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Stochastic plans in SMEs: A novel multidimensional fuzzy logic system (mFLS) approach

Planes estocásticos en PyMEs: Novedoso enfoque de un sistema multidimensional difuso

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ABSTRACT

Manufacturing planning in small and medium enterprises (SMEs) uses a deterministic behavior, and the execution of these plans has a stochastic behavior. The evaluation of the manufacturing planning is based on a simple criterion as job on time or job delayed, without integrating conditions of uncertainty in the cycle times for each job. The aim of this paper is to propose a novel multidimensional stochastic Fuzzy Logic System (msFLS) approach to execute a plan with stochastic behavior in knitting SMEs and their evaluation. In this paper, two main contributions are identified. On one hand, the generation of a multi-dimensional diffuse system is proposed. Normal probability density function is used to generate multi linguistic variables to transform deterministic plans to stochastic plans in knitting SMEs. The fuzzy subsets or linguistic terms are labelled and categorized in a simple and clear language as poor (P), regular (R), good (G) and excellent (E). The Gaussian function was used as a membership function. On the other hand, the second contribution is the use of the sum of frequencies in the stage of implication for the multi-Fuzzy system. This research was validated through an integration of two different intelligent techniques such as the proposed novel msFLS and artificial neural networks. Neural networks were used as a generalization mechanism to perform any stochastic planning in the knitting companies. The inputs and outputs of the fuzzy system are used as training patterns in the neural network. The stages of the proposed approach are explicitly described and applied to random data and validated with real data of SMEs of the South of Guanajuato, Mexico. The proposed system had a positive response in the textile company, which continues to be used to carry out its manufacturing planning and the evaluation of its execution.

Keywords: Stochastic plans, fuzzy system, normal probability density, neural network.

RESUMEN

La planeación de la manufactura en pequeñas y medianas empresas (PYMES) utiliza un comportamiento determinista, y la ejecución de estos planes tiene un comportamiento estocástico. La evaluación de la planeación de manufactura se basa en un criterio simple como trabajo a tiempo o trabajo retrasado, sin integrar condiciones de incertidumbre en los tiempos de ciclo para cada trabajo. En este artículo se propone un enfoque nuevo denominado *sistema estocástico multidimensional de lógica difusa* (msFLS) para realizar un plan con comportamiento estocástico en las pymes de tejido de punto. Esta investigación plantea dos contribuciones principales: La primera es la generación de un sistema difuso multidimensional. La función de densidad de probabilidad normal se utiliza para generar variables multi-lingüísticas como función de transformación del plan determinístico a un plan estocástico en las pymes de tejido de punto. Los subconjuntos difusos o los términos lingüísticos se etiquetan y categorizan en un claro y simple lenguaje como: pobres (P), regulares (R), buenos (G) y excelentes (E). La función gaussiana fue utilizada como función de membresía. El segundo es el uso del indicador "suma de frecuencias" en la etapa de implicación para el sistema multi-difuso. Esta investigación fue validada a través de la integración de dos técnicas inteligentes diferentes: msFLS y redes neuronales. Las redes neuronales se utilizaron como un mecanismo de generalización para realizar cualquier planeación estocástica en las empresas de tejido de punto. Las entradas y salidas del sistema difuso se utilizan como patrones de entrenamiento en la red neuronal. Las etapas del enfoque propuesto se describen explícitamente y se aplican a datos aleatorios múltiples y se validan con datos reales de PYMES del Sur de Guanajuato, México. El sistema propuesto tuvo una respuesta positiva en la empresa textil, el cual sigue utilizándose para realizar sus planeaciones de trabajos y la evaluación de su ejecución.

Palabras clave: Planes estocásticos, Sistema difuso, densidad de probabilidad normal, red neuronal.

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Introducction

It is well known that the outcome of the planning process is the information for the corresponding manufacturing processes and their fixed parameters. Additionally, the machines, tools, and fixtures required are identified in order to perform the manufacturing processes (Haddadzade *et al.*, 2014). Scheduling usually starts from a given set of

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activities, which must satisfy a set of temporal and resource constraints. The result is a schedule in which precise start times are identified and precise resources are allocated to each activity (Bidot *et al*., 2009). However, when activities are executed by workers, the concepts of unary resources and activity duration must be reassessed. The problem is that the committed effort can vary over time, according to workers availability or to the joint execution of different activities (Alfieri *et al*., 2012). In the real world, however, project activities are subject to considerable uncertainty arising from such factors as unproven technology, human performance variability, and natural disruptions (Zhu *et al*., 2007). Under uncertainty conditions, the baseline schedule must be robust, i.e., it must be insensitive to the occurrence of uncertainty events within a given range of magnitude (Alfieri *et al*., 2012). The authors cited above, proposed the definition of a stochastic execution behavior in any deterministic plans. The aim of this paper is to develop a novel multidimensional stochastic Fuzzy Logic System (msFLS) that allows to consider stochastic plans in order to manage uncertainty in small and medium enterprises.

