Predictive Demand Analytics for Inventory Control in Refined Sugar Supply Chain Downstream

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Abstract— **The Company's inability to overcome inventory problems leads to unprepared marketing distributor in anticipating a surge in consumer demand and unavailability of inventory in the warehouse. Long agricultural supply chain problems cause frequent information gaps, inaccurate and integrated inventory predictions from downstream to upstream supply chains, and uncontrolled inventory, these are the phenomenon of the bullwhip effect in the supply chain. To overcome these problems, the marketing distributor needs to predict the demand in the integrated supply chain downstream so that inventory in each chain can be controlled. Based on the data, the existing demand pattern is linear and the right method to use is SVR (Support Vector Regression), which produces the highest level of accuracy and the smallest error. Based on the results of SVR demand forecasting in the supply chain downstream, each chain is then integrated to control inventory, so that the occurrence of the bullwhip effect can be minimized. Then the company can use the aggregate mode to determine the safe upper and lower limit of inventory so that the stability of the demand for refined sugar from the supply chain downstream can always be fulfilled the company.**

***Keywords*— Inventory, Predictive demand, SVR, Refined Sugar**

I. INTRODUCTION

PT PAS sugar division was formed to meet the needs of refined sugar in Indonesia and supplying raw materials to the food, beverage and pharmaceutical industries. PT. PAS produces high quality refined crystalline sugar which includes: affinition, remitting, clarification, depolarization, crystallization, fugalization, drying and packaging [1], only uses environment-friendly raw materials imported from Australia, Brazil, Thailand and Africa. In the beginning, PT. PAS's refined sugar production capacity is 500 tons per day (175,000 tons per year). Since then, employing more than 650 highly dedicated employees, the capacity has increased gradually but rapidly to 750 tons per day, 1,000 tons per day and up to the current refined sugar production capacity, which is 1,750 tons per day (577,500 tons per year). It is presumed that currently the volume of imported refined sugar exceeds actual industrial needs. As a result, there is a surplus of refined sugar that seeps into the GKP market so that the price balance is disrupted. There needs to be a recalculation of the refined sugar demand by the industry so that there is no excess stock that seeps into the GKP market [2]. The trend of demand for refined sugar in the food, beverage and pharmaceutical industries in Indonesia will increase so that the rate of sugar consumption tends to be higher compared to the rate of production which is one of the triggers for the increasing volume of sugar imports [3]. Supply decisions will change patterns due to low flexibility and accumulation of imported stocks.

Information occupies an important role in supply chain management. Every party involved in the supply chain manages information to estimate inventory levels. The parties, from raw material suppliers, finished product distributors, to sellers who sell products to buyers as product end users, will provide inventory in the right amount and on time delivery. They base inventory demand information on historical data. Problems will arise when there is variability in supply demand in the initial stages of the supply chain system. The product supply chain is a network of two agents that integrate with one another, who are involved in the transformation of processes from raw materials to products and product distribution to make better decisions about the flow of material information in the supply chain and provide value to end customers [4][5]. Analytical supply chain focuses on an analytical approach consisting of descriptive, predictive, and prescriptive [6].

Inventory is the main factor to support the smooth running of business activities, inventory can be interpreted as goods stored for use or sale in the future period [7]. Inventory needs to be controlled in order to be able to respond quickly to demands and provide high-quality services [8] to the complex inventory management [9], especially on perishable products that have demand uncertainty, are easily damaged, and require high customer service levels [9]. The Company's inability to overcome inventory problems leads to unprepared marketing distributor in anticipating a surge in consumer demand and unavailability of inventory in the warehouse [10]. Variability occurs when actual inventory demand differs from estimated demand. This difference can be caused by various things, both external factors that cannot be controlled by distributors, and internal factors which are generally due to inaccuracies in estimates [11]. To anticipate the variability in demand for supplies, distributors will usually prepare a large amount of inventory - in case of anticipation of inventory shortages [12].

