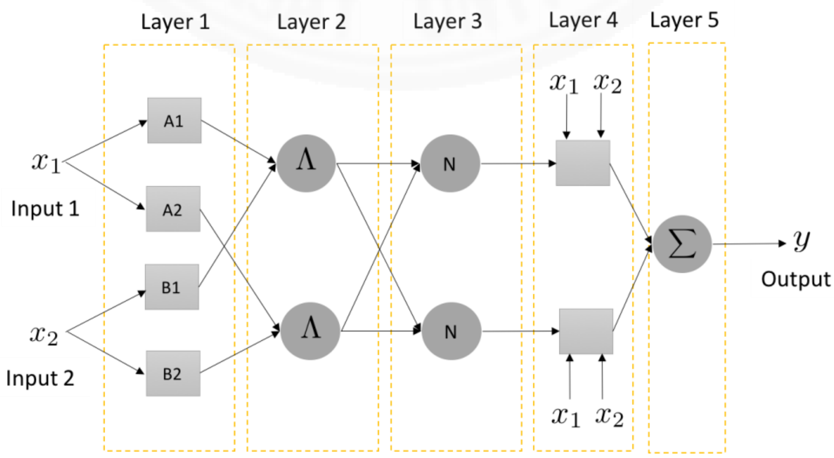


Figure 2 Adaptive Neural Fuzzy Inference System architecture

In the process of calculating in ANFIS, it consists of 5 layers. The details of the functioning in each layer are as follows:

Layer 1: The input layer consists of nodes with adaptive node functions. Output of this layer is equal to:

$$O_{1,i} = \mu A_i(x) \tag{1}$$

i	:	a number of input in the input layer
x	:	input value
A	:	the value of the membership function in this node
$O_{k,i}$	:	the node in the i^{th} position of the k^{th} layer

Membership function are used is the bell-shaped function.

Layer 2: This layer each node computes the product of incoming signals with output given as:

$$O_{2,i} = w_i = \mu\, A_i B_i(y) \tag{2}$$

Layer 3: This layer each node computes the ratio of the firing strength of the rule and the sum of all the firing strengths, with output as:

$$O_{3,j} = w_j = \frac{w_i}{w_1 + w_2} \tag{3}$$

j	:	the previous node in the input layer

Layer 4: This layer function, an equation in the node as:

$$O_{4,1} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i x + r_i) \tag{4}$$

Layer 5: This layer has a single node that computes the overall output as the sum of all incoming signals as:

$$O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

3.5 Recurrent neural networks (RNNs)

RNN is the same concept as ANN BP algorithm. Input(s) feed into input layer and get the result from output layer. But the difference is inside of hidden layer is more complex. In ANN model, hidden layer(s), there are no feedback connections in which outputs of the model are fed back into itself like RNN model. But, because of the complex term, RNN takes the time longer than ANN.

To implement RNN, the setting values are explant along with procedure:

1. Initialization
   a. ALL weight was set at zero.
   b. Random value use Xavier initialization

$$[\frac{-1}{n}, \frac{1}{n}] \quad (6)$$

n : a number of incoming connections from previous layer

2. Forward Propagation

$$S - t = f(Ux_t + Ws_{t-1}) \quad (7)$$

s_t : new state
s_{t-1} : old state
x_t : input vector at some time step
f : rectified linear unit (ReLU)

Output function

$$O_t = softmax(Vs_t) \tag{8}$$

U, W, V : coefficient or weight

3. Calculation the loss

Cross-entropy loss

$$L(y,o) = -\frac{1}{N}\sum_{n\in N} y_n log(o_n) \tag{9}$$

y : the labeled data

o : the output data

4. Stochastic Gradient Descent (SGD)
   a. The direct of reducing error: Gradient on the loss

$$\frac{\partial L}{\partial U}, \frac{\partial L}{\partial V}, \frac{\partial L}{\partial W} \tag{10}$$

   b. Vanishing gradient over time: Long-Short Term Memory (LSTM)

3.6 Gradient Descent (GD)

For experiment using mathematically derivative techniques, the result must be calculated from the function which our data is fitting to find one minimum value of hypothesis. But the function gets 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).

For any fixed x and direction$s$, we can define a function $\phi: R \rightarrow R$ by

$$\phi(\alpha) = f(x + \alpha s) \tag{11}$$

<u>Calculating Process of GD</u>

1. x_0= initial guess
2. For $k = 0, 1, 2, \ldots$.

$$S_k = - \bigtriangledown (f(x_k)) \tag{12}$$

(compute negative gradient)

Choose α_k to minimize $f(x_k + \alpha_k s_k)$ (13)

(performance line search)

$$x_{k+1} = x_k + \alpha_k s_k \tag{14}$$

(update solution)

End

Finally, the result of GD is a hypothesis or linear equation function with the parameter giving an answer value of GD.

3.7 Monthly Time-Delayed Consequence (MTDC) Detection

In order to detect the small rest period on time series data. MTDC Detection method was proposed for finding the point. This method is helpful in detecting the point which is difficult for roughly observes by the human.

In this section, the calculating process of MTDC Detection is explained.

1. Create a gradient-line (straight line) representing the cumulative curve. The process is explained in Figure 3.

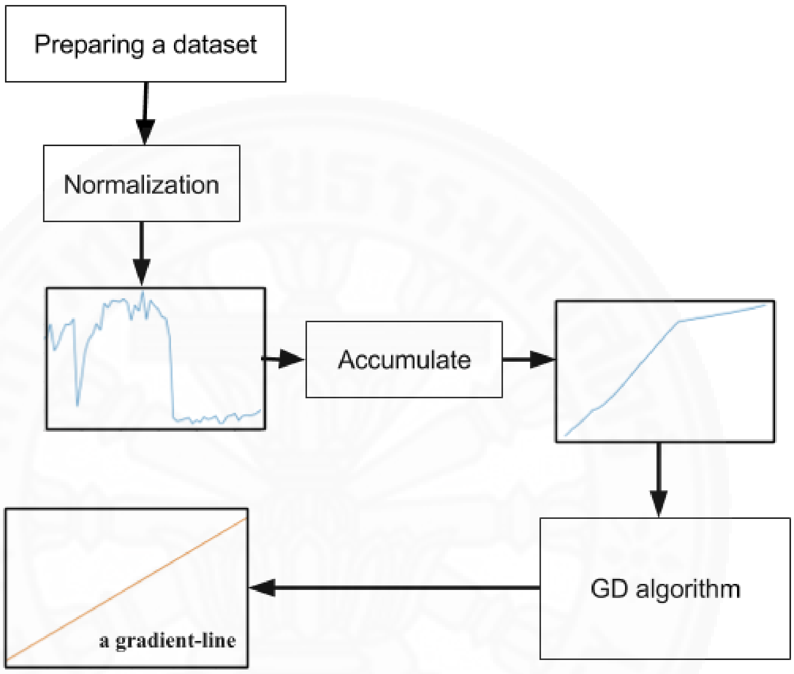


Figure 3 Create a gradient-line for MTDC Detection

2. Compare gradient of a gradient-line and the cumulative curve as Figure 4.

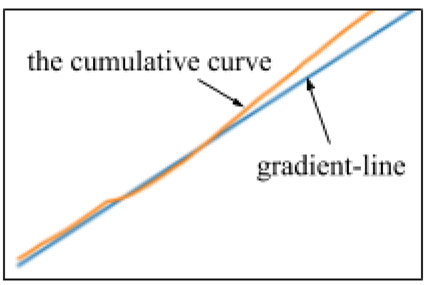


Figure 4 A gradient-line and a cumulative curve for MTDC Detection

3. Consider the difference in Step-II in each index of data

Finally, it was founded that the differential gradient between a gradient-line and the cumulative curve. The differential gradient can approximate that the point of the most of difference is the high changing of the curve.

