# Optimization of Supply Chain based on JIT Pull Control Policies: An Integrated Fuzzy AHP and ANFIS Approach

AYDIN M. TORKABADI
Industrial Systems Engineering
University of Regina
3737 Wascana Parkway, Regina, SK, S4S 0A2
CANADA
torkabam@uregina.ca

RENE V. MAYORGA (corresponding author)
Industrial Systems Engineering
University of Regina
3737 Wascana Parkway, Regina, SK, S4S 0A2
CANADA
Rene.Mayorga@uregina.ca

*Abstract:* This Paper introduces an integrated Fuzzy Analytical Hierarchy (FAHP) and Adaptive neuro-Fuzzy Inference System (ANFIS) to evaluate Just In Time (JIT) control strategies. Three Pull Control Policies (PCPs), Kanaban, ConWIP, and Kanabn-ConWIP Hybrid systems, are identified for implementation. The proposed approach of this study creates a framework for identifying the alternatives and criteria, evaluating the PCPs, and comparing the performance of each policy. The approach is examined by studying a real multi-echelon, multi-stage, and multi-product supply chain network from automotive parts industry. The approach exemplifies the PCPs mechanisms, measurement criteria formulations, and integration of fuzzy theory with multi criteria decision making (MCDM) methods and ANFIS. The evaluation of the PCPs are based on JIT criteria such as inventory level, lead time, and lost demands. Discrete event computer simulation results are the basis of expert interpretation of each policy's performance. The FAHP method is applied to systematically measure the performance of each system. Then, Three ANFIS models are developed for each PCP based on the FAHP input-output results. Finally the ANFIS and FAHP methods are compared as well as the three PCPs.

*Keywords:* Just-In-Time (JIT), Supply Chain Management (SCM), Pull Control Policy, Kanban, ConWIP, Analytical Hierarchy Process (AHP), Fuzzy, Multi Criteria Decision Making (MCDM), Adaptive Neuro-Fuzzy Inference System (ANFIS)

## 1 Introduction

Introduction of strict governmental regulations and the fast changing demand trends require the organizations to implement competitive strategies [1]. However, excessive inventories limit the capability of producers to modify their products in response to change. Blocked by a high level of inventory in the network of a supply chain system, a new product needs to wait behind the existing stock before being introduced to the market. JIT is an ideology first developed to control the inventory level in manufacturing systems. Investigating this ideology in a greater context of SCS – which includes manufacturers, suppliers and distributers – is the focus of this Paper. Here, the objective is to implement, compare and evaluate the JIT policies in a greater context of Supply Chain Management (SCM).

Kanban and ConWIP are the two major pull control policies (PCPs) that were first developed for controlling the production level in manufacturing systems [2]. Both policies use kanban cards that circulate in loops and authorize transactions. The transaction can be a production, assembly, or transportation. The difference between Kanban and ConWIP system is in designing the loops in which the kanban authorizations circulate. If every two neighbouring station have a designated loop of kanban sets the system is Kanaban. If the entire network shares one loop of kanbans the system is ConWIP. Combining the two systems various hybrid pull policies can be developed.

This Paper considers the hybrid systems that are defined based on designing Kanban-ConWIP loops in a network. The procedure to combine the policies and produce hybrid systems is further explained in Section 3.1.

This Papr translates the implementation PCPs from the context of manufacturing to SCM. The recent studies on SCMs emphasize the requirement of supply chain members to effectively communicate between each other [3]. Controlling the inventory level through local communications between suppliers, manufacturers, distributors, and sale points is therefore a significant issue. PCPs are by definition the local communication of supply chain members to control the supply chain inventory via authorization kanbans. However, certain specifications of supply chains require the network to be tailored accordingly.

This Paper proposes an approach to implement PCPs in a multi-product, multi-echelon, and multi-layer network. Such a network is considered to represent a common supply chain network consisting of entities such as suppliers, manufacturers, distributors and sales points. A description of the studied supply chain network is presented in Section 4.2.

The main issues in the field are not limited to what policies enable the controlling and how the policies are reflected in SCM context. But this Paper also seeks to answer to which of the policies is more efficient. Therefore, three goals are sought::

- To identify the JIT strategies for controlling the excessive inventory and improving the response to actual demand.
- To measure the performance of PCPs in multi-product multi-echelon, and multi layer supply chain networks.
- To evaluate the PCP alternatives based on designated criteria with respect to uncertainty.

The implementation of PCPs is reported in various industries. Continued popularity of pull strategies among industry practitioners is apparent from the cases. The literature shows the adaptability PCPs in industries with different environments [4]. Section 2 reviews the literature on PCPs implementation in manufacturing context. A review on JIT implementation in SCMs is also presented. The review shows that despite extensive studies investigating the PCPs in manufacturing context, the research on PCPs implementation is supply chain is limited. This Paper addresses the gap by proposing an approach to identify and implement JIT policies for SCM; and to evaluate the alternatives based on multiple measurement criteria.

The success of JIT implementation in supply chain depends on multiple factors. Achieving lower levels of inventory, together with minimum lost demands and lead time is important in evaluating the PCPs. In response to this significant issue, this Paper is focused on analysing and prioritizing the PCPs based on multiple objectives. The evaluation of measurement criteria, based on SCM expert's judgment, involves uncertainty. The proposed approach in section 4 responds to the ambiguity in linguistic expressions via implementing concepts of fuzzy set theory in Analytical Hierarchy Process (AHP).

The next step of the proposed approach uses the information obtained from AHP to train an intelligent system that that can mimic the decision making process of the expert involved AHP. An adaptive neuro-fuzzy inference system (ANFIS) enhances the system to determine the performance of PCPs by changing the performance criteria.

