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Neuro-fuzzy decision learning on supply chain configuration

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This paper describes the computational automatic supply chain configuration (SCC) based on fuzzy logic prediction actualizing automatically the chain stages considering different customer service level petitions. Each level is selected in accordance with the inference and the knowledge base process supplies (KBPS). The SCC model as an intelligent processes selector (IPS), allows dynamical configuration in accordance with the minimum cost supplies configuration (MCSC) described with the SCC functional error. The basic future decisions set as a knowledge base (KB) using fuzzy rules and inferences, transforms the proposed decisions into actions over the elements required by the process supply (PS). The minimal functional error and the SCC best selection, permits excellent client attention. The adaptive model stages operational SCC is described illustratively using Matlab® software.

Key words: Fuzzy digital learning, neural networks, supply chain configuration.

INTRODUCTION

Intelligent supply chain (ISC) structure is built dynamically considering the competitive actions inside the dynamical world, where customers have different services and product requirements. The enterprises should have new approaches that can help to support customer innovation, flexibility, quality, and excellent service maintenance to increase their competence. The multiple scenarios analysis allows developing the strategies for the supply chain configuration (SCC), considering different customer service levels increasing the decision-making support affecting global efficiency (Croom et al., 2000). ISC viewed as an intelligent process requires a mechanism that deduces previously the customer wishes (requirements or specifications) described dynamically as a class of service (CS). In agreement to CS degree the ISC transforms the service into a specific grade, according to the structure conditions with minimum cost and customer requirements. Therefore, the ISC selected the best attention level answer. An intelligent structure has different supply scenarios with different interpretations, considering the actual customer requirements, having automatic SC changing stage process (Chong and David, 2011). The customer requirements prediction is based on a fuzzy learning system that adjusts dynamically the process stage conditions through the parametre weights with respect to the mean square error criterion or functional error.

The learning system scheme inferences and the knowledge base process is the tool considered as the ISC in accordance with different types of service changes. The learning technique selects the best service for each requirement and obtains the knowledge. Concerning the enterprise processes, the fuzzy intelligent tools viewed as a learning system is an option to obtain

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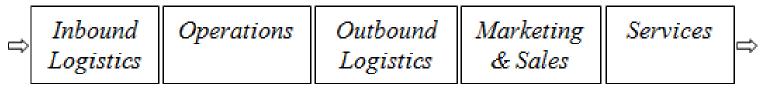

Figure 1. The supply chain stages.

different types of service, dynamically interacting with the customer needs, having an adaptation of the ISC answer in accordance to the possible changes. The customer attention uses a rule set based on the Takagi and Sugeno (TS) mechanism which requires a feedback law, adjusting the process parametres, minimizing the functional error response to updating the process (García et al., 2011).

With this perspective, this paper introduces the Fuzzy learning system (FDF) analyzing and improving the supply chain configuration structure, giving answers levels with respect to the customer requirements, changing the enterprise structure in a natural sense. This selects a specific decision using an ISC configuration in order to give the best service level to each possible scenario. In a novel view, this provides a roadmap improving the enterprise, having a different configuration level support for the supply chain (Korena and Shpitalni, 2010).

SC configuration description

A supply chain integrates a set of links that makes up an economic process from the supplier to the distribution of finished products. Each stage process has to add value as a goal. Each individual stage should be reviewed in order to obtain the best service response. In accordance with the type of service required by the customer and the best response levels at each stage, integrating and optimizing the supply chain for the enterprise structure gives the best service response to the customer. Figure 1 shows the SC in general form (Croom et al., 2000). The SC structure integrates the next stages, as seen in Figure 1:

Inbound logistics: receiving, storing, inventory, control and transportation scheduling.
Operations: machining, packaging, assembly, equipment maintenance, testing.
Outbound logistics: warehousing, order fulfillment, transportation, distribution.
Marketing and sales: channel selection, advertising, promotion, selling, pricing, retailing.
Services: support, repair, installation, training, parts management.

There are different ways to develop a supply chain as an automated intelligent process in order to optimize the enterprise services and make better decisions. Most used is expertise and heuristics. This case used a learning system integrating all the possible SC configurations to an enterprise structure inferring the type of service needed and dynamically selecting the best SC configuration giving the best customer level answer (Craves and Tomlin, 2003; Korena and Shpitalni, 2010). Each stage is analyzed separately, generating more value to the chain. To decide how to configure the SC needs to consider some characteristics that could be changed in order to obtain the best service level required by the customer, for example, the product type, velocity, category, demand, cost, suppliers and other attributes. The best configuration solution is usually defined as minimizing or maximizing a specific variable at each SC stage (Giunipero et al., 2008).

