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Adaptive Neuro-Fuzzy Inference System (ANFIS) Approach to Raw Material Inventory Control at Pt XYZ

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ABSTRACT

Raw material inventory control is important thing for food companies. The adaptive inventory control is able to adapt to changes in the environment, maintain system performance and stability in the face of various problems in the industry, one of which can be applied to controlling raw material inventories. PT XYZ is a jelly drink industry that has a high level of raw material inventory. In 2016 the investment costs incurred by PT XYZ for carrageenan raw materials ranged from 55-566 million IDR. Costs incurred are quite high and require considerable handling in their maintenance. Therefore, a solution is needed to minimize inventory costs without disturbing the business process. The purpose of this study is to analyse the raw materials inventory PT XYZ for jelly drink product. The analysis is carried out on the main raw material, namely agar (carrageenan) which has three suppliers. The method used is BPMN 1.0 and ANFIS (Adaptive Neuro Fuzzy Inference Systems) which form rules of raw material control rules. This method is an alternative decision making and accommodates flexibility in the form of frame work that accommodates uncertainty of information or data that is less accurate. This study uses four input parameters, namely production demand, raw material arrival, usage and stock. The output obtained is in the form of inventory costs. The results of the study are information regarding the role of each actor who stores important data as a sequence of decision making. The application of ANFIS to design a raw material inventory control system using epoch 50 produces 90 rules of rules with testing errors. The average test for the training dataset is 0,00077412 and the test and examination dataset is 0,0006903. Rules of rules obtained can be applied to control raw material inventories.

***Keywords*—** Adaptive System, ANFIS, Raw Material Inventory Control

I. INTRODUCTION

A successful company must have good inventory management. The main problem in an inventory management is determining how many orders. Companies must balance the increase in inventory to maximize customer service or decrease inventory to minimize inventory costs [1] [2]. Both will influence the success of inventory control, one of which is the raw material inventory [3]. Lower costs and increased profits are the main objectives of reducing inventory levels. In theory this can be easily done but practically, it must also be considered about the balance of both [4].

Inventory management of raw materials is critical to achieving profits, efficient and resilient production operations [5]. Many factors caused raw materials inventory to be important to consider for a company including the quality and quantity of raw materials [6]. For food companies, the quantity of raw material inventory and the quality must be very precise because it cannot last long [7]. Uncertainty demand is one of the causes of the difficulty of making a good inventory control model. A method is needed that can overcome uncertainty problems in inventory control.

Adaptive Neuro Fuzzy Inference Systems (ANFIS) is a method that can model the uncertainty in parameters [8]. This adaptive system combines intelligent techniques such as fuzzy and neural networks known ANFIS is a simple data learning technique that uses a fuzzy inference system model to convert several inputs into target output. ANFIS is a kind of artificial neural network based on the fuzzy Takagi-Sugeno inference system. This technique was developed in the early 1990s. This method can integrate both neural networks and the principles of fuzzy logic and both of them in a single framework. This prediction involves membership functions, fuzzy logic operators and if-then rules [9].

PT XYZ is one of the jelly drink companies located in Bogor. PT XYZ has five line of business consisting of two production lines capacity of 21,000 pcs / day and three production lines with a capacity of 15,440 pcs / day. The products produced are cup packaged jelly drinks with six flavors (apples, blackccurents, guava, oranges, mangoes and soursop). Jelly drink is a soft drink product in the form of a gel (thick liquid) which has a weaker gel strength compared to jelly. The raw material for the formation of this gel is agar (carrageenan). The supply of carrageenan at PT XYZ involves three suppliers, namely one main supplier and two backup suppliers. This categorization is done to stabilize prices, quality of carrageenan and overcome if the main supplier cannot fulfill the demand.

The waiting time for orders for these raw materials ranges from four to eight weeks. After being received by the warehouse, quality analysis is carried out with a span of five days if the results are in accordance with the standard, then production can be used. The existence of a fairly long span of time, the industry strives for inventory so as not to disrupt the production process, but this has an impact on the cost of inventory that is quite large. The cost of carrageenan inventory in 2016 can be seen in Table 1.

