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ORIGINAL ARTICLE

Toward learning autonomous pallets by using fuzzy rules, applied in a Conwip system

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Abstract Nowadays, material planning and control strategies are becoming continuously complex tasks spanning from individual plants to logistic networks. In fact, this is the consequence of increasing intricacy in product variants and their respective convolution in networks' structures. Customers ask for specific products with individual characteristics that force companies for more clever performances by more flexibility. For doing so, the existing planning and control systems, which work based on central monitoring and controlling, show some limitations for organizing every operation on time or in the right time. Therefore, in the recent decade, a great attention is put on decentralized control and, to some extent, autonomy. This paper tries to investigate the possibility of combining this new research paradigm with existing strategies in production logistics, in order to improve material handling and control task according to material flow criteria. To show this, an exemplary plant after decoupling point out of a logistic network is considered for simulation and analysis. This combines Conwip system with learning autonomous pallets' concept in a discrete event simulation model. Several decentralized control scenarios are experimented and compared together. Here, the learn methodology is brought to pallets based on fuzzy rules and advantage of closed loop systems.

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1 Introduction

For the last three decades, there has been a surge into researches for material flow handling and production strategies. This has been happened because of the great change in customer expectations and globalization in material supply chain. It is not anymore possible to neglect the competitions beside requirements and being still successful in businesses. Thus, industries have been continuously seeking for new strategies for improving their own and their supply networks' operations, to become competitive. These all result in several thriving production and material flow control systems and strategies. For example, some of which that have been introduced to businesses are mass production, push and pull principles, lean manufacturing, agile manufacturing, flexible manufacturing, and mass customization [1]. In addition, for managing each of these policies, some production and material flow planning and control systems have been introduced. Conventionally, most of the planning and control systems are equipped with a centralized approach, e.g., MRPI, II [2]. These systems collect required information and make the planning and control with an integrated and aggregated approach. However, one of the new research topics in the field of logistics and material flow control reflects a decentralized orientation with employment of autonomous agents [3, 4].

From strategic point of view, logistic networks can be combinations of autonomous members that cooperate with each other in a collaborative manner [1, 2].

This approach can yield into a logistic network with better ability to deal with risks and dynamics happening in local points [3]. The respective member reacts independently to the changes taking place in its own realm. This prohibits proliferation of that to others and consequently fluctuation in the overall performance. However, this independently does not necessarily represent autonomously. But for being autonomous, exchange of information besides self decision making plays crucial roles. Furthermore, it is believed that this strategy can be undertaken in micro-scales too, inside factories and shop floors. In this case, the autonomy concept, instead of network's members, affects directly logistic objects and control systems for handling material flows in real-time operations. This perception of autonomy is the core of a research project called Äutonomous Cooperating Logistics Processes—A Paradigm Shift and its Limitationsřealized in CRC 637 research cluster at Bremen University (for more details, see www.sfb637.uni-bremen.de).

In this paper, by a practice-oriented approach following the autonomy paradigm, a new concept as learning pallets (Lpallets) is introduced. As mentioned above, several policies have been already developed to cope with dynamics and changes in production logistic systems. Therefore, autonomy in logistic branches should take those efforts into account and clarify its own position in contributing to those developed systems. As mentioned, this study over Lpallets has a conceptual as well as experimental (practical) approach; hence, it appeals for practice-oriented methods and strategies. In doing so, a pull principle system is adopted. This is a compatible existing system which has a decentralized approach to control material flow that can be combined with the autonomous control concept. Shortly, the contribution of Lpallets to the autonomy is such explained that they learn systems' behaviors in a closed-loop and then play their roles in an autonomous manner. In this way, the constant work in process (Conwip) system in a factory out of a logistic network, after decoupling point, is chosen to employ Lpallets and analyze this concept [5].

The following sections are organized as follows: Next section briefly explains the general material flow control systems and gives an argument to the consistency of autonomy with the suitable ones. Later, a generic review is given to closed loop systems. Following that application of Lpallets for autonomy is presented. Pull system advantages for autonomy and Lpallets is explained after that. Afterward, the legend of simulation scenario in terms of Lpallets in Conwip is introduced. The next section refers to a short description of fuzzy sets and its application in Lpallets algorithm. Experimental results out of simulation are shown and analyzed later on. At the end, conclusion and further works are given.

2 Two general material flow approaches

Currently, businesses are confronted with continuous changing conditions, called dynamics, which are supposed to be handled by more intelligent strategies. Transient markets, uncertain demands, short product life cycles, and mass customization are some dynamic impulses [6, 7]. For instance, mass customized products force supply networks as well as production plants to shift from the mass production systems, with push approach, to the make-to-order or engineer-to-order production/logistic strategies, with rather pull approach, in order to comply with individual demands. These recent production strategies burden more pressure on logistic systems to operate based on real demand and at the right time. The real-time operation requires an agile system triggered by specific demands. Consequently, some special approaches to the existing material flow systems have been placed in order to handle requirements in one side and constraints on the other side. Therefore, some novel hybrid methods are introduced which combine the advantages of both material flow approaches as push and pull [8, 9].

Nevertheless, push systems, e.g., MRP, result better when high variety exists and demand fluctuates, but still is predictable [10]. However, a common consequence of push systems is over production and inventories. In contrary, pull strategies, e.g., Kanban, comply better with rather stable demand and low variety in products [11, 12]. For example, shifting from totally push system to Kanban system, with fully pull concept, may have some shortcomings in facing uncertainties [13]. Therefore, a clever solution for dealing with such conditions is to employ advantages of several material flow control strategies [5]. For this purpose, some hybrid systems, e.g., Conwip, Polca, G-Polca, are practiced in several situations to overcome those problems [9, 14, 15]. It is claimed that these systems compensate the potential weaknesses of monopole systems and hinder them from getting failed or overproduction. For instance, it is shown here that Conwip system has the ability to moderate fluctuations in lead time when demand volume is limited to supply, while throughput time (TPT) is reduced for production as well. Conversely, the number of outputs may be decreased by applying this control system instead of push without specific demand for finished products.

Furthermore, application of autonomous control in this context has to be compatible with those systems which have the capability of employing autonomous objects besides providing them necessary information exchange. This merit of decentralized control, as a basis for autonomy, is accompanied with pull strategies.

3 Closed loop system review

Practitioners are aware that uncertainty is inherent in processes with human-centered problems as stated by Sakawa et al. [16], specifically for logistic and production operations by Gupta and Maranas [17], insisting on imprecision in information in production systems by Sevastijanov and Róg [18], as well as literature review of Mula et al. [19].

In order to conduct a responsive control of uncertain systems, several solutions are already undertaken. Among them is the exploitation of closed loop systems accompanied with feedbacks control. Obviously, those systems with the ability of feedback reflection are more capable to tackle uncertainties and make suitable adaptations. As Nagy et al. discussed in [20], open loop systems in coping with uncertainty can repeat online open loop operations (optimization) based on feedbacks. This implies closed loop systems by feedback control. Additionally, it shows that the feedbacks can considerably reduce the effects of parameter uncertainties. Although Shi et al. in [21] have employed a closed loop supply chain with several perspectives, their approach reflects another aspect of closed loop systems in a broader scale. They analyzed production planning problem of a closed loop supply chain by uncertain demand and reverse logistics with multi-product. They used mathematical model and made a good review on literatures with closed loop approaches. They clearly present uncertainty in supply chins and demand as well.

Nonetheless, there is always a discussion whether the closed loop feedback systems are pragmatic for current production systems or not? This was expressed by Kogan [22] who proposes more explorations on open loop systems with offline control methods vs. closed loops. But he insists on uncertainties with production and logistic processes as well. On the other hand, there are some control systems that practically use closed loops in inherent manner. These systems facilitate the feedbacks required in controlling the entire system.

As briefly mentioned above, there are some material flow control approaches that resemble closed loop systems in practice. Among them are the pull principle systems like Conwip and Kanban. Kirshnamurthy et al. in [23] analyze Conwip, Kanban, and Polca control strategies as closed queuing networks and express them as closed loops in practice. This was done by Duenyas et al. in [24] as well. Levantesi in his work [25] presents the practice of closed loop systems in material flow control by introducing those pull strategies as closed loop systems. He directly reflects these closed loop systems to the reality by using constant number of fixtures or pallets as the control means. He employed the decomposition technique for better understanding the behavior of the system as well as for managing that in real time. In fact, this decomposition method in our work is interpreted as decentralization approach in autonomy.