If an enterprise needs different service levels with a specific type of service required by the customer an intelligent process has to change to customer specifications. It needs to have different specific SC configurations optimizing the service level. The SC will always keep the same stages, but each of these stages will modify its value to configure the SC to a new service level for the customer needs and the enterprise type of service selected with minimum cost. The following stages allow specific service level in accordance with the SC selected (Chong and David, 2011; Yao, 2010):

(i) The customer invokes a specific type of service required
(ii) The learning process infers the actual customer needs
(iii) The selection stage gets the best supply chain configuration
(iv) The process has an update in order to give the corresponding service level

LEARNING SYSTEM DESCRIPTION

The learning system structure has an intelligent structure that infers a real process change with an actual situation. This improves a dynamical process operation because the learning description will give the best answer condition to update the process configuration and work with the optimal operation level in accordance with the changes. The objective of the learning system is the parametre estimation described as $\hat{a}_k$. When the customer selects a specific type of service described as t_k the enterprise offers the learning system that will obtain the specific parametres sequence of $\hat{a}_k$ to update the learning mechanism. This approximation to the

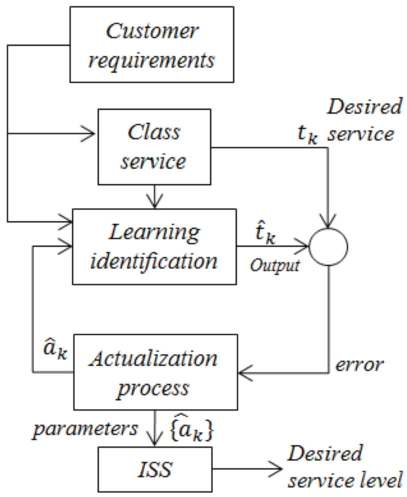

Figure 2. Identification structure services SC model.

desired type of service describes the actual customer requirements automatically (García et al., 2011; Mamdani, 1974).

The learning system has a structure that classifies its answers with different operational levels in order to select the corresponding parametre $\hat{a}_k$ from a knowledge base (KB), using the logic connectors *if-then*, to update the learning system weights describing the actual desired type of service. The next stage called intelligent supply selection (ISS), infers the $\hat{a}_k$ sequence selecting the best SC configuration values with the best service level (Craves and Tomlin, 2003; Zadeh, 1965). Figure 2 shows the learning system operation structure (García et al., 2011; Korena and Shpitalni, 2010; Takagi and Sugeno, 1986).

Figure 2 describes the learning system operation, where t_k represents the actual desired type of service, $\hat{t}_k$ as the signal approximation of the actual service type, e_k is the error between both signals and $\{\hat{a}_k\}$ is the estimated parametres sequence by the learning process representing a specific value sequence identifying the respective type of service. The selection process stage will use the parametres value $\{\hat{a}_k\}$ as a learning process inferring the type of service and selecting the best SC service level (Passino, 1998).

The FLP has a knowledge base, which is limited by the mean square error described in Equation (1). The knowledge base has all the possible values of $\hat{a}_k$ corresponding with the desired input system service. These membership values of $\hat{a}_k$ are selected by a process dynamically update its weights, with the service changes type t_k and the criterion minimizing the estimation error obtaining the best approximation of the learning output system $\hat{t}_k$ (Mamdani, 1974).

$$k\langle J_k, J_k^T\rangle = \lfloor \langle \Delta_k, \Delta_k^T\rangle + (k-1)\langle J_{k-1}, J_{k-1}^T\rangle \rfloor \in \Re^+_{[0,1]} \tag{1}$$

Theorem

Let the learning system description in Equation (2)

$$t_k = at_{k-1} + w_k \tag{2}$$

Where $t_k \in \Re^+$ as the service changes type, $a \in \Re_{[-1,1]}$ as a specific service parametre and, w_k as the actual situation; has an optimal estimation Equation (3).

$$\hat{a}_k \to a + \varepsilon_k \tag{3}$$

Proof

In agreement to $\Delta_k = t_k - \hat{t}_k$, the quadratic form Δ_k^2 into functional error (1) with Equation (2), has Equation (4).