Chapter 4
Materials and Evaluating method

4.1 The Data sets

In this paper, the two example companies are considered, i.e. Company A (an automobile part factory) and Company B (a food processing factory) in Thailand. And each of company contains of two data sets. 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 data sets of each company were collected during 2011 to 2015 in flooding period.

4.2 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 [26]. 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 1:

Table 1 Definition of Disaster Signal (DS)

Damage Level	Definition	Flooding Level (%)
level 1	Without flooding	0%
level 2	Receive the flooding from news (still without flooding)	0%
level 3	Some area	< 30%
level 4	Half area	<30%-60%
level 5	Full area	>60%

4.3 The Performance Indicator

In our experiment, ANN is a supervised neural network (NN). The most NN's uses mean squared error (MSE) to figure out the performance especially in the ANNs model. Also, it is a large digit number so that we can easily observe the result. The MSE is a one of robust method to evaluate ANN's performance because it can deal with both positive and negative values as [25]. In the past, it is commonly known as MSE which can be used well and feasible when no computer was available. Nevertheless, it is still a common method for NN in the present. MSE and is given by the equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - t_i)^2 \tag{15}$$

x_i : the actual value

y_i : the predicted value

Moreover, another performance indicator is Accuracy (%). It is the degree of matching between the predictions and the actual data which is given by:

$$Accuracy(\%) = 100\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - t_i}{t_i}\right)\right) \tag{16}$$

x_i : the actual value

y_i : the predicted value

Chapter5

Experiments and Results

In this chapter, first process is set to prepare the experiment and select the best AI technique which is suitable for the character of the data set. ANN, ANFIS and RNN are compared for choosing the best choice for the four phrases. Then, ANN is the suitable for the data set and used in all experiment. Include with setting values of tools are described in Preliminary Testing. Then, the model is designed to analyze the EPC of each factory which demonstrates their SP in the stock market and simultaneously analyzes the economy in the future. The prediction SP with their history along with the history their EPC.

To tackle the lacking data set problem, Cross-checking method is proposed for using wildly data set. It eliminates a restriction of few data sets for experiment in the training process. Therefore, it approximates the trend of SP a factory by another factory precisely. In order to do experiment in disaster period, Disaster Signal(DS) is an important feature to indicate the damage of the situation. In the Phase-III, the Cross-checking method is used in natural disaster period. As following [], the flooding in Thailand 2011is represent the natural disaster period in this experiment. It was designed to the two models to analyze the economic fluctuation during the disaster time (the hazardous period). Both models have added the disaster signal (DS) to point out the two facts. Finally, the goal is to deal with unseen damages and making accurate predictions in the future.

In the Phrases-IV, it is about the interval, which took small rest period the trend of SPs fluctuates after EPC in the same data set. It is measured by MTDC Detection proposed method.

5.1 Preliminary Testing

5.1.1 Selection and Setting Criteria for AI techniques

Three popular models of AI techniques i.e. ANN, ANFIS and RNN are compared so that one of them is being chosen. The data sets used for the 3 models are set approximately 60% was used for training, 20% for validation and 20% for testing. While the exact models used vary from field to field, the overall setting is the same.

5.1.1.1 The setting value of ANN

Parameters of ANN consist of an input, an output and hidden layer(s). Only the number neurons in the input layer depend on the number of window sliding and a neuron in the output layer. Firstly, the other settings values are used in the same in every process and focus the effect of input features as follow the assumption except the number in hidden layer and number of node were set according to the next experiments.

The experiments for selection the number of hidden layer and nodes inside are classified with 2 prediction models shown as. For all experiment, the models are named for other experiments as follows:

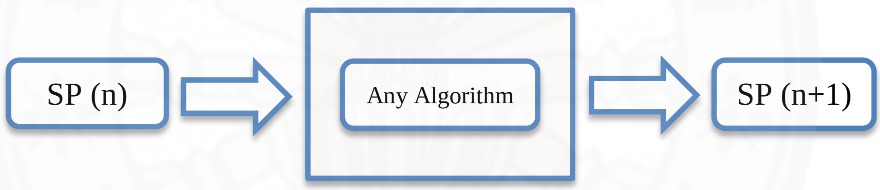


Figure 5 SP predictions (input: SP)

Figure 6 SP predictions (input: SP, EPC)

To select number of hidden layers and neuron(s), MSE and accuracy of each conditions is compared for finding the suitable criteria for each data sets (Factory A and B) according to the models. Recordings of MSE and accuracy is shown in Table 2 – 4 as follows:

Table 2 ANN selection criteria for factory A's data set (input: SP)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000018	97.32%
	5	0.000011	98.11%
	10	0.000013	97.83%
	20	0.000012	98.02%
	50	0.000012	98.05%
2	1	0.000020	97.52%
	5	0.000011	98.04%
	10	0.000012	98.03%
	20	0.00002	97.52%
	50	0.000012	98.05%
3	1	0.000020	97.54%
	5	0.00002	97.51%
	10	0.000019	97.55%
	20	0.000019	97.55%
	50	0.000013	97.96%

According to Factory A's Data set in MODEL A, the best accuracy of all recording in table 2 is 98.11%. Therefore, the suitable number of hidden layers is 1 and neurons in each hidden layer are 5.

Table 3 ANN selection criteria for factory B's data set (input: SP)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000095	93.66%
	5	0.000096	93.65%
	10	0.000093	93.73%
	20	0.000093	93.73%
	50	0.000098	93.63%
2	1	0.000093	93.74%
	5	0.000098	93.41%
	10	0.000093	93.73%
	20	0.000096	93.68%
	50	0.0001	93.35%
3	1	0.000093	93.74%
	5	0.00011	93.22%
	10	0.000093	93.73%
	20	0.000114	93.01%
	50	0.000093	93.58%

According to Factory B's Data set in Model A, the best accuracy of all recording in table 3 is 93.73 - 93.74%. The suitable number of hidden layers is 2 or 3 and neurons in each hidden layer are only 1 or 10. For the neuron number, it should be more than 1 node. Therefore, 2 hidden layers and 10 neurons/layer are selected in this condition.

