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Implementation of Fuzzy and Adaptive Neuro-Fuzzy Inference Systems in Optimization of Production Inventory Problem

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Abstract: Most of the earlier studies in the inventory control and management make assumption that the manufacturing system is reliable and does not fail. However, in the real industrial applications, there is no completely reliable manufacturing system; Machine failure occur and the production does not resume before repair. In this paper we will study and analyze the optimal lot size in a real production system which is not completely reliable. To obtain the optimal production quantity. Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used for modeling and simulation. This approach combines the advantages of rule-base fuzzy system and the learning capability benefit of neural networks. In the case study of cement industry, ANFIS prediction has shown very good agreement with the real production quantity. This model can be extended for any inventory production quantity problems if the industrial data are available.

Keywords: Fuzzy, Adaptive neuro-fuzzy, Optimization, inventory, Production Inventory.

1 Introduction

Inventory management occupies a wide area of research in the production and operations management research field. Its importance is due to it provides flexibility to manage industrial plants, production lines, and maximizing service to customers. A successful company must do a proper management for its inventory. The main problem in inventory management is to determine how much the order be, which will affect in a required balance between two opposing objectives: maximizing customers service which needs increasing inventory size and minimizing the cost of holding inventory by decreasing the inventory size. Maintaining zero inventories minimizes the inventory costs. However, customer service may suffer, and customers may decide to get their needs elsewhere. This is related to cost known as stock-out cost. so it is necessary to minimize stock-out cost and provide a higher level of customer service. [1]. In this area of research, Harris 1913 has put the seed of the economic order quantity model (EOQ), and the economic production quantity (EPQ). The EPQ model deals with determining the most desirable production size under certain production conditions, whereas the EOQ model concerning with finding the optimal inventory size that minimizes the total inventory costs. Most of the recent research in the inventory modeling and control has been done with the assumption that the production system never fails and the produced parts have perfect quality [2]. However, in the real applications, there is no completely reliable manufacturing system; the system may stop due to machines failure and the production do not resume before repair. Nearly all manufacturing systems operate under uncertain machine reliability and jobs processing times. There are no certain capabilities to characterize a great amount of complex production inventory systems because of the unexpected breakdowns, unscheduled maintenance, unplanned repair, etc. Cheng [2] is actually the first who incorporated the imperfect items in the inventory model. The proposed model relates the unit cost of production with quality assurance and process capability, considering that unit cost of production is not fixed, depends on the reliability of the production process. Salameh and Jaber [3] presented the situation of