$$\begin{aligned} k\langle J_k, J_k^T\rangle &= a^2\langle t_{k-1}, t_{k-1}^T\rangle + \langle w_k, w_k^T\rangle - \langle \hat{t}_k, \hat{t}_k^T\rangle + 2a\langle t_{k-1}, w_k^T\rangle \\ &- 2a\langle t_{k-1}, \hat{t}_k^T\rangle - 2\langle w_k, \hat{t}_k^T\rangle + (k-1)\langle J_{k-1}, J_k^T\rangle \end{aligned} \tag{4}$$

In Equation (4) the stochastic gradient with respect to "a" obtaining Equation (5).

$$a = \frac{\langle t_{k-1}, \hat{t}_k^T\rangle - \langle t_{k-1}, w_k^T\rangle}{\langle t_{k-1}, t_{k-1}^T\rangle} \tag{5}$$

Where, the paramtre and perturbation are described respectively in Equation (5).

$$\hat{a}_k \cong \frac{\langle t_{k-1}\hat{t}_k\rangle}{\langle t_{k-1}, t_{k-1}^T\rangle}, \quad \varepsilon_k \cong -\frac{\langle t_{k-1}, w_k^T\rangle}{\langle t_{k-1}, t_{k-1}^T\rangle} \tag{6}$$

Finally, the estimator is optimal and has the form (3). Then the convergence exists when $\langle t_{k-1}, w_k\rangle \to 0$ ∎.

Where "a", represents the reference variable obtaining a specific service parametre; "m" is the number of

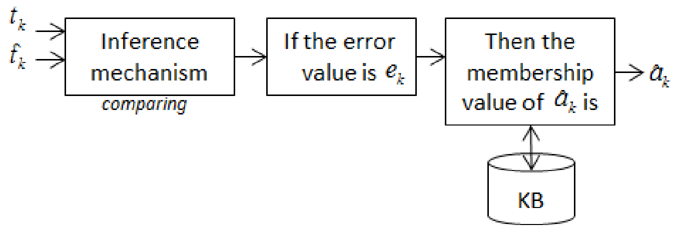

Figure 3. Fuzzy Inference Mechanism based on error values.

elements of each type of service, representing the SC stages number and; "ε_k" represents the region where the results are considered acceptable.

The functional error when $k \to m$, converge to δ_m, where $k\langle \delta_m, \delta_m \rangle = \sum_{i=1}^{m} (\varepsilon_i, \varepsilon_i^T)$ and in recursive form $= \langle \varepsilon_m \varepsilon_m^T \rangle + (m-1)\langle \delta_{m-1}, \delta_{m-1} \rangle$.

For dynamic parametres selection, in accordance with the description of the actual type of service t_k and the *FLP* $\hat{t}_k$, have the best signal approximation. This is an indicator process with respect to the actual type of service parametres. The different operational levels inside the FLP must accomplish the error criterion described in Equation (1) (García et al., 2011).

To extract the learning identification parametres in fuzzy form uses the mechanism shown in Figure 3, and uses the logic connectors *if-then*, based on a TS inference dynamically, selecting the best parametres value to the internal FLP classification levels. The different type of services, use the knowledge base that has the membership values of $\hat{a}_k$.

The fuzzy process with respect to the criterion described as $\lim_{k \to m} J_k \to J_{min}$, makes a selection of the knowledge base parametres, permitting an approximation of the output signal $\hat{t}_k$, to each actual desired service described as t_k. The learning system selection process is in heuristic form, based on probabilistic properties system. This establishes the operational levels bounded by the error functional as: $J_k \subseteq \lfloor \delta_{min}, \delta_{max})$. To each level, the process selects a specific value of $\hat{a}_k$, having as a goal the best approximation of $\hat{t}_k \cong t_k$ (Craves and Tomlin, 2003; Takagi and Sugeno, 1986).

For parametre selection of the KB into the FLP, it is important for the functional error value to take a parametre value from the knowledge base, when the functional error obtains its minimum value, approximating $\hat{t}_k$ to t_k, and is the smallest distance between both values. To each operation level the learning approach has a specific parametre configuration value updating the process mechanism. The goal is obtaining the minimum error difference approximation between the type of service required by the customer and the learning identification deducing the SC specific service level configuration (Korena and Shpitalni, 2010).

