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Compare the forecasting method of artificial neural network and support vector regression model to measure the bullwhip effect in supply chain

E. Fradinata[1,2*], S. Suthummanon[2], W. Suntiamorntut[3], M. M. Noor[4]**

[1]Industrial Engineering, Syiah Kuala University, Banda Aceh 23111, Indonesia
Phone/Fax: 062-0651-7552222
[2]Department of Industrial Engineering, Prince of Songkla University, Hatyai, Thailand.
[3]Computer Engineering, Prince of Songkla University, Hatyai, Thailand.
[4]Faculty of Mechanical & Manufacturing Engineering,
Universiti Malaysia Pahang (UMP), Malaysia.
Corresponding author: *edinata69@gmail.com
**muhamad@ump.edu.my

ABSTRACT

The objective of this study was to compare the Bullwhip Effect (BWE) in the supply chain through two methods and to determine the inventory policy for the uncertainty demand. It would be useful to determine the best forecasting method to predict a certain condition. The two methods are Artificial Neural Network (ANN) and Support Vector Regression (SVR), which would be applied in this study. The data was obtained from the instant noodle dataset where it was in a random normal distribution. The forecasting demands signal have Mean Squared Error (MSE) where it is used to measure the bullwhip effect in the supply chain member. The magnification of order among the member of the supply chain would influence the inventory. It is quite important to understand forecasting techniques and the bullwhip effect for the warehouse manager to manage the inventory in the warehouse, especially in probabilistic demand of the customer. This process determines the appropriate inventory policy for the retailer. The result from this study shows that ANN and SVR have the variance of 0.00491 and 0.07703, the MSE was $1.55e^{-6}$ and $1.53e^{-2}$, and the total BWE was 95.61 and 1237.19 respectively. It concluded that the ANN has a smaller variance than SVR, therefore, the ANN has a better performance than SVR, and the ANN has smaller BWE than SVR. At last, the inventory policy was determined with the continuous review policy for the uncertainty demand in the supply chain member.

***Keywords*:** Artificial neural network; support vector regression; bullwhip effect; supply chain.

INTRODUCTION

This study has the purpose to develop the forecasting techniques from ANN and SVR to measure the BWE in across of supply chain. The ANN was developed from creating the network architecture and SVR used the Steve R. Gun algorithm to produce the statistical characteristics from signal demand. The signal demand from forecasting methods of data mining was carried out to reduce the BWE in the supply chain, it provides more accurately than the traditional forecasting methods [1]. In the real situation, the supply chain faces the difficulty to reduce the BWE from the uncertainty demand. Reducing the BWE could be used the forecasting method to predict the accurate certain demand of the data in the future. The consequence of the accurate forecasting would influence the inventory management system in the warehouse. The consequence of the accurate forecasting would be impacted by the inventory management system in the warehouse [2]. The BWE is the main risk factor for the members of the supply chain to anticipate to minimize the inventory cost [3, 4].

This research explores two methods of data mining techniques ANN, and SVR to reduce the BWE in the instant noodle supply chain then determines the inventory policy. The comparison of forecasting methods between ANN and SVR is still rarely done by the researchers to reduce the BWE. The forecasting model has the statistical characteristic from their source dataset. The bullwhip effect becomes a problem for the member of the supply chain if there is no strategy to anticipate the condition of bullwhip effect, there are four major causes of the bullwhip effect, such as demand forecast, order batching, price fluctuation, rationing, and shortage gaming. The demand forecast is one of the importance of things to reduce the bullwhip effect in the supply chain. The managers are better to understand the risk of minimizing the bullwhip effect. Understanding the causes of BWE helps the managers to develop the strategy to control the inventory in the warehouse [4].

In particular, ANN has its characteristics model when determining customer demand [5]. The process in the ANN is connected between the nodes inside the hidden layers or multilayers then ended with the output layer. Each layer has several neurons and each neuron in the layer is connected to the neurons with the different weights. The input layers received the signal then passed through the hidden layers, then it is processed between the interconnected of weight values and signal of the transfer function to obtain the generalization after the training process [6]. The training process continues to obtain a certain stop-criterion when it is satisfied with the average error between the desired and actual outputs over the training dataset is less than a predetermined threshold. They obtain the output result through the output layers. The training time is determined by various factors where they are influenced by the complexity of the problem, the number of data, the network and the transfer function parameters used. From the training process, the generalization results from the process where it produces the models that can overfit the data, this shows that the optimum process from the selected parameters and statistical result to select the best model [7-11]. This study applies the Backpropagation Artificial Neural Network (BPANN). It means that the backpropagation algorithm is used to train the neural network in the system [12].

The input data entrance to the input layer and the weight in each line should be iterative updating in the training process, the negative gradient of the mean-square error function. The iterative of error between desired and actual output values and slope of an activation function such as sigmoid. The process of weights are controlled and adjusted with the steepest descent direction and for dampened the oscillations to obtain the convergence rate in the networks are controlled by the two parameters of learning rate and momentum factor. The backpropagation brought the error signal to the lower layers. The conforming descent gradient would take a very small value in the leading of the weight adjustment before it out as the output in the input layer.