TABLE I
INVENTORY COST OF CARRAGEENAN IN 2016 OF PT XYZ

Month	Inventory cost (IDR)
January	13,420,000
February	55,937,500
March	511,761,000
April	352,540,500
May	470,501,500
June	745,087,500
July	214,800,000
August	431,837,500
September	358,000,000
October	322,916,000
November	566,087,500
December	480,525,500

With these problems, the right strategies and policies are needed in making decisions when and how many orders are needed in controlling raw material inventories. Therefore, a research on adaptive systems for controlling raw material for jelly drinks at PT XYZ was conducted.

Research Purposes

The purpose of this study is to analyse and design an adaptive system for controlling the inventory of raw materials for PT XYZ jelly drinks.

Research Scopes

The scope of this research is

1. This research was conducted in one of the beverage industries in Bogor (PT XYZ) for controlling raw material inventories. Retrieval of data using observation and interview methods.
2. Analysing the need for controlling raw material inventories using BPMN 1.0, then the prescribed parameters are presented in the form of input and output system designs. After all the data collected was carried out normalization for the integration of adaptive models using ANFIS with the programming language MatLab (Matrix Laboratory). The results of the analysis will then be used as material to design an adaptive system to control the supply of raw materials for jelly drinks.

II. METHODOLOGY

Research Framework

The work step of this research was to analyse the need for controlling raw material inventories using BPMN 1.0. Then, designed an adaptive system using the ANFIS method (MatLab program) with the agreed parameters, demand, amount of raw material receipts, inventory quantity and raw materials usage. The output obtained was in the form of inventory costs. ANFIS is a combination of fuzzy logic systems (FIS-Sugeno models) and artificial neural network. The research design can be seen in Figure 1.

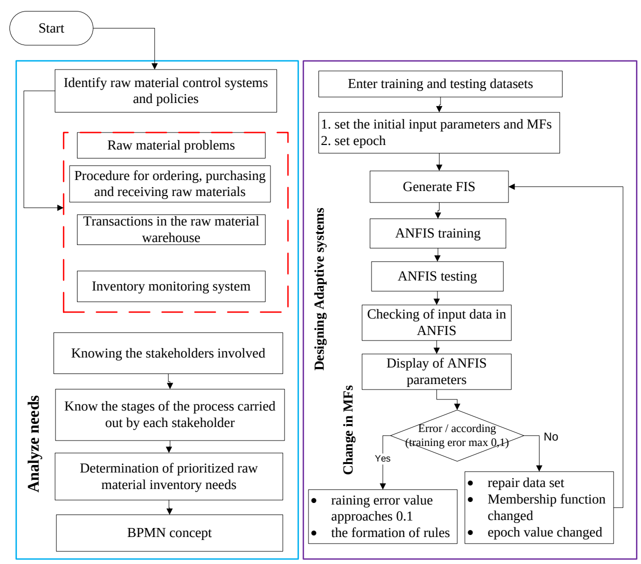

Figure 1: Research Design

Business Process Model and Natation (BPMN)

In BPMN, "business processes" involve the capture of a systematic sequence of business activities. Modeling a business process represents how a business pursues overall goals. In addition, only the process is modeled. BPMN creates a standard bridge between the design of business processes and the implementation process [8]. BPMN is a graphic notation that represents the flow of a business process that is easy to use and understand for business people. The notation in question is the start event, task, intermediate message, end event, gateway and others that have their respective functions. BPMN creates a standard bridge between the design of business processes and the implementation process. There were three steps of BPMN implementation namely analysed the system requirement (identification of actors and stakeholders), identified the flow of task of each actor (activities, events, gateways, swimlanes, artifacts, and sequences flow), and created a visual model of BPMN to get business model of raw material inventory control design.

Adaptive Neuro Fuzzy Infererence System (ANFIS)

ANFIS (Adaptive Neuro-Fuzzy Inference Systems) is also called neuro-fuzzy which is a combination of fuzzy logic systems and artificial neural networks. Setting data on fuzzy inference systems uses algorithms while artificial neural network systems use learning that has several layers consisting of input layers, hidden layers, and output layers. The combination of the two types of controllers is done to complement each other's advantages and reduce the shortcomings of each controller.