Therefore the proposed approach in this Paper, by integrating the Fuzzy theory, AHP, and ANFIS, is novel in the newly growing field of PCP-SCM.

The proposed approach is exemplified by conducting an experiment based on a real case study. The results from the case study reflect the major evaluation priorities from a real supply chain perspective.

## 2 Literature review

Researchers have argued that the better performance of JIT and pull systems is due to their responsiveness to the actual demand [5]. The performance of push type systems relies on the forecasting demand in which errors occur [6]. The amplification of forecasting error, especially in a broad network of supply chain members, negatively impacts the performance. This issue makes JIT a suitable methodology for SCM in comparison to forecast based systems.

Takahashi and Nakamura compared the performance of pull and push systems and proposed a hybrid push-pull policy in SCM context [7]. Their study merely considered Kanban system as a representative for pull systems. Later, Takahashi, Myreshka, and Hirotani investigated three pull type systems in SCM context [8]. The comparison was conducted among ConWIP, synchronized ConWIP, and Kanban systems. One of the significant contributions of their research was prioritizing the inventory level in deferent stations. This issue is significant in the context of SCM as the cost of excessive inventory varies for each supply chain member. Yet, the level of inventory was the mere base of their comparison.

The study by Kojima, Nakashima, and Ohno included important measurement criteria other than inventory level. Their evaluation was based on inventory level, production quantities, and total backlogged demand in stages [9]. However, their supply chain network considered was single layer which does not represent a common supply chain with multiple layers.

Other researchers developed the literature by recognizing common issues in SCM such as, reorders, returns, and risk [10], [11].

It is important to mention that Multi criteria decision making (MCDM) methods have been used for JIT policy evaluation in manufacturing systems [12]. MCDMs are applied in studies that compare several PCPs with regards to multiple measurement criteria[13], [14]. Due to the uncertainty involved in measurement and comparison of criteria, which involves expert judgment, fuzzy set theory principles have been combined with MCDM methods [15]. However, the application of such combinatory methods are applied in manufacturing systems and the studies that use such methods in JIT-SCM are rare.

## 3 Problem formulation

This section presents suitable methods to identify, measure, and evaluate the PCPs in SCM. The identification of the PCPs in section 3.1 recognizes the JIT mechanisms to control the network. In section 3.2 the measurement criteria are explained and formulated. Section 3.3 explains the MCDM evaluation methodology to find the performance ranks for alternatives. Section 3.4 explains the intelligence analysis techniques that are applied to analyse the performance of alternatives

### 3.1 PCP mechanisms

In the Kanban control system, a permission signal/card called kanban is used to control and limit the release of orders to every member of supply chain. Different sets of kanbans circulate in between every immediate member. Members function when there is a kanban that authorizes the operation. Otherwise, a member waits until a kanban is available. Every order that is under process has a kanban attached to it. After the processing, the order and the attached kanban card move to the proceeding member. When the proceeding member receives the order, the kanban returns to the previous station. This repeats until the product is complete at the final station.

A generalization of the kanban system, when there is only one set of kanbans circulating in the entire supply chain, is called ConWIP.

Therefore, it can be regarded as a one-step kanban system. The ConWIP system operates once an order arrives to the ConWIP line. The kanban at the upstream of the supply chain is added to the order. If no kanban is available, the order waits in the backlog, until a kanban becomes available. The order together with the kanban is conveyed through the supply chain. That allows the orders to be processed by members. When the job is processed at the last station, the card is removed and returned to the beginning of the line where it is connected to the next order waiting in the backlog. If there are no new orders backlogged, the kanban stays till a new order arrival. This repeats until all demands are satisfied [16]. In a multi- layer network the final members communicates with all preliminary members (usually suppliers) by transferring the authorization kanban to them all simultaneously.

Considering that there is a member that multiple lines of members feed that specific member, we have a synchronizing point in the network. By assigning that member to be the starting point of a ConWIP loop set for the preceding members and the final point of a ConWIP loop set for the proceeding members, a hybrid system can be developed. The number of Kanabn loops is the highest in Kanban policy followed by hybrid and finally the ConWIP policy has only one loop.

### 3.2 Measurement criteria formulations

The three measurement criteria considered by this study to find the performance of PCPs is the average inventory level (I), the number of backlogged orders (B), and waiting time (W). Following formula is modified for measuring the average inventory level:

$$I = \frac{\sum_{i=1}^{n}\sum_{t=1}^{t_{max}} I_i(t)}{t_{max}} \qquad (1)$$

Where *t* and *n* are the indexes of time and members respectively

To calculate the $I_i(t)$ the following formula is used [8]:

$$I_i(t) = I_i(t-1) + P_i(t-L_i) - P_i(t) \qquad (2)$$

Where $L_i$ is the lead time for member *i* and $P_i(t)$ is the production quantity of member *i* started at *t* and finished after the lead time [8].

Every time that an order arrives and is not satisfied immediately a backlogged order is counted.

$$B = \frac{\sum_{t=1}^{t_{max}} B(t)}{t_{max}} \qquad (3)$$

Where $B(t)$ is the number of counted backlogged orders from *t* until *t+1*.

The time that orders wait to be satisfied is the third measuring criteria.

### 3.3 Multi-Criteria Decision Making Methods

A popular approach to solve MCDM problems is Analytical Hierarchy Process (AHP) [17]. A systematic framework is provided by this approach to consider multiple evaluation criteria. The capability of AHP to include qualitative measures and combine them with quantitative values is advantageous. However the pair-wise comparisons can only be based on crisp values. This shortage is addressed by researchers through introducing the principals of fuzzy set theory to deal with the ambiguity in linguistic expressions. The approach proposed by Chang combines fuzzy set theory with AHP method [18]. Among several Fuzzy AHP methods proposed in the literature, this study applies extent analysis approach of Chang [19] due to its convenience, and proven practicality in industrial cases. Let X = $\{x_1, x_2, . . . , x_n\}$ and U = $\{u_1, u_2, . . . , u_m\}$ be the object and the goal set. Therefore for every objective *m* extent analysis (M) based on each goal can be conducted:

$$M_{gi}^1, M_{gi}^2, \ldots\ldots M_{gi}^m, \quad i = 1,2,\ldots\ldots,n \qquad (4)$$

Where M is a triangular fuzzy number.