Support Vector Machine (SVM) is developed by Vapnik et al (1995) where many attractive features and promising empirical performance [13]. Then, Guns at all (1997) settled the formulation represents the Structural Risk Minimisation (SRM) principle, which has been shown to be superior. Structural Risk Minimisation (SRM) minimizes an upper bound on the expected risk, as opposed to Empirical Risk Minimisation (ERM) that minimizes the error on the training data [1]. SVR regeneration of SVM is what complements SVM with a greater ability to generalize, which is the goal in statistical learning. The SVM is used to solve the classification problems, and then develop more to be used for the regression where it is supported by the support vector methods case by Vapnik et al. [14]. It is a critical aspect of the supply chain members due to the function of the fillrate will influence the service level for the member in the line of the supply chain [15]. Many factors should indeed influence the fillrate of customer needs. Uncontrollably, the customer demand will affect the lead-time for each member of the supply chain. All businesses always concern about the customer demand which is controllable, it would easy for them to prepare the inventory stock level of the warehouse for each member [16, 17]. It means that the business will maximize profitability from the inventory's activities [18].

Therefore, it is reasonable to believe that the best forecasting methods should be determined importantly from the various methods to reduce the BWE in the supply chain. In this case, we would like to create and investigate the performance of two data mining methods to obtain the empirical result. The process of this, it started to identify the optimal parameters for both methods. We also have done the preliminary and published the selection of optimal parameters for ANN and SVR methods. The results of several analyses from the forecasting method and reduce the BWE will be discussed. Some contributions paper about the bullwhip effect and combination methods from other researchers. The quantity and demand order variance ratio is calculated in a way, which does not consider the lead-time variance. The methods of ARIMA, discrete wavelet transformations, ANN- Discrete wavelet transforms (ANN-DWT) model used the sales data to forecast the demand under which demand uncertainty is how to improve the action of the supply chain on this situation the member of the supply chain to magnify the net stock.

The data is collected from cement, automotive and steel processing demand datasets. The popular traditional time series models (AR, MA, ARMA, and ARIMA) are used for the forecasting models when the data series is stationary in nature and follows a linear pattern. They concluded that the ANN-DWT better resulted in performance than ARIMA, and it reduced the BWE and net stock amplification (NSamp) in the supply chain member [19, 20]. The study of ANN and support vector machine (SVM) for reducing BWE used the data of an Iranian automobile components supplier. They concluded that the artificial neural network could forecast more precisely than the other methods aforementioned [21]. ANN is combined with the harmony search; it used to predict the amount of armour stone breakwater stability based on the experimental data by Van der Meer, 1988. The method used the hybrid harmony search (HS) algorithm to determine the optimal initial weight globally in near-training models. Model HS-ANN compared with a conventional ANN model, where it is used with Monte Carlo simulations to determine the initial weight. The result is measured by standard deviation and the training backpropagation (BP) HS-ANN models found that smaller than the conventional ANN model [22]. Another topic is the comparative ANN and SARIMA in the Portland cement supply chain where the data took from the period January 2004 to March 2005 for forecast the demand where they concluded that the ANN was better than SARIMA [23].

In the real situation, it is very crucial for controlling the level of stock across the supply chain [24, 25]. If the company could not control the inventory properly, it could be a significant risk to its business [26]. Good control of the component variables in the warehouse makes the business able to reach its profit progressively. The coordination between the warehouse and the finance department manage the level of stock in the store more efficiently [27]. At the beginning of the years, the company's activity focuses on its own business only. They improve the management system review inside their business and spend much cost to develop a unique system [28]. This technique obtains more effective and efficient results. Nowadays, such a concept does not contribute to the effectiveness of the business. The modern concept is to collaborate and maintain together in the group whatever the inside activities, such as information, inventory, price, and delivery [29, 30]. Reviews these activities have the purpose of increasing the profit of review their business together. Making a group line across and work together will give a profit to each other in the supply chain.

The members of the supply chain determinants always face to the inventory policy when they meet the stochastic demand from the customer. The demand is very difficult, to predict precisely to fulfill the customer need [31]. The member of the supply chain always tries to predict customer demand through some forecasting methods. The problem in the inventory is the demand changed unpredictable, the inventory quantity should be adjusted following the request of the demand. It is the relevance of changing request signals. The adjustment of inventory makes overreacted on the order to adjust to the relevant signals. In other words, the reaction will contribute to the variances in order to belong the members of the supply chain periodically. The variance of the demand would affect the minimum stock of inventory to keep the warehouse economically. The retailer receives the information and keeps the inventory to meet an external demand that is generated from the characteristic of the demand. The order starts with the retailer and updates the inventory each time. Some traditional method has been tried by some researchers, but still not give a comfortable result [32]. This study uses data mining methods such as ANN and SVR to increase the performance of the forecasting method. The accuracy for predicting the point would be minimizing the variance of demand [33].

The main problem of the supply chain for inventory is overreacting to magnify the order to the backward flow of material and in another case; determine the inventory policy is quite important to minimize the holding cost from the inventory. At last, the objectives of this study is to compare the two methods of ANN and SVR and to select the best method. Then applied and used it to forecast the external demand on solving the problem of reducing the BWE in the supply chain member. The study also aim to determine the type of policy from the demand.