ANFIS also allows rules to adapt. ANFIS architecture is functionally the same as Sugeno's fuzzy rule base model. ANFIS modeling is based on the input and output pairs of the previous system, then looks for IF-THEN rules (which map inputs into output) [9]. The ANFIS structure is similar to the FIS structure, and the difference is in determining the parameters of membership functions and FIS rules. According to Aleem [2], one of the ANFIS structures is presented in Figure 2.

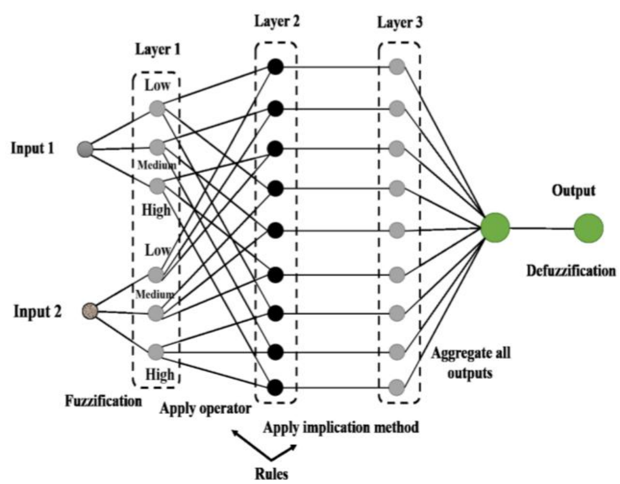

Figure 2: ANFIS Structure with two inputs and one output

The first step in ANFIS modeling was to initialize the fuzzy inference system that best models the application data. The different way could do this step, the first way was to initialize the FIS parameter from preferences, and this method depended on the experience about the distribution of the data set. Another way was to let ANFIS do this with a grid partition or with clustering techniques [2].

According to Jang [10] the fuzzy inference system consists of 5 (five) sections as follows:

1. The rule base consists of a number of fuzzy if-then rules.
   This layer is a layer of fuzzification. In this layer, each neuron is adaptive to the parameters of an activation. The output of each neuron is the degree of membership given by the input membership function. Suppose the Generalized Bell membership function in equation 1:

   $$\mu\,(Z) = \frac{1}{1+(\frac{Z-c_i}{a_i})2b_i} \tag{1.1}$$

   or

   $$\mu\,(Z) = \exp\{\,(\frac{Z-c_i}{a_i})^2\} \tag{1.2}$$

   Where μ : membership degree

   Z : input, in case Z = $Z_{1,t}$ $Z_{2,t}$

   a,*b*,*c*: parameters, *b* = 1.

   If the values of these parameters changed, then the shape of the curve that occurs will also change. These parameters were referred to as premise parameters. Database defines membership functions of fuzzy sets that were used in fuzzy rules, usually, the basis of rules and databases were merged and were called knowledge bases. The operator used was AND.

2. This layer was a fixed neuron (symbol Π) which was the product of all inputs. Each node in this layer functions to calculate the activation power (firing strength) on each rule as a product of all inputs entered or as an operator t-Norm (triangular norm) is found in equation 2:

   $$\varpi_i = \mu A_i . \mu B_i \tag{2}$$

   Where ϖ_i : firing strength of a rule, each neuron represents the i-rule.

   μA_i : degree of membership A

   μB_i : degree of membership B

3. Decision-making unit formed inference operations on rules. Each neuron in the layer was a fixed neuron (given the symbol N), the result of this calculation was called normalized firing strength, found in equation 3:

   $$\varpi_t = \frac{w_i}{w_1+w_2} = 1{,}2 \tag{3}$$

   Where ϖ_t : ratio of firing strength i (w_i) to the sum of the overall firing strength in the second layer

   ϖ_i : firing strength of a rule, each neuron represents the i-rule

4. The fuzzification interface converted the input into degrees that correspond to linguistic values. This layer

was a neuron which was an adaptive neuron to an output, found in equation 4:

$$\varpi_i f_i = \varpi_i \left(\rho_i Z_1, t + q_i z_2 + r_i \right) \qquad (4)$$

Where ϖ_i: *normalized firing strength* in the third layer

ρ_i, q_i, r_i : parameters on these neurons

The defuzzification interface changed the results of fuzzy inference to a compact form of output. This layer was a single neuron (given a symbol), found in equation 5:

$$\sum_t \varpi_i f_i = \frac{\sum i \varpi_i f_i}{\sum i \varpi_i} \qquad (5)$$

Where $\sum_t \varpi_i f_i$: the sum of all output of the fourth layer.