Table 4 ANN selection criteria for factory A's data set (input: SP, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000019	97.19%
	5	0.000012	97.76%
	10	0.00001	98.06%
	20	0.000012	97.76%
	50	0.00001	98.15%
2	1	0.00002	97.54%
	5	0.000012	98.00%
	10	0.000013	97.75%
	20	0.00001	98.15%
	50	0.000011	98.08%
3	1	0.00002	97.54%
	5	0.000020	97.54%
	10	0.000019	97.24%
	20	0.00001	98.19%
	50	0.000009	98.17%

According to Factory A's Data set in MODEL B, the best accuracy of all recording in table 4 is 98.19%. Therefore, the suitable number of hidden layers is 3 and neurons in each hidden layer are 20.

Table 5 ANN selection criteria for factory A's data set (input: SP, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.00009	93.65%
	5	0.000093	93.80%
	10	0.000111	92.99%
	20	0.0005	92.23%
	50	0.000092	93.51%
2	1	0.000087	94.18%
	5	0.0001	93.23%
	10	0.000096	93.58%
	20	0.000093	93.47%
	50	0.000091	93.64%
3	1	0.000087	94.18%
	5	0.000087	94.18%
	10	0.000149	91.69%
	20	0.00011	93.24%
	50	0.000103	93.40%

According to Factory A's Data set in MODEL B, the best accuracy of all recording in table 5 is 94.18%. Therefore, the suitable number of hidden layers is 3 and neurons in each hidden layer are 3.

Table 6 ANN hidden layer selection

Data sets	Model	Hidden Layer	NODE / Hidden Layer
Factory A	Model A	1	5
	Model B	3	20
Factory B	Model A	2	10
	Model B	3	5

As a result, the setting value is used in setting process for the matching prediction pattern as in table 6.

Table 7 Other criteria for ANN

Parameters	Setting	Remark
The number of neurons in the hidden layer(s).	Depend on predicting pattern	Table 2 - 4
Activation	Rectified linear unit (ReLu)	Return f(x) = Max(0, x)
The solver for weight optimization	Lbfgs : LM	'lbfgs' is an optimizer in the family of quasi-Newton methods.
L2 penalty	0.0001	regularization term
Learning Rate initialize	0.0001	
Learning Rate	constant	is a constant learning rate given by "learning_rate_init'

5.1.1.2 The setting value of ANFIS

In the process of calculating in ANFIS, it consists of 5 layers. The details of the functioning in each layer are as follows:

Layer 1: Set as (1), the membership function are used is the bell-shaped function.

$$O_{1,i} = \mu A_i(x),\ \text{for } i = 1, 2$$

Layer 2: Set as (2), each node computes the product of incoming signals with output given as:

$$O_{2,i} = w_i = \mu A_i B_i(y),\ \text{for } i = 1, 2$$

Layer 3: Set as (3), this layer each node computes the ratio of the firing strength of the rule and the sum of all the firing strengths with output as:

$$O_{3,j} = w_j = \frac{w_i}{w_1 + w_2}$$

Layer 4: Set as (4), this layer function, an equation in the node as:

$$O_{4,1} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i x + r_i)$$

Layer 5: Set as (5), this layer has a single node that computes the overall output as the sum of all incoming signals as:

$$O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

5.1.1.3 The setting value of RNN

RNN is the same concept as ANN BBP algorithm. Input(s) feed into input layer and get the result from output layer. But the difference is inside of hidden layer is more complex. In ANN model, the hidden has never calculating feedback but RNN. So, RNN is take time longer than ANN because of the complex term.

5.1.2 Comparison ANN and ANFIS

This experiment, ANN, AI techniques wildly using, is used for testing the relation between EPC and SP are proved by observing the result of stock prediction with BP algorithm. Before this experiment was done, the reason of using ANN is firstly described from other research. According to [2], AI techniques widely used were proposed the comparison of prediction performance of Adaptive Neural Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) with performance analysis two forecasting problems have been considered. First experiment was the sales forecasting for which the real sales data set of cold drinks collected for five months. And the second was the stock price prediction for which the daily stock

Finally, their results showed that both ANFIS and ANN are powerful tools for forecasting problems. The accuracy of the ANFIS for stock market data set is higher than ANN which indicates that ANFIS is better prediction model. But for sales data ANN performs better. Therefore, ANFIS is suitable for SP prediction using data set in

the same area i.e. five daily stock market quantities viz. maximum price, minimum price, price at the time of opening, volume and price at the time of closing. And ANN is suitable for prediction using the different area i.e. maximum temperature, minimum temperature, previous day sale, current day sales and day information.
In order to choose one of them, the performances of ANN and ANFIS are compared by using data set of the monthly EPC and SP of the Factory A and B.

Table 8 MSE of SP prediction using ANN and ANFIS (input: SP)

Data source	**ANN**	**ANFIS**
Factory A (Automobile Parts)	0.00002	0.00015
Factory B (Food Processing)	0.00008	0.00014
Average Accuracy	**97.85%**	**96.63%**

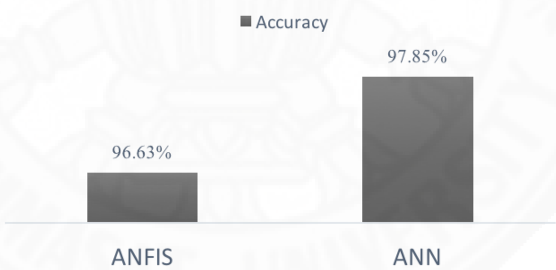


Figure 7 Comparison performance ANN and ANFIS (input: SP)

Table 9 MSE of SP prediction using ANN and ANFIS (input: SP, DS)

Data source	**ANN**	**ANFIS**
Factory A (Automobile Parts)	0.00002	0.00015
Factory B (Food Processing)	0.00008	0.00014
Average Accuracy	**97.85%**	**96.63%**

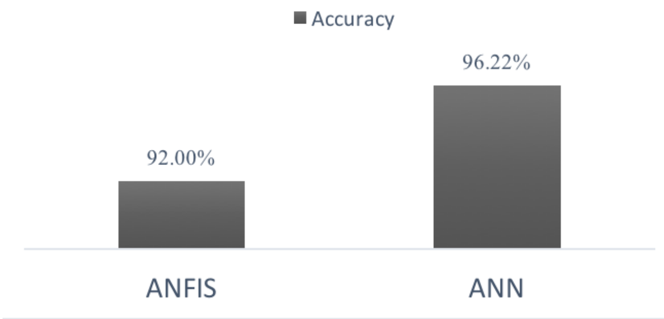


Figure 8 Comparison performance ANN and ANFIS (input: SP, DS)

As the result of comparison between ANN and ANFIS, using data set for this research, the performance of ANN is higher than ANFIS regarding to model A and B. There for ANN is used as a main algorithm in this thesis.

5.1.3 Comparison ANN and RNN

In nowadays, RNN is a famous method of Deep Learning. It is famous using with a single data set such as an EPC data set. In this case, this research is also the RNN to compare performance with ANN to find the suitable algorithm for using in the next issue.