METHODOLOGY

ANN and SVR are the techniques that carried out more precisely in the forecasting model in the area of the linear and nonlinear dataset [34]. ANN is a concept where it is absorbed by the living organism, especially the brain idea [35, 36]. The brain works from the input neurons and then interexchanges the neurons between layers inside the system [37]. In the system, inputs take account to reach the dynamics and flexibility to get a minimum error before obtaining an output. ANN has been implemented in many areas for forecasting method to obtain the best result, due to its flexibility since the ANN produce the good prediction model [38, 39]. It does not require many statistical assumptions, continue and non-continue, parametric and nonparametric data; it can also work in missing dataset [40]. ANN prediction used the back-propagation Levenberg–Marquardt training algorithm that contributes to the good result. The other network can be used the Radial Basis Function Network (RBFN) to get the good result of output for getting the optimum laser parameter [41].

SVR is a method that involves the training points in the small subset to get solution output with a computer [42]. The loss function of SVR is to pretend the optimization in the global optimum area. SVR improves various interesting features and produces better performance [43]. The performance generalization of SVR depends on the determination of the selection of the parameters. Some parameter influence is C, ε (epsilon) and the kernel parameters. Where the C parameter influences the trade-off between the complexity and flatness of the model. For example, if C is too large (infinity), it should minimize the empirical risk only, without regard to model complexity part in the optimization formulation [44, 45]. The advantage of SVR is the linear function can avoid the difficulties in the area of high dimensional piece space where the optimization should be transformed into a dual convex quadratic function [46]. The regression problem, the error should be greater than the threshold ε when the loss function creates it. Furthermore, the loss function produces the decision rules, giving significant algorithmic and representational advantages in a sparse representation. The data determinant of demand transform into the subset of the pool in the hyperplane line, this also means the good line for predict. And all the dots drop in the range of $f\pm(\mathcal{E})$(feasible) [47].

The datum is collected from the determinant of demand data set of the instant noodle industry. The study prepared the dataset before it was used for checking the missing data and synchronized unit. Then, we selected the input variables with the Durbin-Watson method. Six selected variables is designated as an input: Population (D_1), the number of instant noodle buyers (D_2), Price of instant noodle (D_3), Gross Domestic Product (GDP) (D_4), Expectation futures instant noodle price (D_5) , Advertising of the instant noodle (D_6) and Demand of instant noodle (D_Y). The fluctuations of the data have the characteristic of time series data sets from 1 to 100 data sets. They were generated by normal random distribution, and then the variables were selected by using the Durbin-Watson methods to choose the variables to entrance the network. Moreover, the data were normalized in the range of -1 to 1 before the entrance to the system of ANN and SVR [48].

In this case, all variables were entranced to be input variables where they are normalized. From the output, reviews their standard deviation, mean, and mean square error were measured. This was an important technique to generate the variance of order in the beer game software due to the beer game uses the standard deviation and the mean as the entrance variables [49, 50]. At last, then it generated the pattern of the BWE before making a conclusion. The time series forecasting demand approach between ANN and SVR are conducted to identify the order up inventory when the characteristic of the variability pattern in the supply chain. The variability is caused by customer demand behaviors [51]. The instant noodle dataset is used for illustration in this study.

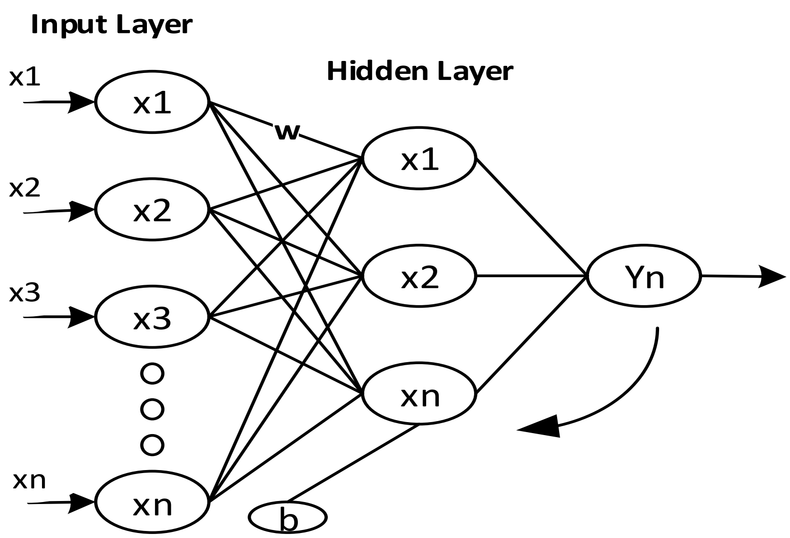

Figure 1. Backpropagation neural network

Neural Network used the back-propagation network with MatLab program to run two methods for calculating the process in the neural network where the variables are separated into three categories: training, validation, and testing with 70%, 15%, and 15%, respectively. The six variables are the input layers. ANN works to speed the process with the training algorithm of Levenberg-Marquardt and using the MSE as a performance indicator. The network works with the transfer function to maintain the data on the range of the transfer function [48]. Adaption learning is increased with the learnGDM. It is shown in Figure 1.

