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Designing an Intelligent Learner Genetic-Fuzzy Model for an Oil Industry supply chain on the basis of Self Organized Maps

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Abstract: The complex challenges and requirements involved in Supply Chain Management (SCM) have forced relevant practitioners to seek out alternative and innovative methods of handling the process. The best of these methods have shown themselves highly flexible in enabling decision makers to adjust their programs in line with 'real' conditions and contingencies, and formulate sound strategy. Within SCM, problems of distribution and allocation are of paramount significance. This paper addresses such problems directly by recommending the adoption of a model that is specifically designed to recognise the need for flexibility in Distribution Systems, while helping to cope with the uncertain parameters impinging on the strategic decision making process.

Key words: Supply Chain (SC), Supply Chain Management (SCM), Fuzzy Inference (FI), Genetic Algorithm (GA), Self Organized Maps (SOM).

1. INTRODUCTION

With the gradual transfer of market power from producers and providers to their customers, products, services and supply networks are being subjected to more and more pressure to provide products of high quality, greater variation and cheaper price, and all in a much shorter time-span. Meeting customer's demands in today's interactive world not only involves producers but also the whole supply chain and its resources. It is therefore imperative for all links in the supply chain to utilize the most appropriate information technologies, apply suitable SCM methods and share their facilities and sources in as harmonious way as possible. These commercial priorities have generated a need for greater agility in SCM as a way of enabling service centred and manufacturing organizations both to survive in the market and operate more profitably [5].

Correspondingly, the enhanced need for management at all levels to make better-informed and more sophisticated decisions in the face more competitive and complicated markets, and amidst the transition from 'information age' to 'knowledge age' has made it even more vital for us to contemplate new mechanisms for arriving at commercial strategy.

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Following the long evolution of mathematics, artificial intelligence, computer sciences, humanities, and biological sciences, modern computational tools based on these science concepts are being created and exploited with a view to counteracting the types of complexity and uncertainty existing in the real world.

The major advances within computational sciences that have the capacity to help us deal with such difficulties are arguably to be found in soft computing. The cornerstone of this computing method is the advent of fuzzy category theory, though it has taken some time to integrate it with the search power of genetic algorithm and the learner capability of nervous networks, and for it to be employed as an efficient and powerful computational method for solving a variety of difficult and analyzing complex systems.

Supply chain requirements and challenges have recently forced modern managers to explore the potential for innovative methods to help them deal with supply chain management (SCM) problems. Ideally, this will involve particular methods with high flexibility which can adapt plans to real conditions and help managers to make their decisions at a moment's notice.

Within SCM, distribution and allocation problems are of paramount significance and due to their

applications in the cross-functional and final parts of SCM problems, they may be deemed to have especially high priority.

In this article, an attempt has been made to combine different concepts in the area of soft computing: a model is presented with the aims of increasing the agility of the supply chain and tackling such problems as the nature of supply chain distributions, dynamic distributions systems (DS), uncertain parameters in DS, management of diverse objectives in DS, the need for flexibility in DS and other factors considered as challenges and designing requirements in an agile model which can be all found in the SCM.

The article is divided into five sections; the introduction is followed by section 2 which presents the statement of the problem. Section 3 deals with examining the approach based on the soft computing in modelling SC and the theoretical principles of SOM. Section 4 is devoted to specifying the characteristics of the designed model and its function is described in a case study. Finally, section 5 draws together our main conclusions.

2. STATEMENT OF THE PROBLEM

2.1. The Components of SCM

A supply chain is that alignment of firms which brings products or services to market [4]. Waters (2003) defined the term as a network of facilities and distribution options that performs the functions of procurement of materials, transformation of these materials into intermediate and finished products, and the distribution of these finished products to customers [3].

Chopra and Meindl (2007) used the similar definition of all the stages involved, directly or indirectly, in fulfilling a customer request. Their definition not only includes the manufacturer and suppliers, but also transporters, warehouses, retailers, and customers themselves [25].

Supply chains encompass the companies and associated business activities that are necessary to design, make, deliver, and use a product or service. They thus entails all the activities involved in fulfilling customer demands and requests [19]. These activities are associated with the flow and transformation of goods from the raw materials stage, through to the end user, as well as the associated information and funds flows. There are four stages in a supply chain: the supply network, the internal supply chain (which are manufacturing plants), distribution systems, and the end users [19].

Businesses depend on their supply chains to provide them with what they need both to survive and thrive. Every business fits into one or more supply chains and has a role to play in each of them. The pace of change and the uncertainty about how markets will evolve has made it increasingly important for companies to be aware of the supply chains they participate in and to understand the roles that they play. Those companies that learn how to build and participate in strong supply chains will likewise have a substantial competitive advantage in their markets [19].

Supply chain management (SCM) helps firms to integrate their business by collaborating with other value chain partners in order to meet the unpredictable demand of the end user. An integrated supply chain, or seamless supply engineered to cope with uncertainty, can profitably satisfy customer demand, while non-integrated manufacturing processes, non-integrated distribution processes and poor relationships with suppliers and customers are recipes for business failure for all trading firms. In the era of time-based competition, a supply chain must possess the capacity to meet the demands of customers for ever-shorter delivery times and to synchronize supply during peaks and troughs in demand [1].

In order to have this kind of ability, any supply chain must be responsive to the needs of the market. Such responsiveness requires speed and a high level of manoeuvrability, which is also termed as ‘agility’. To run a suitably agile SC requires an assessment of the challenges of SC Structure. Undoubtedly approaches which are neither able to rise to all challenges or a majority of them, nor meet the subsequent requirements, do not succeed in accomplishing the appropriate level of agility.

In the following section, we sketch out some of the key challenges and requirements which are essential to the achievement of this state.

2.1.1. The nature of Distributed Supply Chain

Cruz Believes that SC is an open system in which active organizations might enter or leave the system spontaneously, and that because of high interactions

and limitations; it results in distributed and heterogeneous distribution systems [13]. Owing to uncertain and unpredictable parameters, the action environment is always liable to change. So in these circumstances, it is expected that the system will take responsive actions. Nevertheless it should be mentioned that, even while the system is engaged in processing the conditions and making its decisions, environmental conditions are in an ongoing state of flux.

2.1.2. Dynamism of Supply Chain

Due to the fact that SC has a dynamic nature, it is always inclined to gradual development, even as the communications within its different elements are being encoded and decoded. In other words, all the planned objectives, whatever facilities and services comprise the organization's chain of elements, and all the relevant prevailing environmental conditions are assuredly in a continuous process of change [6].