Manfredsson (2016) mentioned that the textile industry in Europe consists mainly of small and medium enterprises, which are a vital part of the European Union economy. A number of systems have been proposed in order to increase the productivity of the textile industry through the SMEs taking into account their main characteristics. Considering that there is a little technological knowledge in small and medium enterprises, Baeza (2016) proposed a methodology called REDUTEX to compete with large-scale enterprises and reduce the lead time in knitting enterprises. Hu *et al*. (2016) proposed lean production systems, to improve organizational performance. In their application to small and medium enterprises, business assistance from external agencies, such as management consultants, is often required. Braga *et al*. (2016) concluded that it exists the role of informal cooperation in business internationalization processes of the Portuguese textile SMEs. Tran & Jeppesen (2016) mentioned that in terms of informal practices, managers and workers share long-lasting cultural norms, expectations, and practices, and expect proper implementation of the Labor Code to treat each other properly. McAdam *et al*. (2014) informed the development of an analytical model that demonstrates the dynamic underlying routines for the absorptive capacity process and the development of a number of summative propositions relating the characteristics of SMEs to Six Sigma and Lean Six Sigma implementations. These investigations concluded that the textile industry is composed of small and medium enterprises. The proposed systems at these researches have been successful in their applications. Knitting is the process of forming fabric by inter-loops of thread in a series of loops connected by needles. Knitted fabrics offer excellent comfort qualities due to their inherent softness and flexibility, this type of clothing has been preferred for a long time due to its elasticity, soft touch, provides light heat, resistance to wrinkles and ease of care (Karthikeyan, Nalankilli, Shanmugasundaram & Prakash, 2016). The planning of scheduled tasks or jobs in any manufacturing or service industry are based on deterministic cycle times. The evaluation of planning execution is based on a very simple criterion, such as job finished on time or job delayed. The conditions of uncertainty present in each job execution are not integrated, making inaccurate delivery estimates. The reason for this research is to perform a stochastic planning based on a novel fuzzy system, which integrates uncertainty conditions by categorizing 4 different ranges to the deterministic cycle times transforming them into stochastic cycle times.

In this research, a novel system to execute stochastic job plans in the production stage based on deterministic plans is proposed, with the aim of having higher reliability in the manufacturing plans of any industry. Presenting a scientific contribution in the development of a stochastic planning in the field of engineering. The proposed approach is validated in a knitting company of South of Guanajuato.

This paper is organized as follows: the literature review is presented in the first section. After that, the development of the methodology with the proposed approach is described. In the third section, the results are shown and finally, the conclusions are presented in the last section.

Literature review

Fuzzy logic and hybrids genetic-fuzzy systems has applications in various productive sectors with successful results. Kir & Yazgan (2016) studied a scheduling problem on a single machine producing dairy products subject to variable due dates, earliness and tardiness penalty costs and sequence dependent setup times. In addition to this, applicability of the schedules was appraised using Fuzzy Axiomatic Design (FAD) to determine earliness and tardiness penalty costs. Rahman *et al*. (2015) have proposed a genetic algorithm based on a scheduling approach with an objective of minimizing the sum of the setup and holding costs. The proposed algorithm has been tested using scenarios from a real-world sanitaryware production system, and the experimental results illustrates that the proposed algorithm can obtain better results in comparison to traditional reactive approaches. Hu (2015) developed a multi-objective genetic algorithm (moGA) for solving the bi-objective model by using a two-part representation scheme. The sensitivities of the algorithmic parameters and tradeoffs between daytime preference and delayed workloads are analyzed by numerical experiments. Each of these researches uses genetic algorithms for optimization of a deterministic sequence of work. However, it is very difficult to implement it precisely due to the implicit variability of factors such as the human factor, machinery and changes in decision-making by supervisors. Therefore, there is an important lack of an evaluation tool of the lead time. Orji & Wei (2015) presented a novel modeling approach of integrating information on supplier behavior in fuzzy environment with system dynamics simulation.

Such modeling technique results in a more reliable and responsible decision support system. Gostimirović *et al*. (2014) reports the development of two intelligent models for the electric discharge machining process using adaptive-neuro-fuzzy-inference system and genetic programming. The results indicate that the genetic programming technique gives slightly smaller deviation of the measured values of model than a neuro-fuzzy model. Chen *et al*. (2013) presented an experimentally verified five-layer and three-phase network, which shows the effectiveness with which the neuro-fuzzy system automatically determines membership functions and selects activation fuzzy rules using both system identification and vibration control examples in engineering applications. Bahador *et al*. (2013) developed an expert system that we called an expert system for control chart patterns recognition for recognition of the common types of control chart patterns. The proposed system includes three main modules: the feature extraction module, the classifier module and the optimization module. Fazlollahtabar & Mahdavi-Amiri (2013) propose a cost estimation model based on a fuzzy rule backpropagation network, configuring the rules to estimate the cost under uncertainty. Pamucar *et al*. (2013) described the Adaptive Neuro Fuzzy Inference System, thus making possible a strategy of coordination of transport assets to formulate an automatic control strategy. This model successfully imitates the decision-making process of the chiefs of logistic support. A multiple linear regression analysis is applied to analyze the rules and identify the effective rules for cost estimation. Then, using a dynamic programming approach, we determine the optimal path of the manufacturing network. Echeverri *et al*. (2012) developed a methodology for evaluating contributions in collaborative systems with implementation of fuzzy logic to the processing of measurement criteria as it is incorporated some level of subjectivity. Zarbini *et al*. (2011) presented an evaluation and selection of suppliers as case study on the Mazandaran textile factory, one of the biggest textile industrial units, in Iran. The effective criteria for ranking the suitable suppliers are evaluated using hierarchical fuzzy TOPSIS model. Guruprasad & Behera (2010) analyzed the application of principal soft computing for the study of textile processes and products as fibre classifications, color grading, yarn and fabric property prediction and even to search for a pleasing garment design. Each of these researches uses neuro fuzzy hybrid or expert systems using the traditional structure of an integrated neural network-fuzzy system. The main limitations or gaps detected in the literature review are threefold: There is a little technological knowledge in SMEs, in order to compete with large-scale enterprises. The sequences obtained by genetic algorithms are deterministic. It is considerably difficult to understand that the execution of the planning is deterministic.