The calculations based on Chang's extent method [18], are provided bellow.

The fuzzy synthetic extent with respect to the *i*th object is obtained as follows:

$$S_i = \sum_{j=1}^{m} M_{gi}^j * \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} \qquad (5)$$

Then the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq (l_1, m_1, u_1)$ is calculated:

$$V(M_2 \geq M_1) = \sup\left[\min(\mu_{M1}(x), \mu_{M2}(y))\right] \qquad (6)$$

And can be equivalently expressed as follows:

$V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_2)$

$$= \mu_{M2}(d) = \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ \ l_1 \geq m_2 \\ \frac{u_2 - l_1}{(m_2 - m_1) - (u_2 - l_1)}, & otherwise \end{cases} \quad (7)$$

Where $d$ is the ordinate of the highest intersection point $D$ between $\mu_{M1}$ and $\mu_{M2}$.

To calculate the degree of possibility for a convex fuzzy number to be greater than $k$ convex fuzzy numbers $M_i$ ($i = 1,2,. . . ,k$) the following formula is used according to Chang

*V (M≥ $M_1$, $M_2$,…….$M_k$) = V[(M≥$M_1$) and (M≥$M_2$) and …..(M≥$M_k$)] = min V (M≥$M_i$), i=1,2,….,k.* (8)

And finally the normalized weight vectors are:

$$W = \left(d\ (A_1),\ d\ (A_2), \dots \dots \dots d\ (A_n)\right)^T \quad (9)$$

Where W is a non-fuzzy number.

### 3.3 Intelligence Analysis

MCDM methods assign a predetermined weight to each criterion and are incapable of incorporating several weights when there is more than one decision maker [20]. Fuzzy set theory is advantageous in dealing with the ambiguity arising from human decision making. The subjectivity in human decision analysis is complex in terms of considering the interdependency and inference of various factors. One of the most applied technique for fuzzy decision analysis, is a based on Fuzzy Inference Systems (FIS), [21], [22]. The FIS includes a set of Fuzzy IF-THEN rules that map the input universe of discourse $X \subset R^n$ to the output universe of discourse $Y \subset R$. The concepts of fuzzy logic are the basis of this transformation [23]. A fuzzy IF-THEN rule is defined in the following format:

IF antecedent(s), THEN consequent(s)

The Mamdani inference system [21], and Takagi and Sugeno inference systems [24] are two Fuzzy Inference Systems extensively used. However, these methods do not provide a systematic approach to define the rules. The rule definition is based on the expert knowledge and there is no defined approach to validate the rules. FIS models consider altered importance weight for objectives and criteria [25]. A membership function is the weighted summation of objectives and criteria satisfaction level and is defined as follow [24]:

$$\mu_D(x) = \sum_{j=1}^{p} w_j \mu_{z_j}(x) + \sum_{r=1}^{h} \beta_r \mu_{g_r}(x)$$
$$\sum_{j=1}^{p} w_j + \sum_{r=1}^{h} \beta_r = 1 \quad (10)$$

Where, $w_j$ and $\beta_r$ are the normalized weights representing the relative significance of objectives and criteria. The definition of membership functions $\mu(x)$ is not based on a systematic framework. Therefore, optimizing "automatically" the system parameters is a challenge in FIS.

The ANFIS developed by Jang [27] is capable of determining the rules and membership functions provided an adequate number of input-output sets are available for training. The learning capability of ANN, and robust properties of fuzzy set theory are integrated in the ANFIS method. By providing adequate number of inputs and outputs, the ANFIS can set the membership functions to convert the crisp inputs into fuzzy values and also generate adequate rules for transferring the fuzzy input into output. The result is a robust FIS that imitates the expert's decision making process. The ANFIS is based on the first order Sugeno type FIS. The reasoning procedure for the first type Sugeno FIS is as follow:

IF $x_1\ is\ \widetilde{A_1^1}\ and\ x_2\ is\ \widetilde{A_2^1} \dots and\ x_n\ is\ \widetilde{A_n^1}$
THEN $y_1 = f_1(x_1,\ x_2, \dots, x_n)$
...
IF $x_1\ is\ \widetilde{A_1^m}\ and\ x_2\ is\ \widetilde{A_2^m} \dots and\ x_n\ is\ \widetilde{A_n^m}$
THEN $y_m = f_m(x_1,\ x_2, \dots, x_n)$ (11)

Where $x_i$ $(i = 1, . . , n)$ are crisp inputs reflected on fuzzy values $A_i^j$ $(j = 1, . . , m)$, and $y_j$ are crisp linear output functions. The system output $\bar{y}$ is a linear weighted function of all rule outputs $y_m$ and is defined as:

$$\bar{y} = \frac{\sum_{j=1}^{m} y_j \prod_{i=1}^{n} \mu_{A_i}(x_i)}{\sum_{j=1}^{m} \prod_{i=1}^{n} \mu_{A_i}(x_i)} \quad (12)$$

The ANN method is used to find the system parameters in which the mean square estimator (MSE) and back-propagation (BP) are applied to train the network. The MSE for optimizing the ANFIS model is defined as follow:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\bar{y} - y)^2 \quad (13)$$

Where $\bar{y}$ is the predicted output, and $y$ is the target found by MCDM method.
Post-regression analysis is performed through coefficient of multiple determination for multiple regression by measuring the R-squared, which is defined as follow:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\bar{y} - y)^2}{\sum_{i=1}^{n}(\bar{y} - Avy)^2} \quad (14)$$

Where *Avy* is the average value of targets.