Based on the work done by the Chatzidimitriou *et al.*, [17], in reaction to environmental dynamism, SC strategies comprise two flexible methods of 'correction' and 'quit'. The method of correction refers to the adjustments to the performance, behaviours, and integration in response to the changes. The equally flexible method of quit involves the abandonment of competition and corresponding inability to meet SC requirements.

These researchers acknowledge that understanding changes in processes or information flows and their impact on SC is crucial to preserving dynamism and helping the SC to adapt itself faster and better to the environmental changes.

2.1.3. Uncertainty in a Supply Chain

Uncertainty is one of the main characteristics of systems which are associated with customers. Gunasekaran *et al.*, believe that the main reason for uncertainty in a SC is its dynamism. They state that a multi level SC is subject to a great deal of uncertainty due to its sets of service providers and the existence of uncertainties of elements in each level [2]. This high level of uncertainty reduces SCM's ability to predict future conditions. Uncertainty surrounding the volume of relevant orders or variations in customers' demand and corresponding supply time are prominent examples of this nature.

2.1.4. The Need for Flexibility in Supply Chain

Gong believes that SC is built upon the integration and continuity of organized processes, such that flexibility of SC to changes originates from the internal flexibility of components and the communicative flexibility to the external environment [31].

Shang *et al.*, consider an adaptive SC to changes as a value chain which is able to produce rapid and accurate responses to changes. In their opinion, sequences of adaptation to changes are maintained as exploring opportunities, speeding up response to expectations and improving processes [14]. They have recommended the following as steps towards achieving flexibility:

- On-line integration;
- Process management and updating SC;
- Event management;
- Component cooperation and coordination;
- Standardizing the environment.

Thus, in their view, in order to integrate information and coordinate processes in SC, a system is required that is able, not only to perform and establish cooperation in an organization or among organizations, but also to analyze and make intelligent decisions.

Choy *et al.* related presume that any tool claiming to be sufficiently sensitive to the type of dynamism we have just described, and to have the ability to adjust SC in reaction to such change, must include the following structural characteristics [18]:

1. Process standardization and communicative concepts exchanged among SC components.
2. Modular Structure: although units may ostensibly be separated from each other within this structure, they can nonetheless be combined with each other, thus providing the advantage to being able to offer more flexibility for the systems involved. To the extent that modular structure makes it unnecessary to repeat unit exchanges, coordination expenses are reduced accordingly.

The challenges and requirements mentioned above encourage managers to seek out new methods for resolving SCM problems. Ideally, these will involve flexible approaches which are able to adapt programs to real conditions and, if need be, help the decision

maker. Since one of the most common methods for SC modelling in recent years is quantitative modelling, a brief overview of this method and its inadequacies in meeting challenges and needs will now be provided.

2.2. Quantitative Modelling, a Common Approach to SC Modelling

Quantitative modelling of systems - incorporating mathematical modelling and operational research approaches - is one of the most pervasive methods for modelling and problem-solving currently in use. Nevertheless, in order to obtain an answer or answers which are optimized, operational research models are in need of a complete and accurate input of relevant data into the model which, in natural conditions, are seldom, if ever, available [20].

Turksen and Fazel Zarandi usefully itemise the most important issues in the area of SC management, such as production planning (programming), stock control, scheduling models, transportation planning, logistics management, and distribution channels, while referring to the fact that all these issues tend to be beset by conditions of uncertainty [12]. They consider lack of certainty, the existence of error and the deficiency of information as the three principal reasons for failing to arrive at accurate appraisals of the decision-making environment.

Li *et al*. maintain that at high levels of decision making in SC, managers are involved in long-term planning in the entire SC and will therefore leap at the prospect of applying those models which might help to simplify the process and improve the quality of their decisions [11]. It is important that any models of this type are not merely mathematical, but arte suitably analytical as well.

Che *et al*. have highlighted the inherent weaknesses of quantitative models. They emphasise the following as the most critical deficiencies [32]:

A. quantitative models' need for accurate input;
B. various difficulties in describing quantitative models for managers;
C. the language used in quantitative models to explain the results and discuss the findings is often considered unintelligible by managers.

It should also be pointed out that, even where appropriate and essential data is available, the task of devising problem-solving, models in operational research is both intellectually demanding and incredibly time-consuming. Furthermore, the costs involved in designing softwares with specific applications, let alone installing hardwares which are suitably compatible, are often prohibitive.. The highly specific and often models are not so much flexible that for each new problem and model there are new costs and complexities [20].

Against all this, however, methods of this nature have been widely used in recent research in relation to prominent issues in SCM. Relaxation, heuristics and Meta heuristics have been among those approaches which have been exploited in modelling and problem solving in operational research to reduce the effect of the difficulties and complexities mentioned above. However, the implementation of quantitative models in recent years has given rise top problems concerning the design and use of such models.

Given what was already mentioned, in order to achieve the appropriate flexibility and gaining agility in SCM, actions should be taken to design and identify methods and tools which can meet the earlier mentioned challenges and needs.

2.3. Distribution System in SCM

Two of the most important aspects in SC are those of allocation and distribution. This particular significance of these two issues lies in the fact that they attract attention both as cross-functional problems and by virtue of their positioning as final links in the SCM chain. Obviously, the two processes are closely interdependent, such that faults inherent to one may have implications for the other [11].

Since the distribution is much more evident in systems which are engaged in physical products, allocation and distribution are sometimes referred to as the distribution system [7]. According to the definition offered by Weigel and Cao [7], this system is composed of a set of computational and operational activities which lead to decisions taken in relation to t determining the quantity, type and mode of delivery of products and services, and how best to configure all the different elements in the chain to ensure the most effective distribution channels.

These are important considerations. The efficacy of the distribution system in SCM influences, not only affects the satisfaction level of the receiving agent in the distribution channel, but also has implications for

such vital considerations as the on-time supply of products and services, reduction in stock expenses, planning for producing products or services, and the overall efficiency of the SC [11].

In systems which outsource distribution agents, the task of ensuring justice in terms of the distribution of effort and wealth among distribution agents, and in organizations which employ internal and external personnel to distribute products and services are among other crucial outcomes of an appropriate distribution system that can contribute to or detract from the efficacy of SC and affect whatever inner tensions are liable to be involved [11].

On the other hand, the distribution system in Sc is classified as complex. Alter [24] believes a system's complexity arises from the number, nature and the ways in which they interact with each other. Scuricini [8] gives prominence to four parameters influencing complexity and mentions that such agents as the numerosity, variety of components, component's type and organizing or interacting way among components, organization and/or the interaction between the elements exert influence on the magnitude of complication.

According to the definitions mentioned above, the distribution system in SC is categorized as complicated because of a numerous host of constraints and variables which tend to pervade this category of systems.