Lázaro and Pérez in their paper [26] make a universal review on closed loop production systems and specially automotive production lines. In their work, previous papers are classified according to their treatments in analyzing closed loops in such environments. They consider the constant number of pallets (as capacity in closed loops) between decoupled closed loop production lines. In particular, they "tackle the analysis of the automobile assembly and pre-assembly lines as a network of machines and intermediate buffers decoupled by intermediate buffers." Besides, they differentiate between stationary and transitory circumstances in working stations. Their underlined contribution refers to analysis of complex networks of closed loops and defining the constant number of pallets in the loops and intermediate buffers. Analysis of blocking and starvation conditions are included in their survey. According to them, starvation and blocking happens when the assembly system is not balanced and the production rates of consecutive stations are not similar. If the downstream station has a higher rate than the upstream one and the buffer in between is empty, the downstream station starves. Blocking happens when the intermediate buffer with limited capacity is full and the production on upstream machine is finished. However, this condition is not completely relevant to the current problem in the paper. Only this phenomenon with its fully conditions may happen between plants; when the transporters are not available blocking occurs and when the products are not ready to get delivered in the presence of transporter, the downstream plant starves. Moreover, Lázaro and Pérez in another work [27] underscore the starvation and blocking phenomena again in a dynamic environment of an automobile assembly line with closed loop network of machines and by a thorough analysis. In doing so, a new modeling method (as a closed loops network) is proposed. They aim at modeling the propagation of disruptions between machines in a closed loop network. Thereby they analyze the effect of the number of pallets in up- and downstream of the network, according the capacity of intermediate buffers as well as the transitory and stationary regime. In the paper, varying capacity for buffers in such an environment is used. The main contribution of this paper is claim by the authors as an enhancement for analyzing and improving the working limits of assembly lines by varying buffers' capacities.

Gershwin and Werner in [28] widely return to the closed loop production systems and express the specific characteristics of closed loop systems. They try to decompose closed manufacturing systems into their building blocks for easy analyzing. They report the suitability of their solution for Conwip and closed loop systems using pallets as Helbert et al. did in [29]. Ip et al. in [30] treat Conwip system as a closed loop and evaluate the difference between single and multi-loop Conwip system. They conclude that the single loop has better performance than the multi one. Consequently, this imitation of closed loops in material flow strategies can bring them the specific privilege of closed loop systems as below.

There are several advantages of closed loop systems over open loops reported in literatures, considering different applications [31]. In addition to simplicity of controlling closed loop systems, they, by having the opportunity to reinforce their experiences and getting feedback from their performances, are able to modify their perceptions to the environment, as in [20]. The underlined advantage of closed loops, as feedbacks, provides a better controller to modify the dynamics of a system and enables it to stabilize the naturally unstable systems, as emphasized by Rowley and Batten [32]. Jansson et al. [33] mention the usability of closed loop system in unstable situations for better learning the conditions. Indeed, learning is also an underlined application of closed loop systems.

Despite the difference of intelligent and adaptive control, learning in closed loops seems practical. However, as Kulvicius et al. [34] state, there is less attention paid to learning of those systems which interact with environment as agents because of their non-stationary situation and their intricate interplay between behavior and plasticity. They consider the learning of global data for faster convergence and using agents for local data to achieve higher accuracy. All in all, as Dorigo and Colombetti [35] and Andry et al. [36] referred to, learning is a mean of autonomy achievement.

4 Application of Lpallets with autonomy

The concept of autonomous logistic processes is orienting into every kind of processes existing in logistic operations as the processes are classified into managerial, operational, and supporting [37]. In the research of autonomy, it is supposed to investigate all processes and objects whether they have the ability to become autonomous and in what level. However, here, the main focus is laid on logistic objects for making them autonomous [38]. Nonetheless, the concerned objects must reflect feasibility in the autonomy merit. This means they should convey consistency with autonomy in order to improve a process or recover any existing lacks in practice.

Respectively, very popular and interesting logistic objects in inbound as well as outbound logistics are the varieties of pallets. The variants of pallets bear the competency of becoming autonomous objects concerning their level of individuality and flexibility. Pallets are particularly attractive because they, by limited capacity and specified varieties, have the possibility to directly control their contents in an individual manner and with enhanced fault tolerance.

This is exactly what the mass customization policy is seeking for [39]. In fact, the mass customization and individuality for products, based on customer demand, is a very common study in the field of production and logistics [40]. The customization strategy can comply with reasoning and justifying employment of autonomy in production logistics and the use of relevant objects, e.g., see [41]. According to the definition of autonomy, each object has the merit of decision making by itself in an equality circumstance [11]. Thus, the autonomous pallets, in this context, seem to be assisting tools for the individualization. Conclusively, pallets are selected to become under investigation for autonomy in this study. Besides, learning can be a method to convey autonomy to decision makers that Lpallets represents this fact.

It should be noticed that although pallets are used extremely for material flow, the notion of Lpallets is not limited to pallets. It concerns any similar objects to pallets, which have the ability to carry limited number of products at outbound as well as inbound (production lines), e.g., bins, boxes, crates, fixtures. Furthermore, pallets have some unique advantages to become a responsive candidate for autonomous controlled logistic object. These benefits are displayed in specific material flow control as pull systems.

5 Pull system for Lpallets and autonomy

As mentioned before, for reducing the bullwhip effects and fluctuations in material flows, some control policies moving toward hybrid strategies are already developed.

In particular, application of Conwip control system seems suitable for arranging the both sides of supply and demand in equilibrium. This specification provides a basement for adopting autonomy in logistic networks. For instance, by using this, a plant, as a member of supply network, is able to monitor its situation in the field of demand as well as supply rates. Therefore, this monitoring brings some independency to that member to control its entrance beside finished products' inventories. This could be done autonomously without being dominated by the predecessors. This autonomous plant has the authority for asking more or less supply, based on its order rate.

In addition to those advantages of autonomy in macro-scale by using hybrid systems, Conwip system gives a glorious benefit to pallets in shop floors. Since pallets are Conwip control means, they may learn the behavior of their working environment. As referred by [11], Conwip control, based on constant work in process, has a limited number of cards or pallets for moving products. Those industries who use pallets, or alike, as pull signals give this opportunity to pallets to experience the situation of production lines and get up-to-date data in each round trip. In the previous sections, it was already explained that Conwip resembles closed loops.

Accordingly, pallets are triggered by respective orders from downstream of the shop to upstream of that and move back through the entire line. In each round, they record some defined metrics for evaluating the performance of the system, lines, supply, and fulfillment operations. By doing this, after some training rounds, just following any changes in the system, they can distinguish them and adapt themselves to the new situation.

Additionally, learning can be a requirement of being autonomous. Moreover to the researches on intelligent products, containers, and autonomous agents (see CRC 637 Autonomous Cooperating Logistic Processes—A Paradigm Shift and its Limitations, http://www.sfb637.uni-bremen.de), learning ability is an alternative to provide required information for autonomously decision making [42]. It is noticeable that this alternative is not in parallel of other options, but rather is complimentary. This learning happens for closed loop systems which can experience new changes.

It is noticeable that learning of pallets without adopting agent negotiation can reduce the technical complexity of information exchange between agents in real time. On the other hand, it reduces the quality of proper decisions based on real-time dynamics in the system, since no exact awareness about other agents' situation is configured. However, in this paper, just the learning capability is experimented and additional contributions will be reported on later works.

6 Conwip simulation scenario

A discrete event simulation model, called Plant Simulation produced by Siemens, is developed for indicating the applicability of the claimed strategy as well as the performance of Lpallets. For this purpose, an exemplary supply network in (Fig. 1) is considered that its ultimate performance is reflected by the last plant. Hence, only the final plant (OEM) out of the

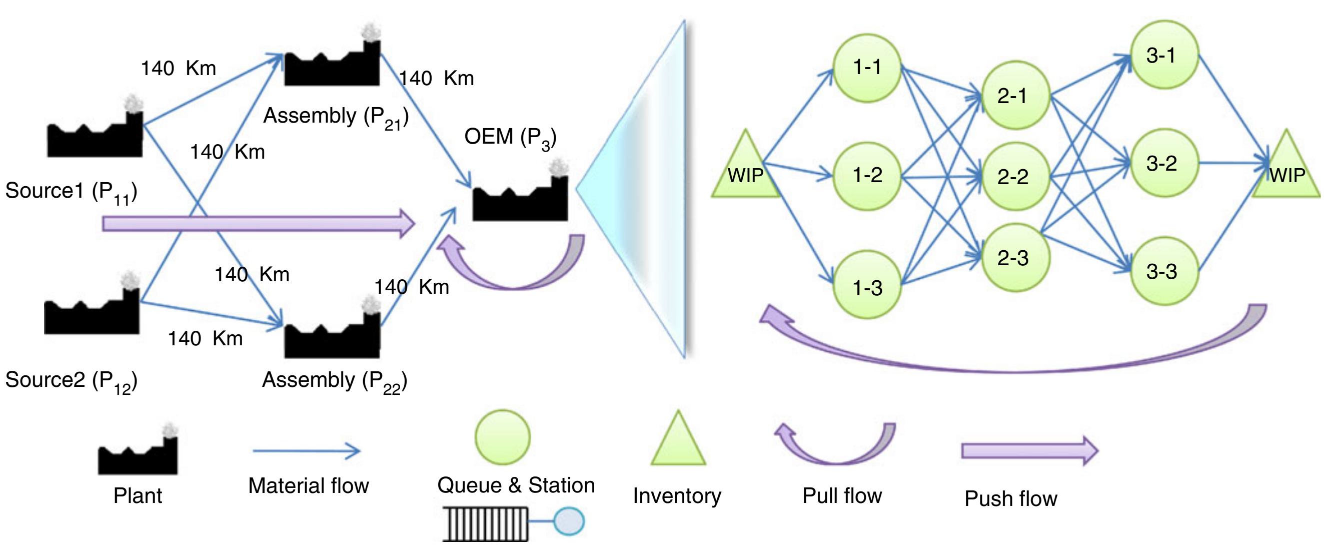

Fig. 1 The logistic (supply) network and the underlined member (OEM) in experimenting the simulation scenario

supply network is selected to reveal the experiments analysis. The topology of the network displays that two source plants, two assembly plants, and one OEM construct the global structure. Each parallel plant has no connection to its counterpart, while the flow of material is fed forward with 140 km distance to the next step plant. Regarding the velocity of transporters, a round trip between two plants takes 4 h. The OEM is located after the decoupling point separated by final customer material pull; for more information, see [11, 43]. This individual plant is intentionally chosen to return its autonomy in the network; by means of decoupling, it can handle material flows just based on its own supply and demand rates. It is shown here that this plant by employing Lpallets and Conwip system is able, to some extent, to coordinate its capacity and internal material flows.