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imperfect production inventory. Extending the traditional EPQ/EOQ model. Considering 100% screening, and marketing defective parts at a reduced price. Building up a mathematical model which is solved by differential calculus. Hejazi et al. [4] propose EPQ model to determine the economic production quantity with reduced pricing, presenting that the inspection process to find defective items identifies the products to four groups: perfect products, imperfect products, defective rework able products and defective non-reworkable products. Nadjafi and Abbasi [5]presented an EPQ model considering process quality cost and depreciation cost functions to be continuous over time. Using Simulated Annealing (SA) and Iterated Local Search (ILS) to get the minimum value of the total cost annually. Modak et al. [6] developed Optimal just-in-time buffer inventory model for random periods preventive maintenance with imperfect quality items to minimize the system running cost by considering holding and shortage costs of items. Found that the buffer capacity should adjusted based on the amount of imperfect quality items to minimize the cost A reliability based multi-item imperfect production inventory models considering uncertain resource constraint under dynamic demand, is proposed by Roul et al. [7]. The defective items are fully or partially reworked. The objective is to maximize profit and solved using generalized reduced gradient method, Hamiltonian (Pontryagins Maximum Principle) with fixed-final time and free-final state system, KuhnTucker conditions. Hsu and Hsu [8] developed vendorbuyer coordination inventory model in an imperfect production process. with shortage backordering. Minimizing the total joint annual costs sustained by the buyer and the vendor. The model is solved analytically. Kassar et al. [9] developed two economic production models (EPQ) with imperfect quality in finished product and raw material. A 100% screening process is applied. The total profit per unit time is maximized analytically to find the optimal economic order quantity. Krishnamoorthi and Panayappan [10] proposed EPQ model that considers both imperfect items and incorrectly not screening out a proportion of defective items, considering rework for regular production defectives and sales return items. He considers shortage in his work, the objective is to minimize the total cost. He solved the model by a simple traditional analytical optimization strategy to get only the optimal production lot size. Most of the previous works has some limitations restrictions such as, demand is constant during time, deterministic lead time, constant item purchasing price, no considerations for shortage of raw material and instantaneous receipt of material. with these limitations these studies are not realistic. To overcome these limitations and simulate areal systems we need to apply artificial intelligence techniques. Although various studies have been applied ANFIS in solving real problems [11–16]. Few researches have been applied artificial intelligence in inventory control for production systems. The first one that initiated the ANFIS method by combining the fuzzy inference system with the structure of adaptive networks was Jang [17]. An inventory control based on fuzzy logic is proposed Samanta [18] using the data for a typical packaging organization in the Sultanate of Oman. Then Samanta and Al-araimi [19] apply the Adaptive Neuro-Fuzzy Inference System to control the inventory of finished product with variable order quantity for a typical packaging organization. A. P. Rotshtein et al. [20] uses fuzzy logic to control inventory problem as an identification problem. The ANFIS method helps in mapping appropriate relationship between the input and output data by applying hybrid learning method to find out the optimal distribution of membership functions [21]. Koulouriotis and Mantas [22] presents different methods like radial basis, feed forward, generalized regression, adaptive neuro fuzzy inference systems, and recurrent networks in Health products sales forecasting. Balazs Lenart and Katarzyna Grzybowska [23] presented An inventory control system based on adaptive neuro-fuzzy logic. N Singh et al, [24] Presented economic production quantity for a single machine unreliable production system including shortages. he showed that the Neuro-fuzzy technique results is superior than the computational view point analytical technique results. Paul et al. [25] used adaptive neuro-fuzzy inference system and artificial neural network in the inventory level forecasting using local factory Real data, with Six input single output parameters showing the superiority of the results obtained by the ANFIS method over ANN results. Aengchuan and Phruksaphanrat [26] made a comparison between the three methods: Fuzzy Inference System (FIS), Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with different membership functions in solving inventory control problem with two inputs and one output. The results showed that the ANFIS model with Gaussian membership functions gave the best solution for inventory minimum total cost. From the literature, few studies in inventory optimization have implemented Fuzzy logic and ANFIS for modeling production inventory systems to obtain reasonable solutions. Unfortunately, most of these studies were focused on solving single input single output inventory problems. However, much effort still needed to model and simulate the production inventory problem with multi input and/or multi output parameters. In this paper we will implement the FIS and ANFIS for EPQ problem in order to show the power of FIS and ANFIS on optimization of inventory problems. First FIS will be applied to describe the relationship between the inputs and outputs parameters for the intended inventory problem with high uncertainty, then the ANN will be used to train the FIS to find out the best membership functions of the FIS after that the corresponding fuzzy rules for the ANFIS model with the final solution will be generated [17, 27]. The remainder of the paper is coordinated as follows: the next section describes the fuzzy inference system (FIS) for EPQ problem. Then, the adaptive-nuero fuzzy inference system (ANFIS) model for optimizing the EPQ problem is illustrated in Section 3. After that, section 4 presents the application of FIS and ANFIS for an industrial case study. Later, Section 5 presents a brief discussion and comparison for the results obtained from FIS and ANFIS. Finally, conclusion for this paper and hints for further future work is provided in section 6.

2 Fuzzy Inference System (FIS)

This section introduces the principles of fuzzy system logic, and the regular steps used in the fuzzy inference system including: fuzzification, inferencing, and Defuzzification processes.

2.1 FIS principles

In 1965, Lotfi Zadeh presented the big contribution of the Fuzzy Logic tool, as a mathematical tool describing the uncertainty in the models [28]. It is a technique deals with imprecision and information granularity. while the wide use of the two-valued binary logic and sets, it is able to solve a great range of problems and fails in such environments. Most real-life problems represented by the language (or logic) to development are inadequate, imprecise, unclear or uncertain information. The tools of the fuzzy logic and fuzzy sets are used to describe the information uncertainty. In the fuzzy logic, variables are represented by linguistic terms, rather than by numerical values. To show this logic, in the phrases Ali is little short, or Ahmed is very fat, the two words little and very are linguistic terms that describe the magnitude of the linguistic fuzzy variables short and fat. The human brain can understand the difference in meaning between these terms, and gather from them he cannot play basketball, and that ahmed may be a slow runner [29]. The fuzzy theory provides a method that helps in representing linguistic variables such as high low, medium, regularly, few. In general, when the relationship between the output and input variables of the system is unknown and cannot be identified mathematically, we can apply fuzzy inference system to govern this relationship and get the best connection between the output and input variables of the system.