Variability of inventory at the downstream level in the supply chain system stage will have implications for greater variability at the upstream level. The closer it is to the upstream level, the variability of inventories will increase, thus forming a pattern like a bullwhip. It creates inefficiencies in terms of increasing total costs, decreasing profitability, increasing inventory storage costs and higher capital costs [13] [14]. A number of large collected data is also called Big Data which gives an impact characteristic for mitigating the effects of variability on inventory [15].

The distribution sector is characterized by the speed of change occurring; the volatility of customer purchasing trends is a well-known concept (which in many cases becomes fashionable). Therefore, large companies must adapt to this change as soon as possible. This fact, added to the large volume of data they handle, makes the advantage of automating the discovery and classification of customer purchasing patterns almost an obligation [16]. Estimating the demand based on the inventory need to project demand patterns in complex environment for short, medium and long-term. The Bullwhip effect is one of the problems that arise in the Supply Chain. Bullwhip effect can be interpreted simply as a distant deviation between existing inventory and demand The major causes of the bullwhip effect are the inaccurate forecasting, rising material prices, market competition, and the demand forecasting which is done lead to overstocking. The said overstocking is due to unbalanced number of demands and supplies due to the lack of accuracy in determining the amount of inventory.

Supply chain analytic that uses big data and complexity in data solutions provides innovative opportunities to overcome demand uncertainty. Deviation estimates and predictive intervals are means to meet requirements so that predictive reliability of demand can be determined [17]. In the case of clarification, which the output is either integers or discrete, the Vector Support Machine is used, while for the case of regression, which the output is either real or continuous number, then Support Vector Regression (SVR) which is a part of the support vector machine is used. By using ε-intensive loss function, SVM can be generalized to perform a function or regression approach [18].

II. METHOD

A. *Identification of Refined Sugar Supply Chain*

Refined Sugar or Refined Crystal Sugar is sucrose sugar produced through the stages of processing raw crystal sugar (RCS) which includes: affinition, remitting, clarification, decolonization, crystallization, fugalization, drying and packaging. Figure 1 below illustrates the supply chain system for refined sugar from the plant to the SMEs for sale to end consumers.

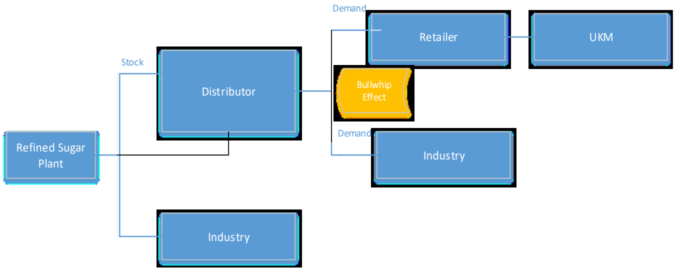

Figure 1 Refined Sugar Supply Chain

B. *Research Framework*

Based on the problems of the refined sugar supply chain that occurred, a framework was created to solve the problem. The initial step is to collect demand data and order data at each chain in the refined sugar supply chain. Next is to calculate the variance of the order and demand. Based on the variance data, how the bullwhip effect occurs in each chain can be identified. The next step to solve the problem in the bullwhip effect is to determine order predictions for each supplier, which is centered on the downstream supply chain using the Support Vector Regression (SVR) method, where the results of this prediction will produce epsilon values as the upper and lower limits used as control for inventory in each supply chain up to the most upstream chain and the minimum error value obtained. The last step is to recalculate the bullwhip effect after using the SVR method. The flow of the thinking framework for this research is illustrated in Figure 2 below.