Before the data was generalized for predicting, the optimal solution from ANN used the whole training dataset randomly in their process. The generalized data dropped in the area of global optima value where it contributes to the feasible solution.

The process of the algorithm is as following as a concept of backpropagation neural network works with the algorithm of:

Phase 1. Input

i. Each input unit receives the signal and forwards it to the hidden layer.
ii. Calculate process for all outputs in the hidden layer.
iii. Calculate all network outputs in the output layer.

Phase 2. Backpropagation

i. Calculate the factor of arithmetic unit output by an error in each unit of the output layer.
ii. The unit of error will be used in a layer to change the weight of dataset.
iii. Calculate the weight change rate x with an accelerated pace.
iv. Calculate the factor deviation in the hidden layer.
v. Calculate the change in weight of dataset

Phase 3. Change the Weight

i. Calculate all weight change in the layers.
ii. The weight change to the hidden layer is leading to the output layer.
iii. Calculate the statistical characteristics to identify the model.

Support Vector Regression (SVR) worked with the amount of 100 sets of data, and they were separated into two parts, 90% was used for training and the rest of 10% was used for testing. The program code was employed from Steve Gunn's algorithm code and then it was modified to take into account the output of the SVR for Number of Support Vectors (NSV), beta, and bias. The testing results from SVR are calculated to get the statistical output. One of the most important ideas in SVR cases is that presenting the solution by means of a small subset of training points gives huge computational advantages. Using the epsilon intensive loss function, we ensure the existence of the global minimum and at the same time optimization of reliable generalization bound [1].

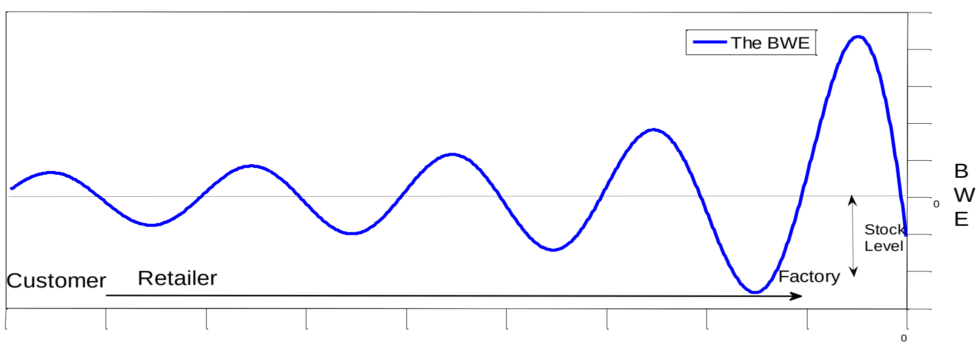

Figure 2. Bullwhip effect in a supply chain member

The demand signal is the result of the forecast demand for ANN models. The supply chain assumes that the external behavior of customer demand has a normal random distribution. The normal density has the function of *f*(*x*) which is called the bell-shaped curve that is symmetric about μ, and that attains its maximum value of $1/\sigma 1/\sigma\sqrt{2\pi}$ ≈0.399/σ for $x = \mu$. The stock level in each member of the supply chain would be different from determining the policy to minimize the cost. The policy allows each member to magnify percent of quantity to anticipate the customer demand. The increasing stock level for each member of the supply chain is illustrated in Figure 2.

RESULTS AND DISCUSSION

Artificial Neural Network set up the optimal parameters of the network where the test just used their type of the transfer function in the network, they were pureln, logsig, and tansig. In this study, they had the value of MSE 0.00289, 0.000807 and 0.000529, respectively. The tansig has the smallest transfer function of the network. The result from the test of the network has been run with the training network to obtain the best performance from that transfer function. The number of hidden layers has one layer and neurons (nodes) in each layer have ten nodes. The training data indicate a suitable good condition before it starts to generalize the dataset to forecast the proper point in the future. Meanwhile, the validation of the ANN has the value of 0.9888, this means that the process of training and generalized the result is quite good. Generally, the optimal condition of ANN is dropped on the global optimal to obtain the result. The accuracy of the technique for forecasting method can be implemented as the signal demand of customer need after it produces the mean squared error. The signal demand produces the variance before it is observed by the retailer. The signal customer demand was identified as the independent, identically, and normal (IIDN) where it is the white noise has the Gaussian distribution. The random residual must be fulfilling the condition of the dataset. Moreover, the examined for the independent use of the coleogram or Ljung box to see the autocorrelation and partial autocorrelation.

Support Vector Regression in this study used Steve Gunn's algorithm code and modified it to take into account the output of SVR function in the program code to obtain the result [1]. In the previous study, we selected the optimal parameter from some parameters, such as linear, e-insensitive for the kernel functions were tested by linear and polynomial, then for the lost function was tested by the e-insensitive. The linear margin results that the ε parameter, which manages the large ε-insensitive area, used to fit the training dataset in the area of boundaries before they were generalized. It is shown in Figure 3.