There are number of ways to model the systems by fuzzy logic: fuzzy linear regression models and rule-based fuzzy models [30], or fuzzy models using cell structure [31]. In our study we focused on the rule-based fuzzy models. In the rule based fuzzy models the relationship between input and output variables are represented in the form of fuzzy if-then rules as it can be said that: (If the antecedent proposition then the consequent proposition). The fuzzy logic system incorporates five steps as shown in Figure 1. It starts with fuzzification process, then the inference system applied including: applying the operator, applying the implication method, and aggregate all outputs to one fuzzy output, finally defuzzify the fuzzy output to numerical values [28, 30].

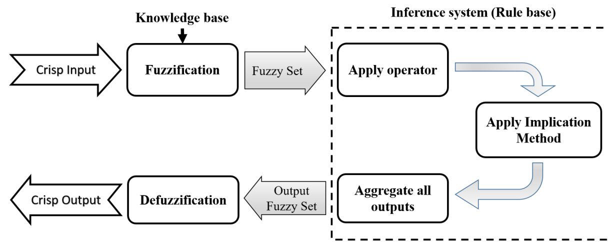

Fig. 1: Principles of the fuzzy logic system

2.2 Fuzzification

The fuzzification process is to represent the non-fuzzy input values in a fuzzy nature by translating the inputs from numerical and crisp values to a linguistic quantity such as low, medium, high. This is achieved by the application of the membership functions related to each fuzzy set in the rule input space. The numerical input values of the input parameters are assigned to membership values to fuzzy sets.

2.3 Inferencing

The inferencing process includes the steps to map the inputs which have been fuzzified (as received with their membership functions after the fuzzification step) to the rule base, and generating a fuzzified output for each rule. After this point we should aggregate the outputs of all rules to one fuzzy output. the conclusion in the rule output space, the output sets memberships degrees are determined based on the input sets membership degrees and the relationships between the input sets. The logic operators that combine the sets in the antecedent defines the relationships between input sets. This process includes three steps based on the rules of the fuzzy logic as follows:

- Apply the operator of the rule when there is more than one part for the antecedent of the rule. This step results in one number (between 0 and 1) represents all parts of the antecedent based on the operator of the rule. In the most common fuzzy logic systems prod (product) methods and the operator AND is taken to be min (minimum). While the operator OR is replaced as max (maximum) [30].
- Apply Implication method: by passing the final number representing all parts of the antecedent to the conclusion fuzzy set (represented by membership

functions) to reshape it to get the final shape of represents the output resulted from each rule. The implication methods applies the same functions which are used in the AND method: min (minimum), which cuts the output conclusion of the fuzzy set, and prod (product), that scales the output fuzzy set.

– Aggregate All fuzzy rules Outputs, since the decision of all rules has been get. The rules outputs must be combined in some way to help in making the final decision. The Aggregation process combines the outputs of each rule which are represented by the fuzzy sets, using the max operator, to get a single fuzzy set representing the output of the system. The Combination process is for each output variable in the fuzzy inference system.

2.4 Defuzzification

Defuzzification process is opposite to the fuzzification process as it represents the fuzzy output results from aggregating all rule consequents in a crisp value. There are five methods can be used in the Defuzzification process: bisector, centroid, smallest of the maximum, middle of maximum and largest of maximum. The most common used method is the centroid. We have used this method in our model.

3 Adaptive Nuero Fuzzy Inference System (ANFIS)

In this section we introduced the principles of the ANFIS system, then explanation for the procedure that the ANFIS passes to optimize the system parameters.

3.1 How ANFIS works

ANFIS combines the benefits of the Fuzzy Inference System (FIS) rule base and the learning benefit of Artificial Neural Networks (ANN), uses FIS rule base to describe the relationship between the output and the input parameters even though the system uncertainty is existed, and ANN to train the data and find the best parameters for the membership functions of the FIS to get the suitable fuzzy rules and membership functions [17, 27]. To estimate the membership function parameters ANFIS uses either back-propagation only or a combination of least squares estimation and back-propagation. Artificial neural networks (ANNs) represents a mathematical information processing systems uses the same logic of the human brains functioning principles in which neurons in biological neural systems link to nodes and synapses correspond to weighted links in ANN.

3.2 ANFIS solution procedure

This part discusses the working steps in the ANFIS system, starting with the FIS selection, then the model structure, and how to train the FIS with the data set, finally validating the trained FIS with some checking data from the industrial application.