# 4 Proposed approach

The approach proposed here provides a framework for recognizing, measuring the performance, and evaluating the JIT PCPs via Fuzzy AHP. The proposed approach also leads to develop a Fuzzy Inference System to evaluate the PCPs.. Figure 1 illustrates the steps of this approach. The solution provided in this study is examined through a case study in section 5.

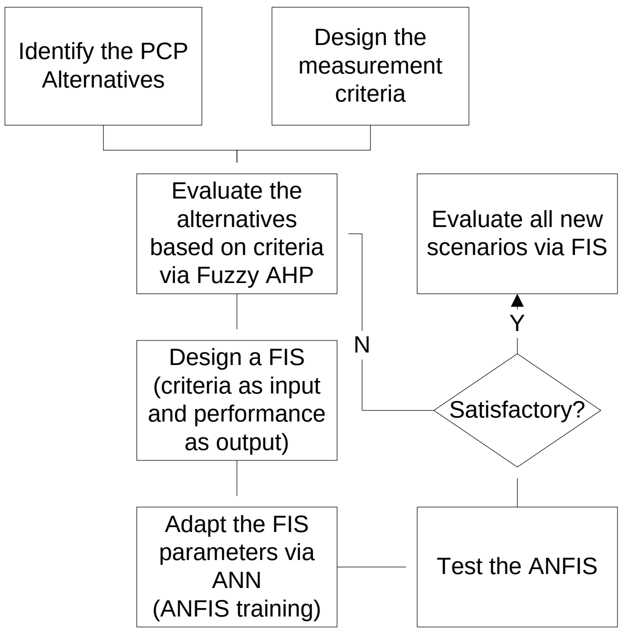


Figure 1 the proposed approach of the study

## 4.1 Identifying the criteria and alternatives

To build the MCDM problem the measurement criteria described in the previous section is considered as the problem criteria and the alternatives are the PCPs. The design of PCPs is based on the properties of the studied case network. Setting the kanban loops between suppliers, manufacturers, distributors and warehouse creates the alternatives.

Each alternative is examined by running discrete event computer simulation models and measuring the performance in terms of inventory level, lead time, and lost demands. The measurement results are the basis for expert judgment and pairwise comparisons.

## 4.2 Fuzzy AHP evaluation

The next step is structuring the model in a hierarchical format. This is a necessity for applying the AHP solution. Therefore, to achieve the objective of better performance, the measurement criteria are laid out horizontally. The last layer is the alternatives. Kanban, ConWIP, and the hybrid PCP are set as the alternatives. ***In this structure each alternative is connected to all three criteria.*** Figure 2 illustrates the hierarchical construction of the AHP method.

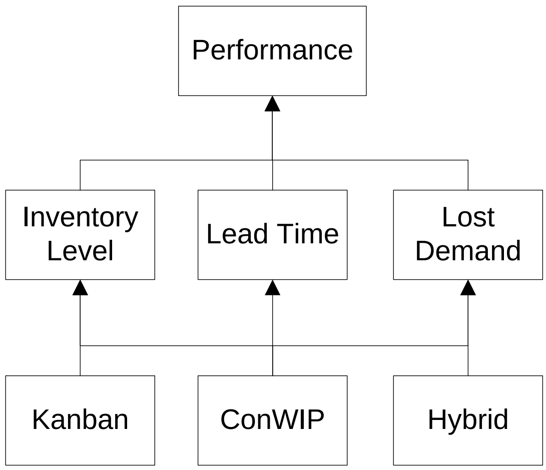


Figure 2 Hierarchical structures of criteria and alternatives for Fuzzy AHP

Then the pair-wise comparison matrices are built between criteria and alternatives. Since the measurement criteria are varying in nature and have different values based on every case, a weight is assigned to the criteria. The Fuzzy AHP technique is applied to find the weights for criteria. Triangular fuzzy numbers presented in Table 1 are used to convey the linguistic expression of the supply chain experts. The linguistic terms for this purpose are expressed to determine the level of importance

Similarly, a pair-wise comparison of alternatives with respect to each criterion is performed. The linguistic expressions reflect the level of efficiency.

| Linguistic scale for importance | Triangular fuzzy scale | Triangular fuzzy reciprocal scale |
|---|---|---|
| Absolutely equal (A) | 1 | (1, 1, 1) |
| Equally Important/efficient (E) | $\tilde{1}$ | (1/2, 1, 5/2) |
| slightly more Important/ efficient (SM) | $\tilde{3}$ | (3/2, 3, 9/2) |
| moderately more Important/ efficient (MM) | $\tilde{5}$ | (7/2, 5, 13/2) |
| strongly more Important/ efficient (TM) | $\tilde{7}$ | (11/2, 7, 19/2) |
| extremely more Important/ efficient (EM) | $\tilde{9}$ | (15/2, 9, 21/2) |

Table 1. Linguistic scales of importance and efficiency for Fuzzy AHP model [28]

### 4.3 Developing the ANFIS model

The adapted ANFIS model for the proposed framework of this Paper consists of three input variables and one output variable. The input variables, as illustrated in Figure 3, are inventory level (IL), lead time (LT), and lost demand (LD). The first layer of the neural network maps each input variable on fuzzy values with three membership functions. $\tilde{A}_j^i$ represents the fuzzy value of input *i* and membership *j*. 3 membership functions are designated for each input which makes a total of 9 membership functions. Therefore, the first layer consists of 9 neurons. The second layer of the network is designed for rule generation. The layer is made of 27 neurons. The third layer is the output membership function that assigns a weight to the output of every rule in the second layer. Finally, the single output of the system is the PCP performance value. The distribution functions for memberships are designed to be Gaussian type. The training algorithm is a hybrid MSE and BP. The number of epochs is 400. And the cut-off condition is once the error is bellow 0.02e4.