In the scenario, three types of products and, respectively, three types of Lpallets are considered to carrying them. These Lpallets have the mission of taking semi-finished products based on corresponding orders from the entrance inventory, carrying them through the stations for processing and delivering them to the exit. In this Conwip system, appearance of an Lpallet in the entrance, triggered by an order, means collection of (regarding its lot size) semi-finished product(s) (SFP) from the entrance inventory and get released to the production line.

As shown in Fig. 1, the shop floor in the OEM plant consists of three steps of operations; in each step, three parallel machines work together, so that each machine has its unbounded buffer size in its predecessor. Indeed, this arrangement resembles a flexible flow shop scheduling problem [44] in generic context. This flexibility and the unbounded intermediate buffers avoid the blocking phenomena, while starvation is a frequent case in this problem. Since the number of pallets in the Conwip system is constant, each congested queue in a station causes a starvation at least in one of the successors. However, a real starvation and blocking happens in the decoupling point at the entrance inventory of OEM. This returns to the constant number of pallets and the uncertain supply rate as well as uncertain availability of pallets at the entrance inventory. Indeed, the availability of products as well as pallets at the entrance inventory are dependent factors to stochastic supply as well as the queues and production rates. However, each machine has a stochastic processing time with normal distribution ($\mu, \sigma = \mu/10$). Table 1 defines the processing times of all product's types in every plant of the network. These values for all plants except the OEM are chosen based on a smooth flow of materials regarding the push principle and the transporters' speed. The values in the OEM are selected regarding the pull principle, the requirement of stock at the entrance inventory, the number of pallets, and the pull demands from customer side. All these values are extracted from several simulation trials. Additionally, the supply of SFPs from predecessor plants has a stochastic nature as well.

Although there are three types of end products, each type of product is combined of two raw materials, each coming from a source. However, this stream flow of sources follows uncertain delivery intervals. So, the stochastic combination of operations and transportations between the network's plants make the supply of SFPs to OEM a fully stochastic natured process too. In the same way, demand interval's distribution follows the probability density function (pdf) of negative exponential, as is in practice [45]. Consequently, these stochastic features cause a very complex dynamic system with vagueness in real-time control decisions.

Generally, the current problem of the supply network is limited to two responsive objectives, to minimize the makespan of the flexible shop floor in OEM, as well as to minimize the waiting time at the entrance inventory of OEM. These two objectives correspond to two approaches to the supply network problem. Indeed, the minimization of the makespan reflects the local throughput time (LTPT) at OEM, affected by internal variables, whereas the minimization of inventory time releases the attention to the global throughput time (GTPT), affected by the previous plants (sources, assemblies, and inter-plant transporters)

Table 1 Processing times of all types of products in all plants of the network

Processing times [h:min] for each plant							
Plant	$P_{11}; P_{12}$			$P_{21}; P_{22}$	P_3 (OEM)		
	Line						
	Deterministic value				Mean value (μ)		
Product	1	2	3	1	1	2	3
Type 1	2:00	3:00	2:30	00:50	2:00	2:40	2:20
Type 2	2:30	2:00	3:00	00:50	2:20	2:00	2:40
Type 3	3:00	2:30	2:00	00:50	2:40	2:20	2:00

variables. However, the direct changes in previous plant from OEM are not considered in the current problem solving. This simplifies the problem, while highlights the role of Lpallets in shop-floor problems. In order to clarify the characteristics of this problem, it is mathematically modeled with a concise description as follows. However, there are several stochastic parameters in the problem, which make uncertain boundaries for the feasible solution space of the problem. For instance, besides the stochastic processing and waiting times at each station, availability of pallets at the entrance inventory (ap_f) and the entrance time of SFPs to this inventory (e_{jf}) result in an uncertain variable of SFPs' release time to the shop floor (r_{jf}). The used notations of this problem are given in the following:

j	number of products $j = 1, ..N$
f	types (family) of products; $f = 1, 2, 3$
k	number of parallel stations in column 1, $k = 1, ..3$
u	number of parallel stations in column 2, $u = 1, ..3$
v	number of parallel stations in column 3, $v = 1, ..3$
ap_f	availability of an empty pallet in family f
W_{kjf}	waiting time of job j family f before operation on machine k
W_{ujf}	waiting time of job j family f before operation on machine u
W_{vjf}	waiting time of job j family f before operation on machine v
t_{kf}	uncertain processing time of product family f on machine k, following $\mathcal{N}(\mu, (\mu/10)^2)$
t_{uf}	uncertain processing time of product family f on machine u, following $\mathcal{N}(\mu, (\mu/10)^2)$
t_{vf}	uncertain processing time of product family f on machine v, following $\mathcal{N}(\mu, (\mu/10)^2)$
r_{jf}	uncertain release time of job j in family f to shop floor
e_{jf}	uncertain entrance time of product j in family f to shop floor, following neg-exponential

$X_{kjf} = 1,$	if job j of type f works on machine k; 0, otherwise
$X_{ujf} = 1,$	if job j of type f works on machine u; 0, otherwise
$X_{vjf} = 1,$	if job j of type f works on machine v; 0, otherwise

Objective Minimization of makespan (total completion time)

$$\min C \tag{1}$$

Minimization of waiting time at the entrance inventory

$$\min \sum_{f=1}^{3} \sum_{j=1}^{N} (r_{jf} - e_{jf}) \tag{2}$$

subject to:

$$\begin{aligned} C = &\sum_{k=1}^{3} \sum_{f=1}^{3} \sum_{j=1}^{J} (X_{kjf} t_{kf} + X_{kjf} W_{kjf}) \\ &+ \sum_{u=1}^{3} \sum_{f=1}^{3} \sum_{j=1}^{J} (X_{ujf} t_{uf} + X_{ujf} W_{ujf}) \\ &+ \sum_{v=1}^{3} \sum_{f=1}^{3} \sum_{j=1}^{J} (X_{vjf} t_{vf} + X_{vjf} W_{vjf}) \end{aligned} \tag{3}$$

$$r_{jf} = \max (ap_f, e_{jf}); \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{4}$$

$$X_{kjf} = 1, \text{ if job } j \text{ of type } f \text{ works on machine } k; 0, \text{ otherwise} \tag{5}$$

$$X_{ujf} = 1, \text{ if job } j \text{ of type } f \text{ works on machine } u; 0, \text{ otherwise} \tag{6}$$

$$X_{vjf} = 1, \text{ if job } j \text{ of type } f \text{ works on machine } v; 0, \text{ otherwise} \tag{7}$$

$$\sum_{k=1}^{3} X_{kjf} = 1; \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{8}$$

$$\sum_{u=1}^{3} X_{ujf} = 1; \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{9}$$

$$\sum_{v=1}^{3} X_{vjf} = 1; \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{10}$$

$$\sum_{k=1}^{3} X_{kjf} = \sum_{u=1}^{3} X_{ujf}; \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{11}$$

$$\sum_{u=1}^{3} X_{ujf} = \sum_{v=1}^{3} X_{vjf}; \forall j = 1, ..., N; \forall f = 1, ..., 3 \tag{12}$$

$$\begin{aligned} &r_{jf} \geq 0, \\ &e_{jf} \geq 0, \\ &ap_f \geq 0, \\ &X_{kjf}, X_{ujf}, X_{vjf} \text{ binary}; \forall f, j, k \end{aligned} \tag{13}$$

The objective function in Eq. 1 defines the intention to minimize the flow time and specially the completion time of the entire 500 products at shop floor of

OEM. The objective function in Eq. 2 represents the desire to minimize the waiting time at the entrance inventory of OEM that reflects the coordination of several uncertain variables to decrease the GTPT. In fact, the availability of Lpallets at the entrance and existence of respective SFPs replenished by previous plants have to get coordinated to bring the optimum result. However, these uncertainties are not conventionally solvable. Moreover, since this mathematical programming problem resembles a flexible scheduling by existence of some stochastic variables, this makes the problem $\mathcal{NP}$-hard to be solved [44]. For example, the availability variables or the release times to shop floor are stochastic that without any pre-assumptions is not possible to be solved conventionally. Additionally, all products are not available at the beginning, which is the requirement of static solution, but they appear stochastically. Nonetheless, by considering some classical assumptions, e.g., deterministic entrance time of SFPs at the entrance inventory and availability time of pallets or unlimited number of pallets, the problem can be conventionally solved by Cplex solver as well as scheduling rules and methods.

