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Research Article

Using Metaheuristic and Fuzzy System for the Optimization of Material Pull in a Push-Pull Flow Logistics Network

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Alternative material flow strategies in logistics networks have crucial influences on the overall performance of the networks. Material flows can follow push, pull, or hybrid systems. To get the advantages of both push and pull flows in networks, the decoupling-point strategy is used as coordination mean. At this point material pull has to get optimized concerning customer orders against pushed replenishment-rates. To compensate the ambiguity and uncertainty of both dynamic flows, fuzzy set theory can practically be applied. This paper has conceptual and mathematical parts to explain the performance of the push-pull flow strategy in a supply network and to give a novel solution for optimizing the pull side employing Conwip system. Alternative numbers of pallets and their lot-sizes circulating in the assembly system are getting optimized in accordance with a multi-objective problem; employing a hybrid approach out of meta-heuristics (genetic algorithm and simulated annealing) and fuzzy system. Two main fuzzy sets as triangular and trapezoidal are applied in this technique for estimating ill-defined waiting times. The configured technique leads to smoother flows between push and pull sides in complex networks. A discrete-event simulation model is developed to analyze this thesis in an exemplary logistics network with dynamics.

1. Introduction

Today, after spanning the extension phase from simple companies towards supply chains and correlated networks, more complex logistics processes have been burdened to industries [1]. Under the pressure of global competitions, continuously changing business environment, mass customized products, and transient demands, not only the individual plant, but also the logistics networks have rather acquired decisive roles for achieving excellence. Accordingly, planning and control of material flows within individual factories and supply networks have become one of the most complex tasks in practices. The complexities accompanied with collaborative logistics networks are the consequences of the paradox in integrating the members of a network, while they have their own requirements and performances [2]. Indeed, material flows, inside shop floors, besides integration, and coordination of flows throughout logistics networks have engaged the most planning and control potentials in manufacturing organizations. Concerning the changing business environment, more flexible systems are required to fulfill customers' demands more quickly [3]. Since being responsive to customers is an inevitable factor for sustainment in such markets [4], several material flow strategies and production systems can be employed, for example, flexible manufacturing systems, hybrid systems, and distributed and autonomous control systems [5–7]. Although mass production originally follows material push strategy by higher production rate and higher benefits, for some other production approaches material pull reflects better performance [8]. Appropriately selecting a material flow system directly contributes to the ultimate performance of production systems. Implementation of push, pull, or both strategies has a direct effect on performances of the overall logistics processes in a network.

Moreover, manufacturing enterprises are confronted with continuous changing conditions inside their processes, called dynamics, which are supposed to be handled by more intelligent strategies. For example, mass customized products force supply networks to follow make-to-order (MTO) or engineer-to-order (ETO) production strategies to comply with individual demands. The recent production strategies burden more pressure on logistics networks to operate based on real demand and at the right time. This issue can result in real-time operations, which impose more agile systems by means of better regulated systems, for example, pull strategies. In the literature it is argued that push strategy, for example, MRP, results better when high variety exists and demand fluctuates [9]. On the contrary, traditional pull strategies, for example, Kanban, comply better with preferably stable demands and low variety in products [10]. Indeed, different material flow strategies have their own benefits and drawbacks. Shifting from totally push systems to Kanban system, that is, fully pull system, may result in some shortcomings in facing uncertainties in new business environments. Therefore, a clever strategy is required to deal with such conditions and to employ advantages of several material flow control strategies [11]. For this purpose, some hybrid systems have been practiced, for example, CONWIP, Polca, and G-Polca, in shop-floor as well as Leagility approach in supply networks [12, 13]. These flow control strategies compensate the potential drawbacks of merely using a strategy and, at the same time, protect production systems from getting failed or overproduction. Furthermore, employment of hybrid strategies supports the targets of responsiveness, quickness, flexibility, reliable delivery, and agility as well as leanness in logistics [11].

In general, most of the above-stated systems have emphasized production and shop-floor logistics, while they can be effectively applied by supply chains and logistics networks as well. For instance, a logistics network with application of material pushup to a specific point, called decoupling point (DC) [14], can have push planning and control systems (like MRP), whereas the downstream of DC can follow pull or hybrid push-pull control system. This is specifically useful for benefiting from both control concepts and still remaining flexible. Nevertheless, coordination of downstream, with pull system, along with upstream, by means of push flow, is a challenging issue in such networks. This specific hybrid system for complex logistics networks is selected to be studied in this paper. Although the current study is a part of a greater research project which proceeds with material flow control throughout supply networks, this paper only focuses on the pull section of hybrid system and tries to optimize the number of carrier carts (pallet) and their lot sizes for smoother flows. For this purpose, a discrete-event simulation scenario of a hybrid logistics network is developed facing dynamics in their processes (material replenishments and demands). In the pull side a CONWIP (constant work in process in pull environment) technique is developed to control the flow of materials and the pallets, representing the control means in CONWIP. Correspondingly, the recommended hybrid concept contributes to the improvement of logistics performance measures, for example, throughput time (TPT), throughput (TP), responsiveness, utilization, and work in process (WIP) [15]. The dynamics include stochastic demands, fluctuating supply, and uncertain processing times of operations that resemble real-world problems in logistics. Several stochastic variables affect material flow control both at shop floors [16] and, in a broader scale, throughout logistics networks. Abundance of dynamic factors and their causal effects on flows' performances make a complex optimization problem of flows in the pull side that aims at the least collection of stocks in the system.

The particular assumption in this paper is that the push side can be optimized by means of MRP system, while optimization of material pull is not straightforward regarding the real-time control and the required coordination of both sides of flows (demand and supply). Therefore, this study highlights the general strategies dealing with uncertainty and fluctuations in material flows over supply networks and at shop floors. Particularly, it complies with two main parts as theoretical comments on the material flow strategies in supply/logistics networks by focusing on better coordination of material pull from DC to final customer. In doing so, a brief introduction is given to possible material flow systems in supply networks, facing uncertain processing times. Then it directly proceeds with a practical solution in the optimization of material flows after DC in networks. In this way, the supply network for optimizing its pull control is developed that considers uncertainty of customer orders, stochastic material push replenishments in DC, and stochastic processing times. For finding the optimum combination of effective factors, genetic algorithm (GA) as a stochastic optimization method, known as metaheuristic, is chosen to solve the optimization problem of pull flows, as in [17]. This optimization procedure regards the number of pallets and lot sizes in the pull section. Besides, to prove the performance of metaheuristics in such a dynamic problem, simulated annealing (SA) is partially experimented too.