Table 10 MSE of SP prediction using ANN and RNN (input: SP)

Data source	ANN	ANFIS
Factory A (Automobile Parts)	0.00002	0.00015
Factory B (Food Processing)	0.00008	0.00014
Average Accuracy	**97.85%**	**96.63%**

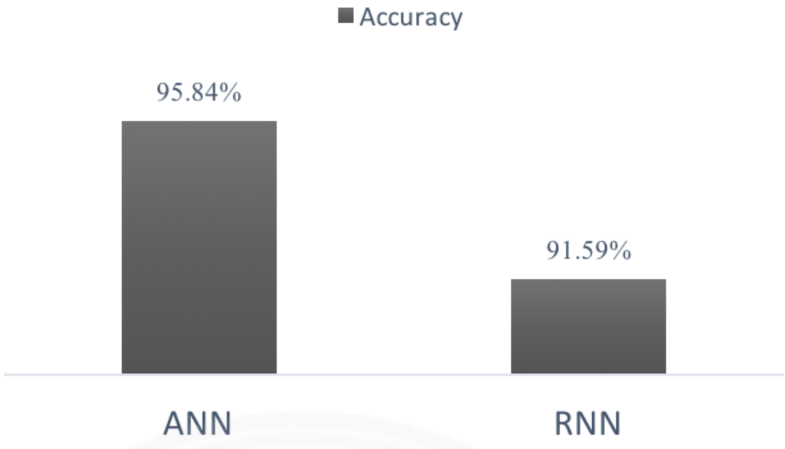


Figure 9 Comparison performance ANN and RNN (input: SP)

Table 11 MSE of SP prediction using ANN and RNN (input: SP, DS)

Data source	**ANN**	**ANFIS**
Factory A (Automobile Parts)	0.00002	0.00015
Factory B (Food Processing)	0.00008	0.00014
Average Accuracy	**96.75%**	**95.97%**

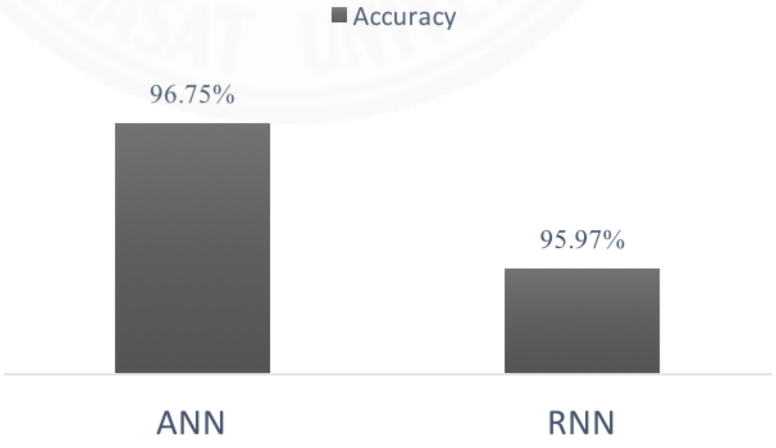


Figure 10 Comparison performance ANN and RNN (input: SP, DS)

As the result of comparison between ANN and RNN, using data set for this research, the performance of ANN is higher than RNN regarding to model A and B. Although RNN is a famous method, but for this data sets, ANN is suitable for doing experiment. There for ANN is used as a main algorithm in this thesis.

5.2 Relationship of Power Consumption and Stock Prices

As mentioned, the relation between EPC and SP is testing. The trend of EPC is used to input to the SP prediction and used the data sets of the two factory. They are then examined the current economic condition by using the observations of the procedures of the SP prediction with using ANN. The monthly SP of Factory A are predicted by using input two features of their monthly by separate to be the 2 models (Model A and B). First use only SP as Model A, and second use both SP and EPC to be the training set. as Model B. Then the two experiments are compared to the relation. Next, the monthly SP of Factory 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 percentages accuracy.

Table 12 The relationship between EPC and SP by ANN

Data source	**Input: SP (MODEL A)**		**Input: SP + EPC (MODEL B)**	
	MSE	Accuracy	MSE	Accuracy
Factory A (Automobile Parts)	0.00002	97.47%	0.00001	98.22%
Factory B (Food Processing)	0.00008	94.21%	0.00007	95.27%

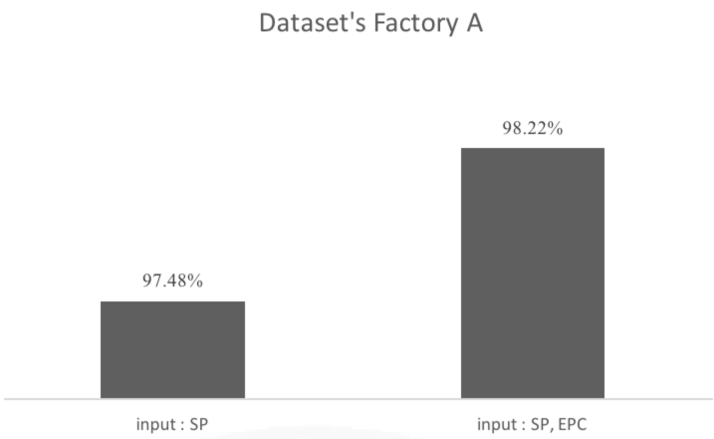


Figure 11 Relationship between EPC and SP using ANN (Factory A's data set)

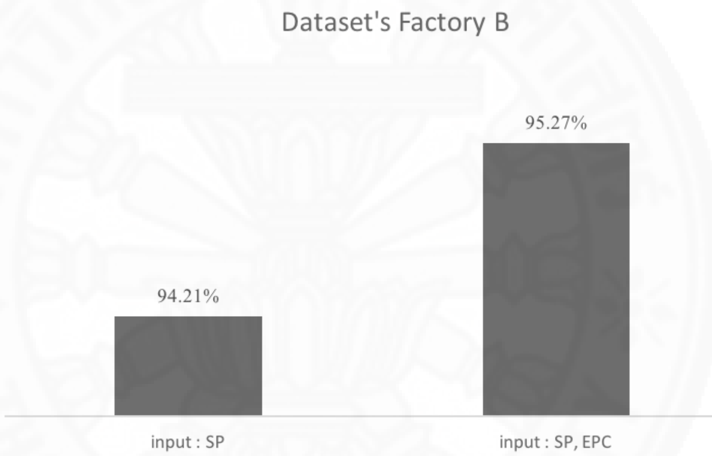


Figure 12 Relationship between EPC and SP using ANN (Factory B's data set)

Moreover, to confirm the relation, ANN, ANIFS and RNN are proposed.