The linear margin at the x-abscissa line varied with the value of 0.02 scale and started from 0.54 until 0.70, it means that the training process starts and end with the generalize points. The different colors between the epsilon boundaries area showed the narrow margin of the dataset in the ε-sensitive loss function in the class of maximization result. This insensitive have the responsibility of controlling the fit of the training dataset. Each color in the margin showed the dots for each data lines from 7 variables (D_1, D_2, D_3, $D4$, D_5, D_6, and D_y). The centerline dropped at the 0.53 then increased to the 0.56 and followed the data of e-insensitive upper bound and lower bound. In here, the insensitive have the duty of controlling the fit of the training dataset where the bias has the value of zero to minimize the implicit bias. The bias was found from the average support vector to interpolation error (*e*). The interpolation has the value of Lagrange multipliers between zero and the upper bound. The interpolation error produces the support vector in the dimension space of those boundaries where they pool enclosing all the data points. The data points were minimized with the Lagrange multipliers where it should minimize the classification error. The penalty is being too far away from predicted line $w\Phi_i + b$ in the epsilon tube are closed enough around the line. In this case, the dots are lie inside the data-tube will have no impact on the final solution with the equivalent to the zero (α_i=0).

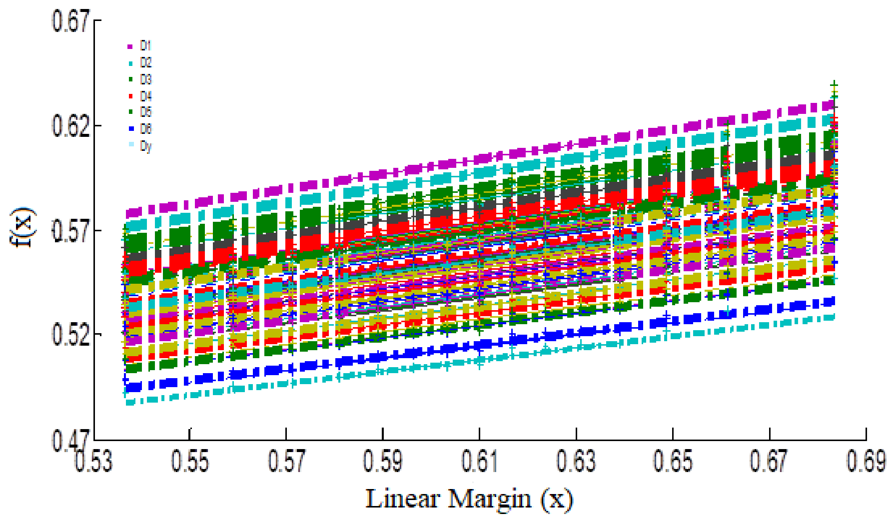

Figure 3. The linear margin of SVR.

Hence, the data set were dropped inside the tube have no impact on the final solution. The loss function used a quadratic function to correspond to the least square error. The training from the optimal parameter selection value and it could be affected by the amount of support vector to build the regression function. The testing resulted from SVR-output than it was calculated to obtain the relevance of standard deviation, mean and variance. The loss function is used by the quadratic function to corresponding to the least square error. The dots data in between the boundaries show in some different colors for classification.

Statistical Result for ANN and SVR

Table 1 exposed the statistical characteristic, such as SD, mean, variance, and the MSE where it was formed from the two methods of ANN and SVR. This table presented the ANN had the value of MSE 1.55e-6 and SVR 1.53e-2. It exposed that the performance of the ANN was better than the SVR method. The variance of ANN was 0.00491 and SVR was 0.0773, it means that the ANN had smaller than SVR, because the ANN when it used the training process and the testing process selected the small random points to protect the overfitting before it generalized the result. ANN obtained the maximum difference in the global optimum solution condition. While, the SVR used only some training to use the data selection to be trained in the training process for classification to obtain the prediction, due to the kernel function in the SVR changed to be a regression model. Furthermore, the SVR could solve the overfitting good in the process of generalization where the quality of estimation used the loss function.

Table 1. The statistic result of variance demand for two methods

	Method	
Statistical	**ANN**	**SVR**
SD	0.07012	0.2775
Mean	0.531	0.2176
Variance	0.00491	0.07703
MSE	$1.55e^{-6}$	$1.53e^{-2}$

The prediction from forecasting demand had the values of standard deviation, mean, and variances illustrated the characteristics of the dataset from these methods at the retailer, wholesaler, distributor, and factory level. The variance for ANN was 0.00491 and SVR was 0.07703. The signal forecast demand entranced at the retailer.

Order Variance for Supply Chain Member

The simulation of the variance order from the beer game software is illustrated in Figure 4. It was varied with the various times in weeks and the ordinate was varied with the items. The Figure illustrated that the red line tells that the retailer starts to order with the amount of eight quantity. Then, the retailer anticipates the policy to keep the minimum stock during the shortage. Since the unpredictable condition of the stochastic signal customer demand, the retailer made the planning of the policy in the warehouse to maximize the revenue from minimizing the holding cost. Moreover, the warehouse manager at the retailer magnified the order 5% until 30% based on the timelines which the fluctuated time, it depended on the condition of the stochastic historical customer demand with the relevance month. Then, the blue line was the wholesaler ordered with 18 items, and in the same way the light red, the wholesaler magnified the order to the distributor. Moreover, the wholesaler ordered to the distributor were 35 items and the manager also magnified the order to the factory. Then, at the last time the green line, the factory produced the items were 45 items to anticipated the orders.