To recognize the uncertain and ill-defined processing times in flows control fuzzy set theory against the conventional crisp estimations is employed. In other words, control of distributed pallets in an optimum manner under an ill-defined circumstance requires more smart control techniques. Therefore, fuzzy system is applied to manage the ambiguous situations in locally decision makings for better routes. Besides, GA and SA are exploited to competently cover the huge range of combinations that a distributed control system may build under dynamics and uncertainty to meet specific demands. The target is to show the importance of metaheuristic methods and fuzzy system in dealing with complex as well as uncertain material flow systems. The main contributions are to show the privileges of fuzzy control system for smoothing the flow of distributed pallets, the contribution of heuristics in approximating the optimum combination values of just some key factors of pull flows in a logistics networks, for example, number of carts, and flexible lot sizes, and the simplicity and applicability of fuzzy set theory in solving multiobjective problems by means of defining satisfaction degrees.

The rest of the paper is organized as follows. Section 2 proceeds with a brief explanation about the types of material flow control systems. Section 3 refers to GA and its approach in solving stochastic optimization problems. Section 4 concisely describes the algorithm of SA as an alternative to GA. Section 5 shortly introduces the application of fuzzy set theory in production and logistics. The logistics network scenario is clearly given in Section 5. The problem solution is displayed in Section 7 that represents the application of fuzzy control system and its set theory in material flow control and solving multiobjective optimization problems. Experimental results are depicted in Section 8 by means of several 3D graphs. The summary and further works are given in Section 9.

2. Material Flow Control System

Generally, the systems of material flow control can be classified into push and pull mechanisms [13]. Each of which systems has some advantages and drawbacks, for example, under control inventory for pull systems and profiting from forecast information for push systems are the advantages of both control mechanisms [18]. In case of uncertainty, that is, variability, and volatility in production networks these flow systems can be used to compensate the undesirable effects of uncertain supply and demand [19]. However, these two pure systems trigger a spectrum of flow strategies between two manufacturing points maybe two workstations or (in a macroscale) two members of a supply network. Below the two control systems and a hybrid approach of them are concisely explained.

2.1. Material Push Control. Conventionally, material flow systems have been worked in accordance to push-flow control, by means of pushing materials to next processing steps as soon as processing of them is finished at the current step. In other words, the production (flow) of materials is planned beforehand based on forecasted demand or some predefined information about demand. However, if the production line or workstations are not balanced together, work in process (WIP) may be collected everywhere as well as overproduction may occur, as the consequence of this performance. Indeed, push control mechanism is assumed more appropriate for mass production and make-to-forecast (MTF) strategies with balanced lines [20]. Nevertheless, line balancing is a challenging issue by itself when the production system (order, supply, processing-time) is unstable. Material requirement planning (MRPI) is a well-known method categorized as a push control system [18]. According to the MRPI mechanism, flow of materials is planned in advance based on forecasted demand and without any concern about real capacity or current demand. Despite the fact that capacity utilization is quite high with push specifications (in advance planning and predefined logistics operations), this control mechanism suffers from some shortcomings. These drawbacks are basically in opposite to logistics' targets, that is, they result in higher WIP and inventory level, blind production, and less flexibility in plan and schedule. Moreover, in spite of the specifications in pure push mechanisms, some authors partially classify drum-buffer-rope (DBR), starvation avoidance, G-Polca, and even CONWIP mechanisms as push control systems [13, 21, 22]. Nevertheless, classification of some of these systems as pure push mechanisms does not completely reflect their performances, for example, CONWIP.

2.2. Material Pull Control. In contrast, generally, material pull control usually operates based on current demand of the upstream customer. This control strategy is originated by Toyota production system (TPS) in the form of Kanban system [23]. The material pull mechanism in the context of TPS has made a breakthrough at Toyota and later at other adherent industries for a long time. Nonetheless, this flow mechanism encounters some difficulties when demand is oscillating and processes are inherently uncertain [24, 25]. The strategy of pull mechanism is simply to fulfill the required material of customer (internal/external) just in time (JIT), so that ideally no blockage and starvation occur. Normally, blockage and starvation happen to pull mechanism, while in push with infinite capacity only starvation can be realized [26]. In addition to Kanban and partially the CONWIP, the Paired-Cell Overlapping Loops of Cards with Authorization (Polca) [27] and in part the Synchro-MRP [28] can be categorized in the pull control system as well. However these two later mechanisms, like the other semipush mechanisms, exploit some aspects of push control. In this manner, several hybrid control systems have been developed to resolve the drawbacks accompanied with pure pull or push systems. Among them CONWIP and Polca mechanisms can be mentioned.

2.3. Hybrid Push-Pull Control. Contrary to MRP system, as a centralized control mechanism with push approach, pull mechanisms are categorized as distributed control systems. As mentioned before, pull control generally works based on WIP limitation and current demand of the local working area, whilst push systems perform based on predefined material flow plans with considering forecasts. However, simultaneous application of both push and pull systems reflects a twofold view by a seamless control of material flow, while it streams the flow. In developing a hybrid system following contributions occur. Firstly, by employing a push mechanism (by a central control) the release dates of operations in global context can be defined. Meanwhile, in contributing to the global context, the employed pull control performs based on local situations of WIP to facilitate smoother flows. Consequently, in this context, global and local factors interact with each other in a positive manner. This approach enhances the coordination of the entire logistic system facing dynamic challenges. However, simultaneous employment of the push and the pull systems is not necessarily required. Inspired by shop floors control systems, some suggested control strategies for logistic networks can be sorted as follows:

(i) dividing the entire logistic network into two parts as push and pull, which is broadly discussed as Leagile supply chains [29],

(ii) employing both the push and the pull control systems simultaneously within each member of the network or throughout the whole network, like: CONWIP and G-Polca (this type needs high flexibility entirely which is subject to have distributed and intelligent control system),

(iii) inspired by Polca, dividing the network into paired-cells and applying the material release date by push system as well as WIP limitation by pull cards.