Table 13 The relationship between EPC and SP by ANFIS

Data source	**Input : SP**		**Input : SP + EPC**	
	MSE	Accuracy	MSE	Accuracy
Factory A (Automobile Parts)	0.00015	96.39%	0.00003	96.88%
Factory B (Food Processing)	0.00014	91.71%	0.00013	92.29%

Table 14 The relationship between EPC and SP by RNN

Data source	Input : SP		Input : SP + EPC	
	MSE	Accuracy	MSE	Accuracy
Factory A (Automobile Parts)	0.00002	89.76%	0.0002	96.67%
Factory B (Food Processing)	0.00028	86.80%	0.00022	88.30%

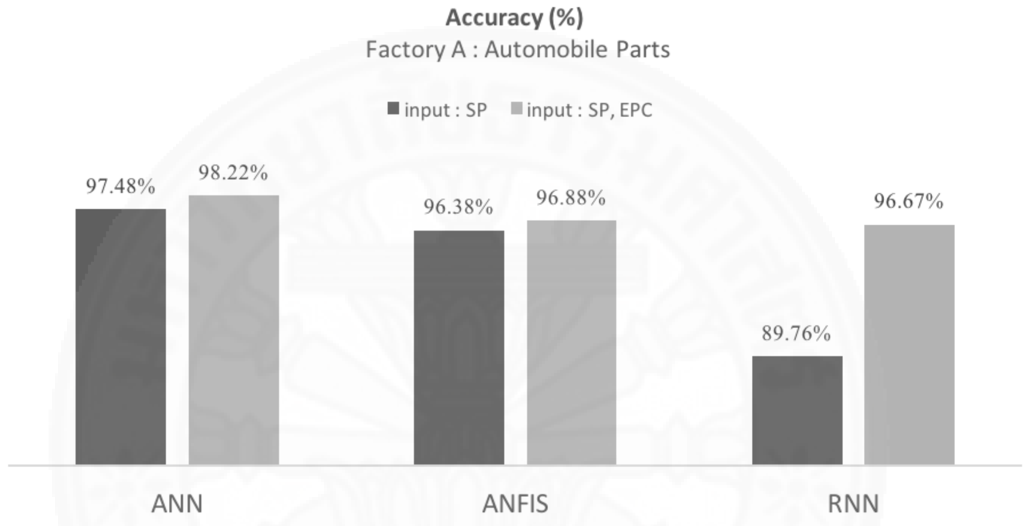


Figure 13 Comparison the performance input SP and EPC, SP using ANN, ANFIS and RNN (Factory A's data set)

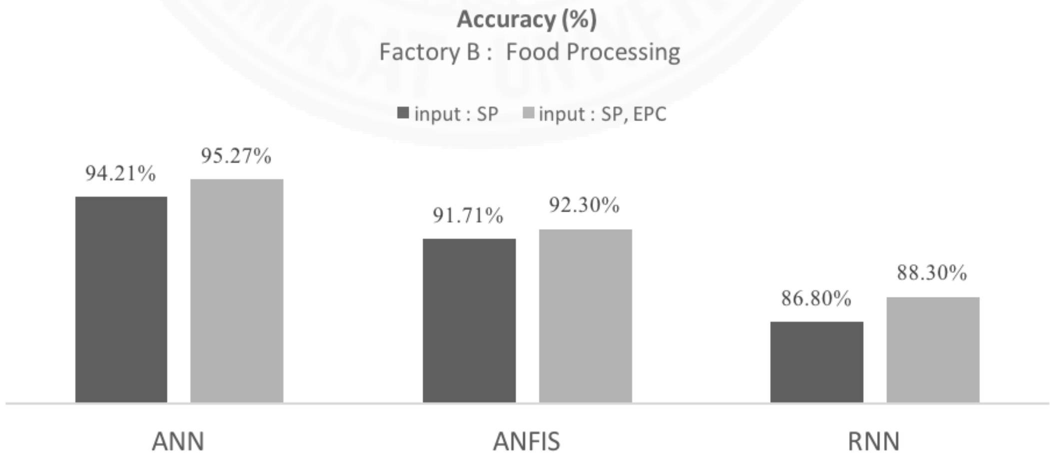


Figure 14 Comparison the performance input SP and EPC, SP using ANN, ANFIS and RNN (Factory B's data set)

The result of Phase-I shows the performance by accuracy. The performance of Factory A shown in Figure 13. The accuracy of SP prediction using ANN, ANFIS and RANN, their performances are increased after adding EPC feature to be input or changing from Model A to Model B. And the performance of Company B is shown in Figure 14. The accuracy of the SP prediction using the 3 algorithms their performances are also increased after adding the EPC input or changing from set input: SP to SP, EPC.

From the results, they show that EPC can improve the performance of SP prediction for the two factory examples' data sets. Three algorithms, ANN, ANFIS and RNN, can show the relation EPC and SP in predicting method. According to 5.1, ANN is a suitable algorithm for this research. Then the next step, ANN is used for doing all experiment. And the Cross-Checking method which is the propose method of this research uses ANN for implementation.

5.3 Cross Domain Checking (XDC) Method

This section proposes Cross-Checking method for using in natural disaster period. The concept of the method is the same previous prediction, but the difference is the training data set is used from another factory. Therefore, experiments are choosing the two data sets to test with the proposed method i.e. SP of Factory A is predicted by using the model which is trained from Factory B's data set. And SP of Factory B is predicted by using the model which is trained from Factory A's data set. The reason of proposing is making prediction in any area with no history data set. In factory using electricity energy, they are stopping the process of using EPC of producing their products. This should happen when any factory facing with disaster period. So, it is the idea that proposal to tackle prediction in natural disaster period with lacking data set. The natural disaster period is representing by Flooding in Thailand 2011.

In order to selecting input feature for Cross-Checking method, this experiment consists of 4 sub-experiments as following:

5.3.1 Preliminary Cross Domain Checking (XDC) test

For proposing Cross-Checking method, the suitable hidden layer selection is defined following training data set. The reason is the output of Cross-Checking method is another data set and it has not enough for train. It use only predict and in the real, it is unseen data.

5.3.1.1 XDC with SP

Cross-checking of the SP prediction is proposed in this sub-experiment use only SP to be an input. First, the trends of SP of Factory A are predicted on ANN model having the training data sets of the Factory B. And second, the trends of SP of Factory B are predicted on ANN model having the training data sets of the Factory A. Finally, the performances in each process are shown in Table 15.

Table 15 ANN XDC selection criteria of factory A's data set (input: SP)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000014	97.89%
	5	0.000014	97.91%
	10	0.000014	97.90%
	20	0.000014	97.88%
	50	0.000018	97.59%
2	1	0.000014	97.91%
	5	0.000021	97.38%
	10	0.000014	97.89%
	20	0.000016	97.73%
	50	0.000027	96.97%
3	1	0.000014	97.89%
	5	0.000032	96.56%
	10	0.000014	97.90%
	20	0.000041	95.95%
	50	0.000018	97.60%

Table 16 ANN XDC selection criteria of factory B's data set (input: SP)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000239	88.79%
	5	0.000091	93.79%
	10	0.0001	93.09%
	20	0.000089	93.81%
	50	0.00009	93.80%
2	1	0.000265	88.08%
	5	0.00087	93.84%
2	10	0.000089	93.10%
	20	0.000261	88.18%
	50	0.000091	93.79%
3	1	0.000251	88.45%
	5	0.000263	88.13%
	10	0.000244	88.64%
	20	0.000246	88.59%
	50	0.000092	93.76%

5.3.1.2 XDC with SP, DS

This sub-experiment is the same concept of the previous, but the damage level of the flood (DS) (Table 1) is added to the predicting model to point the damage in each place. And evaluating the result is the same concept.