ISC selection process

The learning system architecture integrates a stage process selection that uses the parametres obtained from the previous learning stage described as $\{\hat{a}_k\}$ to each type of service level. This stage operates as a neural net that deduces the best SC configuration in accordance to the actual type of service. First, training the knowledge base network (KBN), the learning system gets the representative parametre sequences to each level previously at the training stage (implementation). It selects the value sequence to each type of service in $\{a_{kBn}\}$. All the possible $\{a_{KBn}\}$ describes different levels stored in the KBN of the Neural Net. This makes a classification of the different SC service levels with the possible type of service to be selected by the customer (Chong and David, 2011; Marcek, 2004).

This stage selection makes a comparison between the actual learning identification parametres $\{\hat{a}_k\}$ and each sequence $\{a_{kBn}\}$ stored previously in the knowledge base network obtaining the error value. The error rank establishes the correspondence to SC configuration using fuzzy rules which recognize and select the configuration service type. The TS inference has the sequence described as $[\{\hat{a}_k\}, \{a_{kBn}\}]$. Figure 4, shows the network structure to select the SC configuration (Marcek, 2004).

The neural architecture represents the stages, which obtain the parametre information described as $\{\hat{a}_k\}$ in the learning system. This process starts with first layer (input) and continues to the other neurons, in the hidden layer. The neuronal structure process from the previous nodes allows the following stages, having as a goal identifying the corresponding SC configuration (Marcek, 2004):

(i)Inference layer: The error criterion service level described as D_e, into the rank $[0, \varepsilon_k]$, $\varepsilon_k \in \Re^+$, makes a comparison of actual $\{\hat{a}_k\}$ and the $\{a_{kB_n}\}$ stored in the knowledge base. The minimum error distance between values considers the rank error

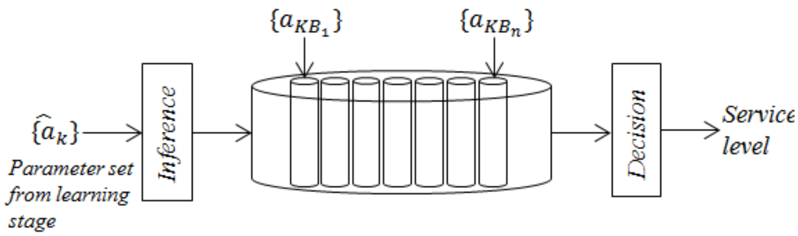

Figure 4. Supply chain configuration selection.

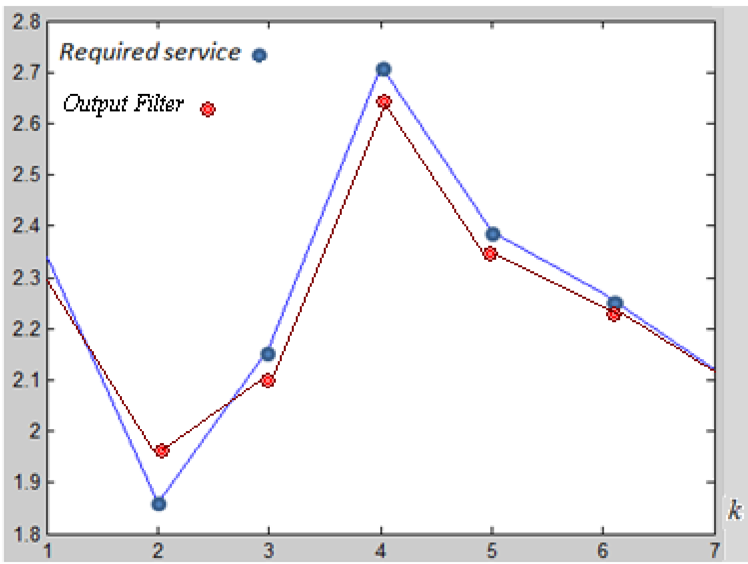

Figure 5. Learning stage applied into identification parametres.

defined previously (García et al., 2011). The error is described by the distance between the $\{\hat{a}_k\}$ as actual parametres value and the stored sample $\{a_{kBn}\}$, given that $d(\{\hat{a}_k\},\{a_{ID}\}) \in \{D_a\} | \{D_a\} \subset R^+_{[0,\varepsilon_k]}$, then $\{\hat{a}_k\}$ has a *membership function* into the *knowledge base* neural net corresponding to SC configuration. However, in the case of $d(\{\hat{a}_k\},\{a_{ID}\}) \notin \{D_a\}$, then $\{\hat{a}_k\}$ does not belongs to the network, then there is no type of service required by the customer and it cannot select a corresponding SC configuration.