These listed options are some assisting strategies for profiting from alternative material flow controls in case of fluctuations and variations in demand and supply. However, in realizing these three alternatives material flow scheduling, that is, work dispatching rules and workload balancing (particularly in shop floors echelon), is still a challenging issue in that order. Nevertheless, in this paper, the first proposed option is considered to be analyzed with regard to inventory control and work dispatching (assignment) concerns. Indeed, this hybrid flow system is being practiced in manufacturing industries like automotive [30, 31], for example, Daimler AG locates its DC before painting shop of bodies. Here, the downstream of a logistic network with material pull flow is optimized to coordinate the collision point (DC) of both push and pull flows close to the end customer. The flows in this point require to be optimized to avoid any condition of overloaded inventory. Respectively, the tasks of workloads balancing and job dispatching are assigned to an autonomous control system, which is briefly explained in the next section [32]. This autonomous control basically follows the bottleneck control rule, but is based on self-decisions of autonomous objects and less queue length estimation (QLE) [33].

3. Logistic Network Scenario

3.1. General Structure. Today, thanks to the achievements in simulation, complex problems, like material flow control in logistic networks with a broad solution space, can be solved easier and quicker. A combination out of simulation and heuristic methods with quick response time is preferred to those conventional model-based mathematical solutions with relatively long optimization time. This holds specifically true for alternating circumstances in industries. In this regard, an exemplary logistic network scenario is modeled by discrete-event simulation software to present the improvement of material pull flow in a push-pull flow mechanism throughout the network.

Plant-Simulation is a discrete-event based simulation package developed by Siemens. The inventory policy, service levels, and so forth are arbitrary adjustable. However, in the current simulation, the policy of entrance inventory at OEM is set to priority rules (depending on the availability of respective pallets for the products in the inventory), and the rest buffers and inventories are set to first-in-first-out (FIFO) policy. The service level of the simulated production network at the inventory is dependent on the transport means and sources production rates. But the geranial service level is reflected into the satisfaction degree of the manager by means of more total delivery (throughput) at the customer side. Moreover, the inputs of the simulation model are some distribution functions for generating production intervals at sources and also some stochastic demands for sinking these produced products at the exit of OEM. The general outputs of the simulation are several statistics of performance indicators of production systems that some are used by the optimization function.

However, the enhancement in material flows by means of this mechanism is achieved by simulating metaheuristics, that is, GA and SA, for flows in this study. It is shown that metaheuristic algorithms can just optimize two factors (out of several potential ones) at the pull side of the network to reflect a reasonable solution for smoothing the flows throughout the network. Indeed, this contribution directly coordinates the push-pull collision point just by optimizing the pull-side material flow. The simulation model is developed to apply an offline optimization approach, using GA as the main contribution and using SA as the justification of GA performance. However, metaheuristics may be employed as online or real-time control system. For example, in practice, this can be carried out by autonomous pallets within a pull principle production system [32, 34].

In material pull systems, pallets (or any means of transport like fixtures) circulate permanently within logistics systems; thus, such pallets can be used as pull signals [24]. Pallets as local and distributed logistic objects have the chance to concurrently evaluate the system and decide for optimizing the sequence of the next steps without a global controller. Since GA and SA are global search techniques [35], the optimization process is considered to be offline to have all data at once; so that it makes it possible to use the entire information at the original equipment manufacturer (OEM) in the exemplary network.

The simulated network is constructed out of three steps of processing plants. In step one, two source plants (P_{11}, P_{12}) are considered to produce three types of raw materials. Each plant produces the counterparts of the other raw materials at the other source plant. Every type of raw material has to be assembled with its counterpart in the next step. The step two has two assembly plants (P_{21}, P_{22}), which have comparable processing capabilities. Therefore, the plants in step one are fully connected to the plants in step two, so that the semifinished parts can be allocated to them based on bottleneck control concept; that is, the plant with less queuing in entrance inventory has priority. Finally, the plants in step two transfer their assembled products (which are now just three types) to the last plant (OEM). This specific structure of the network reflects several characteristics of a complex logistic network, for example, differentiation and alternation in supply of counterpart products from different suppliers, arrangement of DC close to the end customer, and smart allocation of pushed replenishments by considering the current requirement of either customer plant. DC can be shifted to customer side or supplier side depending to the production strategy; this issue is already experimented in [24]. Universally, from the sources up to the entrance of OEM products are pushed regarding the forecasted demands and existing plan, whilst just inside OEM (in downstream from the entrance inventory) pull principle is applied. This strategy is to meet fluctuations in demands of final customer for the three final-product types over the simulation time horizon. Figure 1 shows the overview of the exemplary network.

In order to reflect alternations in demand of each type of product, orders are triggered to OEM with time intervals

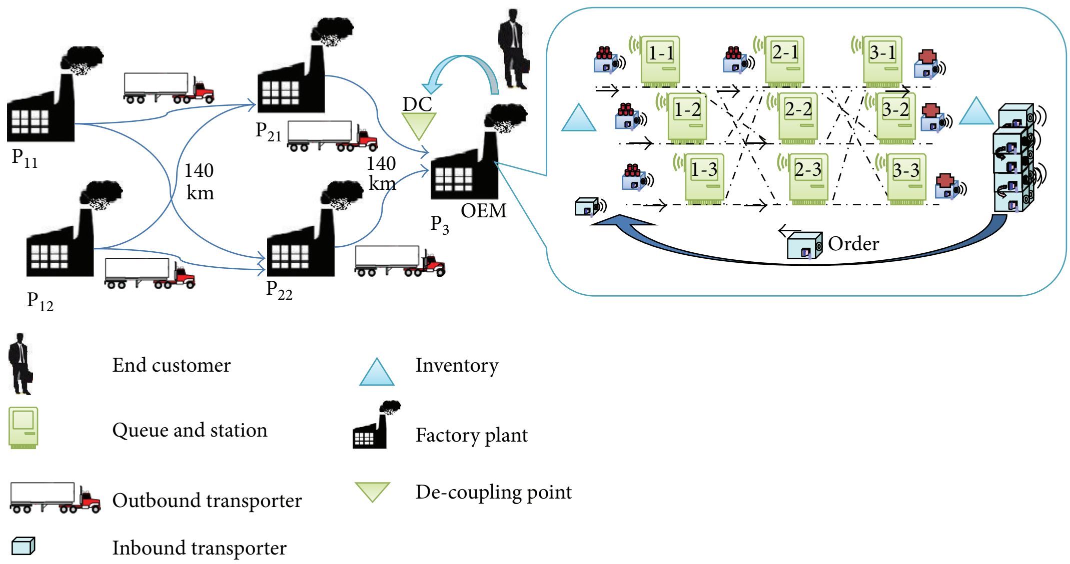

Figure 1: Exemplary push-pull network, with lasting each round trip 4 hours for transporters.