Table 15 ANN XDC selection criteria of factory A's data set (input: SP, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000033	6.47%
	5	0.000150	93.55%
	10	0.000108	93.32%
	20	0.000152	93.60%
	50	0.000158	93.59%
2	1	0.000020	88.38%
	5	0.000072	83.72%
	10	0.000023	90.49%
	20	0.000026	87.11%
	50	0.00014	93.50%
3	1	0.000020	88.38%
	5	0.000020	88.38%
	10	0.000035	86.10%
	20	0.000020	88.42%
	50	0.000149	93.57%

Table 18 ANN XDC selection criteria of factory B's data set (input: SP, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000015	97.85%
	5	0.000017	97.68%
	10	0.000017	97.66%
	20	0.000017	97.65%
	50	0.000013	97.97%
2	1	0.000059	95.31%
	5	0.000025	97.12%
	10	0.000017	97.69%
	20	0.000017	97.69%
	50	0.000016	97.69%
3	1	0.000059	95.31%
	5	0.000059	95.31%
	10	0.000021	97.45%
	20	0.000017	97.69%
	50	0.000016	97.75%

5.3.1.3 XDC with SP, EPC

This sub-experiment is the same concept of the previous, but the trend of EPC feature is added to the predicting model to point the relation between EPC and SP which has proved in 5.2. And evaluating the result is the previous

Table 16 ANN selection criteria of factory A's data set (input: SP, EPC)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000116	92.50%
	5	0.000024	97.16%
	10	0.000356	86.58%
	20	0.000151	91.36%
	50	0.000184	90.43%
2	1	0.000056	95.31%
	5	0.000187	90.34%
	10	0.000018	97.38%
	20	0.000168	90.86%
	50	0.000106	92.87%
3	1	0.000059	95.31%
	5	0.000059	95.31%
	10	0.0019	68.62%
	20	0.000195	90.19%
	50	0.000195	90.19%

Table 17 ANN selection criteria of factory B's data set (input: SP, EPC)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.00002	88.45%
	5	0.003	93.79%
	10	0.000117	93.58%
	20	0.000039	92.14%
	50	0.00021	93.77%
2	1	0.00002	88.38%
	5	0.000183	93.86%
	10	0.000039	92.123%
	20	0.000205	93.78%
	50	0.000209	93.76%
3	1	0.00002	88.38%
	5	0.00002	88.38%
	10	0.000021	88.35%
	20	0.000215	93.80%
	50	0.000215	93.80%

5.3.1.4 XDC with SP, EPC and DS

This sub-experiment is the same concept of the previous, but the trend of EPC and DS feature are added to the predicting model. And evaluating the result is the previous

Table 18 The setting of ANN XDC of factory A's data set (input: SP, EPC, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000033	92.60%
	5	0.000372	93.79%
	10	0.00323	94.25%
	20	0.00343	94.03%
	50	0.000198	95.50%
2	1	0.000302	94.45%
	5	0.000324	94.23%
	10	0.000580	91.58%
	20	0.000343	94.03%
	50	0.000198	95.40%
3	1	0.000298	94.50%
	5	0.000032	92.48%
	10	0.000708	89.71%
	20	0.000289	94.58%
	50	0.000133	95.19%

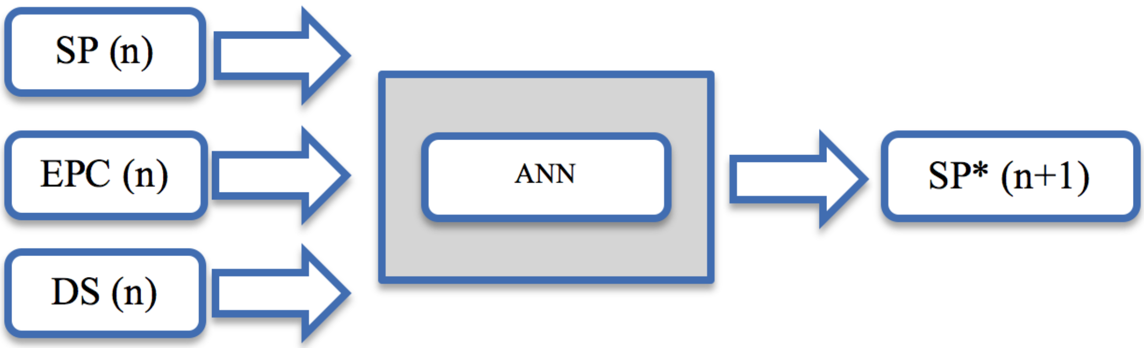
Table 19 The setting of ANN XDC of factory B's data set (input: SP, EPC, DS)

Number of hidden layers	Number of Neuron(s) / a layer	MSE	ACCURACY
1	1	0.000238	89.39%
	5	0.00271	65.78%
	10	0.00006	95.13%
	20	0.000821	79.61%
	50	0.00799	79.90%
2	1	0.0014	73.25%
	5	0.000853	79.21%
	10	0.0001	93.44%
	20	0.0019	68.77%
	50	0.000211	90.09%
3	1	0.0014	72.93%
	5	0.000032	96.39%
	10	0.004172	53.45%
	20	0.002829	61.71%
	50	0.00299	60.69%

Finally, we get the suitable number hidden layer and neurons for Cross-Check as Table 19 and 20; we got criteria and Cross-Checking Method to test to the next 5.4

Table 20 Hidden layers selection of XDC using ANN

Training Data set	Input	Hidden Layer	Index of Neurons/ Hidden Layer
Factory A	SP	1	5
	SP,EPC	3	5
	SP, DS	1	20
	SP, EPC, DS	1	50
Factory B	SP	2	10
	SP, EPC	3	5
	SP, DS	1	50
	SP, EPC, DS	3	5



n : a number of months,
* : data of another data set

Figure 15 XDC for the SP prediction

Although the performance of Cross-Checking Method is less than direct prediction as 0.17% for training Factory B's data set to predict Factory A's SP and 8.2% for training Factory A's data set to predict Factory B's SP. But they still work on the natural period. It is helpful when needing prediction of the manufacturing sector without their data set or not enough; the Cross-Checking should to tackle this problem.