(ii)Actualization layer: This stage makes the update of the SC configuration value to the service level required for the process in accordance with the actual type of service selected by the customer, using a set of fuzzy rules (*if-then*) to this inference process (Korena and Shpitalni, 2010). If the $\{a_{kBn}\}$ set value from the Bn is the service level 1, then the SC configuration is selected.

SIMULATION

For simulation there are five possible supply chain options to choose in order to satisfy customer needs with the minimum cost. First, the customer configures their requirements in the database, and the learning identification stage obtains the parametres that corresponds to customer needs. The network gets the parametres and makes a selection of the best corresponding supply chain configuration complying with customer selection with minimum cost for the business, which provides a dynamic decision making different possible service levels (García et al., 2011; Zadeh, 1965). Figure 5, shows the learning approximation requirements in order to obtain the parametres to be used in the selection stage. Figure 6, is the learning stage convergence (1) based on the mean square error in accordance with the approximations. In the selection process, the network has an inference stage that compares the learning stage parametre values with the values stored into the knowledge base. This comparison process is shown in Figure 7.

Figure 8, shows the possible supply chains configurations stored at the knowledge base. It could have more configurations stored, considering the capacity and flexibility of the company. In accordance with customer needs and the error distance of Figure 7,

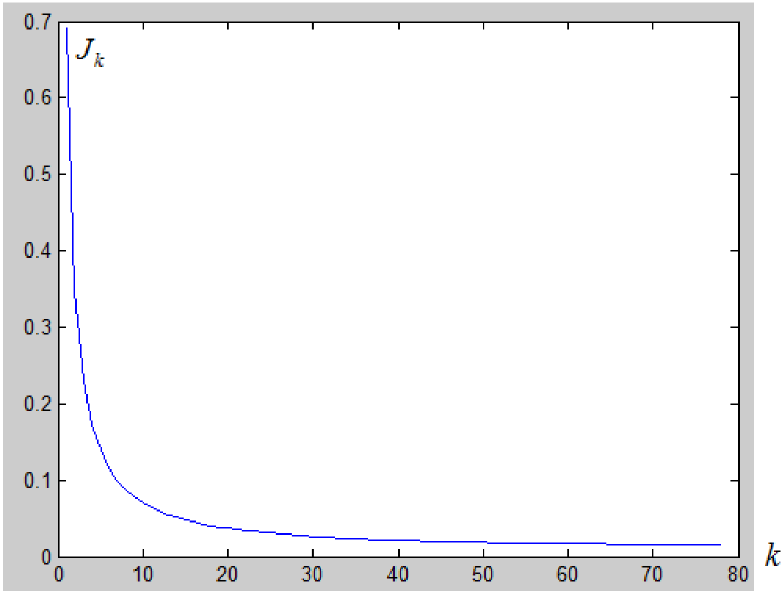

Figure 6. Recursive stage error.

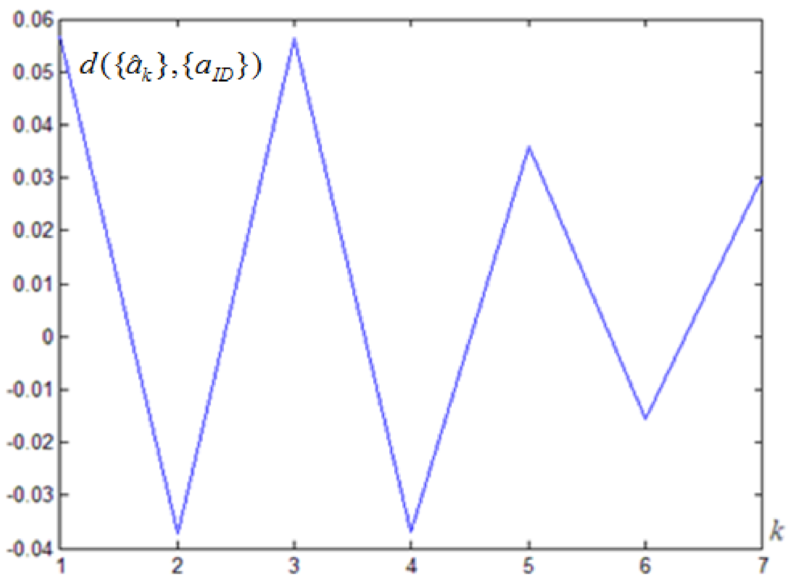

Figure 7. Error inference at the network stage.

one supply configuration will be selected. The service level represents the supply chain selected in the process. Figure 9 shows the configuration with the minimum cost, considering the best service for customer requirements.