Furthermore, for bearing learning ability to pallets, some fuzzy rules, as controller, are adopted to judge and learn the behaviors. This is particularly applicable because of uncertain nature of the supply, demand, and operation times. Although using fuzzy logic is not the only way of judging and learning, it is one of the alternatives studied in this paper. The exclusive fuzzy rules transmit decision variants that the pallets may confront with them.

Lpallets, after carrying respective product(s), record all data about the time. It means they save important criteria, e.g., waiting time in a passed queue and its respective processing time in station, the code name of station, and the average time expended by so far pallets passed through this station. To some extent, these data are recorded in Lpallet as the source of knowledge and decision making. Briefly, based on defined fuzzy set, linguistic judgments with membership values are carried out for every passed station. These judgments are the foundation of later decision makings about routing selection.

7 Applied fuzzy set

Today, the ambition for solving realistic problems is rising. Nonetheless, for complying with this request, much more detailed data are required which usually are not accurately available. According to Zadeh [46], by increasing the complexity of a system, our judgment about its behavior gets imprecise till a threshold that is not possible to precisely judge it. In this case, because of the variety in uncertainty sources, probability theory is not responsive anymore. On the other hand, fuzzy set theory is a powerful set theory for characterizing the uncertain nature of practical operations, specifically here in logistics. As mentioned, any human-centered problems or processes, e.g., processing times, transportation, and due dates, carry uncertainties, representing randomness, vagueness, and ambiguity [16]. As stated by Zimmermann, fuzzy set theory offers a powerful mathematical framework that can analyze and characterize vague conceptual phenomena [47]. It is also mentioned that because of limited memory capacity of human or technical systems, perception of all data is sophisticated. This complexity can be reduced, to some suitable degree, by using fuzzy system. For instance, in logistics, stochastic customers' orders or available information about the entire logistic processes are imprecise elements for decision makers. In practice, planning and control of production and material flow are done based on aggregated or average values of available data. This mostly returns to lack of information, and not necessarily randomness in nature.

Application of fuzzy set theory, by using fuzzy numbers, membership functions, and defining fuzzy rules, can distinguish and compromise existing uncertainty accompanied with imprecision in data. Consequently, it can be said that the theory suits to vague or ill-defined problems. Particularly in logistic networks, uncertain processes times with stochastic nature, e.g., normal or exponential distribution, besides complexity in calculating accurate factors, cause imprecise decisions over material flow scheduling and control. This problem can be solved by taking into account its fuzzy nature and arranging fuzzy rules for better resulting decisions.

IF-Then fuzzy rules reflect the policy of the decision maker in terms of problem's objectives [48]. Additionally, those rules and their respective partitions in fuzzy domains may be learned through a learning phase or defined by experts in advance. In this paper, they are defined in advance but the domains in partitions may be learned. In general, fuzzy set is mathematically defined as follows [49]:

Definition 1 If X is a space with generic elements of x, and $\mu e_{\widetilde{Y}} : X \to M \subseteq [0, 1]$ is the characteristic function that maps X to membership space M. Then the following set of pairs uniquely represents a fuzzy set.

$$\widetilde{Y} = \left\{x, \mu e_{\widetilde{Y}}(x) | x \in X\right\} \tag{14}$$

Several shapes can be used for defining membership functions of fuzzy sets; among them are triangular, trapezoidal, Gaussian, and s-curve [48, 50]. Triangular fuzzy membership function, because of its simple arithmetic operations, is usually considered for modeling uncertain processing times. Representation of triangular fuzzy number (TFN) of ($\tilde{Y}$) is done by a triplet (y_1, y_2, y_3). Whereas y_1 is the lower bound and y_3 is the upper bound of ($\tilde{Y}$) with membership degree of zero ($\mu e_{\tilde{Y}} = 0$), y_2 is the modal point (middle range) with membership degree of one ($\mu e_{\tilde{Y}} = 1$). This type of fuzzy membership is also chosen to be used for the current problem.

8 Applied methodology

Since complexity is an unavoidable characteristic of the current and prospective logistic and production systems, this importance must be handled by more intelligent solutions. Development of Lpallets is a promising solution to deal with such. Indeed, an Lpallet consists of a controller which has the ability of learning. For this paper, the controller is based on fuzzy system with alternative applications. It is decided to examine the performance of Lpallets in a job dispatching problem within a flexible shop floor problem. In doing so, Lpallets undertake this mission in a real-time manner without reconsidering any predefined schedule. It is assumed that an Lpallets based on several algorithm is able to organize its own decisions on routing. In addition to a control method for deterministic condition, several control methods are introduced here to challenge the uncertainty at production environment. Among them, two prominent ones are as: first, Lpallets with independent learning and judgement ability for estimating the performance of parallel stations and selecting the best route (LP). Second the Lpallets with no judgement ability, but with reliance on uncertain estimation of queue sizes (NoLP). Generally, the performance algorithms of the used fuzzy system are inspired by the five steps of such a system as fuzzification, application of fuzzy operators, implication of antecedences to consequents in fuzzy rules, aggregation of the consequents, and defuzzification based on Mamdani fuzzy rule-based system, see [51]. The employed algorithm for each capability are explained below. However, the alternatives are not limited to these two, and each of them is explained in below and in the section of results analysis.

Considering the current problem, after a while flowing through the lines and collecting experience, now an Lpallet, derived from its judgments, is able to select a route and proceed over it. This ability is achieved by two procedures as: judgment process and route selection. Although these procedures are not independent in performance, they have two separate operating algorithms. The entire judgment process works based on the algorithm in Fig. 2.

Initially, different shapes of membership function are practiced for the fuzzy sets, concerning linguistic judgments for experienced stations and queues by Lpallets. All of these shapes are assumed to have flexible boundaries due to their moving average values. However, among all shapes, the most reasonable one is the triangular function with variable space. The boundaries of the triangular membership function are flexible by means of control chart for individuals, i.e., upper control limit (UCL) and lower control limit (LCL) for boundaries [UCL LCL], inspired by statistical process control; for more information, see [52].

Now, the fuzzification and linguistic judgment process for the specific boundary [UCL LCL] are rendered according to its algorithm (see Fig. 3). In this algorithm, the number of experienced values in an Lpallet (denoted by i) configures LCL and UCL, which reflect the membership values and the linguistic judgments regarding the rule-based system. Indeed,

Fig. 2 Algorithm of judgment process

```
Begin
    If the operation instation is done then
        Reflect the waiting time and cycle time into fuzzy judgment
         operator
        begin
        fuzzify the crisp input value of waiting plus cycle time into
        membership value by the respective membership function
        Judge this membership value of the queue and station by
        linguistic terms
        Record this membership and linguistic judgment into the pallet
        end;
End;
```

Fig. 3 Algorithm of fuzzification for judgment process

Begin

i= experienced samples number

$fa = min_{1 \le k \le i}(x_k)$, $fb = max_{1 \le k \le i}(x_k)$, $Rang = fb - fa$,

$avg = \bar{x} = \sum_{k=1}^{sample} \frac{x_k}{sample}$, $Med = \frac{fb-fa}{2}$,

$Aavg = \sum_{k=1}^{i} \frac{\bar{x}_k}{i}$, $ARang = \sum_{k=1}^{i} \frac{Rang_k}{i}$,

$UCL = Aavg + (E_E) \times ARang$, $LCL = max(Aavg - (E_E) \times ARang, 0)$

$E_E = 1.468$

If $x \le Aavg$ *and* $x > \frac{(LCL+Aavg)}{2}$	*then*	$\mu e = \frac{x - \frac{(LCL+Aavg)}{2}}{Aavg - (\frac{LCL+Aavg}{2})}$	*is normal*
If $x < \frac{(UCL+Aavg)}{2}$ *and* $x > (aavg)$	*then*	$\mu e = \frac{\frac{(UCL+Aavg)}{2} - x}{(\frac{UCL+Aavg}{2}) - Aavg}$	*is normal*
If $x > aavg$ *and* $x \le UCL$	*then*	$\mu e = \frac{x - Aavg}{UCL - Aavg}$	*is bad*
If $x < aavg$ *and* $x \ge LCL$	*then*	$\mu e = \frac{Aavg - x}{Aavg - LCL}$	*is good*
If $x > UCL$	*then*	$\mu e = 1$	*is bad*
If $x < LCL$	*then*	$\mu e = 1$	*is good*

End;

the values of UCL and LCL are achieved from the experienced values (processing time + waiting time in queue) by Lpallets, see also Fig. 7.

In fact, there are two alternatives in the presence of vagueness for dispatching pallets to parallel stations. The first alternative is to rely on the imprecise linguistic terms about queues at the moment, called here (NoLP), and is not pertinent to the judgment process. These linguistic terms define the best station for dispatching (see Fig. 4).