3.2.1 Initial FIS selection

The first step in the ANFIS modeling is to initialize the fuzzy inference system that best model the data of your application and this step can be done by different ways: the first way is to initialize the FIS parameters from your own preference and this way depends on your experience about the distribution of the data set. Another way is to let the ANFIS to do this for you by the grid partitioning or by the clustering techniques.

3.2.2 ANFIS Model Structure

The ANFIS model structure is similar to the FIS structure but the difference is in the way to estimate the membership functions parameters and the rules of the FIS. The structure of the ANFIS is looks like thats shown in Figure 2.

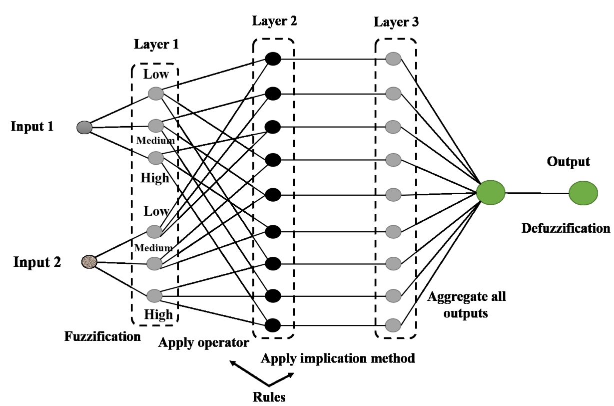

Fig. 2: ANFIS Structure for two inputs, three layers and one output

3.2.3 ANFIS Model Training

The ANFIS is used to train the FIS model to match the training data presented to it. This training process modifies the membership functions of the initial FIS and its rules to best model the data set of the application. In ANFIS there are two common parameter optimization methods for FIS training: one uses the gradient descent method (back propagation method) and the other is hybrid method which is mixed between the gradient descent method and the least squares [29].The training process will stop after the training error reaches specified value depends on the application.

3.2.4 ANFIS model validation

Model validation is the process done to the FIS after training to check has the FIS model predicts the data set applied to it with in the specified error or not.

4 Industrial Case Study

A real Rawmill problem is discussed in this paper as a case study of economic production quantity. Rawmill is an intermediate process in cement industry used to grind and mix the raw materials into rawmix" during the cement manufacturing process. Then Rawmix is fed to a the kiln furnace, which transforms it into clinker, after that clinker is ground to make cement in the cement final mill. The stage of the Raw milling process effectively defines the chemical composition (and therefore physical properties) of the final product of cement, and has a large effect in the efficiency of the whole cement manufacturing process. A schematic diagram for the manufacturing inventory system of the Rawmill is shown in Figure 3. In our study the chemical content of all input raw materials is assumed to be ineffective, so that the main input parameters are the amount of each raw materials and the availability of the Rawmill.

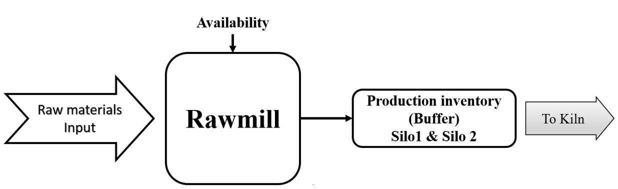

Fig. 3: A schematic diagram for the manufacturing inventory system of the Rawmill

The main input raw materials to the Rawmill are Mix (Limestone and Clay), High Grade Lime Stone (H.G.L.S), Iron ore, Sand and Serpentinite. The input quantities of these materials is uncertain due to the uncertainty of its chemical composition. The availability of the mill is highly uncertain due to the random stoppage of the mill because sudden problems. The mill is working to feed the kiln directly and if there is no supply to the kiln it should be stopped, so it is required to maximize the production size as possible to prevent this problem. FIS and FIS with ANFIS models were proposed to maximize the total production size of the Rawmill and find the most significant input in this problem, then the results were compared with the data collected from the cement industry. 365 data set are collected from monitoring the Rawmill for one complete year. Figures 4, 5 and 6, visualizes the fluctuation in the input parameters of the Rawmill in 31 days.