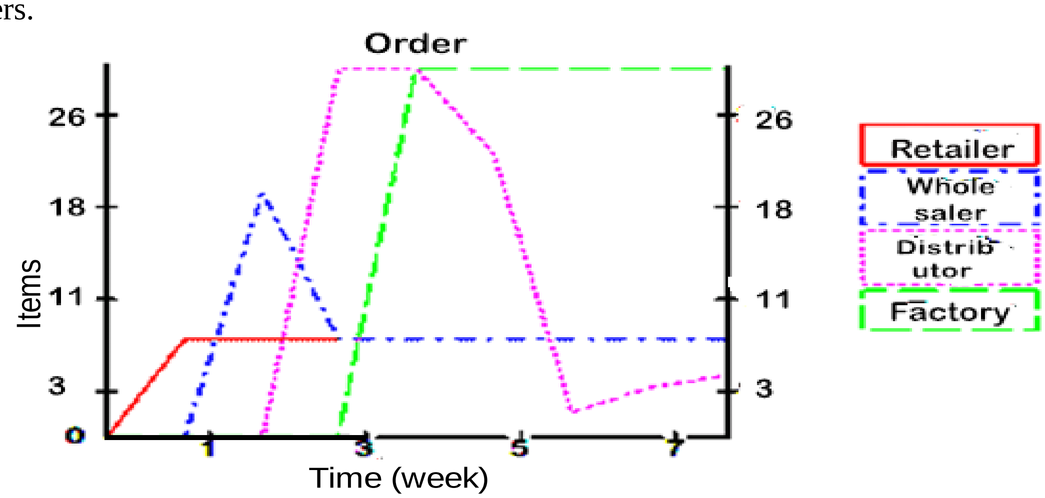

Figure 4. The simulation of order for supply chain member with beer game software.

Moreover, the graph for the variance orders in each member of the supply chain is taken account to measure the existence of the bullwhip effect across the supply chain. The variance order is simulated with the beer game software to predict the variance orders across the supply chain. The magnified of variances obtained an order to generate the statistical output from each member of the supply chain. The variance tended to increase is from retailers, wholesalers, distributors, and factory for both methods.

The variance order increased would influence the member to anticipate the minimum stock more safely during the shortage. The ordered with the period is 7 weeks. The lead-time for an order placed by that player, plus *X* time estimated of the standard deviation during the lead-time. Then, the inventories system has placed an order to set up an order quantity of goods. After, the first seven weeks were adjusted to account for start-up by not ordering demand during the first week at the wholesaler, the first of three weeks at the distributor and the first three weeks at the factory. This policy is called the update *s*. Since the signal external demand from customer is difficult to predict the habitual of customer need. Sometime the manager inventory might change to other policy to anticipate the minimum stock to the customer demand, especially in the probabilistic demand. This situation tended to magnify the order between the members. The member of the supply chain some time might be modified the policy after periodic reviewed. It depends on the situation of customer demand where it should produce the standard deviation of the external demand. The period of ordered might change if the situation of buffer stock was not on safely to fulfill the filrate of customer demand where the manager usually uses the computer program to quickly review.

In the practice, the managers manage the strategic condition where they could use their knowledge to solve the complexity problem between the market demand and the capacity of the warehouse. In this game, the manager manages the customer demand would be fulfilled slightly to deliver to the customer while to keep the minimum safety stock in the warehouse.

The statistical output of variance order for this study was given in Table 2, where it drew the member of the supply chain, which produced the statistical characteristic from ANN and SVR. It explained that each member of the supply chains such as a retailer, wholesaler, distributor, and factory have difference statistical characteristic value. The two methods of ANN and SVR had a correlation to mean, variance, and SD.

Table 2. Statistical result variance order of supply chain member

Supply Chain Members	Statistics	Method	
		ANN	SVR
Retailer	Mean	4	4
	SD	0.10	0.10
	Variance	0.01	0.01
Wholesaler	Mean	3.69	1.20
	SD	1.07	3.10
	Variance	1.14	1.44
Distributor	Mean	3.38	1.60
	SD	1.44	3.20
	Variance	2.07	2.56
Factory	Mean	3.08	1.83
	SD	1.69	2.80
	Variance	2.86	3.35

For the first time at the retailer, the variance is under one and has close value 0.1. It means that when the retailer received the information from the customer it still kept in the warehouse. Then the retailer magnified the order to the wholesaler to get the order with the variance value was 1.14. Moreover, with the same way the distributor order to the factory with the magnified the order was 2.07 and the same say the factory level was 3.35-variance order. From this table, it illustrated that the BWE presented in the line of the supply chain with the increasing value of order variance in each member of the supply chain. Increasing variance in supply chain member influences the difference production or order to the supplier in the factory. While, for the SVR has the value of variances were 0.01, 1.44, 2.56 and 3.35 for the retailer, wholesaler, distributor, and factory respectively. This means that the bullwhip effects present in both methods of the supply chain member.