The research proposed in this manuscript explores a single mamdani fuzzy system through a novel multidimensional fuzzy system which evaluates and ranks the implementation of the planned tasks, based on an environment with multidimensional uncertainty. This study exposes a transformation function of any deterministic plans to stochastic plans through a novel multidimensional fuzzy stochastic gray box. Each job of the optimal sequence represents a linguistic variable. Each fuzzy system generates a pattern for the training of a neural network to evaluate the stochastic plans.

Methodology

The methodology is based on the conceptualization of the deterministic plans and their stochastic execution. The research was carried out with the support of some textile entrepreneurs. A critical stage was to carry out the analysis of the production processes, allowing to understand the behavior of the deterministic planning and stocastic execution of those plans. Finally, the proposed msFLS approach was developed, which would allow companies to evaluate their execution performance and compete with other large scale businesses. The proposed approach was simulated using Matlab code. See Figure 1.

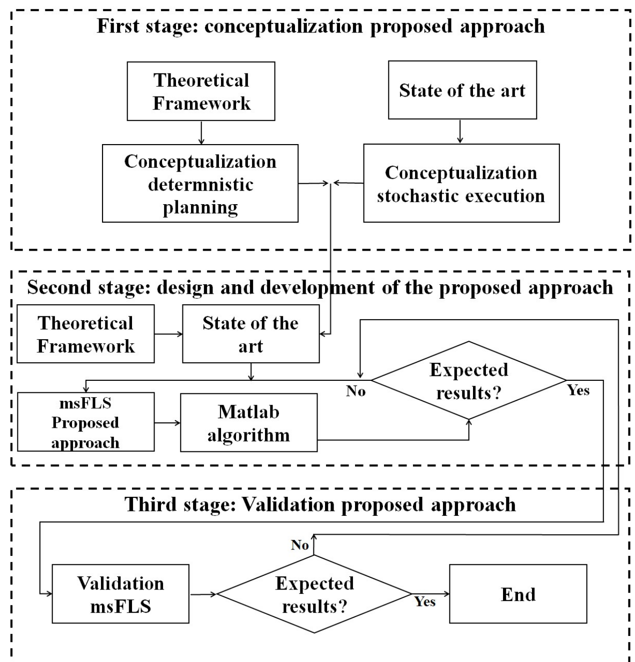

Figure 1. Methodology.
Source: Authors

msFLS Approach

The aim of this article is to provide an approach to realize and evaluate a stochastic plan of a job sequence. This approach consists of three modules: stochastic classification, training and validation. The proposed research presents msFLS approach for the small and medium enterprises to plan and evaluate the performance of their execution. See Figure 2.

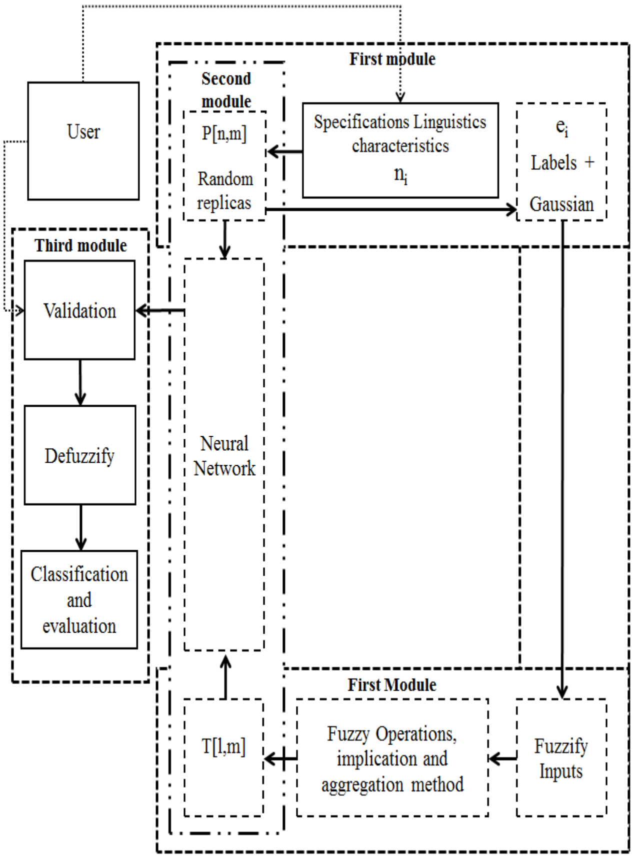

Figure 2. Methodology proposed approach.
Source: Authors

Classification module (gray box system): Random replicas

The structure of a Multi Stocastic Fuzzy Neural system used in this research is similar to a multi-layer feed-forward NN. The proposed approach has input and output layers or stages and four hidden layers that represent a multi stocastic replicas, membership functions and fuzzy rules. Figure 3 shows a Multi Fuzzy Stochastic system that corresponds to a novel multi Mamdani fuzzy inference model. For simplicity, we assume that the Neuro Fuzzy system has two inputs, m random replicas and m outputs. Accordingly, there is an optimal sequence obtained by an expert or some genetic algorithm of n nodes in layer 1, multi stocastic replicas established in layer 2. Nodes in layer 2 represent multi LFS nodes that directly transmit input signals to the next layer. Layer 3 have used a bell-shaped membership function to fuzzify each random multi replicas of the input variables. The normal distribution function is used to generate multi linguistic variables. The fuzzy subsets or linguistic terms are labelled as poor (P), regular (R), good (G) and excellent (E). Thus, layer 4 performs frequency count for each linguistic label. Nodes in layer 5 constitute "fuzzy rule nodes" based on Frecuency distribution. The sum of each linguistic label by number of replication is performed and the maximum sum of frequencies is identified. The links related to layer 4 and layer 5 define the premises and consequences of the rule nodes, respectively. Layer 6 has the defuzzify evaluation of the novel multi fuzzy system proposed and represents the output layer.