In the case of the distribution system constituting the last level of a simple SC of a hypothetical product, any number of different factors may add complexity to the process involved. Among the type of issues potentially involved are: the variability of transportation means and of their technical and quality capacities and constraints; the existence of variety of distributable products and different quantities of each order; structural differences in carriage vehicles and distribution agents; varying priorities for the supply of products type and their significance; the variability of supply centres and their geographical dispersion; and the diversity and variety of customers and their significance.

The above-mentioned factors may be quantitative or qualitative in nature. The actual volume and intensity of such factors may also vary according to different environmental conditions. Additionally, it should be acknowledged that presentable goods or services and distribution agents are dynamic both in number and in terms of their own particular attributes. On the other hand, some of the objectives and constraints placed on this system are qualitative by nature and therefore not quantitatively measurable. These objectives are not necessarily unidirectional, and some are even contradictory, though all have to be taken into account simultaneously. The degree of importance of these objectives during the process of decision-making varies according to different environmental conditions.

As can be seen, the distribution system in an SC has a profound effect on its agility and efficacy alike. To achieve the requisite agility and efficacy, it faces the type of challenges and requirements alluded to earlier in this paper. It is evident that all the challenges and requirements affecting an efficient and agile SC are hidden, and waiting to be unearthed, in any particular distribution system.

Taken from the above, it is apparent that a truly efficient and agile model should must effectively incorporate relevant quantitative and qualitative information relating to the above-mentioned characteristics; it should be capable of rapidly responding to a diversity of environmental changes, and be sufficiently adaptable as to be able to generate decisions on a relatively impromptu basis in the face of developments that have not been reasonably anticipated. Finally, such a mechanism should be able to adapt accordingly to previous errors by showing a capacity to environmental changes should be used. Learn and self-correct.

3. SC MODELLING BASED ON SOFT COMPUTING

Starting in 1975, when John Holand, in his famous book "Adaptation in Natural and Artificial Systems", mooted the genetic algorithm (GA) to optimize the Control problems, and researchers at the IBM laboratory advocated the simulation annealing (SA) as a strong way of investigation for response space, soft computing and evolutional algorithms became looked upon as a possible decision making panacea.

Maione (2003) believes that optimization based on evolutional algorithms, has been one of the greatest scientific developments 20th century. This stride forward, allied to advancements in computer technology and increasing demands for more sophisticated ways of dealing with practical commercial problems, has inspired researchers from a

variety of different scientific backgrounds to turn consider the possible application of evolutional algorithms [9 and 21].

Although soft computing entered the calculation area a little late, the fast development of calculating tools and attempt to design more intelligent systems, has increasingly accelerated its evolution and generated relevant research within such diverse disciplines as robotics and philosophy. The acknowledged ability of soft computing to confront complex systems has caused these views to advance swiftly, and with great compatibility towards other experimental and human sciences, such as computing, communication studies, robotics, economics, ecological studies and the humanities [9].

In contrast to 'classical' or 'hard' computing, classical or the so-called hard computing, soft computing seeks to adapt itself more to the uncertainty and the vagueness of the real world. Nervous networks and genetic algorithm are the main component elements of soft computing, although some tools such as rough sets are also considered as relevant secondary methods [33], [34].Based on defining a limitation on lack of clarity and certainty, soft computing attempts to present appropriate, powerful, and cheap solutions to the problems of complex systems.

Among the reasons for the rapid growth and development of the evolutional algorithms family and wider soft computing, we can cite their relative simplicity of usage, combined with their undoubted (and almost paradoxical) power and applicability. To face a very complicated problem with these methods, demands that the following three requirements regarding basic information are satisfied:

1. Variables of problems decision making should be identified and understood;
2. The value of each possible response should be calculable;
3. The dominant limitations to problem and the method of producing the practicable responses should be identified [9].

Before moving on to consider our proposed model, it is imperative that we pause, first, to consider other relevant SOM concepts which sit alongside ideas embedded in the evolutionary algorithms literature as useful components of our argument.

3.1. The Basic Concepts of SOM

Self organizing maps are of nervous networks type, with an unsupervised learning capability which makes them highly powerful in terms of analyzing complex spaces [27].

Such a model of nervous networks was first introduced by Kohonen in 1981 [28], who exploited the nerves of the retina as the foundation of a model. In 1984, this model was practically used to recognize speech and to convert it to text [28]. Now SOMs are routinely used in data mining and complex spaces display [16]; in clustering the spaces with high dimensions; and in particular, in processing pictures, process control, project management, financial analyses, and industrial and medical diagnostics. A more comprehensive list of the possible engineering applications of SOM has been provided by [29].

The basis of SOM involves mapping spaces with high dimensions (specifications) into two or three-dimensions, so that the minimum information is lost and the information hidden in relations among the data can also be identified and displayed. This method is capable of displaying the correlation between data, information and their mutual, simultaneous effects they might be having on each other.

These capabilities result from mapping the nonlinear relations among the data using a geometrical mean on a two or three dimension neuron network. A two-dimension neuron network of neurons is usually referred to as a neuron map. Each map consists of a set of neurons which are organized in a tidy manner, and shapes the structure of the network in such a way that the most similar neurons are put beside each other. Figure 1 indicates a view of SOM topology.

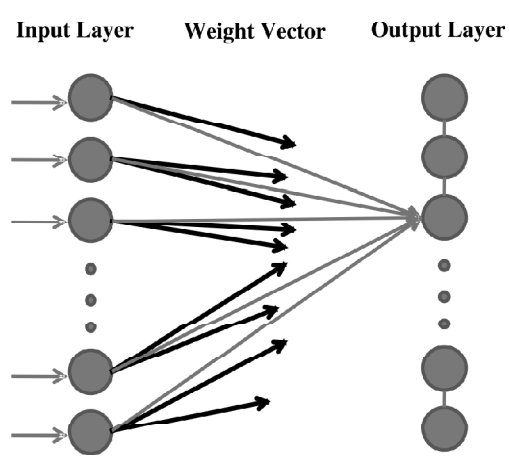

Figure 1: Topology of Self-organizing Neural Network [28]

Each neuron corresponds to an information vector, with the dimension numbers equal to the dimension number of the information space under analysis. In other words, each neuron is a representative of each section of information space.

3.1.1. SOM Training

The SOM's training is based on competitive learning algorithm which is unsupervised (without using the proper vector). First of all, the weight vector corresponding to each neuron is accidentally produced and the preliminary structure of the network is shaped and then, in the process of network training, the weight vector corresponding to each neuron is adjusted in such a way as to cover an information part of the space under analysis. Thus, in those space parts with higher data density, there will be more neurons and the network topology is shaped, similar to the joint distribution of space specifications.