Table 21 Comparison prediction between XDC and without XDC

Type	Factory A (input: SP, EPC)		Factory B (input: SP, EPC input)	
	MSE	Accuracy	MSE	Accuracy
Direct Prediction	0.00549	92.07%	0.000660	94.34%
Cross-Checking Method	0.000564	91.90%	0.0003374	86.14%

As a result, the error of direct prediction is less than Cross-Checking method. It means the direct or normal prediction is better than using other data set for training in the model. However, using XDC, although it has more error approximately 1 % than the normal, but it still useful in the problem of no data for prediction in some area. Also, the performance is acceptable for predict with the data in this research. Therefore, Cross-Checking is proposed and used for doing the experiment in the next step.

5.4 SP Prediction Using Cross-Checking Method in Natural Disaster Period

In this case, SP is analyzed during the natural disaster period which is represented by Flooding of Thailand 2011 using Cross-Checking Method. The DS is taken into account in this phase to understand the factor of the flood. The method is devised into 4 experiments regarding to types and amount of input feature(s). First, the feature input of prediction is only SP feature. Second, the feature inputs of prediction are SP and adding DS. So, the effect of the flood with DS and without DS is investigated. For the third and fourth, the feature input of prediction are SP and adding EPC and forth, SP, DS and EPC respectively. The results are obtained in Table 23, 24, 25 and 26. Finally, the experiment results show the performance by using MSE and Accuracy.

Table 22 The performance of XDC (input: SP) in the flooding period

Sliding window(n)	**Input feature : SP**			
	Training : Factory B		**Training : Factory A**	
	Testing : Factory A		**Testing : Factory B**	
	MSE	**ACCURACY (%)**	**MSE**	**ACCURACY (%)**
n = 1	0.0969	98.88	0.0857	97.88
n = 2	0.0976	97.91	0.1025	95.97
n = 3	0.1062	98.83	0.1239	98.08
n = 4	0.1035	98.84	0.0767	98.52
n = 5	0.1741	98.60	0.1273	98.45

Table 23 The performance of XDC (input: SP, DS) in the flooding period

Sliding window(n)	Input feature : SP, DS			
	Training : Factory B		Training : Factory A	
	Testing : Factory A		Testing : Factory B	
	MSE	ACCURACY (%)	MSE	ACCURACY (%)
n = 1	5.8445	92.77	0.0911	97.21
n = 2	13.3855	88.48	0.0827	97.72
n = 3	5.6213	93.40	0.1163	96.98
n = 4	2.7538	95.48	0.1056	96.27
n = 5	4.3793	95.21	0.1123	96.59

Table 24 The performance of XDC (input: SP, EPC) in the flooding period

Sliding window(n)	Input feature : SP, EPC			
	Training : Factory B		Training : Factory A	
	Testing : Factory A		Testing : Factory B	
	MSE	ACCURACY (%)	MSE	ACCURACY (%)
n = 1	0.0927	99.81	0.1008	98.69
n = 2	0.0901	98.20	0.0896	97.30
n = 3	0.0923	99.58	0.0712	99.56
n = 4	0.1139	99.75	0.0849	99.44
n = 5	0.1965	99.55	0.1208	99.57

Table 25 The performance of XDC (input: SP, EPC, DS) in the flooding period

Sliding window(n)	Input feature : SP, EPC, DS			
	Training : Factory B		Training : Factory A	
	Testing : Factory A		Testing : Factory B	
	MSE	ACCURACY (%)	MSE	ACCURACY (%)
n = 1	0.108	99.77	0.0799	98.90
n = 2	0.1514	97.84	0.0705	97.35
n = 3	0.1266	99.63	0.0804	99.43
n = 4	0.0413	98.94	0.0807	99.52
n = 5	0.087	99.92	0.0818	99.63

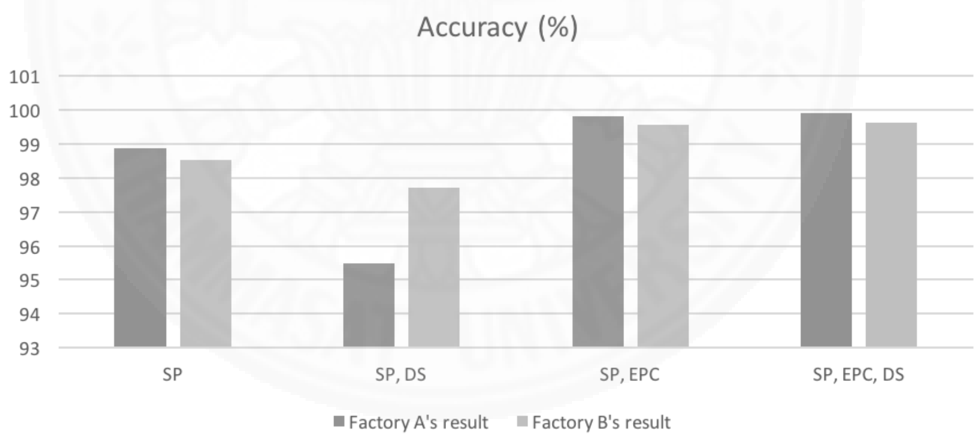


Figure 16 The performance of XDC with the feature input(s)

As a result, Cross-Checking method can use for predicting SP for data set of Factory A and B. According to the accuracy, the prediction which uses a set input of SP, EPC, and DS is better than SP, EPC and SP. But the performance is the lowest when the feature inputs have SP and DS. Therefore, the prediction should take SP, EPC, and DS to be input together. Moreover, the set of inputs which includes with EPC improve performance of the Cross-Checking method.

5.5 Implementing MTDC Detection

While EPC is dramatically had decreased and almost occurs at the beginning of natural disaster period which have to turn-off machine in manufacturing section. After that, it took small rest period the trend of SPs fluctuates after EPC in the same data set. The interval, which was called "time-delay", is measured by Monthly Time-Delayed Consequence (MTDC) Detection proposed method.

So, this section is implement MTDC detection for calculating time delay between 2 trends of data sets. The 2 trends are trend of EPC and SP in a unique manufacturing factory. And, the time delay is found by MTDC detection.

Table 29 MTDC Detection of Factory A's data set

Month	MTDC Detection Data set : EPC	MTDC Detection Data set : SP	DS
Aug 2011	12.24390687	6.17342089	30-60%
Sep 2011	69.10901326	8.39859326	> 60%
Oct 2011	45.27541773	6.00034553	> 60%
Nov 2011	18.25657264	24.5161631	30-60%
Dec 2011	7.068600439	24.14566871	-
Jan 2012	2.221728804	23.03528677	-
Feb 2012	7.664818198	19.32593273	-
Mar 2012	1.821793941	10.43020542	-
Apr 2012	12.24390687	9.315965425	-

Table 30 MTDC Detection of Factory B’s data set

Month	MTDC Detection Data set : EPC	MTDC Detection Data set : SP	DS
Aug 2011	10.60168213	11.30954805	-
Sep 2011	81.72992435	15.00579443	30-60%
Oct 2011	1.257313387	12.07669332	> 60%
Nov 2011	5.72865697	78.9383708	30-60%
Dec 2011	1.44683567	66.07125029	30-60%
Jan 2012	1.775016256	54.04101632	-
Feb 2012	0.544989143	41.48772713	-
Mar 2012	0.605813423	24.19208358	-
Apr 2012	3.642799035	17.91544097	-

As the result from MTDC Detection, the trend of SP has Time-delay comparing EPC approximately 3 months.