On the other hand, the second alternative is to use the Lpallets and employing their judgment ability, called (LP). After judging stations, in order to select the best parallel station out of three, the route selection algorithm is triggered. Here an extension happens to the both linguistic terms out of current situation of queues and the recorded judgments inside an Lpallet. Finally, the decision for dispatching is made by the extension principle of Zadeh [53], see Fig. 5 for its algorithm. Theorem 1 explains the extension principle of Zadeh.

Theorem 1 *Let $\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_n$ be independent fuzzy numbers with membership functions of $\mu e_1, \mu e_2, ..., \mu e_n$, respectively, and $f : R^n \to R$ a function. Then according to the extension principle, the membership function μ of $\tilde{Y} = f(\tilde{y}_1, \tilde{y}_2, ..., \tilde{y}_n)$ can be derived as:*

$$\mu e_{\tilde{Y}}(X) = \sup_{x_i \in X_i; i=1,2,...,n} \min \mu e_{\tilde{y}_i}(X_i) \tag{15}$$

Here, the Mamdani fuzzy inference system [54, 55] is applied. Besides, the defuzzification method is the weighted average [56] that its estimation algorithm is presented in Fig. 6.

Graphical representative of the fuzzy associative memory (FAM) for selection of successor station based on experienced judgments and current imprecise linguistic terms of successors is displayed in Fig. 7.

Table 2 represents the performance of fuzzy rules with the presence of queue linguistic terms, used in extension. Table 3 defines the FAM in case of min operator for several records (experiences).

Fig. 4 Algorithm of route selection, relying on linguistic terms of queues

Begin

For i=1 to number of successors

Check linguistic terms and membership value of queue (i)

If the term is "Speedy" then has priority 1

If the term is "Lowspeedy" then has priority 2

If the term is "Nospeedy" then has priority 3

Next;

Take the maximum membership value in each priority

Choose the Queue with higher priority and membership value

End;

Fig. 5 Algorithm of route selection by extension principle, using judgment process

Begin
While i≤number of succesors do
begin
Check the linguistic term and its membership value of station (i)
In Lpallet, check linguistic judgments and membership values of last three records about queue & station number (i)
Take the min operator of the last three records in Lpallet, see table 3
Take the max (OR) operator between this derived value of Lpallet and the membership value of linguistic judgment in station (i) (Zadeh extension, see Fig. 7)
Imply the membership values out of premise of respective fuzzy rule to the consequent by alpha cut method (truncation)
Aggregate the consequent membership values by method sum
Defuzzify the fuzzy values of consequences to crisp value for the successor
end;
end;
Compare the crisp values of each successor and take the one with the least value as selected successor
(Call Judgment algorithm)
End;

In order to compare the performance of the stated LP method, some alternatives are used, e.g., a robust autonomous control, developed for such problems, called queue length estimator (QLE). Briefly, the advantage of QLE is that in each decision point, the decision maker compares all precise queue length and correspondingly the waiting time of all parallel queues. In this case, the queue with the least waiting time is chosen, see [11, 57]. However, for adopting uncertainty in processing time, the performance of QLE must be adjusted. This adjusted QLE is called (QLE.Fuzzy). The performance of the adjusted method is exactly the same as QLE, but the processing time of every existing pallet in a queue is fuzzy configured. Here, a triplet fuzzy number $(\mu-\sigma, \mu, \mu+\sigma)$ represent normal processing times, where μ is the mean and σ is the variance of normal distribution. Then in a queue, the fuzzy numbers are summed up, so that $\tilde{A}+\tilde{U}=(a_1+u_1, a_2+u_2, a_3+u_3)$. Additionally, for comparing two TFNs, a ranking method must be employed that here the Sakawa ranking method is applied [58, 59], i.e., $\tilde{A}<\tilde{U}$ if $(a_1+2a_2+a_3)/4<(u_1+2u_2+u_3)/4, a_2<u_2, a_3-a_1<u_3-u_1$.

Fig. 6 Algorithm of the defuzzification method

Begin
m_1 = *max (membership value of Good station, Speedy station)*
m_2 = *max (membership value of Normal station, Lowspeedy station)*
m_3 = *max (membership value of Bad station, Nospeedy station)*
If $(m_1 \wedge m_2 \wedge m_3) \neq 0$ *then*
Crisp value of the respective queue & station = $\frac{\left[(a+(c-a)\times m_1)+\left(m_2\times\frac{(d-b)}{2}+b\right)+(c+(e-c)\times m_3)\right]}{m_1+m_2+m_3}$
elseif $(m_1 \wedge m_2) \neq 0$ *then*
Crisp value of the respective queue & station= $\frac{\left[(a+(c-a)\times m_1)+\left(m_2\times\frac{(d-b)}{2}+b\right)\right]}{m_1+m_2}$
elseif $(m_1 \wedge m_3) \neq 0$ *then*
Crisp value of the respective queue & station= $\frac{[(a+(c-a)\times m_1)+(c+(e-c)\times m_3)]}{m_1+m_3}$
elseif $(m_2 \wedge m_3) \neq 0$ *then*
Crisp value of the respective queue & station= $\frac{\left[\left(m_2\times\frac{(d-b)}{2}+b\right)+(c+(e-c)\times m_3)\right]}{m_2+m_3}$
elseif $(m_1) \neq 0$ *then*
Crisp value of the respective queue & station= $\frac{[(a+(c-a)\times m_1)]}{m_1}$
elseif $(m_2) \neq 0$ *then*
Crisp value of the respective queue & station= $\frac{\left[\left(m_2\times\frac{(d-b)}{2}+b\right)\right]}{m_2}$
End;

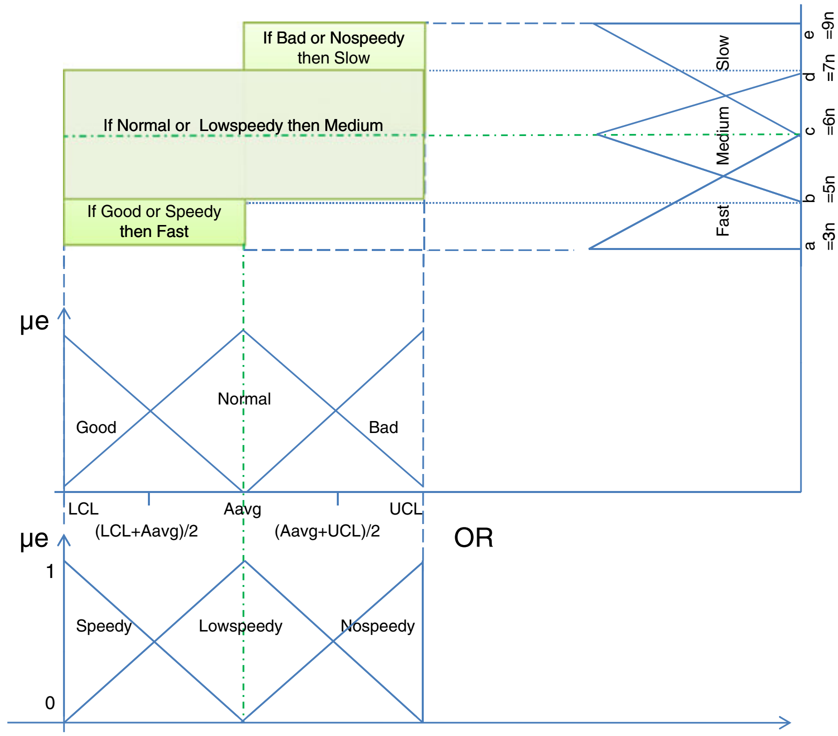

Fig. 7 Applied Fuzzy associative memory

It is noticeable that in QLE and QLE.Fuzzy, precise information about the queue length must be available, which is supposed unlikely under vagueness.

9 Analysis of simulation results

Several experiments are conducted for this study; firstly, LTPT of different control methods, by one piece in pallets' lot size, is compared. Secondly, this is experimented for alternative lot sizes in pallets. Thirdly, these states are compared with two flow alternatives as push and pull. Fourthly, LTPT and GTPT of the methods are compared against each other in the presence of stochastic breakdowns for all stations. For this last experiment, not only TPT of the methods but utilization of stations, WIP, and the makespan of all 500 final products in each type are given.

Choosing the inflow of the source plants as Gamma pdf, by ($\alpha = 1.6586, \beta = 1.5745$), causes stochastic replenishments in OEM that its mixed average can be approximated best-fit to Gumbel max distribution ($\sigma = 1.0915, \mu = 1.9612$). At the same time, customers' orders come with neg-exponential pdf ($\lambda = 1/\beta = 0.385$) as it is likely in practice [45].

Condensed supply and demand rates compromise the influence of previous plants upon shortage in entrance inventory. Nonetheless, the fully stochastic system with random supply, demand, and operations addresses a fully dynamic system with highly variable factors. Additionally, ambiguity in recognizing the exact state of buffers (queues) and stations in each event leads to imprecise decisions for choosing the best successors. Consequently, it results in higher GTPT for the general network and higher LTPT in the OEM.