The Bullwhip Effect with ANN and SVR

In the rule of BWE, if the ratio of BWE is more than 1, it indicates that the BWE is presented across the supply chain. The two methods in the specified ratio of the bullwhip effect from the retailer to the factory in the supply chain member. Since the control of the net stock in the warehouse must be under control to obtain the minimum cost in the warehouse. The order from the management at the warehouse goes to the backward member to magnify it. The decision is magnified must be rational and accurate each period of the order. The opposite of it, if the variance demand is higher than the order of retailer the BWE will not occur. Table 3 is the bullwhip effect from the retailer, wholesaler, distributor, and factory for ANN and SVR methods. It showed that the value of 0.130 is less than one, it means that the bullwhip effect does not occur in the supply chain member for the ANN method, but for the SVR, it occurs with a value of 2.033 for the retailer level. The bullwhip effect is increased for wholesaler, distributor and factory level for both methods. The increased value for the supply chain members is 0.13, 18.692, 33.321 and 43.471 respectively for ANN and 2.033, 232.790, 421.630 and 580.740 respectively for SVR in the member of the supply chain.

The signal demand came from the customer to the retailer at the probability condition. Then, the retailer manager anticipated the uncertain demand from customer to magnify the order to the wholesaler to get the maximum revenue. The other tiers from wholesaler to distributor and distributor to factory do the same sense to magnify the orders to anticipate the probabilistic demand. It can be seen in Table 3.

Table 3. The bullwhip effect from ANN and SVR

Bullwhip effect	**Methods**	
	ANN	**SVR**
Retailer	0.13	2.033
Wholesaler	18.692	232.790
Distributor	33.321	421.630
Factory	43.471	580.740

The ration of the bullwhip effect, ANN has a smaller BWE compared to the SVR due to the differences in variances and standard deviation. For the variance, ANN has small variance due to the probability of signal demand to the retailer has smaller than the SVR. The signal demand between ANN and SVR obtain the different result when the information is dropped at the retailer at the supply chain, it starts to magnify the information to anticipate the uncertain condition of customer demand. In this situation, the manager decides the inventory policy to optimal condition through the quantity, cost and time.

The Inventory Policy

The inventory kept on the proper stochastic because the unexpected variance condition obtains the difficulty of managing the lead-time and the cycle time of reordering is to fulfill the inventory in the supply chain members. It means that the workload of the specific quantity is related to the variance and weight factor from the signal demand. It means that the manager of the retailer would consider preparing the cycle period for preparing the safety stock on the uncertain average demand from the customer. If the order is higher than the demand anticipated when the external demand, it should be the bullwhip effect occurred in the members of the supply chain. The situation when controlled the inventory periodically to solve the uncertain situation due to BWE occurred, the manager would be used the policy to continue review unpredicted anticipated demand.

The Total BWE

The total bullwhip effect could be calculated to add the variance among the member of the supply chain, it was drawn in Figure 5. It gave the information that the blue bar with the value of total BWE was 1237.19 of SVR, and another light blue bar showed that the ANN had the total BWE was 95.61. From the figure, we can conclude that the SVR was higher than the light blue of ANN with the value of the total BWE.

The Illustration of the Wave BWE for ANN and SVR

The illustration of the bullwhip effect occurred in the members of the supply chain for the ANN method is shown in Figure 6. The figure was divided by the four parts to illustrate the variance signal demand for four members of the supply chain. The member was on the x-abscissa 100 points difference variance with varying time and the y-ordinate for the BWE of ANN. The blue line was the signal demand forward to the factory. The line shows fluctuate from the retailer, wholesaler, distributor, and factory in variance customer demand. While the red line displayed fluctuate in the smaller variance started to magnify in each member from the retailer than followed by the wholesaler, distributor, and factory, the wave line tended to increase from the retailer to the factory. The green line was the center of the variance demand dataset on zero inventories position.

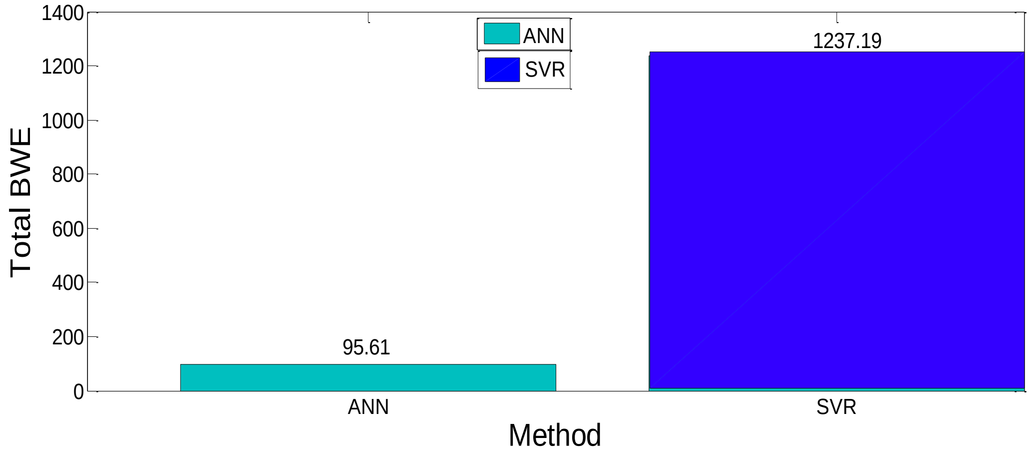

Figure 5. Total bullwhip effect of ANN and SVR for the member of the supply chain