III. RESULTS AND DISCUSSION

Analysis of Raw Material Inventory Control System

Analysis needs were done to obtain detailed information in controlling the needs of each element (actor) of its business process. The business process in controlling PT XYZ's jelly beverage raw material inventory used BPMN 1.0. The actors involved consisted of four parts, namely the raw material warehouse sub-department, PPIC management, purchasing management and suppliers. Each actor played a role following his duties. The process of PT XYZ jelly drink raw material inventory can be seen in Figure 3 while Figure 4 regarding the purchase process.

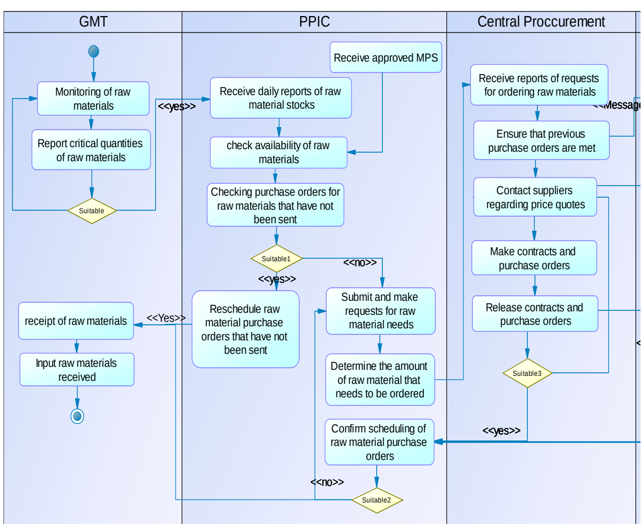

Figure 3: Raw materials processing of jelly drinks in PT XYZ

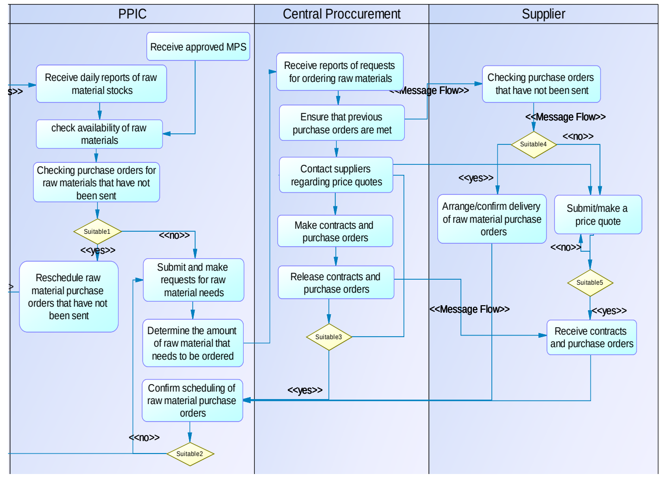

Figure 4 Process for purchasing PT XYZ jelly beverage raw materials

PPIC management received reports on the availability of raw materials from the warehouse section every day. Furthermore, PPIC ensured that the availability of raw materials was sufficient for production. If the availability of raw materials was insufficient, PPIC would schedule the delivery of raw materials that have been ordered in advance. Conversely, if all orders have been realized, PPIC submitted a reorder request. The purchasing department would contact suppliers and arrange purchase contracts. After the purchase contract was agreed upon, the supplier would send the raw materials according to the schedule and the number of shipments organized by PPIC.

Design of Raw Material Inventory Control Systems

The process of controlling raw material inventory used historical data from 2015 to 2017 as many as 156 data pairs using four input parameters with an output. Some historical data used can be seen in Table 2. The testing process was done to find out how much the model would use the learning rate.