For every PCP an ANFIS model is developed and the performance of the three alternatives, Kanban, COnWIP nad Hybrid models, are compared.

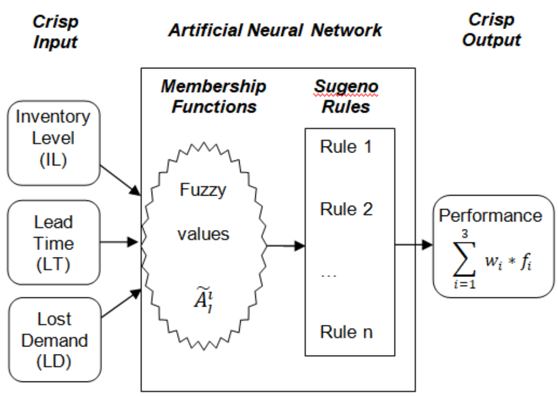


Figure 3 general structure of ANFIS model

## 5 Case Study

To evaluate the proposed approach, the implementation of the Kanban, ConWIP and hybrid PCP are examined for a real case. ImantakCo. supply chain that produces electro-mechanical parts for a car manufacturer is selected for this study. The company's supply chain has applied Lean techniques to eliminate the wasteful steps in production distribution.

The supply chain includes two parallel layers, each including a supplier and a manufacturer. Then an assembly plant is the synchronizing member that is fed by the two lines. A distributer is located after the plant and finally a warehouse where the final product is stored for customer demand.

### 5.1 Implementation

To implement Kanban policy in the proposed model, for each neighbouring station exclusive kanbans are designated. kanbans are only circulating within the assigned work station. For the suggested production and assembly line 6 sets of kanban loops are considered.

For the ConWIP implementation there is only one group of kanbans that circulate in between all members. Once a part reaches the end of the supply chain the kanban travels back to the suppliers.

For the hybrid system there are three sets of kanbans. The first set circulates between the warehouse and the synchronizing member which is the plant. This loop creates a three stage ConWIP sub-system. The other two loops are set between the plant and each supplier. Similarly, they each create a three stage ConWIP sub-system.

| IL | LT | LD | Performance | |
|---|---|---|---|---|
| 7.2 | 4.9 | 4.9 | 0.49 | * |
| 3.5 | 2.1 | 2.8 | 0.34 | |
| 5.6 | 7.2 | 3.1 | 0.46 | * |
| 5.3 | 4.9 | 6.2 | 0.47 | |
| 3.7 | 2.7 | 7.0 | 0.39 | * |
| 7.6 | 4.3 | 6.5 | 0.54 | |
| 2.3 | 6.3 | 5.8 | 0.33 | * |
| 2.2 | 7.3 | 4.6 | 0.33 | |
| 5.7 | 4.5 | 3.8 | 0.46 | * |
| 8.0 | 3.7 | 4.0 | 0.41 | |
| 4.3 | 2.1 | 5.1 | 0.39 | * |
| 3.3 | 5.8 | 5.4 | 0.38 | |
| 4.9 | 7.3 | 7.3 | 0.50 | * |
| 7.7 | 2.7 | 6.9 | 0.57 | |
| 3.3 | 7.5 | 5.8 | 0.39 | * |
| 6.6 | 2.2 | 5.1 | 0.45 | |
| 5.8 | 3.3 | 7.8 | 0.47 | * |
| 3.1 | 5.1 | 4.3 | 0.36 | |
| 2.8 | 4.1 | 7.0 | 0.37 | * |
| 3.0 | 7.0 | 3.0 | 0.36 | |
| 3.3 | 3.8 | 7.3 | 0.39 | * |
| 5.0 | 7.4 | 2.6 | 0.43 | |
| 6.3 | 2.4 | 7.9 | 0.50 | * |
| 3.8 | 2.7 | 2.0 | 0.35 | |
| 2.9 | 2.0 | 3.8 | 0.35 | * |
| 6.0 | 3.4 | 7.6 | 0.48 | |
| 5.8 | 7.8 | 4.8 | 0.46 | * |
| 3.2 | 2.6 | 5.1 | 0.37 | |
| 6.6 | 2.7 | 6.3 | 0.50 | * |
| 5.5 | 4.1 | 7.7 | 0.46 | |

Table 2 Fuzzy AHP performance results for hybrid system

Measuring the criteria is conducted through 1000 runs of discrete event computer simulation with 100 warm up rounds. The evaluation of results via FAHP technique for the hybrid system is presented in the Table 2. This Table shows the desirability of the criteria. For example, a lower inventory level has higher desirability, or a higher lost demand has lower desirability. The rows that are marked with a "*" are used as input-output sets in the ANFIS training.

The Matlab2016a software was used to develop the ANFIS. 3 models are developed for each of the Kanban, ConWIP, and Hybrid PCPs. Figure 4 shows the structure of the model for all the three policies. The inputs each are assigned three membership functions in the "inputmf" layer. The rule layer is based on Sugeno FIS. The "outputmf" layer combines the output from each rule to find the single output of the model which is the PCP performance.