Table 1: Processing times for each product on each line.

Plant	P_{11}; P_{12}			P_{21}; P_{22}	P_3 (OEM)		
	Processing times [h:min] for each plant; Line						
	Deterministic value				Mean value (μu)		
Product type	1	2	3	1	1	2	3
Type 1	2:00	3:00	2:30	0:50	2:00	2:40	2:20
Type 2	2:30	2:00	3:00	0:50	2:20	2:00	2:40
Type 3	3:00	2:30	2:00	0:50	2:40	2:20	2:00

following the exponential distribution in the first alternative and normal distribution in the second one. Hence, final demand is stochastic based on time intervals between each order of products. Equation (1) represents the used negative exponential distribution (Neg-Exp) for intervals. Neg-Exp is a common model for representing the intervals of customer random arrivals as Johnston and Boylan [36] say "... with a random arrival of independent customers, the order arrival process could be modeled as a Poisson stream and, therefore, a negative exponential distribution would be a realistic model for the inter-order interval." Moreover, consideration of normal distribution by practice oriented studies is also typical, for example, [37], and it is considered to be experimented against the first alternative. For the first alternative, the mean value (2 hours and 30 minutes βe = 2:30 for each type) is assumed a bit bigger than the mean supply rate to collect WIP at the entrance inventory of OEM. The mean value and the variance in (1) are respectively denoted by ($\mu u = 1/\beta e$ and $\sigma^2 = \beta e^2$). For the second alternative, the mean value is 2 hours and 30 minutes: μu = 2:30 and the standard deviation is ($\sigma = 10$ min):

$$f(x) = \frac{1}{\beta e} \cdot \exp\left(-\frac{x}{\beta e}\right). \quad (1)$$

It is noticeable that inside each plant, except the assembly ones in step 2, a 3×3 matrix of workstations is devised. This matrix configures three similar production lines in parallel, which are fully coupled to every workstation in the next column. This resembles the flexible flow shop problem in general and is selected based on a predefined problem at the research cluster CRC 637 about autonomy in logistics at the Bremen University (http://www.logdynamics.com/).

However, the purpose of this fully coupled system is to simulate a highly flexible logistic system with the capability of employing autonomous logistic objects for self-organizing material flow. As one alternative, autonomous objects by collecting local information about successive queues (buffers in front of each station) and by using bottleneck control rule decide which route has the least waiting time to proceed. This specific control system (called QLE) has been discussed in previous papers, for example, [7, 10, 11, 33]. Alternatively, without considering any autonomous carrier objects, a conventional flow control (Conv) can be developed to just proceed through the stations with the least predefined processing times without any updating. These are later experimented in the simulation. Table 1 shows the processing times of each workstation inside every plant of the network. Just for OEM the processing times are considered stochastic

Table 2: Applied notations in the problem.

Notation	Description
$\mu u = 1/\beta e$	Mean value of distribution
σ	Standard deviation
X	Random variable
P	Product type, $p = 1 \cdots P$; $P = 3$
T	Time, $t = 0 \cdots T$; $T = 80 \times 24$ hours
ALTPT_p	Average local throughput time (in OEM at T)
AGTPT_p	Average global throughput time at T
TD_p	Total delivery of product p at time T
$\mu_{\widetilde{A}}$	Membership value of fuzzy set $\widetilde{A}$
$Lsize$	Capacity of a pallet [1 10]
e	Upper bound of the fuzzy number μ
WIP_p	Maximum OEM inventory
φ, δ	Importance weights; may be chosen arbitrarily by decision-maker
f_i	Fitness value of chromosome i
Pr_i	Selection probability value of chromosome i
Te	Current temperature in SA
Te_{min}	The least temperature in SA
c	The cycle number in the loop of SA
$\widetilde{A}$	Fuzzy set
$NPallet$	Number of pallets in system [10 60]
b	Lower bound of the fuzzy number μ

with the normal distribution, where the standard deviation is equal to ($\sigma = \mu u/10$). Besides, the mean of processing times is identical to the mean intervals of products' replenishment. These values are empirically extracted from several simulation runs toward smoother and coordinated flows. Each simulation experiment is run for 80 days each 24 hours to make authentic results.

The used flow strategy in the simulation is as follows. In step 1, materials are discharged to the network based on release dates following normal distribution. The normal distribution is arbitrarily assumed for time intervals between each release with $\mu u = 50$ min and $\sigma = 5$ min. Correspondingly, the three product types are randomly released to the system and pushed forward to the next step. In contrast, in downstream of the network customer orders are triggered within a stochastic manner, using exponential time intervals. The downstream control of pull material at OEM operates based on a form of CONWIP system. In other words, the orders pull the semifinished products from the entrance inventory of OEM and then the pallets are pushed toward the exit of OEM. Availability of circulating pallets at the entrance of OEM is the signal of stated demand and the pull signal. In fact, pallets do the duty of CONWIP cards or signals here. They are pushed by the merit of autonomous control (self-selection of next station with least queue) to the downstream of the shop-floor after picking up their respective products [32]. Eventually, uncertainties in the pushed replenishments at the entrance inventory and the stochastic pulled orders result in a chaotic performance at the collision (decoupling) point of push-pull. Therefore, this chaotic system must get coordinated toward an optimum solution with less inventory quantity.