Chapter6
Conclusion

The RNN algorithm is an AI technique or ANFIS is can be a good method in some prediction, but ANN is suitable as a method for SP prediction with an EPC feature in manufacturing sector.

From the experiment in chapter 5, the result indicates that using EPC as an input feature in SP prediction process improve performance of prediction as the data set in manufacturing sector. It means that behavior consuming electric energy of the factory in manufacturing sector affects to their financial movement reflexing the trend of SP. Nevertheless, to predict the SP of any manufacturing sector more precisely, EPC input feature is the one that should have.

In natural disaster occur, flooding, the effect of EPC is more clearly than normal period regarding the result that the performance has increased after adding EPC input feature (see in Figure.11, 12, 13, 14 and 16). Then, XDC method is proposed for the predicting in the natural disaster period that lack of data set. Because, the training process can use data set from another indusial factory but in manufacturing sector, so we can approximate the result from anywhere without recording data set. It is useful when need to prediction SP in manufacturing factory that has a small data set or lacking data.

There are 2 data sets the trends are synchronizing in some period but have time delay in each other. According to the observations for data set of this research, EPC is dramatically had decreased at the beginning of the disaster period. After that, it took a small rest period, time-delay, of the trend of SPs fluctuates after EPC in the same data set. The time-delay is can be approximately by MTDC detection. However, this method can be adjusted to another area that needs to mark the point that has highly changing the trend of data.

References

Books and Book Articles

27. Russell, S., & Norving, P. (2010). *Artificial Intelligence: A Modern Approach*. 3th edition. Pearson.

28. Heath, M. (2002). *Scientific Computingl: An Introductory Survey*. 2th edition. Mc Graw Hill.

Articles

1. Skolthanarat, S., Lewlomphaisarl, U., &Tungpimolrut, K. (2014). Short-trem Load Forecasting Algorithm and Optimization in Smart Grid Operations and Planning. *2014 IEEE Conference on Technologies for Sustainability*, 9-11 OCT 2014 (pp. 165-171). Phoenix, Arizona.

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

6. Khan, Z. H., Alin, T. S., & Hussain, A. (2011). Price Prediction of Share Market using Artificial Neural Network. *International Journal of Computer Applications*. *22*(2), 42-47.

7. Brédart, X. (2014). *Bankruptcy Prediction Model Using Neural Networks*. Retieved May 12, 2016, from http://dx.doi.org/10.5430/afr.v3n2p124

8. Raminder, K. (1998). An artificial neural network approach to predicting the outcome of Chapter 11 bankruptcy. *Journal od Business and Economic Studies*, *4*(1), 57-73.

9. Atiya, A. F. (2001). Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results. *IEEE Transactions on Neural Networks*, *12*(4), 929-935.

10. Ravi Kumar, P., Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. *European Journal of Operational Research. 180*, 1-28.

11. Jardin, P., V. (2010). Predicting bankruptcy using neural networks and other classification methods: The influence of variable selection techniques on model accuracy. *European Journal of Operational Research. Neurocomputing. 73,* 2047–2060.

12. Roli, P. (2013). Corporate Bankruptcy Prediction using Backpropogation Neural Network. *International Journal of Engineering and ManagementSciences. 4*(2), 98-101.

13. Bode, J. (1998). Decision support with neural networks in the management of research and development: Concepts and application to cost estimation. *Information & Management. 34,* 33-40.

14. Abhishek, C., Kumar, A., Vitta, H., Srivastava, P. (2010). Test Effort Estimation Using Neural Network. *J. Software Engineering & Application. 3,* 331-340.

15. Eletter, S. & Yaseen, S. (2010). Applying Neural Networks for Loan Decisions in the Jordanian Commercial Banking System. *IJCSNS International Journal of Computer Science and Network Security, 10*(1), 209-214.

16. Nazari, M., & Alidadi, M. (2013). Measuring Credit Risk of Bank Customers Using Artificial Neural Network. *Journal of Management Research, 5*(2), 17-27.

17. Hartana, R. K., & Richards, G. G. (1990). Harmonic Source Monitoring And Identification using Neural Networks. *IEEE Transaction on Power Systems, 5*(4), 1098-1104.

18. Zhou, D., Annakkage, U. D., & Rajapakse, A. (2010). Online Monitoring of Voltage Stability Margin Using an Artificial Neural Network. *IEEE Transaction on Power Systems, 25*(3), 1566-1574.

19. Cardoso, G. Jr., Rolim, J., & Zürn, H. (2010). Identifying the Primary Fault Section After Contingencies in Bulk Power Systems. *IEEE Transaction on Power Delivery, 23*(3), 1335-1342.

20. Cardoso, G. Jr., Rolim, J., & Zürn, H. (2004). Application of Neural-Network Modules to Electric Power System Fault Section Estimation. *IEEE Transaction on Power Delivery, 19*(3), 1034-1041.

21. EL-Keib, A.A., Ma, X., & Rajapakse, A. (1995). Applaction of Artifical Neural Networkd in Voltage Stability Assessment. *IEEE Transaction on Power Systems, 10*(4), 1890-1896.

22. Hecht-Nielsen, R. (1989). Theory of the Backpropagation Neural Network. *I2001 IEEE International Joint Conference on Neural Networks (IJCNN1989), 1,* 593-605.

23. Hagan, M. T., & Menhaj, M. B. (1994). Training Feedforward Networks with Marquardt Algorithm. *IEEE Transection NEURAL NETWORK* 44th, *5*(6), 989-993.

24. Ranganthan, A.(2004). TheLevenberg-MarquardtAlgorithm.

25. Liano, K. (1996). Robust Error Measure for Supervised Neural Network Learning with Outliners. *IEEE Transaction Neural Networks, 7*, 246-250.

Electronic Media

26. GISTDA, (2016). Thailand Flood Monitoring System. Retrieved May 1, 2016 from http://flood.gistda.or.th/

3. Grudnitski, G., & Osburn, L. (1999). Forecasting S&P and gold futures prices: An application of neural networks. *l*(13), 6, Retrieved May 11, 2016, from https://www.researchgate.net/publication/229709827

4. Ql, M., (1993). Nonlinear Predictability of Stock Returns Using Financial and Economic Variables. *l*(17), 4, Retrieved May 13, 2016, from http://www.jstor.org/stable/1392399?seq=1&cid=pdf-reference- references_tab_contents

5. Vanstone, B., & Finnie, G. (2006, August). *Combining Technical Analysis and Neural Networks in The Australian Stockmarket.* Conference Paper paresent at the Information Technology papers of Bond Business School, Australia , Retrieved May 13, 2016, from http://epublications.bond.edu.au/infotech_pubs/16

29. Ng, A. *Machine Learning*. Retrieved May 25, 2016, from http://www.coursera.org