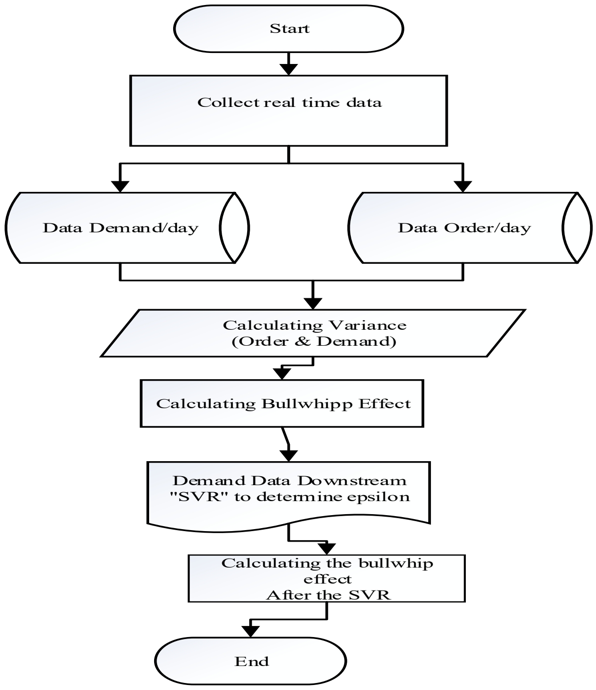

Figure 2. Research Framework

The Bullwhip effect can be determined based on the variance value of the order divided by the demand variance. The following is a formula for calculating the bullwhip effect for each chain.

$$bullwhip = \frac{variance\ of\ order}{variance\ of\ demand} = \frac{\sigma^2_{order}}{\sigma^2_{demand}} \dots (1)$$

Traditional regression procedures/statistic often expressed as a process that produces a function f (x) that has the smallest deviation between the predicted and observed responses experimentally for all training examples. One of the main characteristics of Support Vector Regression (SVR) is that instead of minimizing observed training errors, SVR tries to minimize common error limits to achieve general performance [20] . In SV− ε regression, the purpose is to find the function f (x) which has the most deviation ε from the target actually obtained, namely for all training data and at the same time as uniform as possible. SVR ε *equivalent* with the accuracy of the approximation of the training data.

A low ε value is associated with a high value in the slack variable t (*) i and a high approximation accuracy, otherwise a high value for ε is associated with a low value of t (*) I and a low approximation accuracy. In SVR support vector is training data located at and outside the boundary ε. Cases of linear functions are explained in the following form:

$$f(x) = \langle \omega, x \rangle + b \text{ with } \omega \in N, b \in \Re \dots (2)$$

$$Min \frac{1}{2}\|\omega\|^2$$

$$subject\ to \begin{cases} y_i - \langle \omega, x_i \rangle - b \leq \varepsilon \\ \langle \omega, x_i \rangle + b - y_i \leq \varepsilon \end{cases} \dots (3)$$

Uncertainty caused by observation errors or methods used to compare models and observations on Support Vector Regression using the following formulation [21]

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \qquad RMSE = \sqrt{\frac{i}{n}\sum_{i=1}^{n} e_i^2} \dots (4)$$

III. RESULT AND DISCUSSION

The first thing to do at this stage of the results and analysis is to collect demand data by the marketing department at the distributor in *real time*. The following is the demand data collected by the marketing department which will be the prediction of orders in each chain involved in the downstream refined sugar supply chain.

Table 1. Demand data per Time

Day	***Demand/Prediction Order***		
	Customer	*Distributor*	*Factory*
1	3	8	4
2	4	6	5
3	8	6	4
4	4	6	6
5	6	6	10
6	9	8	14
7	8	10	18
8	12	14	22
9	15	20	26
10	26	26	30
11	35	40	34
12	40	41	47
13	45	47	50
14	54	50	46
15	49	54	58
16	59	57	69
17	60	63	65
18	62	66	70
19	63	65	66

Based on these data, it is known that there is a bullwhip effect in each chain. This can be proven by the graph in Figure 3 and the bullwhip effect calculation that has been done between prediction orders at the factory and customer demand.