3.2. Problem Statement. The current network scenario resembles a multiobjective optimization problem that minimizes the average local throughput time (ATPT), the average global throughput time (AGTPT), and the entrance inventory (WIP) of OEM, as well as maximizing the total deliveries (TD) to the end customers. Since there are several stochastic and vague defined variables which directly or indirectly influence the performance of the model and the optimization process, this problem is very complex to be formulated and solved by conventional mathematical solutions. Thus, as an alternative solution it is decided to employ simulation with the assistance of metaheuristics to realize the objective of the problem without mathematically modeling the existing constraints. These multiobjectives can be compactly written in one objective form with minimization target like (2). The used notations for the multiobjectives are given in Table 2. However, the unique objective out of the multiobjectives can only be formulated in a compact equation when all single objectives have a unique unit or they all can be written without units. Therefore, further synthesis is required to achieve a uniform objective equation. This is broadly explained in the solution section:

$$\text{Min} \sum_{P} \left(\frac{\text{ALTPT}_p + \text{AGTPT}_p + \text{WIP}_p \times \varphi}{\text{TD}_p \times \delta} \right). \tag{2}$$

To explain this optimization problem, material flow flexibility as well as push rate (uncertainty in replenishment time of semifinished products) has to be considered. On the other side, the stochastic time of customer orders on the pull side have to be taken into account as well. For this purpose, the flexibilities in the simulation are as considered as flexible lot sizes and number of cyclic pallets in carrying products, which are the optimization factors. Besides, the autonomous control for pallets in selecting their own routes is another flexibility factor. This issue is not heighted in this paper, for more information see [32]. However, one great accompanied complexity with this scenario is the on-time arrangement of empty pallets to be available at the entrance inventory to pick up the upcoming products. This arrangement has to regard the respective orders of each product pallet. It can be optimally achieved when supply, demand, and production rates at OEM are coordinated with each other as much as possible. Thus, an intelligent heuristic algorithm plus several experiments is required to find the optimality of the decisive variables in those regards.

Since the time of pushed replenishments as well as upcoming demands is uncertain (leading to fluctuations), the number of pallets (CONWIP carts) and lot sizes can be considered as optimizing factors for making tradeoffs in the oscillating flow problem. However, their exact contributions to the objective are mathematically difficult to be defined in advance. These characteristics of the problem make strong reasons for employing simulation and heuristic methods for solving it in a proper way.

As aforementioned, the selected heuristics for the current problem are GA and SA. Here, the core target is to show the suitability of the metaheuristics (e.g., GA and SA) for optimization material flow throughout the network. For instance, in using GA it can be possible just to minimize a fitness function of a problem, like (2), to achieve the optimum objectives within an evolutionary procedure. Additionally, with regard to the vague information about processing and waiting times and other processes at the shop floor of OEM, the superiority of fuzzy sets in better distinguishing uncertain processing times is to be explored. Besides, application of fuzzy set theory can facilitate the normalization and unification of the disparate multiobjectives of the model, which is represented following.

4. Genetic Algorithm

In general, a number of optimization methodologies have been introduced to solve complex problems, for example, nonlinear and NP-hard. As a competent evolutionary technique, GA is defined as a stochastic optimization method based on heuristic procedures [38]. It has been shown that GA is able to approximately find the optimum solution for complex problems within a fairly quick time. Universally, optimization process of GA starts with randomly generating a population of solutions (individuals), which are in the format of genotype. The specification of a solution can be stored in one or more chromosomes that a chromosome by itself is made of an ordered sequence of single genes. In each gene a single parameter of a coded solution (genotype) is stored. In fact, a genotype carries the coded solution, whose decoded form to the original solution is called phenotype. Moreover, the position of a gene in a chromosome is named locus [39]. Frequently, to codify a problem the binary-based encoding procedure is selected; nonetheless, encoding is not limited to binary values, for example, integer values are used here.

Basically, the initial population, which is normally generated randomly, is subject to get improved to achieve the optimum solution. In doing so, GA employs two strong driving engines to produce new solutions without having any knowledge in prior, that is, selection and adaption operations, in which crossover and mutation functions are driving engines. Generally, for crossover function two individuals from a population are considered to be merged and produce either one child (offspring) or two children. Respectively, there are one-point or multipoint crossover procedures for running this function in GA. Similarly, mutation is also a function of optimization procedure which avoids local traps. For example, changing a gene in an individual and shifting one/some gene(s) from one locus to other one(s) are two ways of mutation procedure. Inversion of an individual's genes can be assumed as mutation as well. Basically, the procedure of GA applied in this paper can be reflected as in Figure 2.

Furthermore, optimization elements in GA are dependent on fitness function values, evolution of individuals, and selection method [40]. Fitness function is an objective function to evaluate individuals and assigning a fitness value to each of them. Accordingly, the fitness values of individuals in a generation define the chance (probability) of each individual in being selected for the next generation. Usually, the best individuals breed the next generation and eliminate the weak performing solutions. In doing so, after generating enough new individuals in a generation each fitness value of them is measured. Afterwards, depending on the type of selection operator, their selection probabilities, proportional to each other, can be calculated. Correspondingly, weak individuals are substituted by those with better performances in solving the problem as the parents for the next generation. Afterwards, the new population of solutions is produced by means of reproduction operator.

However, selection methods can have different mechanisms for selecting the parents of the next generation, for example, roulette-wheel selection, stochastic remainder selection, stochastic universal sampling, and tournament selection [41]. For the sake of simplicity in this paper and regarding the homogeneity merit in defining probabilities, the roulette-wheel selection method is employed to evaluate the solutions. Indeed, the roulette-wheel function measures a probability of selection for each individual by getting the mean value of the fitness (f_i) of an individual in proportion to all observations of the fitness values. Equation (3) defines the probability function of roulette-wheel selection. Here, N is the number of individuals in current population. The higher the probability value, the more chances the individuals have to get selected. Furthermore, SA as another metaheuristic technique can be used as an alternative to GA in some optimization problems. This technique can justify the performance of GA in the specific application at the current problem:

$$\mathrm{Pr}_i = \frac{f_i}{\sum_{j=1}^{N} f_j}. \quad (3)$$

5. Simulated Annealing

Simulated annealing is a stochastic search technique inspired by statistical mechanics. Similar to GA, the metaheuristic algorithm of SA is suitable for solving global optimization problems with large solution space. The algorithm is initially introduced by [41] based on the physical annealing process in metallurgy. Basically, SA performs according to the low-energy state principle in aligning metal atoms, which is dependent on gradually cooling the temperature in annealing process similar to thermodynamics. The general algorithm of this method is shown in Figure 3. In this work, the step function, in decreasing the temperature after each loop, follows (4), where Te notices the current temperature, $\mathrm{Te}_{\min}$ is the least temperature, and c denotes the cycle number in the loop. For more information about different strategies in SA see also [40, 42]:

$$\mathrm{Step} = \exp\left(\frac{c-1}{\ln\left(\mathrm{Te}/\mathrm{Te}_{\min}\right)}\right). \quad (4)$$