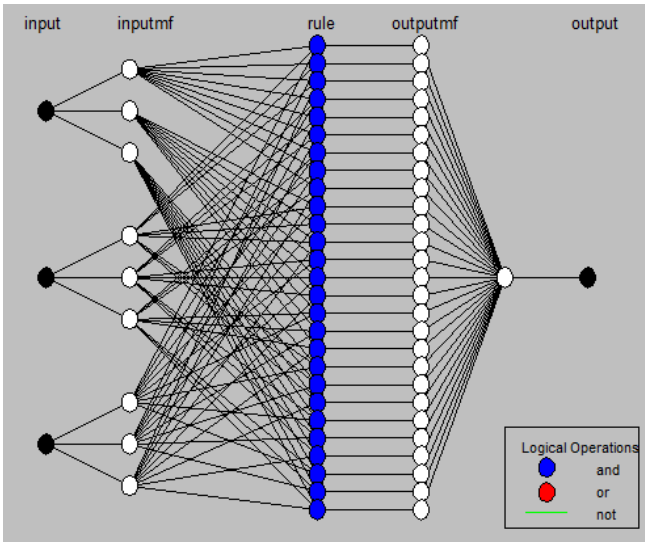


Figure 4 architecture of ANFIS model

The ANFIS model was trained independently for each Kanaban, ConWIP, and Hybrid system. The input-output sets to train each network were obtained from the fuzzy AHP results. Table 2 shows a part of data used for training the hybrid system. The remaining of the data from fuzzy AHP was used for checking the models.

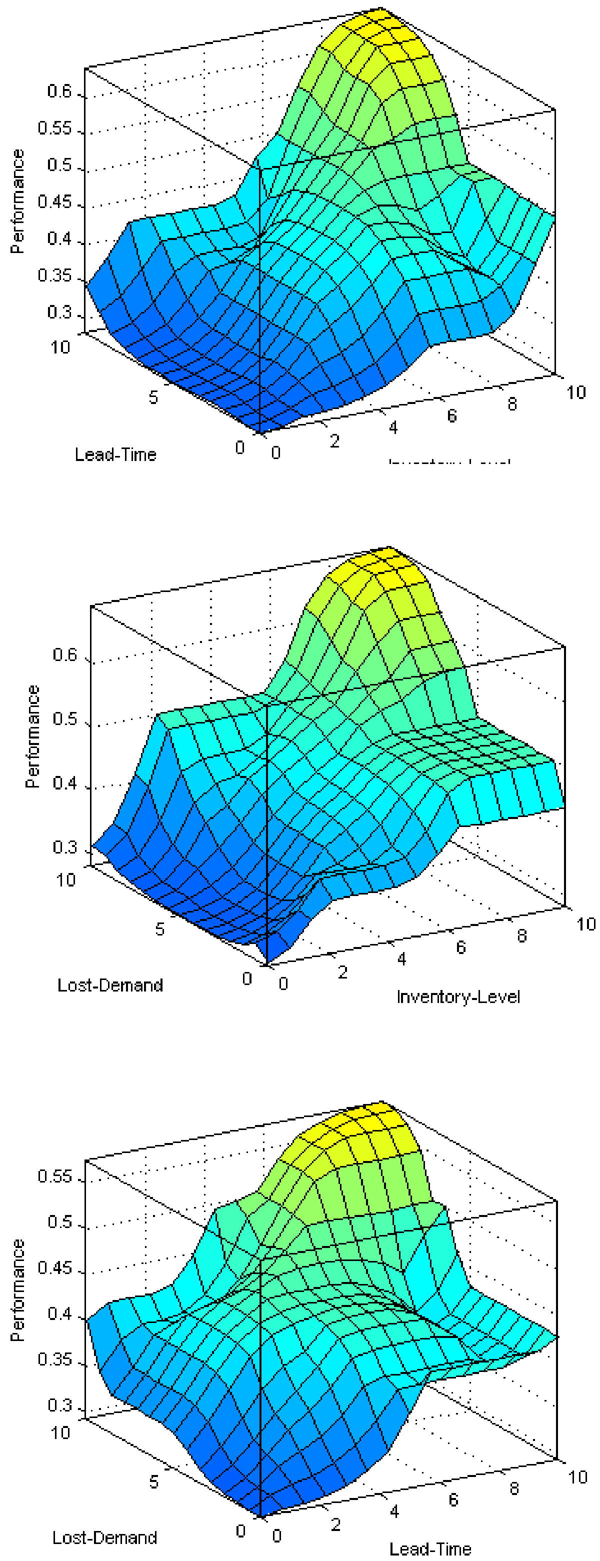


Figure 5 Inference of input parameters on hybrid PCP performance based on ANFIS model

### 5.2 Results

The performance surface for the hybrid system is illustrated in figure 5. The first illustration is the inference of lead time and inventory level in the performance of hybrid policy. The higher input score means the better condition of criteria. Therefore a low distribution of inventory in the supply chain refers to a high score IL criteria input. Similarly, a low number of lost demands and lead time means high score LD and LT inputs. The results show that the performance of hybrid PCP is high once all the criteria are highly improved.

On the other hand, the low scored input criteria result in a very poor PCP performance. The performance improves sharply once the input criteria reach a medium level. The improvement is more sensitive to inventory level compared to lead time in medium spectrum as it shows in the first illustration.

An important observation from the first and second figure 5 illustrations is that once the IL has a very low score, the performance of the hybrid PCP hardly improves by changing the other criteria. Therefore, if a supply chain manages to satisfy the demand or improve the lead time by compromising the inventory level; for example, by stocking high levels of inventory in every stage, yet the performance will be very low based on the model.

Another important observation is that, as it shown in figure 5; the performance in hybrid systems increases significantly once the inputs reach a medium level. The suitability of the hybrid systems for situations where the criteria are in medium range is further discussed by comparing the output of all three PCPs.

### 5.3 Comparisons

Two major areas of comparison are considered. First, is a comparison between MCDM and intelligent system methods to find the performance of JIT strategies based on multiple criteria. Second, is a comparison between Kanban, ConWIP and Hybrid PCPs for implementation in supply chain management context.

The study shows that fuzzy AHP is a robust method to generate adequate input-output sets required for training an ANFIS model.