Training and validation module (black box system):

The neural network feed-forward backpropagation is the second intelligent module.

The Neural Network Toolbox is used to create a network. The network consists of vector J [n, m] like a input data obtained by the fuzzy multidimensional stochastic system proposed in this research and vector T [n, 1] like a output data obtained from the outputs of a multi fuzzy stochastic module. A feedforward network is created with two layers of n input elements ten tansig hidden neurons, and four output neurons purelin. System reliability pattern recognition neural network is measured by testing the network with hundreds of input vectors with varying amounts of noise.

The interactive validation is the third module of IMPES system.

Validation is an assessment of the vector E [n] for multiple executions of planning lead time customer delivery. An average of all dates final assessment evaluates and ranks with the corresponding linguistic label. The evaluation range is 1-10.

Results

The tasks scheduling is performed by the production supervisor through the rule first in, first out. He estimated the completion time of each task and ultimately make the evaluation on two criteria: finished on time or delayed. Eight assigned tasks are estimated. See Equations (1) and (2).

Deterministic sequence (Fist in First out)

$$Ds = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \end{bmatrix} \tag{1}$$

Expected Deterministic Lead time

$$EDLT = \begin{bmatrix} 8.2099 & 10.1249 & 11.3148 & 12.2126 & 17.7457 & 16.3337 & 18.8959 & 14.2716 \end{bmatrix} \tag{2}$$

An input matrix is generated with the transpose of the values obtained in Equation (2). See Equation (3).

$$Inputs^T = EDLT \tag{3}$$

At the present approach each deterministic parameter represents a linguistic variable. 10 replicates for each variable are generated. Function normal probability distribution is used. See Equation (4).

Each linguistic variable is fuzzify in four linguistic labels: Bad, Regular, Good and Excellent.

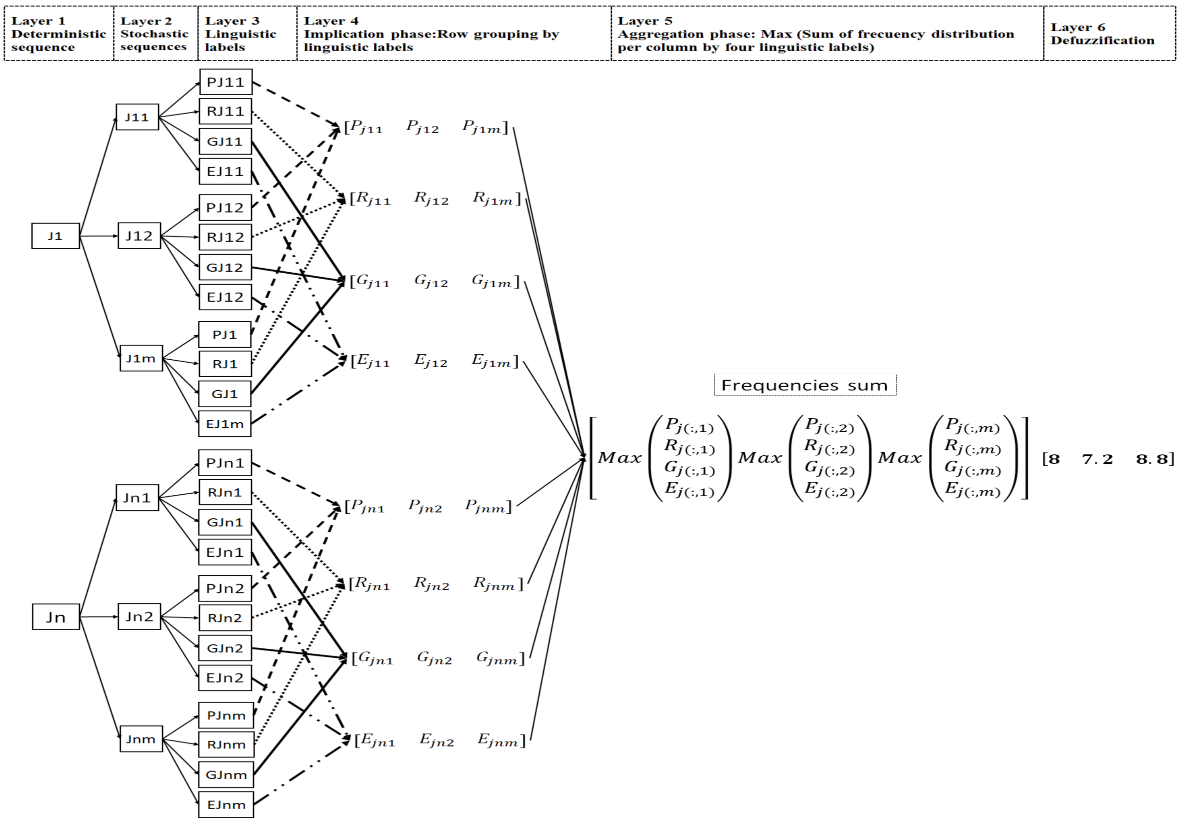

Figure 3. Gray Box System.
Source: Authors

Equation (5) shows the coded values of the linguistic label: *Bad*.