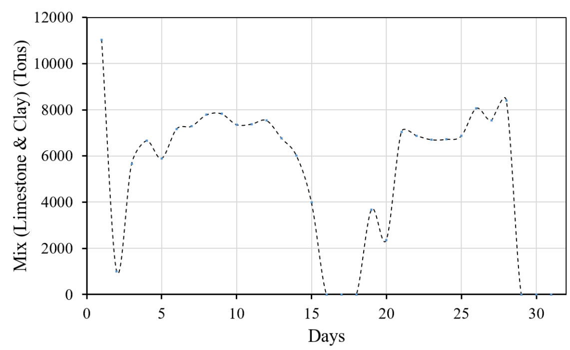

Fig. 4: Fluctuation of Mix (Limestone and Clay) in 31 days

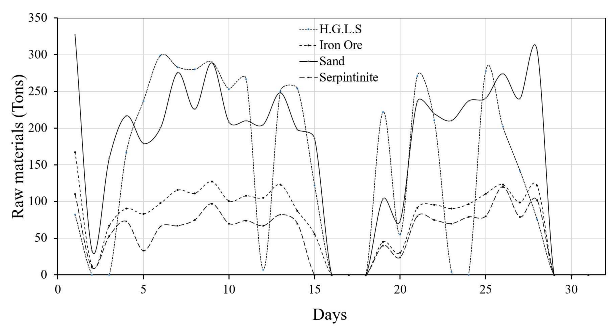

Fig. 5: Fluctuation of H.GLS, Iron Ore. Sand and Serpentinite in 31 days

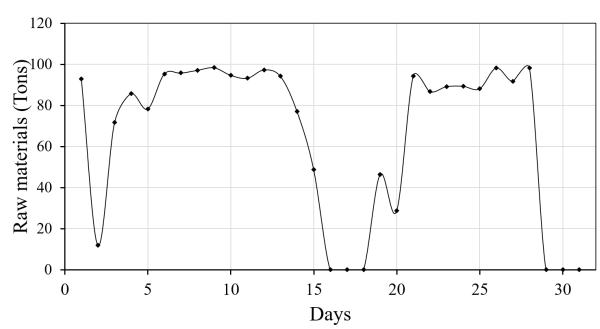

Fig. 6: Fluctuation of the Rawmill Availability in 31 days

4.1 FIS model for prediction of the production quantity

The developed structure of the fuzzy EPQ model consists of six input variables affecting in the optimum production quantity as the output variable. The six inputs are: Availability of the mill, Mix (Limestone and Clay), High Grade Lime Stone (H.G.L.S), Iron ore, Sand and Serpentinite. These parameters are fuzzified with three membership functions taken the Gaussian membership function. The production quantity of the Rawmill is fuzzified with three Gaussian membership functions. The structure of the FIS model is shown in Figure 7. The input membership functions over the real input ranges are shown in Figure 10.

Fig. 7: FIS Structure for forecasting inventory level

4.2 ANFIS Model for prediction of the production quantity

The ANFIS model for the studied problem consists of six inputs as Availability of the mill, Mix (Limestone and Clay), High Grade Lime Stone (H.G.L.S), Iron ore, Sand and Serpentinite which are fuzzified with three Gaussian membership functions and trained according to the training data to get the best membership functions parameters as shown in Figure 11, Then the FIS model is provided to the ANFIS model and the data are loaded to train the FIS parameters to match the data set. After training the trained FIS is validated with checking data and the results for training and validating are shown in the results section. The ANFIS Structure for estimating inventory level is shown in Figure 8. Figure 9 presents a flowchart discusses the steps to apply the ANFIS on our model.

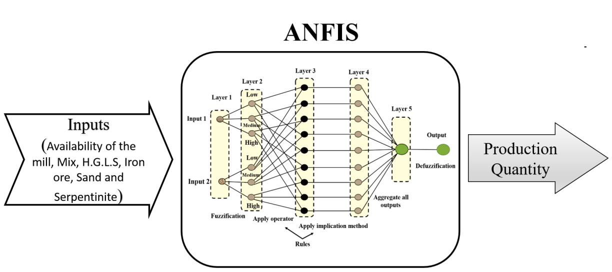

Fig. 8: ANFIS Structure for forecasting inventory level (production quantity)