All simulation alternatives are evaluated based on 500 delivery products; thus, the simulation run times vary. It is noticeable that the first 100 products out of 600 delivery products are omitted from the simulation results, to cover the warm-up period. However, in the first experiment, by considering vague data, application

Table 2 Performance of fuzzy rules with the presence of queue linguistic terms, applied in extension

OR	Good	Normal	Bad
Speedy	Fast	Fast	Medium
Low speedy	Fast	Medium	Slow
No speedy	Medium	Slow	Slow

Table 3 Representation of fuzzy rules without the presence of queue linguistic terms

AND	Good	Normal	Bad
Good	Fast	Fast	Medium
Normal	Fast	Medium	Slow
Bad	Medium	Slow	Slow

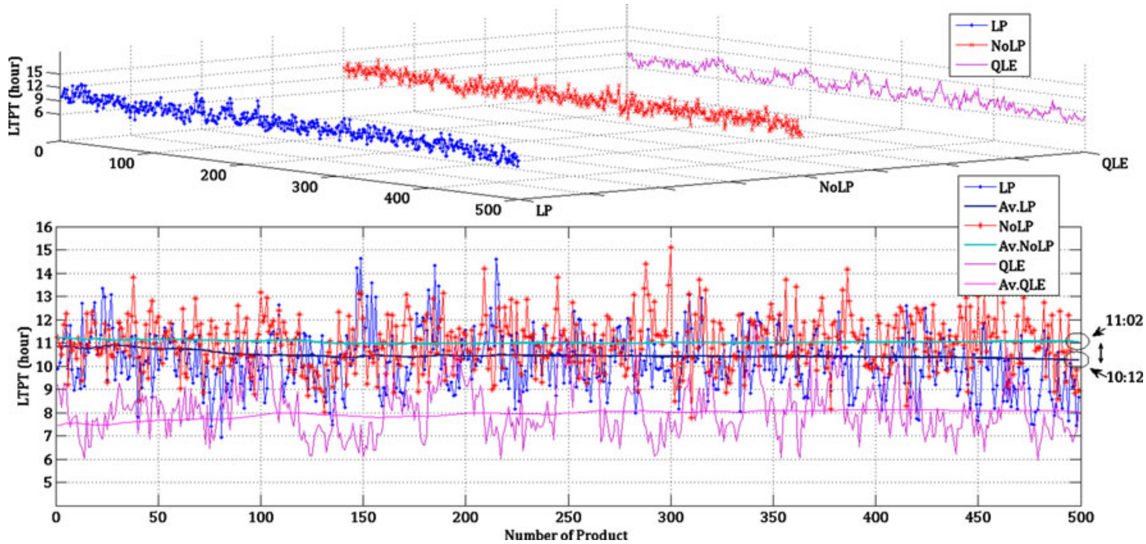

Fig. 8 Comparison of LTPT for LP, NoLP, and QLE in first pdf circumstance

of Lpallets shows an improvement of 49 min in overall average LTPT (ALTPT), see Fig. 8.

In Fig. 8, three alternatives are compared against each other: application of Lpallets with judgment capability (LP), without using Lpallets relying just on linguistic terms of parallel queues based on imprecise information of queues (NoLP), and the precise estimation of waiting time in each parallel queue and station based on real QLE.

As it can be seen, the trend of ALTPT in Lpallet (Av.LP) is smoothly inclining toward 10 h that reflects learning, while ALTPT in NoLpallet (Av.NoLP) constantly follows over 11 h. However, the QLE is just covered for comparison and is not compatible with the assumed vague available data.

Furthermore, by changing the inflow of the source plants to neg-exponential ($\lambda = 1/\beta = 0.33$), the inflow stream to the OEM changes. In the same way, again the pdf of the mixed average of all types of supply is approximated by Gumbel Max distribution ($\sigma = 1.33$, $\mu = 2.36$), see Fig. 9. This proves that although changes in flow pdf of previous nodes have effects on the replenishment distribution in OEM, its pdf stays the same, in general.

Simultaneously, the customer orders' pdf is changed that can be approximated by neg-exponential ($\lambda = 1/\beta = 0.37$), see Fig. 10.

These changes indicate a better sensitive analysis for the entire network as well as inside the emphasized plant. This time, not only one piece flow but the influence of different lot sizes of pallets is experimented. In this case, LP alternative has two variants: LP with constant lot size (LP-No-Va) and LP with flexible lot size (LP-Va). Regarding the learning ability, in lot

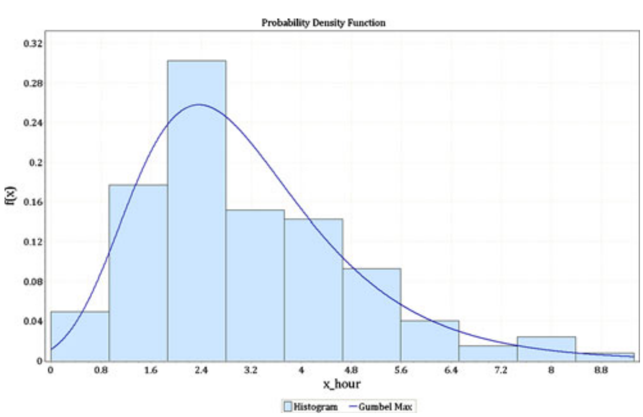

Fig. 9 Probability density function of the average of all three types of products inflow in OEM

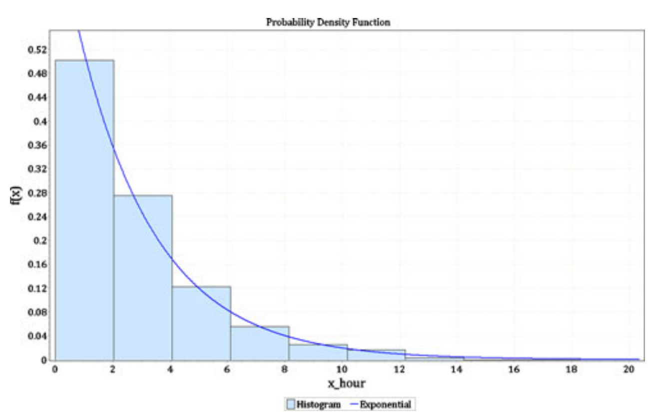

Fig. 10 Probability density function of coming orders

Table 4 ALTPT in different alternatives for Conwip flow control

	ALTPT (h)		
	Lot = 1	Lot = 2	Lot = 3
QLE	7.19	15.52	23.62
LP-No-Va	9.71	20.86	32.52
LP-Va	9.71	18.86	29.76
No-LP	10.49	22.17	33.66

sizes with more than one, Lpallets are able to reduce their lot size temporarily in the presence of congestions. This happens concerning the previous judgments for the first tier stations, i.e., if the judgment was bad, then in this round Lpallet takes one piece less than the real lot size. Table 4 shows ALTPT in different alternatives with Conwip control.

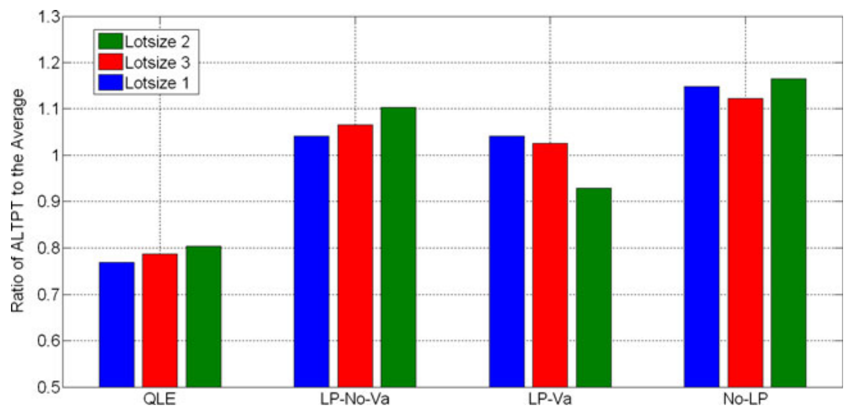

Fig. 11 Ratio of ALTPT to average of all alternatives with different lot sizes

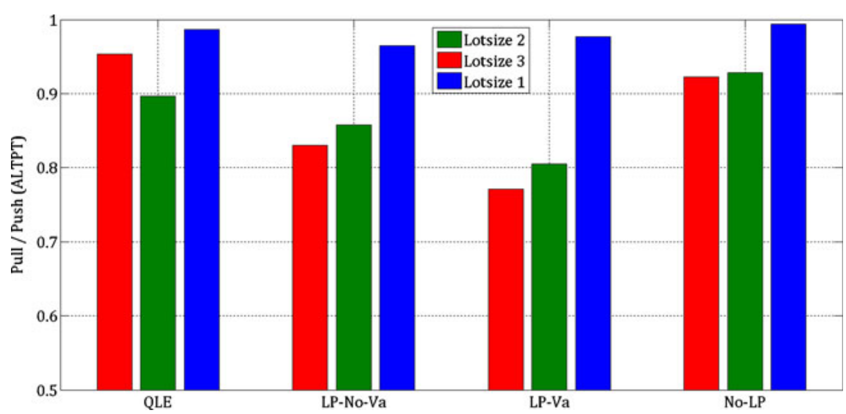

Fig. 12 Ratio of ALTPT in pull to push for all alternatives with different lot sizes