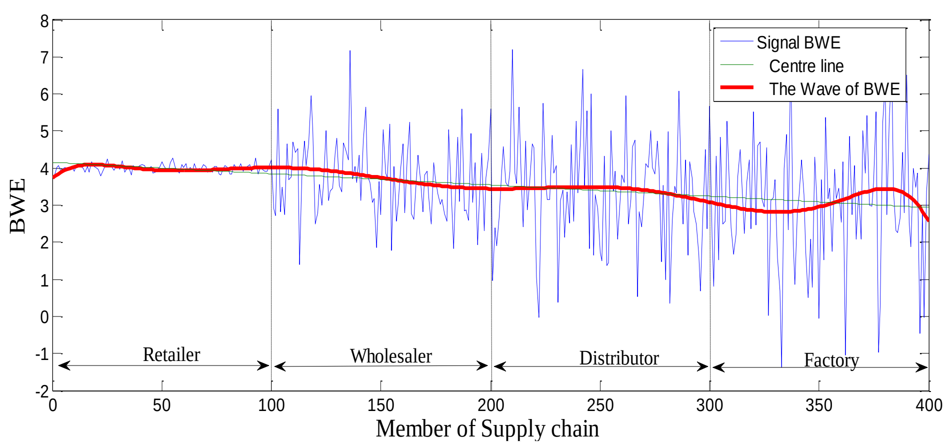

Figure 6. The illustration of the bullwhip effect in the supply chain with ANN

The illustration of the bullwhip effect in the supply chain for the SVR method, is shown in Figure 7. The figure has the x-abscissa 100 points variance time and the y-ordinate for the BWE of SVR. The blue line was the signal demand from retailer to factory. The signal demand tended to fluctuate in various time and member. Other red line showed that the smaller variance started to magnify from the retailer to factory. The wave line tended to increase from retailer to factory, the green line was the center of the variance demand for each member of the supply chain. The green line shows the zero inventories position.

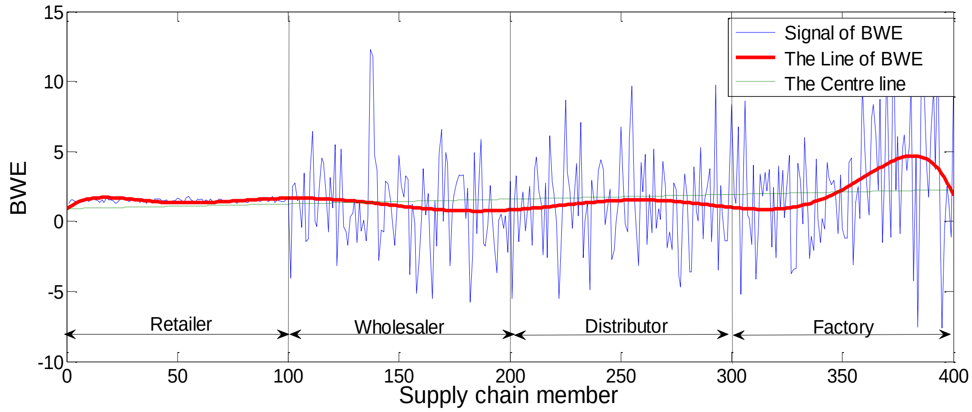

Figure 7. The illustration of the bullwhip effect in the supply chain with SVR.

At last, both of the two methods showed different result where the wave of BWE for ANN was smaller than the SVR. The members of the SC magnified review their orders to anticipate the uncertain demand and to keep safely reviews their safety stock.

CONCLUSION

The argument from this study that the ANN and SVR have a small variance of 0.00491 and 0.07703 with the difference is 0.07212 (14.6%). The performance of the two methods have MSE $1.55e^{-6}$ and $1.53e^{-2}$, and the total BWE for both methods have 95.61 and 1237.19 respectively. There are three conclusions that we can take into consideration in this study.

- ANN was better than the SVR due to contribute the smaller mean square error, whether the SVR could be an attractive promising forecasting method.
- The better forecasting performance should produce smaller magnify of the bullwhip effect in the members of a supply chain.
- The policies used the continuing periodic inventory review policy to anticipate the high bullwhip effect from the external demand. The inventory was reviewed continuously where the order was placed when the inventory under the net of safety stock or at the reorder point at the particular level.

The ANN and SVR are the methods of data mining which can be flexible to use for forecasting method to predict the certain point in the dataset and used the type of continuing periodic inventory review policy to manage the inventory in the warehouse.

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