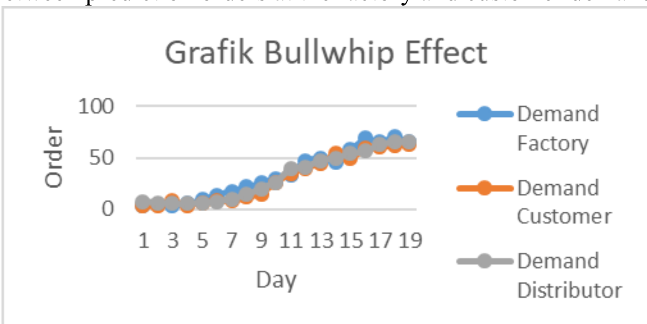

Figure 3. Bullwhip Effect Graph 1 Refined Sugar

Based on the demand / order data above, the value of *the bullwhip* that occurs between the factory and the distributor can be found, as well as the bullwhip between the distributor and the customer. Table 2 below shows the value of the bullwhip effect.

Table 2. The First Bullwhip Effect

Supply	**Variance of Order**	**Variance of Demand**	**Bullwhip Effect**
Factory	606,3748	588,3467	1,030642
Distributor	588,3467	547,3979	1,074806
Customer	547,3979	542,7018	1,008653

Based on the table above, it can be seen that the value of the bullwhip effect in each chain has a value of more than 1, then from these results, improvements will be made using the

Support Vector Regression (SVR) method. The following are the results of the prediction of demand and order in the refined sugar supply chain using the SVR method and R software along with the graph in figure 4.

Day	Demand/Order Prediction	
	Customer	Distributor
1	3	3,71
2	4	3,92
3	8	4,35
4	4	4,78
5	6	5,29
6	9	6,39
7	8	8,7
8	12	12,7
9	15	18,4
10	26	25,3
11	35	32,6
12	40	39,6
13	45	45,7
14	54	50,8
15	49	54,9
16	59	58,2
17	60	60,7
18	62	62,2
19	63	62,3

Figure 4. Demand/Order Prediction with SVR

Parameters:
SVM-Type: eps-regression
SVM-Kernel: radial
cost: 4 gamma: 1 epsilon: 0.03 RMSE = 2.146306

After getting the demand and order prediction data with a minimum value of epsilon = 3 and RMSE for the error of 2.146306, the demand analytics graph produced is as follows, where the bullwhip effect is close to 0, there is no bullwhip that occurs.

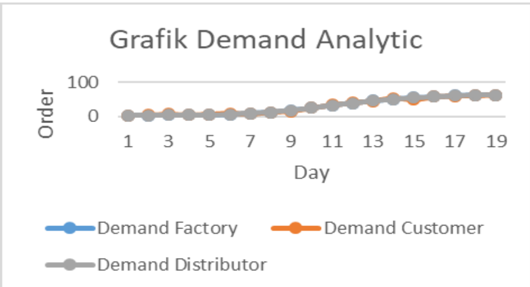

Figure 4. Demand Analytics Graph

IV. Conclusion

The bullwhip effect phenomenon is often found in agricultural supply chains because there are often information gaps, inventory predictions from downstream to upstream supply chains that are inaccurate and integrated, causing inventory to be out of control. This study has succeeded in overcoming the bullwhip effect phenomenon in refined sugar inventory, with the method used to overcome the problem of the bullwhip effect phenomenon is the SVR (Support Vector Regression) method and using R software. The parameters resulted are SVM-Type: eps-regression, SVM- Kernel: radial, cost: 4, gamma: 1, epsilon: 0.03, RMSE = 2.146306 because the demand data is linear.

With the SVR method, the prediction of demand without the bullwhip effect in the downstream integrated supply chain is generated so that it can control inventory in each chain. The research carried out is still on the application of SVR for Predictive Demand Analytics on refined sugar, and can be applied to predict inventory in other agricultural fields.

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