$$Inputs^T = \begin{bmatrix} 7,8178 & 9,3686 & 9,7875 & 5,1363 & 8,6441 & 8,9545 & 9,0922 & 8,2733 & 8,3466 & 6,6388 \\ 10,4357 & 10,4843 & 11,6911 & 8,9105 & 12,4403 & 11,4397 & 11,3757 & 8,1537 & 7,1030 & 11,9341 \\ 11,8872 & 10,5741 & 10,0259 & 10,1533 & 12,0553 & 13,3501 & 13,0324 & 10,5905 & 8,6741 & 11,2905 \\ 11,5498 & 9,4444 & 10,9924 & 11,3563 & 14,7928 & 11,6630 & 13,2424 & 11,0040 & 11,6835 & 14,9681 \\ 16,3833 & 19,7108 & 17,4256 & 19,8701 & 19,6662 & 16,4004 & 18,9201 & 19,9014 & 18,7414 & 16,4374 \\ 18,1024 & 19,6959 & 57,9970 & 17,3643 & 20,6623 & 11,9651 & 14,7137 & 13,7076 & 14,9312 & 18,3454 \\ 20,0316 & 17,2255 & 19,0052 & 18,7835 & 15,8198 & 18,8526 & 17,1430 & 18,4097 & 18,8833 & 17,7578 \\ 13,8271 & 14,3977 & 13,0874 & 17,0055 & 13,5090 & 13,3185 & 15,4888 & 16,3400 & 14,0113 & 12,8920 \end{bmatrix} \quad (4)$$

$$Bad = \begin{bmatrix} 0 & 0,3004 & 0,1437 & 0,0275 & 0 & 0 & 0 & 0 & 0 & 0,4991 \\ 0 & 0 & 0,4548 & 0,3125 & 0,1341 & 0,6041 & 0,6429 & 0,0740 & 0,0039 & 0,3255 \\ 0 & 0 & 0,1769 & 0,2224 & 0 & 0,3430 & 0,5190 & 0 & 0,0057 & 0 \\ 0 & 0,1090 & 0,8561 & 0 & 0,0052 & 0 & 0,2387 & 0,8616 & 0 & 0,0029 \\ 1 & 0,0039 & 0 & 0,0023 & 0,0046 & 0,9999 & 0,0401 & 0,0021 & 0 & 0,9985 \\ 1 & 0,2809 & 0 & 0,7615 & 0,0378 & 0,0000 & 0,0032 & 0,0001 & 0,0066 & 0,9709 \\ 1 & 0,0195 & 0 & 0 & 0,0001 & 0 & 0,0154 & 0 & 0 & 0,0754 \\ 0 & 0 & 0,7607 & 0,0064 & 0 & 0 & 0,2514 & 0,0425 & 0 & 0,6459 \end{bmatrix} \quad (5)$$

The values at zero (0) means that no exist degree of membership within the range set. Four decimal values with zero (0,0000) means they have a degree of membership in the range set very low and the decimal format cannot appreciate the value respectively.

For each linguistic label, a count and frequency sum are performed and used on implication stage. See Equations (6), (8), (10) and (12).

Count and Sum of Bad Frecuency distribution. See Equation (6).

$$Bad = \begin{bmatrix} 3 & 5 & 5 & 6 & 5 & 4 & 7 & 5 & 3 & 7 \end{bmatrix} \quad (6)$$

Equation (7) shows the coded values of the linguistic label: *Regular*.

$$Regular = \begin{bmatrix} 0 & 0,1179 & 0,0318 & 0,0017 & 0 & 0 & 0 & 0 & 0 & 0,4991 \\ 0 & 0 & 0,2464 & 0,1265 & 0,0281 & 0,4082 & 0,4560 & 0,0098 & 0,0001 & 0,1359 \\ 0 & 0 & 0,0460 & 0,0691 & 0 & 0,1492 & 0,3116 & 0 & 0,0001 & 0 \\ 0 & 0,0194 & 0,7587 & 0,9673 & 0,0001 & 0 & 0,0784 & 0,7674 & 0 & 0,0000 \\ 1 & 0,0001 & 0 & 0,0000 & 0,0001 & 0,9997 & 0,0033 & 0,0000 & 0,0071 & 0,9974 \\ 1 & 0,1047 & 0 & 0,6161 & 0,0030 & 0,0000 & 0,0000 & 0,0000 & 0,0001 & 0,9489 \\ 1 & 0,0009 & 0 & 0 & 0,0000 & 0 & 0,0006 & 0 & 0 & 0,0101 \\ 0 & 0 & 0,6149 & 0,0001 & 0,9140 & 0,7946 & 0,0859 & 0,0037 & 0 & 0,4597 \end{bmatrix} \quad (7)$$

Count and Sum of Regular Frecuency distribution. See Equation (8).

$$Regular = \begin{bmatrix} 3 & 5 & 5 & 7 & 6 & 5 & 8 & 5 & 4 & 7 \end{bmatrix} \quad (8)$$

Equation (9) shows the coded values of the linguistic label: *Good*.

$$Good = \begin{bmatrix} 0 & 0,0081 & 0,0004 & 0,0000 & 0 & 0,0755 & 0,0389 & 0 & 0 & 0,0620 \\ 0 & 0 & 0,0428 & 0,0095 & 0,0003 & 0,1332 & 0,1708 & 0,0000 & 0,0000 & 0,0112 \\ 1 & 0,0318 & 0,0010 & 0,0024 & 0,9450 & 0,0138 & 0,0726 & 0,0346 & 0,0000 & 0 \\ 1 & 0,0001 & 0,5372 & 0,9279 & 0,0000 & 0,9747 & 0,0032 & 0,5511 & 0,9649 & 0,0000 \\ 1 & 0,0000 & 0 & 0,0000 & 0,0000 & 0,9994 & 0,0000 & 0,0000 & 0,0000 & 0,9942 \\ 1 & 0,0062 & 0 & 0,3363 & 0,0000 & 0,0000 & 0,0000 & 0,0000 & 0,0000 & 0,8887 \\ 1 & 0,0000 & 0 & 0 & 0,0000 & 0 & 0,0000 & 0 & 0 & 0,0000 \\ 0 & 0 & 0,3348 & 0,0000 & 0,8168 & 0,5961 & 0,0040 & 0,0000 & 0 & 0,1740 \end{bmatrix} \quad (9)$$