However, the requirement for the training the artificial neural networks in ANFIS model is to have adequate and suitable sets of input-output. The lack of data for rare situations in which some of the input criteria are significantly high and some others are significantly low, results in misrepresentation of those edges by the ANFIS model. Still, for majority of real cases in which the input criteria are not significantly varying the ANFIS results are highly satisfactory. Table 3 compares the output from FAHP and ANFIS models for the case in which the inputs are linguistically interpreted as good.

| **PCPs** | **Performance Weight (IL = 6.2, LD = 5.3, LT =6.1)** | | **Rank** |
|---|---|---|---|
| | **FAHP** | **ANFIS** | |
| **Kanban** | 0.264 | 0.198 | 3 |
| **ConWIP** | 0.352 | 0.302 | 2 |
| **Hybrid** | 0.384 | 0.390 | 1 |

Table 3 comparison of PCPs based on both fuzzy AHP and ANFIS methods for a specific input.

The scores for inventory level, lost demand and lead time are 6.2, 5.3, and 6.1, respectively. The Table 3 shows that based on both models the hybrid system is superior to Kanban and ConWIP PCPs.

Comparisons of Kanban, ConWIP and Hybrid PCPs show that there are no superior strategies in general. The performance of the systems differs based on the conditions of the supply chain. Due to the varying nature of the criteria to evaluate the performance of PCPs; the expert knowledge and interpretation plays a significant role.

The Figure 6 illustrates the influence of the two major criteria, inventory level and lead time, in the performance of the alternatives. The figure shows the superiority of Kanban system for conditions that the inventory levels and lead times are highly satisfactory. On the other hand, when the criteria are not satisfactory, ConWIP system outperforms the other alternatives. For the majority of the cases, that the criteria are mostly average, the Hybrid system is the most suitable PCP.

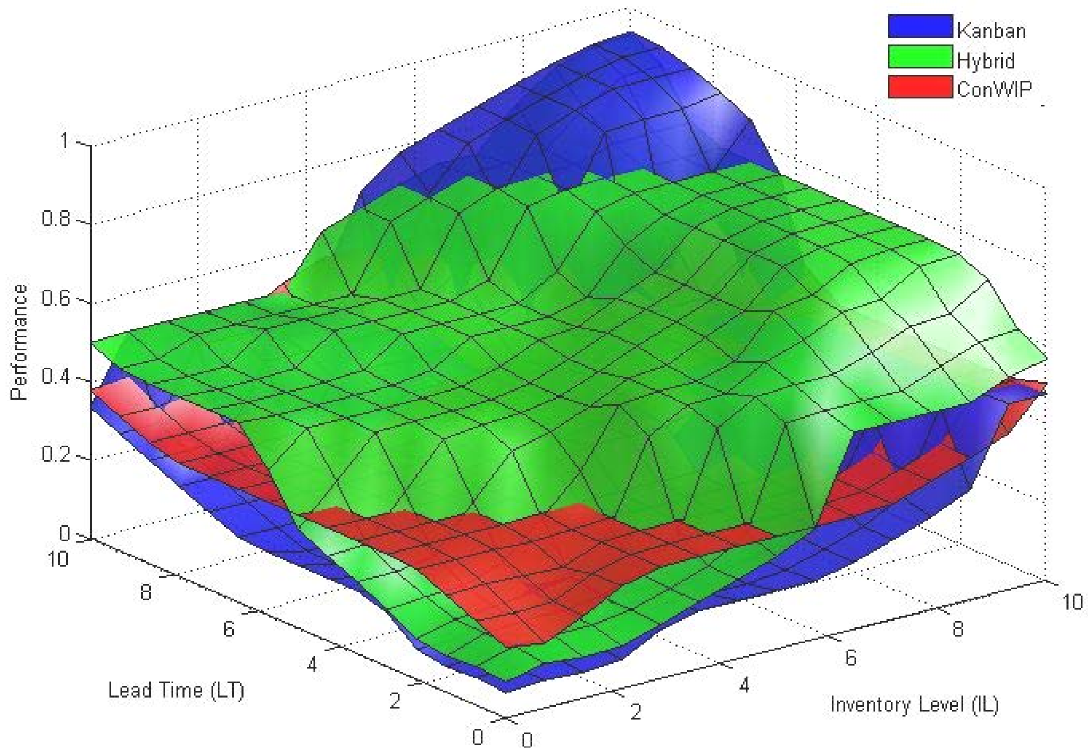


Figure 6 areas of superiority for Kanabn, ConWIP, and hybrid system base on LT and IL

## 6 Conclusions

The JIT is practiced widely to minimize the costs and improve the performance. Reserving minimum work in process is aimed by the JIT system. This Paper shows how Kanban, ConWIP and hybrid PCPs can be implemented in the context of SCM. The evaluation results of PCPs have been contradictory in recent studies in the literature. This Paper clarifies the role of expert knowledge in interpreting the performance of the system based on JIT criteria. FAHP is introduced here as a systematic approach to incorporate the decision makers' judgment and also to train the ANFIS model. The ANFIS is capable to imitate the judgment of experts to interpret the inference of the criteria on overall PCP performance. The ANFIS is capable of properly setting the fuzzy membership functions to transform the crisp criteria values to fuzzy values. It also generates the Sugeno rules to obtain the performance values for each control policy. Finally, this Paper has compared the results from the ANFIS model with the FAHP and scored the strategies based on each method. A detailed comparison of the three PCPs shows that there is no superior JIT strategy in general. The performance of the strategies varies by the change in supply chain properties and measuring criteria. Kanban policy is found to be superior for balanced networks with highly satisfactory inventory levels and order satisfactions. However, ConWIP is superior when the measuring criteria are not satisfactory. The Hybrid system shows a better performance in conditions that the performance criteria are average.