The special use of cooling procedure assists the algorithm to avoid local optimum solutions and optimistically escape

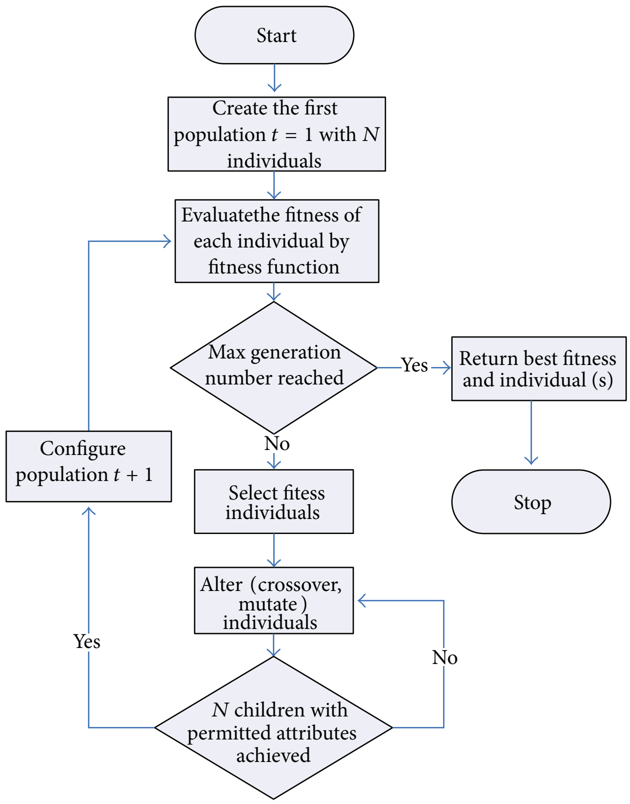

Figure 2: General genetic algorithm.

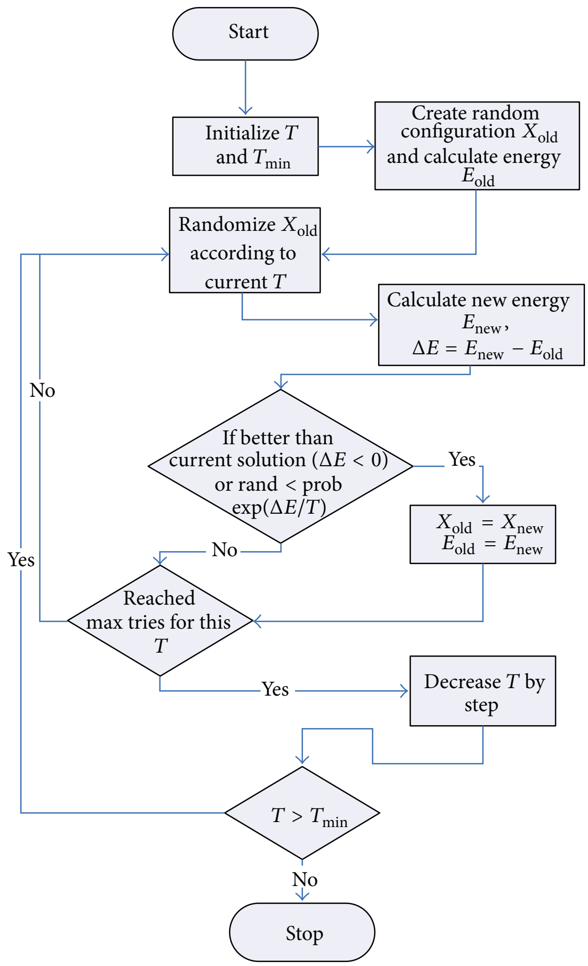

Figure 3: The flow chart of SA algorithm.

from local traps towards global optimum in a given amount of time.

6. Review on Fuzzy Set Application

Fuzzy set theory is considered as a powerful set theory for characterizing ill-defined, uncertain, and stochastic nature of practical operations in complex systems [43], like vagueness in logistics [44]. Practitioners are aware that any human-centered problems in industries, for example, processing times, due dates, and delivery time, forecasting, are uncertain and imprecise in nature [45]. Specially, in case of logistics operations it can be seen that customers' orders appear stochastically with ambiguity, so that the respective information is usually imprecise throughout supply networks. For this purpose, a fuzzy control system by employing fuzzy numbers, their membership functions, and defining fuzzy rules (fuzzy inferring) can distinguish the existing uncertainties as well as making tradeoffs in case of imprecision in practice.

In particular here, stochastic processing times, thanks to normal or exponential distribution, causes imprecise estimation over the waiting times in queues and, consequently, uncertain material flow scheduling and control. This problem can be better solved by taking into account the fuzzy nature of the operations and arranging fuzzy rules for inferring improved decisions. Respectively, IF-Then inference fuzzy rules reflect the policy of decision makers for the objectives of similar problems [46].

Desirably, fuzzy sets can directly assist the solution of normalizing multiobjective problems [47] with disparate and conflicting targets. Introduction of satisfaction degree by means of fuzzy sets theory enables decision makers to transform the multiobjectives of such problems into a normalized unique linear and unitless objective. This alternative reflects the satisfaction's amount of a decision maker in achieving (near)-/optimized values for each single objective and, thereupon, builds tradeoffs between them. This is briefly explained in the solution section. Depending on each objective, various fuzzy membership functions can be employed to reflect the satisfaction of decision maker. However, the functions should be simple for arithmetic operations. A good application of this solution is recently presented by [46].