Count and Sum of Good Frecuency distribution. See Equation (10).

$$Good = \begin{bmatrix} 5 & 6 & 5 & 7 & 7 & 7 & 8 & 6 & 5 & 7 \end{bmatrix} \quad (10)$$

Equation (11) shows the coded values of the linguistic label: *Excellent*.

$$Excellent = \begin{bmatrix} 1 & 0,0000 & 0,0000 & 0,0000 & 0,0042 & 0,0000 & 0,0000 & 0 & 0 & 0,0000 \\ 1 & 0,9813 & 0,0000 & 0,0000 & 0,0000 & 0,0003 & 0,0009 & 0,0000 & 0,0000 & 0,0000 \\ 1 & 0,0000 & 0,0000 & 0,0000 & 0,7976 & 0,0000 & 0,0000 & 0,0000 & 0,0000 & 0 \\ 1 & 0,0000 & 0,0833 & 0,7412 & 0,0000 & 0,9026 & 0,0000 & 0,0923 & 0,8668 & 0,0000 \\ 1 & 0,0000 & 0,0002 & 0,0000 & 0,0000 & 0,9977 & 0,0000 & 0,0000 & 0,0000 & 0,9769 \\ 1 & 0,0000 & 0,0000 & 0,0128 & 0,0000 & 0,0000 & 0,0000 & 0,0000 & 0,0000 & 0,6236 \\ 1 & 0,0000 & 0 & 0 & 0,0000 & 0 & 0,0000 & 0,0000 & 0 & 0,0000 \\ 1 & 0 & 0,0126 & 0,0000 & 0,4451 & 0,1263 & 0,0000 & 0,0000 & 0,7623 & 0,0009 \end{bmatrix} \quad (11)$$

Count and Sum of Excellent Frecuency distribution. See Equation (12).

$$Excellent = \begin{bmatrix} 8 & 7 & 7 & 7 & 8 & 7 & 8 & 7 & 6 & 7 \end{bmatrix} \quad (12)$$

The summary of the sum of frequencies is observed in the following matrix, which were used as fuzzy operators in stage 4. Numbers in bold represent the maximum values of the sum of frequencies of each linguistic label. See Equation 13.

$$\mathrm{Re}\,sume = \begin{bmatrix} 3 & 5 & 5 & 6 & 5 & 4 & 7 & 5 & 3 & \mathbf{7} \\ 3 & 5 & 5 & \mathbf{7} & 6 & 5 & \mathbf{8} & 5 & 4 & 7 \\ 5 & 6 & 5 & 7 & 7 & \mathbf{7} & 8 & 6 & 5 & 7 \\ \mathbf{8} & \mathbf{7} & \mathbf{7} & 7 & \mathbf{8} & 7 & 8 & \mathbf{7} & \mathbf{6} & 7 \end{bmatrix} \quad (13)$$

For each maximum value of the frequency sum, its membership value is identified and used in stage 5 of implication. When there is a tie in the sum of frequencies, the highest value of the membership function is sought and used as the output of the fuzzy system.

Linguistic label Bad: Only corresponds 1 maximum Frecuency sum of 10th column. The maximum value of column 10 is identified in the matrix of the Bad linguistic label with location (5,10). See Matrix Bad.

Linguistic label Regular: Only corresponds 2 maximum Frecuency sum of 4th and 7th columns. The maximum value of column 4 and 7 are identified in the matrix of the Regular linguistic label with locations (4,4) and (2,7). See Matrix Regular.

Linguistic label: Only corresponds 1 maximum Frecuency sum of 6th column. The maximum value of column 6 is identified in the matrix of the Good linguistic label with location (5,6). See Matrix Good.

Linguistic label *Excellent*: Corresponds 6 maximum Frecuency sum of 1th, 2th, 3th, 5th, 8th and 9th columns. The maximum values of column 1, 2, 3, 5, 8 y 9 are identified in the matrix of the Good linguistic label with locations (8,1), (2,2), (4,3), (3,5), (4,8), (4,9). See Matrix *Excellent*.

The linguistic label is identified with the maximum sum frequency and the maximum value is identified in the corresponding matrix. This value represents the output of msFLS proposed. See Equation (14).

$$Output = \begin{bmatrix} 1,0000 & 0,9813 & 0,0833 & 0,9673 & 0,7976 & 0,9994 & 0,4560 & 0,0923 & 0,8668 & 0,9985 \end{bmatrix} \quad (14)$$

It generalizes stochastic plan evaluation via a neural network. The training is done with the inputs and outputs of the msFLS. See Figure 4.

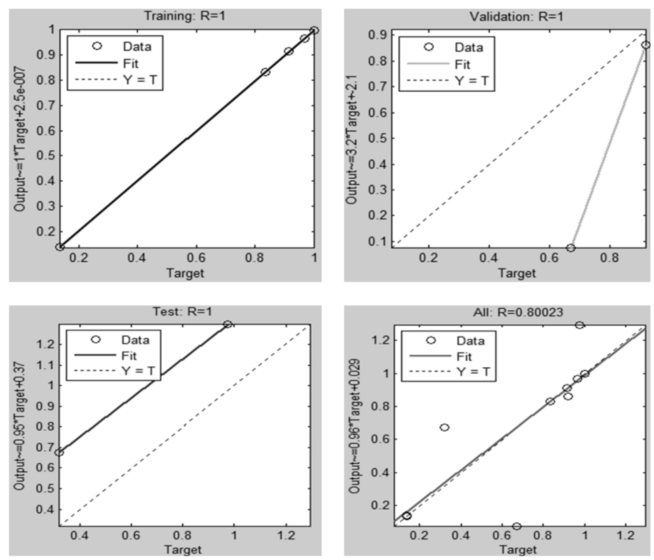

Figure 4. Neural network.
Source: Authors

Finally, the evaluation of stochastic plan of job orders is done.