TABLE II
INPUT AND OUTPUT DATA OF RAW MATERIAL INVENTORY CONTROL

INPUT				OUTPUT
Demand (box)	Raw material arrival (kg)	Inventory stock (kg)	Raw material usage (kg)	Inventory cost (IDR)
280,125	-	17,350	1,800	2,469,901,000
249,000	-	17,350	1,600	2,469,901,000
287,113	1,000	14,450	925	2,222,495,000
354,013	1,550	16,075	2,050	2,372,807,500
232,950	975	14,025	2,500	2,183,182,500
398,304	3,000	6,225	2,675	667,915,900
493,290	-	6,550	3,550	910,145,725
438,912	5,000	2,450	2,675	385,203,700
406,296	5,000	4,775	3,425	405,318,400
406,296	2,500	6,350	4,275	482,263,450
283,072	-	11,050	400	1,098,199,700

Determination of Base Rules

The rule base made in this study was found in Table 2. Each input has input criteria, namely demand with five criteria (very low, low, medium, high and very high), amount arrival of raw material and inventory stock with three criteria (many, standard and few) and raw material usage with two criteria (standard and nonstandard). Then the rules obtained were 90 rules. An example of a rule is presented in Table 3.

TABLE II
EXAMPLES OF RULES GENERATED FROM 90 INVENTORY COSTS

rule	If and	then
1	Low demand, lots of raw material arrivals, lots of stock and standard raw material usage	Very large
2	Low demand, sufficient raw material arrival, lots of stock and standard raw material usage	Large
3	Moderate demand, sufficient raw material, sufficient stock and standard raw material usage	Optimal
4	Moderate demand, sufficient raw material, lack of stock and standard raw material usage	Small
5	High demand, less raw material arrival, lack of stock and standard raw material usage	Very small

a. Training process

The learning algorithm used was hybrid by setting the output variables (forward) and fuzzy set variables (backward). In forward pass, with fixed premise parameters, the approach to estimating the least squared error is used to update the consequent parameters and to pass the errors to the backward pass. In the backward pass, the parameters are fixed, and the gradient descent method is applied to update the premise parameters. The premise and consequent parameters will be identified for MF and FIS by repeating the forward and backward passes [11].

So, ANFIS used a combination of the least-square method (the determination of the consequent parameters) and the gradient-descent backpropagation method (studying the premise parameters to correct the signal errors that occur). The number of epochs used was 50.

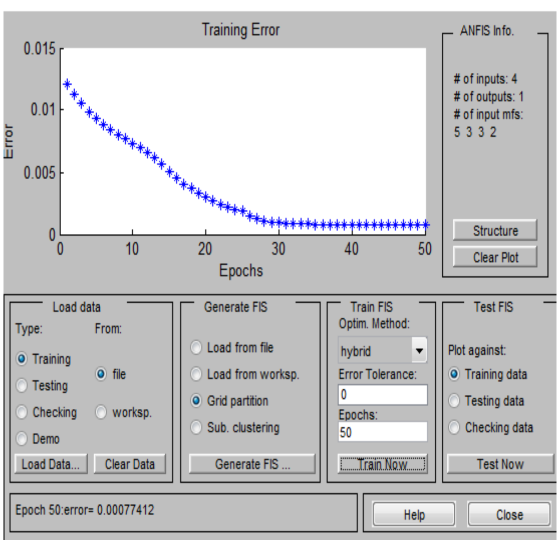

Figure 5: ANFIS Training

It can be seen in Figure 5 that training errors begin to decrease rapidly to epoch 20. At epoch 50, it still decreases with the smallest level, and the error curve becomes almost linear. Therefore, the maximum number of epochs considered for training, testing and checking in this study was 50.

Trained ANFIS was tested for training, testing and checking datasets. The average testing error for testing of the training dataset was 0,00077412, for the test and examination dataset was 0,00069037. Figure 6 shows a test of the training dataset. Meanwhile, testing of the test dataset is shown in Figure 7.