Table 5 Ratio of ALTPT for each alternative to the average of all alternatives in same lot control system

Method	ALTPT (h)					
	Lot 1		Lot 2		Lot 3	
	Push	Pull	Push	Pull	Push	Pull
QLE	0.77	0.77	0.78	0.80	0.71	0.79
LP-No-Va	1.06	1.05	1.09	1.08	1.13	1.09
LP-Va	1.05	1.05	1.05	0.97	1.11	0.99
No-LP	1.11	1.13	1.07	1.14	1.05	1.13

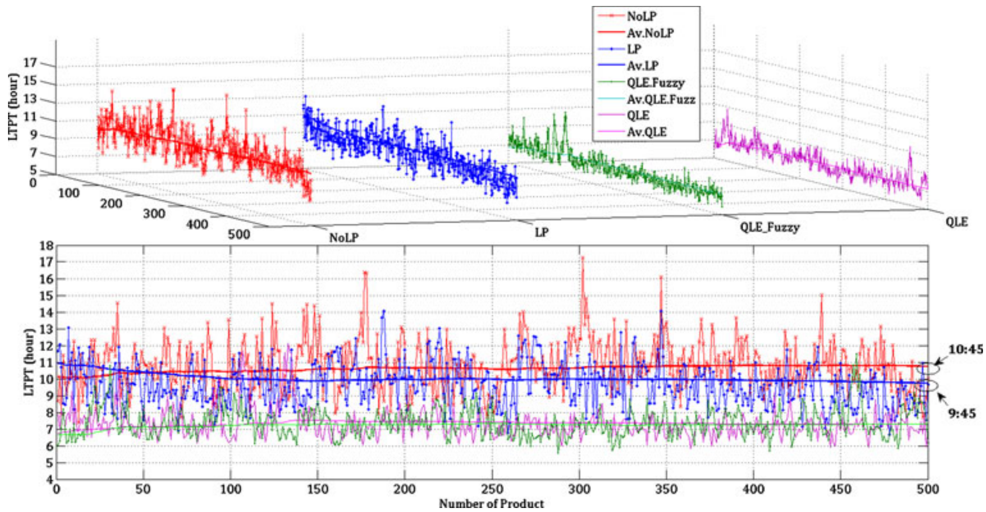

Fig. 13 Comparison of LTPT for LP, NoLP, QLE.Fuzzy, and QLE in second pdf circumstance

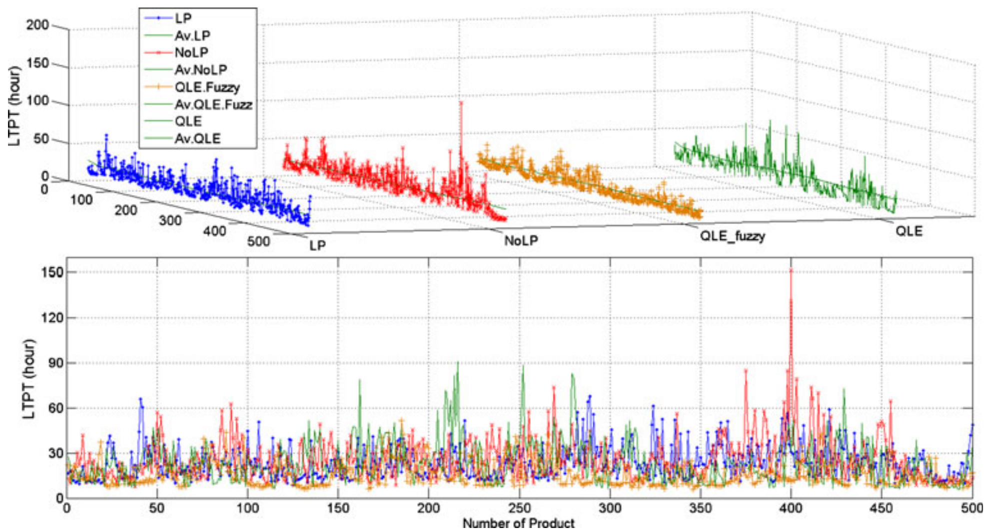

Fig. 14 Comparison of alternatives with breakdowns in second pdf circumstance

Accordingly, the ratio of ALTPT of each control method to the average of all methods, in each lot size, is compared in Fig. 11.

Additionally, in order to compare the adopted pull strategy with material push, the ALTPT ratios of pull to push are displayed on Fig. 12.

It is noticeable that although by using push system there is a short increase in the number of delivered products, the LTPT increases by hours. This is because the queue numbers sophisticatedly rise in the network. Eventually, the higher the LTPT, the lesser the delivered products in a time frame. On the other hand, by increasing the intervals between two orders, the rate of overproduction between interval times and simultaneously LTPT increases in push.

Table 5 presents the ratio of ALTPT for each alternative to the average of all alternatives in the same lot control system. This happens by three different lot sizes and with push and pull systems. It can be seen that one piece flow as an objective of lean manufacturing makes better results. Additionally, it shows that pull system has more consistency with LP method.

However, the less the incoming orders' rate, the more the discrepancy between push LTPT and pull LTPT is expected. Note that GTPT of the entire batch (500 products of each type) in push system shows a fall in comparison to pull Conwip. This is because the entrance inventory may be eliminated or reduced

Table 6 Matrix of stations' availability in percentage

Station	Station availability (%)		
	1	2	3
1	80	90	80
2	80	90	80
3	80	90	80

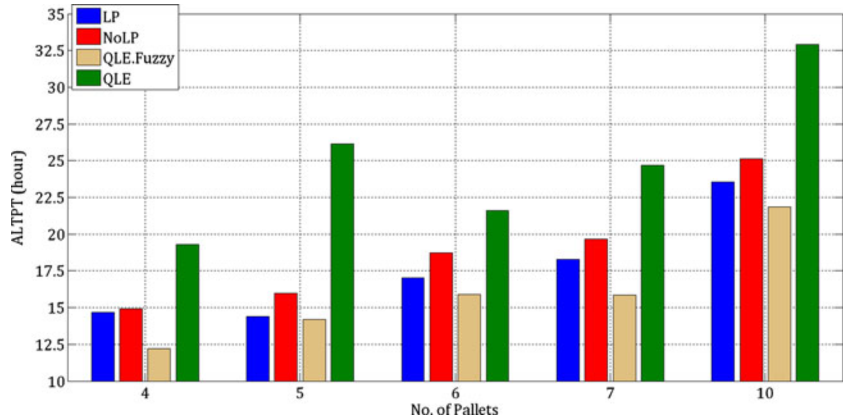

Fig. 15 ALTPT in the presence of different no. of pallets, for all alternatives

which affect the waiting time there. While the lead time of assembling SFPs to finished products is removed in push, the finished product inventory may increases dramatically. Therefore, these may cause a decrease in GTPT whereas the autonomy of a single plant can be beat by push material, since there is no self-control on both inventories.

Furthermore, by considering breakdowns for stations, the LP scenario reflects again a positive performance in comparison with the other cases as QLE and NoLP. Here, in addition to the conventional performance of QLE with precise estimation of queues' waiting times, fuzzy system is included to the estimation process of QLE in order to take uncertainty into consideration. Figure 13 presents the alternative methods without breakdowns, while Fig. 14 depicts the same alternatives under breakdown circumstance.

However, in both figures, the best emerged operating method is QLE with fuzzy capability (QLE.Fuzzy). Table 6 shows the matrix of stations' availability that each mean repair time (MRT) is assumed to be 1 day. Nonetheless, the best performing method in the previous experiments was QLE that by considering breakdowns presents the worst case.

In Fig. 14, the LTPT of the introduced methods are illustrated. Here, the standard deviation of LP $=$ $11:33$ h, NoLP $=14:20$ h, QLE $=15:01$ h, and QLE.Fuzzy $=8:23$ h. This reveals a more stable performance for LP in the absence of QLE.Fuzzy case.

So far, for all experiments, the number of available pallets for each type of product was considered constant as six. Nevertheless, by increasing the number of pallets (no. of pallet), the ALTPT and AGTPT change. This is caused by the rise in queue lengths of stations as well as decrease in entrance inventory.

The comparison of ALTPT between current control methods in alternating the number of pallets is shown in Fig. 15. At the same time, the trend of AGTPT for the similar comparison is given in Fig. 16.

By compromising the behaviors of ALTPT and AGTPT, it can be concluded that in LP method the best performing no. of pallet equals to 5. This shows a tradeoff between different decision factors, see [60].

In addition, Table 7 reflects the performance of all methods with different no. of pallets in numerical experiments.