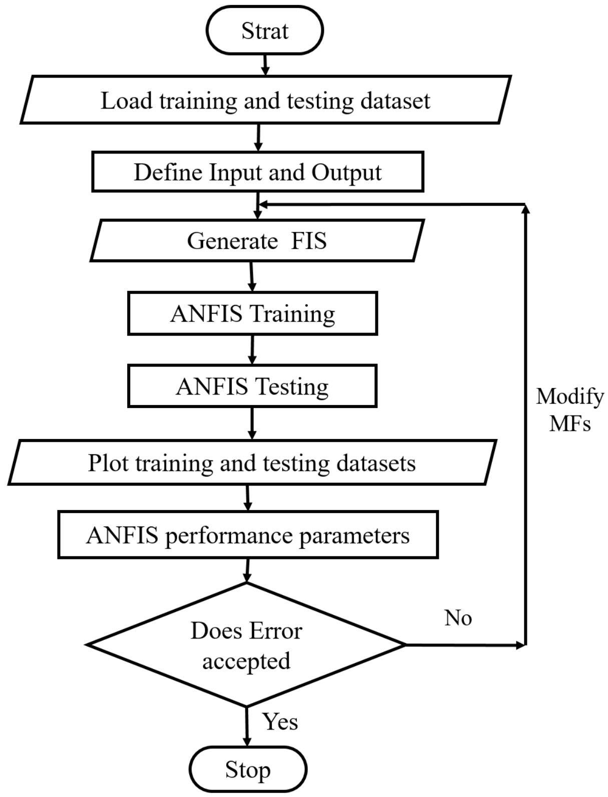

Fig. 9: Flowchart of the developed ANFIS program

5 Results and Discussion

This section shows, discusses and compares the obtained results from the FIS and ANFIS algorithms in terms of production quantity, error and absolute error.

5.1 FIS results

The obtained production quantity predicted from FIS as a function of iron ore, sand and H.G.LS is shown in Figure 12. From the figure it is clearly shown that the output surface of the production quantity increases with the sand increasing, whereas it increases with iron ore increasing to a certain value of the iron ore, after that it decreases with the iron ore increasing. the same effect of the iron ore is clearly shown with the H.G.L.S. where at certain amount of the H.G.L.S. the production quantity is maximum. The maximum amount of the production quantity can be obtained at high sand amount. The output surface is smooth since number of rules is sufficient enough to simulate and forecasting the inventory level. The number of rules is 729 rules all of them were used in the analysis whereas the Gaussian shape of the membership functions is good choice for the input and output data [14].