The algorithm of SOM training is composed of four stages [27]:

Selecting mapping parameters such as dimensions and weight vector so that they correspond to each and every neuron.

Presenting the data under analysis to the network and finding out the most corresponding neuron for each input data vector (record). The records can be simultaneously offered to the network and/or each time one record, respectively, and the training operation is begun. Each record such as X, consisting of the quantitative value of n specifications which can be indicated as the equation 1:

$$X = [X_1, X_2, \ldots X_n] \in \Re^n \quad (1)$$

If weight vector of the neuron is defined as bellow:

$$m_t = [m_{t1}, m_{t2}, \ldots m_{tn}] \in \Re^n \quad (2)$$

Then, corresponding to each input record, the best matching unit or winner neuron is identified based on equation 3.

$$c = \arg\min_t \{d(X, m_t)\} \quad (3)$$

In which C indicates the winner neuron and $d(X, m_t)$ is the Euclid's distance between the record and the weight vector of the neuron that is calculated by Equation 4.

$$d(X, Y) = \| X - Y \| \quad (4)$$

3. Up-dating the weight vector corresponding to each neuron using Equation 5.

$$m_i(t + 1) = m_i(t) + \alpha(t)\, h_{ci}(t)\, [X(t) - m_i(t)] \quad (5)$$

In which, $0 < \alpha < 1$ is the learning rate and $h_{ci}(t)$ indicates the neighbourhood rate of i neuron with the c neuron (winner neuron). The neighbourhood rate of i neuron with the winner neuron is obtained from equation 6.

$$h_{ct} = e^{\frac{\|r_c - r_i\|^2}{2\sigma^2(t)}} \quad (6)$$

In the equation 6, σ is the controller of the function domain and is eventually decreased during the training process.

Also r_i and r_c are respectively the situations of i and c neurons in SOM [27].

Evaluating the algorithm ending (rule unless the rule is set), the algorithm will continue from the second step.

Since the SOMs training algorithm is structured on the basis of Euclid's distance, the data of each dimension of the space under analysis should be normalized and standardized separately.

At the end of SOMs training stage, a neuron map is obtained that is, in fact, a summary of the space under analysis of the network. Presenting each new information vector of the space under analysis to the network, Euclid's distance of weight vector corresponding to each neuron to the input vector is obtained; and based on that, the extent of motivation of each neuron is calculated. Then, the neuron with the highest extent of motivation is selected as the winner.

3.1.2. Exhibiting the Space under Analysis using SOMs

After SOM training, n-dimension weight vectors are obtained with the same number as the neurons selected for the network. Each vector is the indicator of a part of the space under analysis. By selecting the proper number of neurons, network dimensions and the proper network training, exhibiting the weight vectors corresponding to each map's neurons can truly show the space under analysis. Thus, relating to each specification's value in the weight vector, a RGB(Red-Green-Blue) vector and consequently a color is considered in a way that all values can be shown in a

colored spectrum from dark blue (for lowest values) to dark red (for highest values). In this way, for each specification, the color of each neuron is identified and the map related to that specification is obtained. With the specifications' maps, it is then possible to evaluate the mutual relation between them (using a correlation test). For example, the same color of the corresponding parts of two maps indicates the correlation of the corresponding specifications in those maps. The intensity of color difference or similarity between maps can show the correlation rate between two variables in different parts of the space. Moreover, quantitative criteria can be calculated for that. It is possible that the intensity, and even the kind of correlation between two specifications in various parts of the space, are different and affected by the values of other specifications that all can be truly shown using SOMs.

Figure 2 indicates a sample of SOM's usage in analyzing complex models and exhibiting the simultaneous effects of different variables on each other. It is clear from this figure that the space under analysis has five dimensions. Comparing the maps with each other, the following results can be extracted:

1. Variables V_2 and V_5 and also V_1 and V_4 have inverse correlation in their entire change domain. (When V_2 is red (takes high values), V_5 is blue (takes low values) and vice versa). Although the correlation rate of and is fixed almost in all parts of the space, the same is not applicable to variables and.
2. Variables V_3 and V_5 are inversely correlated but the correlation rate in different parts of the space is diverse and less than the correlation rate of V_2 and V_5.
3. Variables V_2 and V_3 are directly correlated but their correlation rate is dependent to the values of other variables.
4. The correlation of variables V_1 and V_4 with V_5 is completely non-linear and its rate in various parts of the space is different. The important issue is that maximum and minimum values of V_5 probably occurred in medium values of V_1 and V_4.

3.1.3. U-Matrix

One of the other outputs of SOMs is the classification matrix and, corresponding to that, the classification maps itself. The elements of this matrix show the

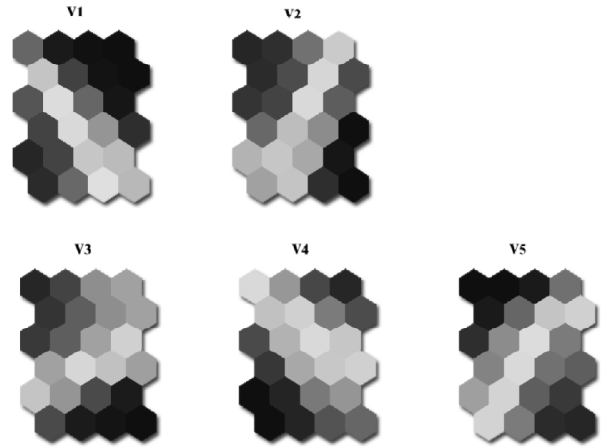

Figure 2: SOMs usage in Simultaneous Analysis of Non-linear Relations between Variables

algebraic interval of neighbor neurons from each other. If the specifications of two parts of the space under analysis are similar, then the algebraic interval between the weight vectors of the neurons related to them is not too significant. In other words, both neurons are in the same cluster of the space under analysis. Oppositely, the more the algebraic distance between the neighbor neurons, the more different their corresponding spaces will be. Thus, they can be categorized into two separate clusters. Figure 3 indicates a U-Matrix with some clusters and sub-clusters from a 62- dimension space.