Below ten different stochastic performances are evaluated based on the deterministic estimate by the supervisor. See Equations (15) and (16).

Det Lead time

$$DetLeadTime = \begin{bmatrix} 8,2099 & 10,1249 & 11,3148 & 12,2126 & 17,7457 & 16,3337 & 18,8959 & 14,2716 \end{bmatrix} \quad (15)$$

$$Validation = \begin{bmatrix} 8,2501 & 8,2553 & 8,1703 & 8,2548 & 18,1928 & 8,2319 & 8,2755 & 8,0943 & 8,2173 & 8,1476 \\ 10,0807 & 10,0989 & 10,0413 & 10,1904 & 10,0997 & 10,1014 & 10,1247 & 10,1625 & 10,1347 & 10,1456 \\ 11,2835 & 11,3508 & 11,2565 & 11,3116 & 11,3260 & 11,4249 & 11,3273 & 11,3055 & 11,3439 & 11,2385 \\ 12,2726 & 12,2276 & 12,2945 & 12,2170 & 12,1740 & 12,2086 & 12,2653 & 12,1171 & 12,1608 & 12,1155 \\ 17,8056 & 17,7557 & 17,7583 & 17,7067 & 17,7617 & 17,7186 & 17,7230 & 17,7083 & 17,7862 & 17,7194 \\ 16,3572 & 16,3399 & 16,3236 & 16,3451 & 16,3001 & 16,3283 & 16,3087 & 16,3427 & 16,3670 & 16,2297 \\ 18,9358 & 18,8785 & 18,8483 & 18,8281 & 18,8633 & 18,8570 & 18,8813 & 18,8889 & 18,9728 & 18,9489 \\ 14,2115 & 14,1557 & 14,2614 & 14,2799 & 14,2616 & 14,2788 & 14,2445 & 14,2424 & 14,3368 & 14,2878 \end{bmatrix} \quad (16)$$

Ten different scenarios validation with no significative variation in the differences of deterministic plan and stochastic execution were validated. See Table 1.

Table 1. Comparative real evaluation and proposed approach

Deterministic plan	Stochastic plan	Real evaluation	Proposed evaluation	Stochastic plan	Real evaluation	Proposed evaluation
8,2099	8,2501	Delayed	*Subjective evaluation:*	8,2553	Delayed	*Subjective evaluation:*
10,1249	10.0807	On time		10,0989	On time	
11,3148	11,2835	On time		11,3508	Delayed	
12,2126	12,2726	Delayed	*Quality is good*	12,2276	Delayed	*Quality is good*
17,7457	17,8056	Delayed		17,7557	On time	
16,3337	16,3572	Delayed	*Objective evaluation*	16,3399	Delayed	*Objective evaluation*
18,8959	18,9358	Delayed		18,8785	On time	
14,2716	14,2115	On time	*7,1118*	14,1557	On time	*7,1632*

Deterministic plan	Stochastic plan	Real evaluation	Proposed approach	Stochastic plan	Real evaluation	Proposed approach
8,2099	8,1703	On time	*Subjective evaluation:*	8,2548	Delayed	*Subjective evaluation:*
10,1249	10,0413	On time		10,1904	Delayed	
11,3148	11,2565	On time	*Quality is good*	11,3116	On time	*Quality is good*
12,2126	12,2945	Delayed		12,2170	Delayed	
17,7457	17,7583	Delayed		17,7067	On time	
16,3337	16,3236	On time	*Objective evaluation*	16,3451	Delayed	*Objective evaluation*
18,8959	18,8483	On time		18,8281	On time	
14,2716	14,2614	On time	*7,4028*	14,2799	Delayed	*7,6758*

Deterministic plan	Stochastic plan execution	Real evaluation	Proposed approach	Stochastic plan execution	Real evaluation	Proposed approach
8,2099	8,1928	On time	*Subjective evaluation:*	8,2319	Delayed	*Subjective evaluation:*
10,1249	10,0997	On time		10,1014	On time	
11,3148	11,3260	Delayed	*Quality is good*	11,4249	Delayed	*Quality is good*
12,2126	12,1740	On time		12,2086	On time	
17,7457	17,7617	Delayed	*Objective evaluation*	17,7187	On time	*Objective evaluation*
16,3337	16,3001	On time		16,3283	On time	
18,8959	18,8633	On time		18,8570	On time	
14,2716	14,2616	On time	*7,4582*	14,2788	Delayed	*7,5226*

Deterministic plan	Stochastic plan execution	Real evaluation	Proposed approach	Stochastic plan execution	Real evaluation	Proposed approach
8,2099	8,2755	Delayed	*Subjective evaluation:*	8,0943	On time	*Subjective evaluation:*
10,1249	10,1247	On time		10,1625	Delayed	
11,3148	11,3273	Delayed	*Quality is good*	11,3055	On time	*Quality is good*
12,2126	12,2653	Delayed		12,1171	On time	
17,7457	17,7230	On time	*Objective evaluation*	17,7083	On time	*Objective evaluation*
16,3337	16,3087	On time		16,3427	Delayed	
18,8959	18,8813	On time		18,8889	On time	
14,2716	14,2445	On time	*7,3824*	14,2424	On time	*7,6623*