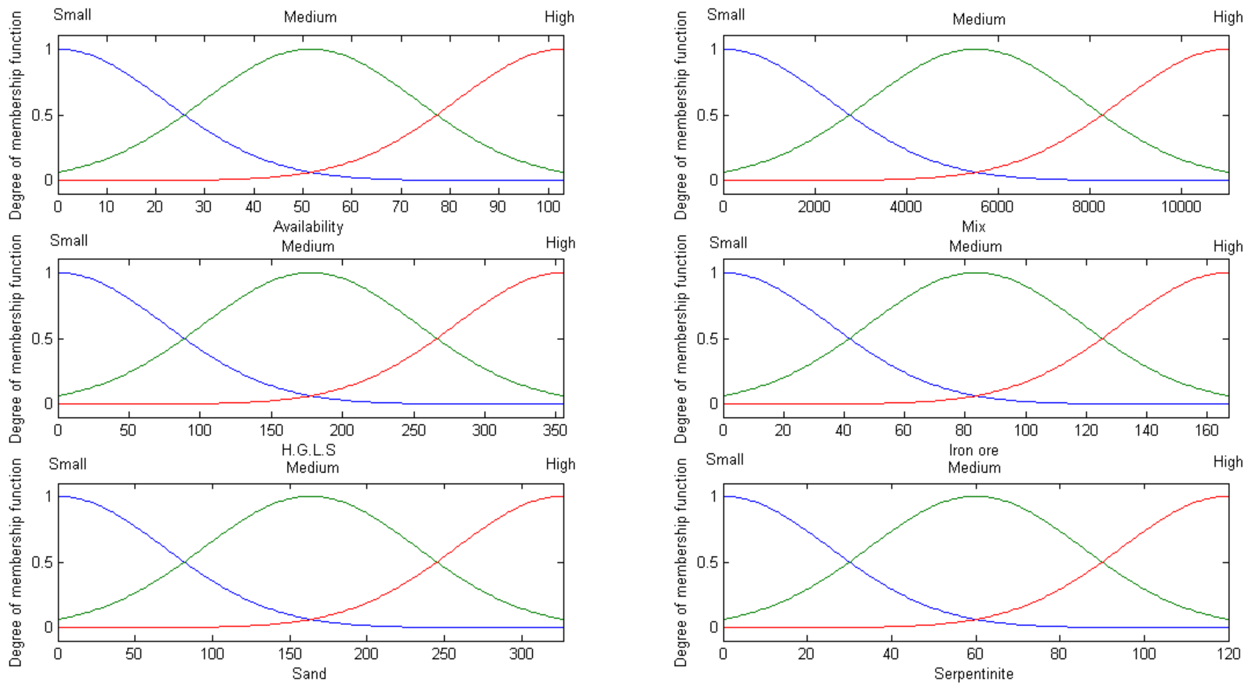

Fig. 10: Input membership functions over real input ranges

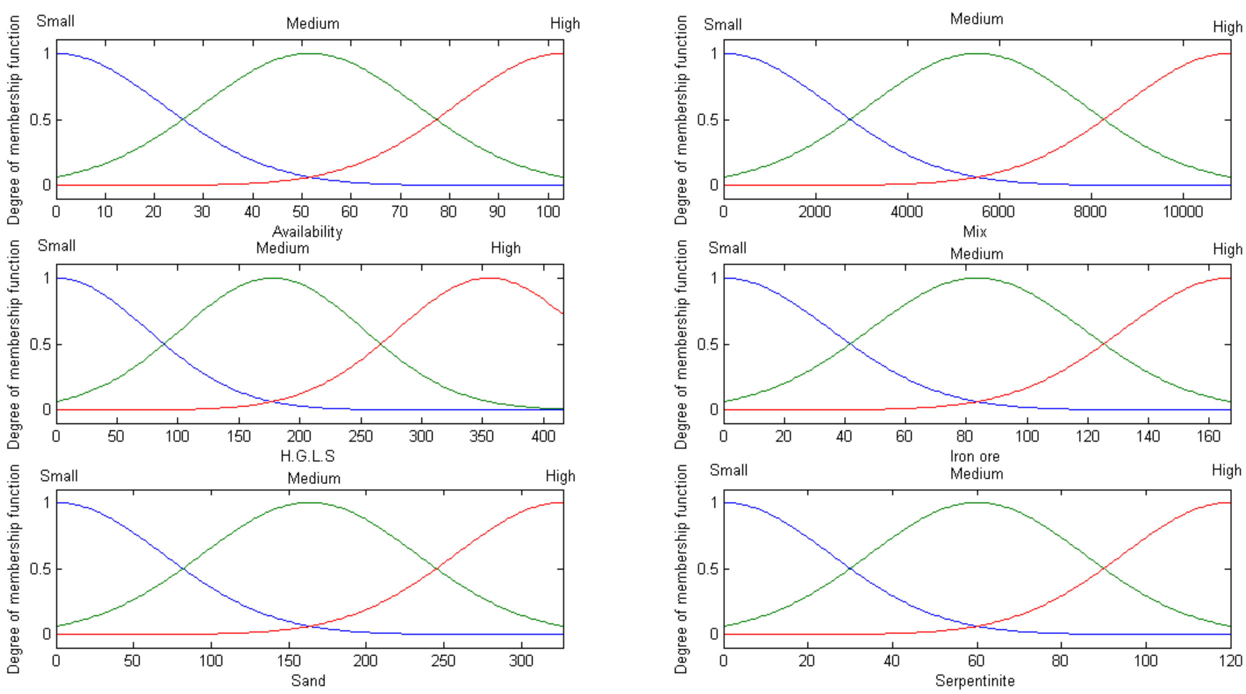

Fig. 11: Input membership functions after training

5.2 ANFIS results

The results obtained from ANFIS are shown in Figure 13. It is shown from the figure that similar effect of the input parameters on the production quantity resulted from the FIS model is incurred in the ANFIS model. The value of the production quantity is greater than thats obtained from FIS model. The curves of training and checking of the proposed FIS and ANFIS models of the industrial data are shown in Figure 14. It is clear the difference between trained and checked data is insignificant. The output surfaces of production quantity are also getting smoother than FIS although number of rules did not change. This is because, Gaussian membership functions got even better after have being trained by ANFIS for the input and output data [14].