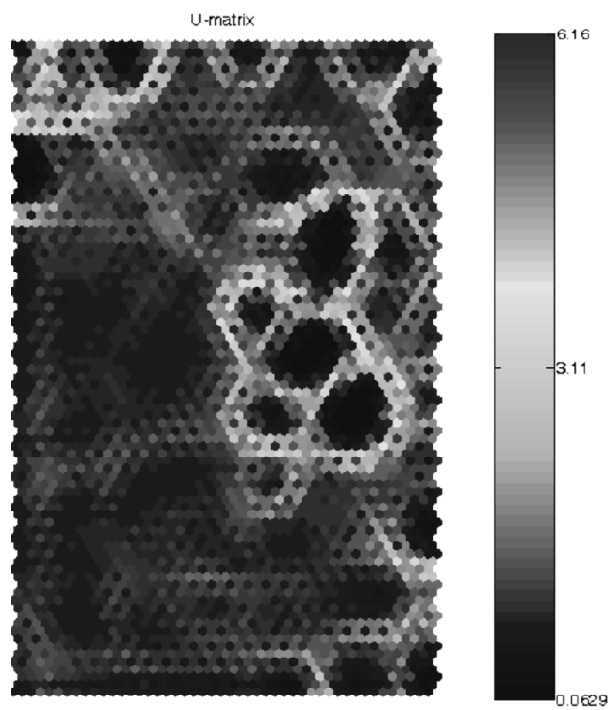

Figure 3: U-Matrix. Some Clusters are Named by Capital Letters

1-Proposed model: In this section, we finally set about outlining our proposed model. Our argument will employ concepts drawn from the area of soft computing which have been highlighted in our prior disdcussion. As indicated in table 1, of comparable tools, the only system that can be investigated in the model of research is the fuzzy inference system. According to the information in table 1, it is clear that Mamdani models are more mental, and that rules of these systems are usually laid down by experts; but in the Sogeno model, most rules are set by extending non-fuzzy equations available in the system. In this study, we have therefore selected the Mamdani fuzzy inference system as the basis of our approach.

Table 1
Comparison of Different Tools for Approximating Utility of Each Entity Driver- order in Research Model

Tool's name	*Advantages*	*Disadvantages*
Expert system	- Perceivable for decision- maker - mapping the system knowledge	Rules of the system, their sequence and selection logic in research problem is not clear
Feed forward multi-layer neural network	- ability to approximate the most complicated mapping function from input to output - learning ability	- There is no data from history of system for educating network and they can't be produced because exact utility function of decision-maker is not available.
Mamdani fuzzy inference system	- working on the basis of expression rules and completely comprehensible - learning ability - ability to use detailed system knowledge	- Network performance depends on all calculated utilities for built entities and common learning techniques in neural network can't be applied to solve the problem. - decision- making method is not comprehensible to the user
Sogeno fuzzy inference system	- quick - learning ability - ability to use detailed system knowledge	- less comprehensible than Mamdani system to users

Due to the fact that the fuzzy inference system is generally applicable to a variety of cases in the area under discussion,, its components (elements) and parameters including rules, variables, membership functions, and the type of operations should be selected according to the case and the place of application [26]. It is noteworthy that considering the fact that most information is kept by operation (prod) t-norm to multiplication and the aggregation of the rule weight in each rule output, and (prob or) s-norm operation to add and integrate the results of the rules and the comprehensibility of center of area method for fuzzification which was shown to be relatively preferable to other operations in Jang [15] studies, this operation was used in this research.

In the next step, rules weight should be determined. To this end, expert opinions in the form of multiple-criteria decision-making methods can be utilized.

The first stage of designing is the identification of input variables into the fuzzy inference system. Input variables vary in different cases of the problem but in the said distribution system in this study, it is always the output variable, "allocation priority". In the next step, the amount that can be allocated to each of the input and output variables is determined. In this stage, the set of linguistic expressions corresponding to each of the input and output variables of the fuzzy inference system are defined. After defining the input variables and linguistic expressions corresponding to each of them, rules of the system can be laid down on the basis of the results of the system and through experts.

Following this, the, rules weight is determined by using expert opinions in the form of multiple- criteria decision-making methods. One of the current procedures for weighing, which has been used in this research, is analytical hierarchical procedure (AHP). In this procedure, experts determine the weight of rules through a couple comparisons of rules.

4.1. The Process of Learning in the Proposed Model

Each component of SC is involved in various activities - such as: planning and controlling stock, quality

control, procurement, marketing, relationships with customers, sale, distribution, etc. Therefore, concerning MAS definitions and concepts, an SC can be considered as MAS in which each element of chain has the status of an agent. On the other hand, each component of SC can be viewed as MAS in which every agent communicates with other MAS of SC in addition to their interaction with other agents of MAS they are a member of. So each SC can be seen as a system of n agents in which the magnitude of n depends on the number of activities, the nature of performance and complexity of SC in question. Any agent required to model distribution system in this article must have a policy function with great learning ability.

Learning process of the allocating agent is designed according to figure 4. As we can see from this figure, the learning part is associated with short-term memory and decision-making part of the allocating agent. Short-term memory provides the data required for the learning section, the learning section, in turn, affects decisions by adjusting parameters of agent policy function [23].

The main processes of learning section of the allocating agent are indicated by numbers from 1-4 to 4-4 in Figure 4. These processes are, respectively:

1-4 process: deterring the ratio of conflict data to all data;

2-4 process: producing teaching prototypes;

3-4 process: adjusting policy function parameters;

4-4 process: updating short- term and long-term memory of agent;

Short-term and long-term memories serve as an information bank of the environment in which specifications vectors in each second saves agents' decisions and behaviour.

After going through the following stages, some of the records in working memory (short-term) memory are used to teach decision-making methods to the allocation agent.

At the adjustment sector of policy function parameters, the objective is to adjust the allocating agent's decision- making method. Given the fact that, in the proposed model, the policy function agent is comprised of a fuzzy inference core, learning involves adjusting the agent's fuzzy inference system parameters in a determined domain to reduce the conflict between the expert human operators' decision-making and the fuzzy inference system. Of the fuzzy inference system parameters that make the system acquire learning ability are:

1- Fuzzy rules;
2- Membership functions of shape parameters;
3- Rules weight;
4- Influence method of rules weight on output rule;
5- Method of integrating output rules with each other;
6- Defuzzification method.

In this research, it has been assumed that rules are being laid down by experts and the fact that expert opinions are being used in the framework of different procedures of weighing to determine the weight of rules and also a limited domain has been considered for changing rules weight. Thus, these cases are not taken into account in the learning process.

As stated in section 4, the appropriate procedure for aggregating rules weight in rule output is integrating rules outputs with each other and defuzzification according to s-norm, t-norm procedures and the center of area procedure. As a result, learning is not an issue of concern in the case of these parameters of the inference system and we have therefore refused to change them.

Consequently, learning in the proposed model is restricted to changing the followings:

1. rules weight in the defined domain;
2. Shape parameters of fuzzy membership functions of linguistic expressions in the restricted area.

To adjust the above-mentioned parameters, when a collection of input-output data is available, different methods can be employed, such as [30]:

1. Reinforcement learning family method such as Q-learning;
2. Neural network's different methods of learning and teaching such as method of back propagation error;
3. Different nonlinear optimization algorithms such as descending gradient;
4. Different Meta-Heuristic optimization algorithms such as genetic algorithm.