Deterministic plan	Stochastic plan execution	Real evaluation	Proposed approach	Stochastic plan execution	Real evaluation	Proposed approach
8,2099	8,2173	Delayed	*Subjective evalua-tion:*	8,1476	On time	*Subjective evaluation:*
10,1249	10,1347	Delayed		10,1456	Delayed	
11,3148	11,3439	Delayed		11,2385	On time	*Quality is good*
12,2126	12,1608	On time	*Quality is good*	12,1155	On time	
17,7457	17,7862	Delayed		17,7194	On time	
16,3337	16,3670	Delayed		16,2297	On time	*Objective evaluation*
18,8959	18,9728	Delayed	*Objective evalua-tion*	18,9489	Delayed	
14,2716	14,3368	Delayed		14,2878	Delayed	*7,5752*
			7,4853			

Source: Authors

$$Evaluation = [7{,}1118 \quad 7{,}1632 \quad 7{,}4028 \quad 7{,}6758 \quad 7{,}4582 \quad 7{,}5226 \quad 7{,}3824 \quad 7{,}6623 \quad 7{,}4853 \quad 7{,}5752] \quad (17)$$

$$Meanevaluation = 7{,}4440 \quad (18)$$

Quality is Good

Equations (17) and (18) show the objective and decoded evaluation of the stochastic plans.

The outputs of the neural network are decoded with the following proposed procedure. The obtained prediction is transformed into a scale of 1-10, multiplying by the factor 10. The average of the obtained predictions is calculated and finally they are categorized in the following ranges.

Greater than 8,75 the rating is excellent

Greater than 7 and 8,75 the rating is good

Greater than or equal to 5 and 7 the rating is regular

Less than 5 the rating is poor.

Deterministic plans are evaluated based on execution criteria in time or delayed. The proposed approach evaluates the execution of the plan in a stochastic way based on a neural network, which is trained by the outputs of the proposed fuzzy system categorized into four linguistic labels as a poorly executed, regular, good or excellent plan. A new procedure is used in the implication and agreggation phase, based on the sum of frequencies for each linguistic label.

The proposed approach can be replicated in any productive sector and obtain stochastic plans, integrating the uncertainty in the fulfillment of each assigned task. It starts with the deterministic values to finish each task. For each of the values, n replicates are obtained using the normal probability density function. The basic parameters of the distribution are obtained from the deterministic values. Four linguistic labels are categorized with different ranges for each of them. The poor label uses a range of 1 unit of time in addition to the average of the data. The regular label uses a range of 0,75 units of time in addition to the average of the data. The good label uses an additional range of 0,5 units of time in addition to the average of the data. Finally, the excellent label uses an additional range of 0,25 units of time to the average of the data.

The fuzzified data is obtained in 4 matrices, one for each linguistic label. One of the main contributions of the research is to use a statistical procedure to perform the stages of aggregation and involvement. A frequency count is performed for coded values greater than zero for each column of the matrix as an aggregation mechanism. The implication stage identifies the column with the highest frequency count taking into account the values of the four matrices. Once the columns with the highest frequency values have been identified, the maximum value of the encoded values is identified, which represents the output of the proposed diffuse system. To generalize and evaluate the execution of the activities a neural network is used, where the input values are represented by the deterministic plan values and the outputs are the results of the proposed fuzzy system. The network is trained and finally the evaluation of the activities is decoded. Each of the results of the network is multiplied by a factor of 10 to have the results on a simple scale from 1 to 10.

Finally, the results are categorized using the four linguistic labels to give an understandable result. Values under five get a result of poor. Values greater than or equal to five and 7,0 obtain a regular result. Values greater than or equal to 7,0 and 8,75 obtain a good rating. Values greater than 8,75 obtain an excellent rating

Conclusions

The use of deterministic plans and stochastic execution theory for structuring the research and deepening the enquiry in a critical manner has proved to be useful by conceptualizing msFLS approach as new knowledge being incorporated within a Knitting SMEs. For the theory of stochastic execution, the present study transforms a deterministic sequence plan in a multidimensional stochastic system. The research has shown the evaluation of stochastic plans based on transformation of deterministic plans. Production planning and scheduling attempts to utilize resources efficiently, complete various jobs subject to their specific operational sequences, and eventually achieves a certain level of responsiveness and efficiency in Knitting SMEs. Comprehensive assessment system for evaluating and categorizing in a simple and clear language as poor (P), regular (R), good (G) and excellent (E) the execution of the plans of textile manufacturing was designed, which consists of three modules. A novel multi stochastic fuzzy system is proposed as first module, using normal probability density function to generate multi training patterns of a deterministic sequence obtained by production supervisor and are used by the second neural network module. The first MIMO module evaluates the degree of membership of the planning as a target linguistic vector T with n linguistic input variables. The second module is a two-layer feed-forward network created with a vector J as multi stochastic input, ten hidden tansig neurons, and n purelin output neuron. The third module evaluates the degree of membership of the variable execution planning for a lead time parameter and classifies as linguistic label correspondent. This intelligent design allows an integrator assessment classificatory to the real lead time measures of the stochastic planning. The frequency sum indicator was used at the involvement stage as a contribution to the expert systems. The proposed approach was conceptualized in knitting enterprises of the southern region of the Guanajuato state in Mexico, achieving an evaluation of a stochastic plans of time delivery. The proposed system had a positive response by the manager of the company, which is still used to carry out the manufacturing planning for the week, as well as the evaluation of the execution of the plan. Due to the simple and clear language that is used as evaluation of the tasks, the administrative staff immediately integrated it as their planning tool. As future work is to design a fabric evaluation system by a supply chain management with a genetic-neuro-fuzzy approach and to develop a dynamic system incorporating uncertainty and expert knowledge using fuzzy logic.

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