The current study can be extended by considering more criteria. The Fuzzy inference Systems are capable of including qualitative criteria that are important for evaluating the PCPs. Training the ANFIS model via other MCDM methods and comparing the results is another area for further research.

**Acknowledgment**

This paper research has been supported by a grant (No: 155147-2013) from the Natural Sciences and Engineering Research Council of Canada (NSERC).

**References**

[1] Pourjavad, E, Mayorga, R., (2017) Optimizing Performance Measurement of Manufacturing Systems with Mamdani Fuzzy Inference System, Journal of Intelligent Manufacturing, doi:10.1007/s10845-017-1307-5.

[2] Thürer, M., Fernandes, N. O., Stevenson, M., Ting Qu T. (2017) On the Backlog-Sequencing Decision for Extending the Applicability of ConWIP to High-Variety Contexts: An Assessment by Simulation, International Journal of Production Research 55 (16): 4695–4711.

[3] Long, T.B., Blok, V., Coninx, I. (2016) Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from The Netherlands, France, Switzerland and Italy. J. Clean. Prod. 112, 9-21.

[4] Ni, Y. and Wang, Y. (2015), A double decoupling postponement approach for integrated mixed flow production systems, Kybernetes, Vol. 44 No. 5, pp. 705-720.

[5] Takahashi,K., Nakamura, N. (1998) Ordering alternatives in JIT production systems. Production Planning and Control 9 (8),784–794.

[6] Kimura,O., Terada, H. (1981) Design and analysis of pull system: A method of multi-stage production control, International Journal of Production Research 19 (3), 241–253.

[7] Takahashi, K.,Nakamura, N.,2004. Push,pull,or hybrid control in supply chain management. Proceedings of the International Conference on Industrial Engineering and Production Management,Quebec,August, 2001, pp. MD3.1.2.1–MD3.1.2.10.

[8] Takahashi, K., Myreshka, Hirotani, D. (2005) Comparing CONWIP, synchronized CONWIP, and Kanban in complex supply chains, Int. J. Production Economics 93–94, 25–40

[9] Kojima, M., Nakashima, K., Ohno, K. (2008) Performance evaluation of SCM in JIT environment, Int. J. Production Economics 115 439– 443

[10] Nakashima, K., Gupta, S. M. (2012) A study on the risk management of multi Kanban system in a closed loop supply chain, Int. J. Production Economics 139 (2012) 65–68

[11] Wang, S., Sarker, B.R. (2005) An assembly-type supply chain system controlled by kanbans under a just-in-time delivery policy, European Journal of Operational Research 162,153–172

[12] Sharma, S., & Agrawalb, N. (2009). Selection of a pull production control policy under different demand situations for a manufacturing system by AHP-algorithm. Computers & Operations Research , 36(5), 1622-1632.

[13] Pourjavad, E., Shirouyehzad, H., (2014) Analyzing Maintenance Strategies by FANP Considering RAM Criteria; a Case Study, International Journal of Logistics Systems and Management (IJLSM),Vol. 18, No.3, pp. 302-321

[14] Pourjavad, E., Shirouyehzad, H., (2014) Evaluating Manufacturing Systems by Fuzzy ANP: a Case Study, International Journal of Applied Management Science, Vol. 6, No. 1, pp. 65-83.

[15] Sharma, S. , Agrawal, N. (2012) Application of fuzzy techniques in a multistage manufacturing system Int J Adv Manuf Technol 60: 397.

[16] Spearman, M., Woodruff, D., & Hopp, W. (1990) CONWIP: a pull alternative to kanban. International Journal of Production Research , 28(5), 879-894.

[17] Pourjavad, E., Shirouyehzad, H. (2014) Analyzing Maintenance Strategies by FANP Considering RAM Criteria; a Case Study, International Journal of Logistics Systems and Management, Vol. 18, No.3, pp. 302-321.

[18] Chang, D.Y. (1996) Applications of the extent analysis method on fuzzy AHP, European Journal of Operational Research, Vol. 95, No. 3, pp.649–655.

[19]Chang, D.Y. (1992) Extent Analysis and Synthetic Decision, Optimization Techniques and Applications, World Scientific, Singapore.

[20] Saghaei, A., Didehkhani, H. (2011) Developing an integrated model for the evaluation and selection of six sigma projects based on ANFIS and fuzzy goal programming Expert Systems with Applications 38 (1), 721-728

[21] Mamdani, E.H., Assilian, S. (1975) An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies. 7(1), 1–13.

[22] Kahraman, C., & Büyüközkan, G. (2008) A combined fuzzy AHP and fuzzy goal programming approach for effective six-sigma project selection. Journal of Multiple-Valued Logic and Soft Computing, 14(6).

[23] Jang, R., Sun, C. T., & Mizutani, E. (1996) Neuro-fuzzy and soft computing. Prentice Hall.

[24] Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. IEEE Transactions on Systems Man and Cybernetics, 15(1), 116–132.

[25] Pourjavad, E, Mayorga, R. (2017) A comparative study and measuring performance of manufacturing systems with Mamdani fuzzy inference system, Journal of Intelligent Manufacturing, doi:10.1007/s10845-017-1307-5.

[26] Tiwari, R. N., Dharmar, S., Rao, J. R. (1987) Fuzzy goal programming – An additive model. Fuzzy Sets and Systems, 24, 27–34.

[27] Jang, R. (1993). ANFIS: Adaptive-network-based fuzzy inference systems. IEEE Transactions on Systems, Man, and Cybernetics, 23, 665–685.

[28] Pourjavad, E, Torkabadi, A. M., Mayorga, R, (2017) Identification of Green Supply Chain Pressures for Business Implementation, International Journal of Economics and Management Systems, Vol. 2, 330-335.