Meanwhile the application of neural networks in adjusting fuzzy inference system parameters attracted

lots of attention, but these methods suffer from some disadvantages to be used in this article the main ones of these are:

1. Teaching data are not in input/output format. Due to the learning nature in Distribution Systems model, types of system teaching data are not in input/output format. Although these types of teaching data can also be used in neural networks form, more complicated algorithms and structures need to be designed compared with those of common algorithms in neural networks [30];
2. Learning and teaching methods of family of neural networks are all based on nonlinear methods. With regard to the variable numbers (threshold value and synapse weights) and complication of search areas, possibility of converging to on inaccurate optimum local solution is so high [30].

For such reasons, the use of Meta heuristic algorithms, such as genetic algorithms, are preferable to the neural networks.

Considering the above items, and confirmation of item 2 (about nonlinear optimization algorithms in proposed model), super creative search algorithms are preferred to neural networks.

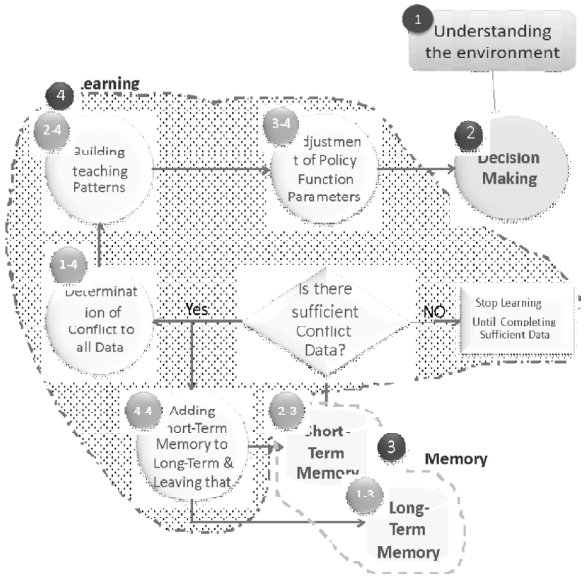

Figure 4: Allocating Agent Learning Process

Among meta-heuristic methods, mechanisms with efficient search ability in continuous spaces must be chosen. For the same reason, methods such as the ant colony algorithm-a searching device for discrete spaces - and other continuous versions deemed too inefficient, are waved aside [30].

Among meta-heuristic methods with searching ability in continuous spaces there are various algorithms; one of them, genetic algorithm, has great searching power parallel to its searching space, and is therefore a popular method of adjusting fuzzy inference system [30].

4.2. Case Study and Numerical Results

In this article, a national Oil Products and Distribution System[2] were investigated. The company provides the main source of revenue at the national level for the host country. SCM and oil products distribution is one of the critical parts of economy (in the above country) and can be studied from lots of different perspectives. First, oil products fulfil a significant rule in all aspects of the country's economy and their adequate supply and distribution have a great impact on the economy and economical security of the country. Similarly, due to the fact that oil products are consumed directly by families and final consumers, their appropriate supply and distribution can also promote public welfare and social security [22].

It is important to mention that it was assumed in this article that oil products are transported using trucks and here are referred to as an order-driver entity.

4.3. Defining Fuzzy Input and Output Variables

In order to design fuzzy inference system in the case at hand, it is first essential that input and output variables in the fuzzy inference system are effectively defined. This task is now attempted. in relation to these types of variable.

The output variable in this research is the allocation priority, which indicates the magnitude of the allocation priority of each authorized order to the driver (taking into consideration all relevant conditions of orders and drivers). The higher allocation priority, the higher utility of the corresponding order to be allocated to the applicant, is that of the oil tanker driver.

Interviews with expert figures were used as a way of formulating linguistic terms to apply to this fuzzy variable. It was revealed that, at the point of allocating the product to the driver, the distribution unit operator makes decisions based on 5 probable cases. In other

words, according to the mental and behavioural model of each operator, based on different variables - such as: the customer's order priority, product priority, application priority, the last time the product submitted to the customer, the number of cargoes geographically allocated to this distribution agent in this shift , the driver's expected station, the utility of the station, etc - five classes of product allocation to the distribution agent can be conceived as very low, low, medium, high, and very high in priority. Then the interviewed experts were asked to determine the operator mental quality model range at an interval of (0, 1) for 5 earlier mentioned cases by numerical values.

In adopting Zimmermann's [10] suggestion that triangular membership functions be used for expressing linguistic terms in human systems; all fuzzy variables in this article were assumed to be triangular.

So linguistic terms range of this fuzzy variable are defined as below (1-5):

```
Relation 1   Very Low = Triangular{0,0,0.2}
Relation 2   Low =Triangular{0,0,0.4}
Relation 3   Medium =Triangular{0.1,0.5,0.9}
Relation 4   High=Triangular{0.6,1,1}
Relation 5   Very High =Triangular{0.8,1,1}
```

4.4. Input Variables of the Fuzzy Inference System

Based, once more, on interviews with experts, 11 input variables were extracted for their relevance to the fuzzy inference system in our oil product distribution system. These were: product priority, customer priority, region priority, latest submission time, the tolerance of the oil tanker capacity, cost of oil tanker preparation, oil tanker waiting time, distance to the driver's desired station, station utility, utility of the deriver's expected station and justice index.

4.5. Definition of the Linguistic Terms of each Fuzzy Variable

A paucity of available information required us to apply the three linguistic terms of low, medium and high for input fuzzy variables.

In much the same way that all fuzzy numbers were assumed to be triangular, the unavailability of information about system, parameters of functions led to variables being defined in terms of a 1-5 relationship. It is noticeable that, in model designing to accommodate the learning process, triangular terms parameters for each fuzzy variable was adjusted to show system performance approaching optimum.

4.6. Rules Definition

In order to arrive at definitions of Distribution Systems rules, based on input and output variables, we resorted to our expert interview data. The 35 rules arising from this process are distilled into the following 6-15 relations.

Primary rules weighing is achieved by experts' contributions and by AHP without any normalizing stage. Table 2 shows the number of each rule, together with its primary weight. The purpose of primary rules weighing in AHP is to make the sum of options weight equal to 1; while this is not necessary in determining the weights of fuzzy rules.