In order to verify the performance of our simulation model in general, a flexible flow shop scheduling

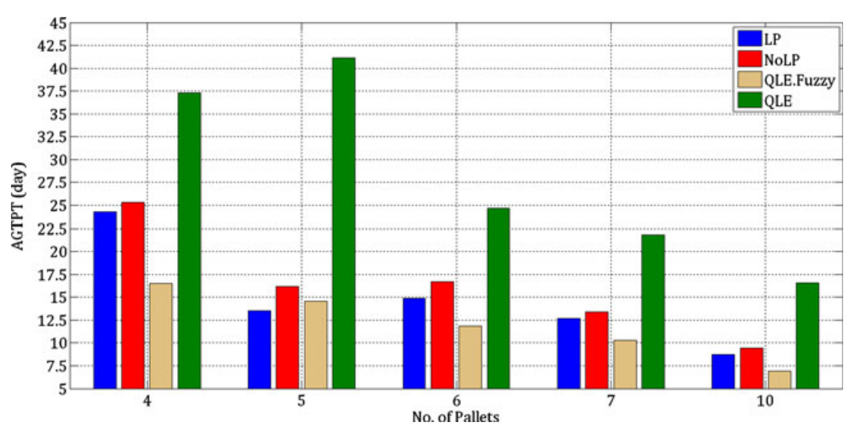

Fig. 16 AGTPT in the presence of different no. of pallets, for all alternatives

Table 7 Numerical experiments in alternative no. of pallets and control method in Conwip with breakdowns

Control method	ALTPT (h)	AGTPT (day)	Makespan (day/h)	WIP	Av-Utilization (%)
NoPallets			4		
LP	14.69	24.31	115:09	606	55.88
NoLP	14.94	25.30	116:14	626	55.86
QLE.Fuzzy	12.22	16.51	102:03	467	58.50
QLE	19.28	37.29	142:05	750	41.27
NoPallets			5		
LP	14.38	13.51	98:15	409	62.53
NoLP	15.96	16.17	99:14	428	65.02
QLE.Fuzzy	14.19	14.53	96:13	351	63.18
QLE	26.14	41.14	147:12	856	41.07
NoPallets			6		
LP	17.04	14.90	97:00	383	65.37
NoLP	18.74	16.70	97:03	392	67.93
QLE.Fuzzy	15.91	11.87	93:21	342	65.33
QLE	21.59	24.67	114:03	583	52.59
NoPallets			7		
LP	18.29	12.70	91:01	288	70.16
NoLP	19.66	13.41	93:23	296	67.26
QLE.Fuzzy	15.87	10.31	84:12	190	70.99
QLE	24.69	21.79	109:10	612	55.61
NoPallets			10		
LP	23.57	8.71	86:09	167	74.24
NoLP	25.14	9.44	85:13	258	75.93
QLE.Fuzzy	21.86	6.94	83:01	108	75.37
QLE	32.90	16.57	102:06	426	59.63

problem with conventional characteristics is considered to be solved classically, i.e., no breakdowns, 48 jobs to be processed (16 each type), normal processing times (see Table 1), neg-exponential release times $\beta = 2$ h, and offline manner. Table 8 compares the completion times (Cmax) of our simulation methods and the classical solutions for scheduling, using dispatching rules, i.e., shortest processing time (SPT) and longest processing time (LPT), first come first serve (FCFS), and general shifting bottlenecks routine (GSBR).

The free version of LENKIN scheduling system is utilized to operate the scheduling; thus, number of jobs is limited here. However, it should be mentioned that such limited jobs may not cover a proper learning phase. Additionally, in classical solutions, global information about the problem (e.g., all jobs, release, and due dates) must be available as well as no constraints can be assumed in terms of carries number and pull approach. Nonetheless, in the current study with its individual approach, no general information is required.

10 Conclusion and further work

This paper was generally divided into two parts as conceptual and experimental sections. In the first part after a short introduction, a general concept about the material flow control systems was explained. Later, to clarify the basis of Lpallets' concept, an introduction was given to closed loop systems, and respectively, the privileges of closed loops for learning purpose were briefly mentioned. Afterward, application of Lpallets in logistics was described. Then, for entering into the second part, as experimental section, a practice oriented scenario was presented to show the advantages of using Lpallets in Conwip control systems. A concise description of the relevant mathematical model for the

Table 8 Comparison of simulation methods with classical scheduling algorithms

Release time (neg-exp)	SPT	LPT	FCFS	GSBR	LP	NoLP	QLE.Fuzzy
$\beta = 120$	3,890	3,890	3,890	3,890	3,336	3,653	3,140
$\beta = 90$	2,756	3,364	2,622	2,610	3,248	3,483	3,338

considered problem was given respectively. Following them, the employed fuzzy set to control the Lpallets was explained in details. At the end, the simulation results of the scenario under different circumstances were analyzed, and the assumptions in the simulation were compared together by means of graphs and tables. In analyzing the performance of Lpallets (LP) under several conditions, the superiority of LP compared to other methods is perceived, although this advantage was proportional.

Together with evaluating LP, some other effective factors in logistics were presented here as well. For instance, there was a comparison of the performances of push material vs. pull material, the role of number of carriers (pallets) in congesting the queues, makespan, and utilization. Eventually the difference between ambiguous and exact information was given in NoLP and QLE methods. Additionally, it was shown that despite knowing the exact number of pallets in queues, facing uncertainty in processing time, the sole QLE does not work properly, while the considering fuzzy numbers (QLE.fuzzy) outperforms all other methods. Indeed, the purpose of this paper is to show the usability of Lpallets in the presence of uncertainty, e.g., with availability of vague information. Thus, QLE is just applicable as an absolute optimum method when the processing times are deterministic.

In addition to the application of closed loops network for flexible flow shop systems and pull system after decoupling point in supply networks, the main contribution of this work is the introduction of Lpallets and application of them in real time dispatching of jobs to machines in uncertain environments. This novelty as a superior solution for uncertain shop floors was justified by several varieties and alternatives in the production circumstance, in which Lpallets' sorts presented relatively better performances. It is noticeable that the conventional methods (e.g., deterministic scheduling) has no application in this case. In general, Lpallets, as autonomous logistic objects, have the mission of self-organization in material flow systems by means of fuzzy controller. The fuzzy controller, embedded in each Lpallet, works based on Mamdani-type by means of fuzzification, application of fuzzy operators, implication of antecedences to consequents in fuzzy rules, aggregation of the consequents, and defuzzification.

In the controller after experiencing each station the waiting + processing times are recorded as input to the fuzzy controller of an Lpallet to judge the performance of that queue and station by linguistic terms. This kind of controller application has shown a responsive performance in the experimented alternatives. Initially, several experiments were conducted including comparison of different control methods (e.g., QLE, LP) for material flow with measurement of LTPT with lot size of one. These were accomplished by alternating the supply with stochastic flow rates in the sources and their effects on the replenishment rate at the entrance inventory of OEM. These were examined with material push and pull as well as with more than one lot size to evaluate the influence of Lpallets' lot size and material flow system on the measure criteria. It was illustrated that push system has better result.

Two main specific forms of fuzzy set system were used in this paper for Lpallets: firstly, as a pure learning controller inside each Lpallet without any information from successors and just solely performing based on its own experienced records and secondly, as fuzzy sets instead of crisp values in QLE method that checks the successors' queues by means of fuzzy sets, when the processing times are stochastic. Both alternatives showed better results than deterministic estimations in QLE and NoLP. By the appearance of breakdowns in stations, the production system configured a very complex and unpredictable system, in which the makespan, utilization, WIP, and TPT displayed better records by means of LP and QLE.Fuzzy. These all mean the autonomous learning pallets with various intelligent methods for real-time control and learning bring satisfactory results.

Furthermore, to justify the performance of the simulation as well as the strategies employed in the study, they are compared against some conventional solutions (SPT, LPT, FCFS, GSBR) for scheduling flexible flow shop problem. The performance of the claim strategies are fairly comparable with the solutions in a deterministic environment with fully recognized values in processing times and supply times. Conclusively, in this paper, just a control and learning methodology (i.e., fuzzy controller) with learning (adjustment) capability was exploited, which has shown some advantages to the entities' (Lpallets) as well as the entire system's performance. Nevertheless, except the novel flexible structure for the fuzzy membership functions in the FAM, the fuzzy system here took no direct error into account for adapting its rules and structure to current performances of the production system. In addition, no direct negotiation happened between autonomous entities (Lpallets here), which may enhance the merit of adaptability. Nevertheless, the learning methodology can be equipped with more intelligent methodologies.

As further works, there are some requirements in terms of fuzzy domain classification and more precision in mapping the inputs into the outputs, by considering feedback errors. This performance can be improved by the assistance of neural networks. In addition, some evolutionary techniques can be applied to avoid local traps in generating new combinations of variables and learning. Besides, evolutionary technique can be used for directly experimenting new alternatives for Lpallets in their routing decisions. For instance, a suitable evolutionary technique is genetic algorithm and the related features like genetic programming. Application of these evolutionary techniques and neuro-fuzzy methods as learning as well as control techniques for Lpallets is the subject of future works for the authors.

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