In addition to the above privilege of fuzzy set theory in operational problems, estimation of imprecise waiting times at each buffer of stations can also be a suitable application of fuzzy sets in material flow control. In order to configure the best routing for each specific material with alternative processing times among several possibilities, different fuzzy functions can be employed for time estimation. Indeed, fuzzy numbers simulate the imprecise processing and waiting times of parts in each processing steps.

In General, several shapes can be applied for defining membership functions in fuzzy sets that amongst them are triangular, trapezoidal, Gaussian, and s-curve [48]. Each of these functions can be allocated to a specific application in industry; nonetheless, the arithmetic operations of them are usually not similar and easy handling. For instance, the triangular fuzzy membership function, because of its simple arithmetic operations, is often considered in the literature for modeling uncertain processing times. This membership function is represented by a triplet (a_1, a_2, a_3) as defined by (5); see Figure 4. While a_1 is the lower bound and a_3 is the upper bound of the fuzzy number $(\widetilde{A})$ with membership degrees of zero $(\mu_{\widetilde{A}} = 0)$, a_2 is the modal point (middle range) with membership degree of one $(\mu_{\widetilde{A}} = 1)$. However, the other simple function to be used in manufacturing operations is trapezoidal. This function is denoted by a quadruple (a_1, a_2, a_3, a_4) and can be defined by (6), see Figure 4. Trapezoidal function has almost the same arithmetic characteristics of triangular functions based on Zadeh extension principle [49]. Thus, it is also comfortable to be used in straightforward computations [50]. On this basis, these two functions are selected to be employed in this paper:

$$\mu_{\widetilde{A}} = \begin{cases} 0 \xrightarrow{\text{if}} x \le a_1 \vee x \ge a_2, \\ \dfrac{x - a_1}{a_2 - a_1} \xrightarrow{\text{if}} a_1 \le x \le a_2, \\ \dfrac{a_3 - x}{a_3 - a_2} \xrightarrow{\text{if}} a_2 \le x \le a_3,\ x, a_1, a_2, a_3 \in R, \end{cases} \tag{5}$$

$$\mu_{\widetilde{A}} = \begin{cases} 0 \xrightarrow{\text{if}} x \le a_1 \vee x \ge a_3, \\ \dfrac{x - a_1}{a_2 - a_1} \xrightarrow{\text{if}} a_1 \le x \le a_2, \\ 1 \xrightarrow{\text{if}} a_2 \le x \le a_3, \\ \dfrac{a_4 - x}{a_4 - a_3} \xrightarrow{\text{if}} a_3 \le x \le a_4,\ x, a_1, a_2, a_3, a_4 \in R. \end{cases} \tag{6}$$

The arithmetic operations of fuzzy numbers are also alternative according to the shape of the membership functions and the employed method. For instance, the addition of two triangular or trapezoidal numbers can be defined by (7) and (8), respectively, as defined by [45, 51–53]:

$$\widetilde{A} + \widetilde{B} = \left(a_1 + b_1, a_2 + b_2, a_3 + b_3; \min\left(\mu_{\widetilde{A}} + \mu_{\widetilde{B}}\right)\right), \tag{7}$$

$$\widetilde{A} + \widetilde{B} = \left(a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4; \min\left(\mu_{\widetilde{A}} + \mu_{\widetilde{B}}\right)\right). \tag{8}$$

However, ranking of fuzzy sets is not as simple as classical sets. Several methods are given in the literature, which aim at discriminating (ranking) fuzzy numbers; see [54]. However, most of the methods in the literature are computationally expensive for simulation with moderated capability for computing in a short time. Therefore, two practical and easy methods out of several are selected to rank the selected fuzzy sets (i.e., triangular and trapezoidal). For this purpose, [45] three simple ranking criteria were adopted to be sequentially used to discriminate triangular fuzzy sets. Firstly, criterion (9) is calculated as the greatest associate ordinary number; if the order of fuzzy numbers is cleared the criteria (10) and (11) are not required. Otherwise, (10) calculates the mode of the numbers to order them; if not criterion (11) is calculated to complete ranking procedure:

$$C_1\left(\widetilde{A}\right) = \frac{a_1 + 2a_2 + a_3}{4}, \tag{9}$$

$$C_2\left(\widetilde{A}\right) = a_2, \tag{10}$$

$$C_2\left(\widetilde{A}\right) = a_3 - a_1. \tag{11}$$

Similarly, to discriminate trapezoidal fuzzy numbers some criteria are needed. However, trapezoidal fuzzy numbers are not as easy as triangular ones to be ranked. Rao et al. [55] developed a "method for ranking fuzzy numbers based on the Circumcenter of Centroids and uses an index of optimism to reflect the decision maker's optimistic attitude and also an index of modality that represents the neutrality of the decision maker." Briefly explained, based on the Centroid of a trapezoid, as its balancing point, they divide the trapezoid into three plane figures as two triangles on two sides and one rectangle in the middle. Then, the Circumcenter of the Centroids of these three planes is considered as the reference point to rank generalized fuzzy numbers. Hence, the Circumcenter of the built triangle within a generalized trapezoidal fuzzy number $\widetilde{A} = (a_1, a_2, a_3, a_4; \mu)$ can be calculated by the following equation:

$$\begin{aligned} S_{\widetilde{A}}\left(\overline{x}_0, \overline{y}_0\right) &= \left(\frac{a_1 + 2a_2 + 2a_3 + a_4}{6},\right. \\ &\quad \left.\frac{\left(2a_1 + a_2 - 3a_3\right)\left(2a_4 + a_3 - 3a_2\right) + 5\mu^2}{12\mu}\right). \end{aligned} \tag{12}$$

Accordingly, the associated index with the ranking is as (13), where $\alpha \in [0, 1]$ denotes the index of optimism. If $\alpha = 0$ the decision maker is pessimistic but if $\alpha = 1$ the decision maker is totally optimistic. In this paper moderated decision maker is chosen, that is, $\alpha = 0.5$:

$$I_\alpha\left(\widetilde{A}\right) = \alpha\overline{y}_0 + (1 - \alpha)\,\overline{x}_0. \tag{13}$$