Product_Priority: Relation 6

If Product_Priority=Low then Priority=Low;If Product_Priority=Medium then Priority=Medium;If Product_Priority=High then Priority=High;

Customer_Priority: Relation 7

If Customer_Priority=Low then Priority=Low;If Customer_Priority=Medium then Priority=Medium;If Customer_Priority=High then Priority=High;

Location_Priority: Relation 8

If Location_Priority=Low then Priority=Low;If Location_Priority=Medium then Priority=Medium;If Location_Priority=High then Priority=High;

Last_Delivery_Time_Priority: Relation 9

If Last_Delivery_Time_Priority=Low then Priority=Low;If Last_Delivery_Time_Priority=Medium then Priority=Medium;If Last_Delivery_Time_Priority=High then Priority=High;

Vol_Tolerance: Relation 10

If Vol_Tolerance=Low then Priority=Low;If Vol_Tolerance=Medium then Priority=Medium;If Vol_Tolerance=High then Priority=High;

Setup_Cost: Relation 11

If Setup_Cost=Low then Priority=Low;If Setup_Cost=Medium then Priority=Medium;If Setup_Cost=High then Priority=High;

Queue_Time: Relation 12

If Queue_Time=Low then Priority=Low;If Queue_Time=Medium then Priority=Medium;If Queue_Time=High then Priority=High;

Distance: Relation 13

If Distance=Low then Priority=Low;If Distance=Medium then Priority=Medium;If Distance=High then Priority=High;

Justice_Index & Station_Priority: Relation 14

If (Station_Utility=Medium) then Priority=Medium;If (Justice_Index=Low) and (Station_Utility=Low) then Priority=Very Low;If (Justice_Index=Low) and (Station_Utility=High) then Priority=Very High;If (Justice_Index=Medium) and (Station_Utility=Low) then Priority=Low;If (Justice_Index=Medium) and (Station_Utility=High) then Priority=High;If (Justice_Index=High) and (Station_Utility=Low) then Priority=Very High;If (Justice_Index=High) and (Station_Utility=High) then Priority=Very Low;

Justice_Index & Driver_Station_Priority: Relation 15

If (Driver_Station_Utility=Medium) then Priority=Medium;If (Justice_Index=Low) and (Driver_Station_Utility=Low)then Priority = Very Low;If (Justice_Index=Low) and (Driver_Station_Utility=High) then Priority=Very High;If (Justice_Index=Medium) and (Driver_Station_Utility=Low) then Priority=Low;If (Justice_Index=Medium) and (Driver_Station_Utility=High) then Priority=High;If (Justice_Index=High) and (Driver_Station_Utility=Low) then Priority=Very High;If (Justice_Index=High) and (Driver_Station_Utility=High) then Priority=Very Low;

4.7. Allocating Agent Learning

In such a huge and strategically critical concern as the oil product distribution system, managers often balk at assigning everything to a mechanical system and much prefer to rely on the judgement and intervention of human operators skilled in bargaining with transfer agents. It is therefore important to emphasise that relevant human and automatic elements are considered interrelated and complementary to each other [23].

The automatic part of the allocating agent ***m*** provides the human operator with enormous different suggestions and then he/she begins to negotiate with transfer agent distribution applicant. The human operator is obliged to allocate one of the priorities at his or her disposal, preferably the first one, to the transfer agent, but he or she might allocate an entity which is out of the proposed list for different reasons to the applicant.

When this happens, a conflict record will be registered. The ability of the automatic part to analyze the conflict records, and to improve its performance in such a way as to minimize the contradictions between human expert operator behaviour and automatic part of the system, is called “learning”.

Within this process, it is important to bear in mind that:

1. All conflict records are not necessarily true ones. Some conflicts might have arisen due to some illegal relationships between the human operator and transfer agents.
2. Parameters of decision-making system of the automatic part should be changed in such a way that it leads to the least change in the main system and does not ignore items considered in designing the system so that it minimizes the deviation of automatic and human part behaviour.

The main processes of allocating the agent learning part are as follows.

Process 1-4 determining ratio of conflict data to all data;

Process 2-4 producing educational patterns;

Process 3-4 adjusting policy function parameters;

Process 4-4 Updating short and long term memory of an agent.

4.8. Analysis of the Simultaneous Effect of Genetic Algorithm Parameters and Selecting Appropriate Values of Crossover Rate and Mutation Rate

The chromosome coding method exploited in this article is based on an encoding method applied to real members, and each chromosome string is comprised of two parts. The first part included 35 genes relating to rules weight, and the second part consisted of 15 genes of fuzzy variable linguistic terms. In the proposed Genetic algorithm, the first population consisted of 10000 randomly produced chromosomes. Since the second part of the chromosome is a function of special

rules and was defined based on triangular fuzzy numbers, the first random population must have been controlled before using them to see whether it is authorized or not form the point of view of the produced population, The computable objective function for each member of society was considered, based on minimizing deviation from the objective (in this article deviation from the objective is equal to deterrence of proposed utility form declared utility about optional choice by operator in case the operator chooses an option different form the proposed option of system). The algorithm was stopped if the response was not improved in 200 consequent iterations. The fitness function calculation in this paper is based on rank method and selection is based on mutation method (rate 10%).

One of the important issues in exploiting Meta-heuristic algorithms such as genetic algorithm is to appropriately regulate the parameters. To regulate the parameters in algorithm, the efficiency of the algorithm in solving the case at issue should be frequently investigated by changing one parameter and fixing the other parameters. By using the statistical analysis, the appropriate magnitude can be suggested for the parameters. The main problem inherent in these methods is the fact that they ignore the mutual effects of these parameters on each other. In order to overcome such a problem, such techniques as clustering and space display were used to simultaneously analyze the genetic algorithm parameters (mutation rate and crossover rate) on the basis of SOM. To this end, 10000 informational records were picked out from an archive of allocation unit activities.

Therefore, the designed genetic algorithm in learning part is run 10000 times on the basis of registered data from system natural performance and altering two parameters of crossover and mutation rate. Each time the mean of square errors (MSE) obtained through comparing fuzzy inference responses with allocating unit operator performance results (MSE of objective function) was calculated. Finally 10000 informational records were obtained from the simultaneous effect of different parameters in genetic algorithm for different values of crossover and mutation rate. The data collected by the use of MATLAB software and a toolbox of self organized maps in two visual dimensions was analyzed (Fig 5).