CONCLUSIONS

The supply chain in the learning system needs a Neuro-fuzzy model with dynamical decisions offering to the customer different possible service levels. In this paper customer service was viewed with the decisions selected in an intelligent form, estimating the best coefficients required by the supply process. The decisions were defined in the knowledge base using inferences rules and transformed into actions required for the supply process. Automatically, all the supply structure was adjusted in accordance with customer needs and minimum cost. The

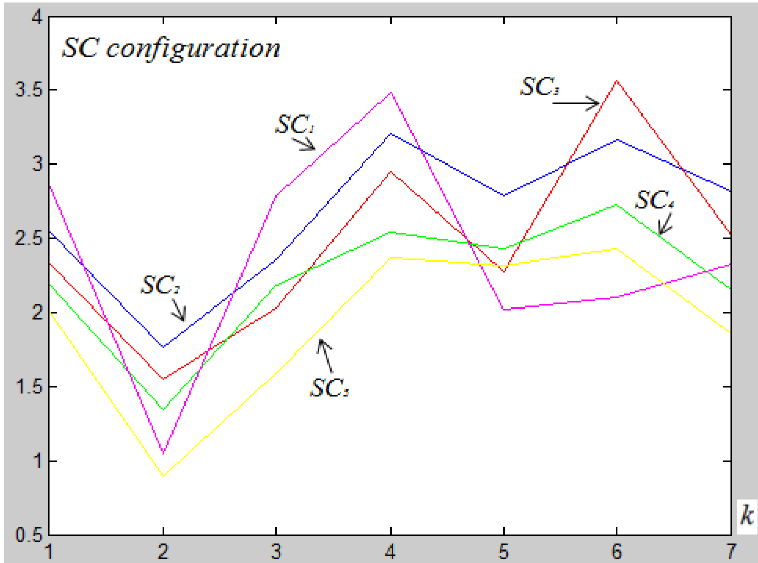

Figure 8. Supply chain set to be selected in the network.

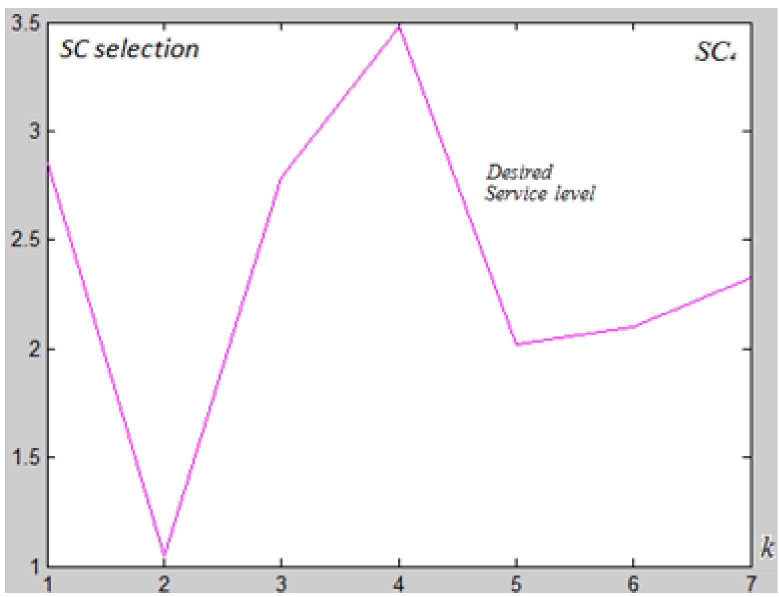

Figure 9. Supply chain selected with the minimum cost as a service level.

simulation of this process shows the operation of the dynamic supply chain using a learning process that describes customer requirements obtaining the parametres, and then the supply chain selection process with a neural network structure.

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