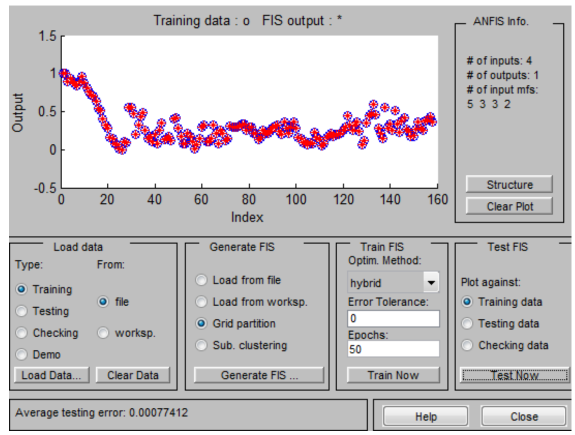

Figure 6: Testing of the training dataset

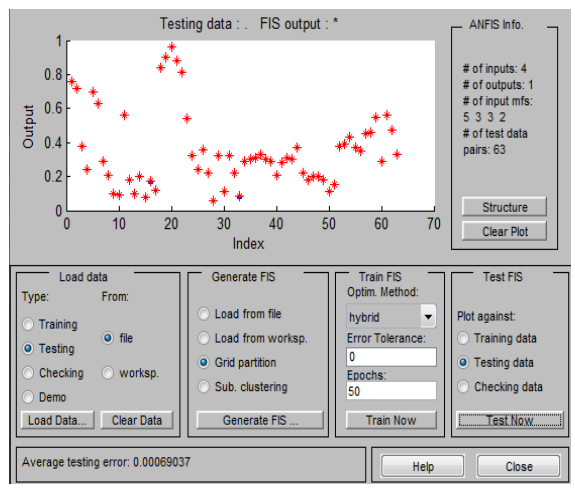

Figure 7: Testing of the testing dataset

Basic rules are the main part of a fuzzy inference system, and the quality of results depends on fuzzy rules. The punishment procedure, known as the composition of inference rules, can be concluded by generalizations of qualitative information stored in the knowledge base. Fuzzy rules can be solved with natural language. In Figure 8, the ANFIS structure transition creates rules during the learning conversion process.

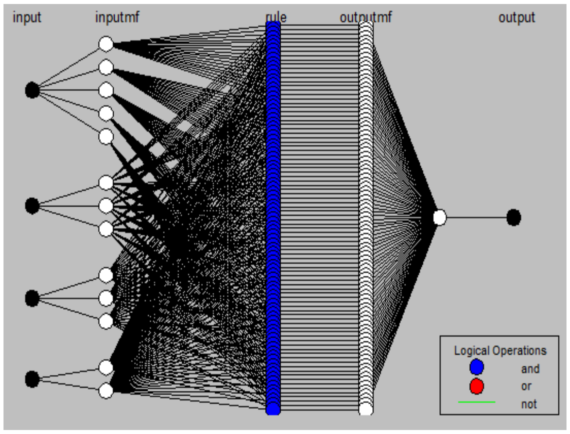

Figure 8: ANFIS structure in controlling raw material inventories

Although this fuzzy logic-based method cannot be one hundred percent accurate, this method can be applied in the real world. In this study, the four input parameters used are considered to represent optimal and stable inventory costs. Trained ANFIS showed that each input had a relationship with the output. If demand for production increased, then the supply of raw materials increased so that inventory costs were high. Furthermore, if the quantity of raw material arrivals was following the order from the demand, then the inventory cost could be controlled. Likewise, with the inventory parameters and the use of raw materials, if the supply was stable and the use of raw materials followed the standard, then the demand for production would be fulfilled, and the cost of inventory was optimal.

IV. CONCLUSION AND RECOMMENDATION

Conclusion

Based on the results of research in controlling raw material inventories, some conclusions were taken as follows:

1. Need analysis used BPMN 1.0 which showed the conceptual model of raw material inventory control to optimize inventory costs without inhibiting production. This analysis provided information on the assignment of each actor who stores important data in the order of decision making.
2. ANFIS as an artificial intelligence-based technique could be applied to controlling raw material inventories. The trained ANFIS was tested using four parameters and epoch 50 so that rules were formed as much as 90. The average testing error for testing the training dataset was 0,00077412, and the test and examination dataset was 0,00069037.

Recommendation

Determination of parameters, the use of datasets for controlling raw material inventories is recommended to be studied further to become a reference in determining the next period so that the rules formed can be applied.

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