As shown in Figure 7 and on the basis of knowledge extraction rules form self-organized maps, the results obtained were as follows:

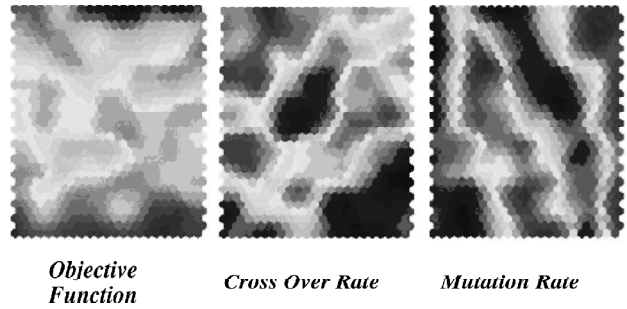

Figure 5: Analyses of Simultaneous Operator Effect and Different Genetic Algorithm on its Performance

- Low crossover rate raises objective function value and decreases algorithm efficiency. If crossover rate exceeds 0.9, it has the reverse effect on the objective function. After all, the crossover rate between 0.7- 0.8 is assumed an appropriate rate. In the algorithm used in this article the crossover rate of 0.7 (P_c=0.7) was drawn upon. It should be mentioned that One-Point Crossover Method was applied.
- Mutation rate impact on algorithm efficiency and objective function value in studied domain is not noticeable; but on examination of the maps it is expected that high mutation rate (about to 0.1) can reduce objective function. So it seems that the suitable mutation rate must be searched at the interval of (0.02, 0.03). In the algorithm applied in this article, mutation rate of 0.03 (P_m=0.03) was adopted. Mutation method is of uniform type, as well.

In order to assess results of the proposed model in oil product Distribution Systems, the proposed model and algorithms were re-written in Delphi software. Designed software was running for a month in the morning shift in one of oil product distribution regional fuel storage depot to allocate gasoline and diesel.

At the end of pilot phase, studying informational records revealed that about 4126 conflict records had been saved in the system. In other words, of 17613 times of allocating operations, proposed allocation priority of system has been in conflict 4126 times with the proposed allocation of operator. These figures show that about 23% of the operator's performance contradicted the system proposals.

Based on the obtained results and learning algorithms referred to earlier in proposed model, the learning process of the system was run. The following results regarding two learnable problems in question were proposed by the system.

4.8.1. Rules Weight

At table 2, rules primary weight and corrected weight of the system rules are represented after learning.

Table 2
Primary Weight and Corrected Weight after Learning

Rule No.	*Primary Rule Weight*	*Corrected Rule Weight*	*Rule No.*	*Primary Rule Weight*	*Corrected Rule Weight*
1	0.15	0.35	19	0.35	0.39
1	0.21	0.41	20	0.25	0.35
3	0.35	0.52	21	0.71	0.71
4	0.59	0.61	22	0.52	0.59
5	0.39	0.45	23	0.34	0.34
6	0.84	0.79	24	0.72	0.63
7	0.42	0.42	25	0.68	0.59
8	0.38	0.44	26	0.15	0.34
9	0.62	0.59	27	0.39	0.39
10	0.82	0.73	28	0.12	0.34
11	0.3	0.32	29	0.42	0.54
12	0.49	0.49	30	0.23	0.56
13	0.18	0.27	31	0.29	0.71
14	0.55	0.55	32	0.79	0.63
15	0.82	0.72	33	0.59	0.59
16	0.22	0.34	34	0.84	0.7
17	0.89	0.61	35	0.42	0.53
18	0.69	0.69			

4.8.2. Shape Parameters of Membership Functions

Table 3 indicates primary membership function and values after system's learning for output and input variables.

Table 3
Shape Parameters of Primary Membership Function and after Learning

Shape parameters of member ship function after learning	*Shape parameters of primary membership function*
Very Low = Triangular {0, 0, 0.23}	Very Low= Triangular {0, 0, 0.2}
Low=Triangular {0, 0, 0.36}	Low=Triangular {0, 0, 0.4}
Medium=Triangular {0.07, 0.47, 0.83}	Medium=Triangular {0.1, 0.5, 0.9}
High=Triangular {0.64, 1, 1}	High=Triangular {0.6, 1, 1}
Very High=Triangular {0.75, 1, 1}	Very High=Triangular {0.8, 1, 1}

After and during the learning process, the proposed system (which was allocating two products of gasoline and diesel) was investigated for another month again in the morning shift. At the end of period of the study, informational records revealed that about 393 true conflict records had been saved. In other words, of 17577 times of allocation operation about 393 times the proposed allocation priority of system conflicted with the operator's allocation. The figures show that about 2. 2% of operator's performance went against the system proposals.

Table 4
Performance Comparison of Proposed System

Indicator name	*Amount at the 1st month*	*Amount at the 2ed month*	*Amount at the 3rd month*
Number of Delivered orders in the morning shift	6286	5879	5869
Volume of submitted orders in the morning shift (million liter)	420	393	392
Number of loaded oil- tanker	627	587	584
Indicator of fair order distribution in the morning shift	71	73	78
Number of customers	79	79	79
Number of customer's complaints per month	32	27	19
Number of agents and driver's complaints	57	44	28
Average waiting times for drivers to load (minutes)	43	39	22
Average waiting times for customers to receive order (minutes)	280	265	230
Number of transport agencies	34	34	34
Number of tankers in the morning shift	194	194	194
percentage of allocation system conflict	——	0.23	0.022

Our findings indicate that the proposed system was able to have considerable impact in terms of: ensuring fairness of order distribution indicator; bringing about reductions in the number of customers, agents and drivers' complaints; and decreasing in the average waiting time of drivers and customers. Among other advantages yielded by the proposed model was a reduction in the allocation time spent with_oil tanker drivers. Given the reduction in the product allocation

and drivers' waiting time it can be expected that the operational loading capacity and response to the storage depot orders will increase satisfactorily. This also paves the way for a downsizing in the number of operators typically involved in the allocation system; By and large, the system results in reducing surplus costs of energy; makes it possible to change decision-making parameters rapidly (such as adding or changing decision-making rules, rules weight, membership function shape, etc.); promotes the flexibility of the system; and contributes to management's knowledge and expertise regarding Distribution Systems.

5. CONCLUSION

One of the greatest outcomes of computational sciences in recent decades is soft computing. In contrast to so-called classical or 'hard' computing, soft computing seeks to adapt itself with greater determination to the uncertainties and vagaries characterising the real world. In this article, we hope to have contributed to this growing tradition by constructing a vmodel, based on existing knowledge around the fuzzy inference system, genetic algorithm, and SOM, that has shown itself capable pf promoting greater agility within SCM.

Utilizing SOM in a model relating to allocation and distribution of the entities in the supply chain of oil products as an efficient tool in analyzing the simultaneous effects of genetic algorithm parameters and selecting the appropriate parameters in related computations can be considered as a novel contribution to the ongoing quest to produce more sophisticated problem-solving devices. By replacing existing methods with SOM for regulating genetic algorithm parameters, it was possible to bring about a variety of advantages, such as the possibility of simultaneously analyzing effects of parameters and enabling users to more effectively understand them. In short, the proposed model can justifiably lay claim to having created a more flexible, comprehensive, economical and logical approach to the vital function of SCM.

Note

1. For purpose of confidentiality name of country and the oil company is omitted.

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