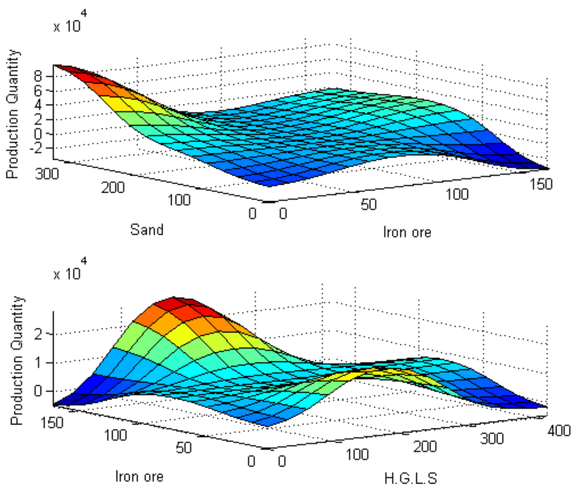

Fig. 12: FIS results for production quantity

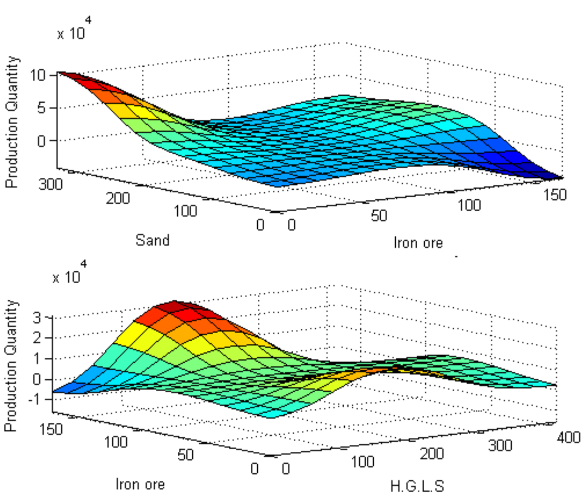

Fig. 13: ANFIS results for production quantity

Point	Experimental	FIS	ANFIS
1	6773	6770.14	6770.64
2	7509	7509.13	7508.83
3	3835	3834.88	3835.06

Table 1: Validation of the results with the industrial data

5.3 Comparison between FIS and ANFIS results

To predict the amount of production inventory the trained FIS model. Then ANFIS is applied and the results from the FIS alone are compared with the ANFIS results. After that these results are compared with the collected data from the cement industry in order to validate the model and determine the superiority of ANFIS over FIS techniques. In Figure 15 the comparison between FIS and ANFIS absolute relative errors is illustrated, as the absolute relative errors are calculated based on the industrial data. The error for each method does not exceed 0.0005 which make these methods acceptable to a high degree with the industrial data. Table 1 summarizes the validation of the data obtained from the two methods. From the Table we can infer that ANFIS is efficient and strongly recommended for solution of inventory control.

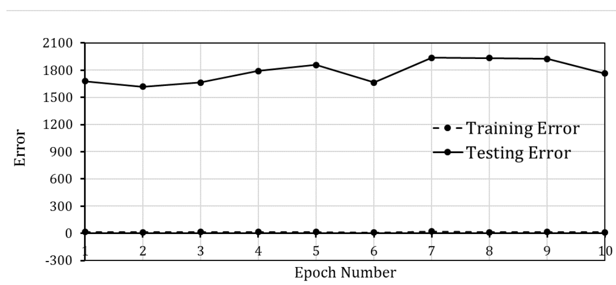

Fig. 14: Training and checking curves of the industrial data

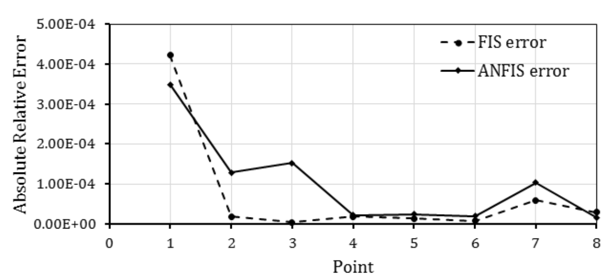

Fig. 15: Comparison between FIS and ANFIS absolute relative errors

6 Conclusion

The inventory control problem has been studied, modeled, simulated and validated for an unreliable production system using black bock technique. This paper can be concluded in the following points:

- An unreliable production system has been studied and analyzed by FIS and ANFIS in order to get the optimal lot size of the inventory.
- The main concept of the Fuzzy Inference System (FIS) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) have been explained and implemented to model and simulate the optimal production quantity problem.
- The used approach combines the benefits of rule-base fuzzy system with the learning capability of neural networks.
- Industrial data of real case study in cement industry was used for model validation,
- The simulation results revealed that the adaptive neuro-fuzzy technique and FIS give good results. The predicted values have shown very good agreement with the real production quantity since the absolute relative error does not exceed 0.0005.
- The FIS and ANFIS solution techniques are highly recommended for inventory problems with the industrial data.
- The developed models can be extended for any inventory production quantity problems if the industrial data are available.

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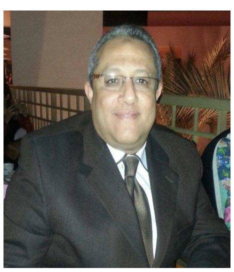

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