However, Rao et al. [55] argue that this index dose not suffice the discrimination of fuzzy numbers, since it "uses only the extreme values of the Circumcenter of Centroids." Therefore, they add another index of modality to that as in (14). Here, $\beta \in [0, 1]$ is the index of modality to denote the importance weight of the central value versus the two extreme values of $(\overline{x}_0, \overline{y}_0)$. This value is taken as $\beta = 0.5$ in this paper:

$$I_{\alpha,\beta}\left(\widetilde{A}\right) = \beta\left(\frac{\left(\overline{x}_0 + \overline{y}_0\right)}{2}\right) + (1 - \beta)\, I_\alpha\left(\widetilde{A}\right). \tag{14}$$

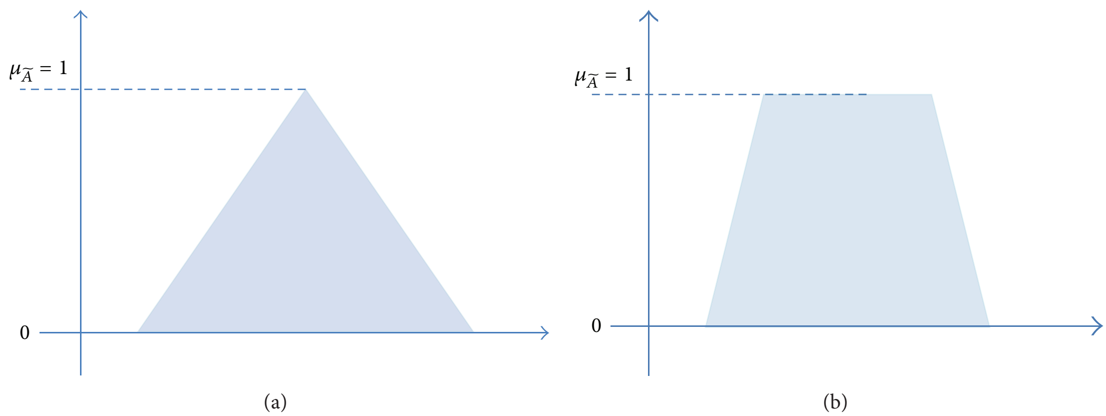

Figure 4: (a) Triangular membership function. (b) Trapezoidal membership function.

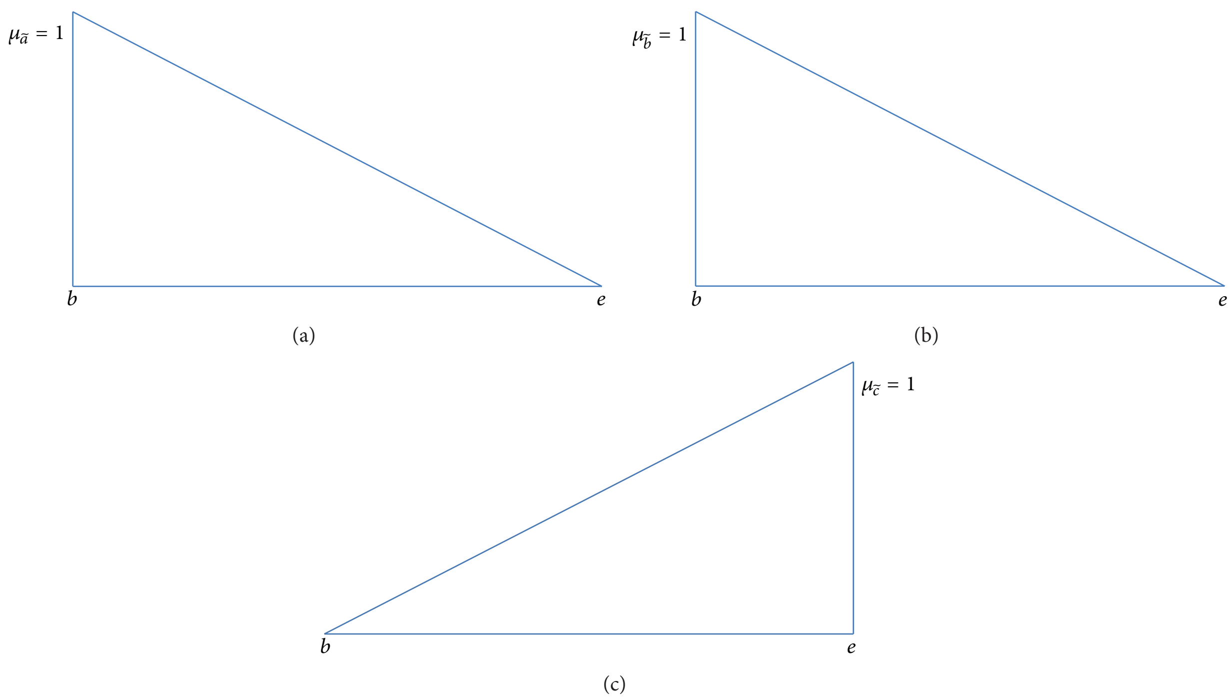

Figure 5: Membership functions for (a) minimization of TPT. (b) minimization of WIP. (c) maximization of TD.

Now, in order to rank the generalized trapezoidal fuzzy numbers the ranking function (15) has to be used, which defines the Euclidean distance from the Circumcenter of the Centroids and the original point:

$$R\left(\widetilde{A}\right) = \sqrt{\overline{x}_0^2 + \overline{y}_0^2}. \qquad (15)$$

Each fuzzy number with bigger $R(\widetilde{A})$ is considered as greater number than the others. However, in case of equal values for this ranking function, the index of modality $I_{\alpha,\beta}(\widetilde{A})$ has to be subsequently calculated to rank the numbers. This method regarding its computational ease is adopted to compare trapezoidal fuzzy waiting times in material flow control.

7. Problem Formulation (Solution)

This section complies with formulating the exemplary problem of this study by taking into account the heuristics and fuzzy set theory. Since the objectives of this problem cover both directions of minimization (ATPT and WIP) as well as maximization (TD), besides consisting of two different units (time and number), these objectives must be properly homogenized (normalized). A suitable solution for making the objectives homogeneous is to transform them into their corresponding satisfaction degrees. Practitioners are aware of the contradictory nature of optimization problems and the realistic constraints accompanied with them. Therefore, it is quite common in practice to make some tradeoffs by managers between the goals to be optimized. The art of

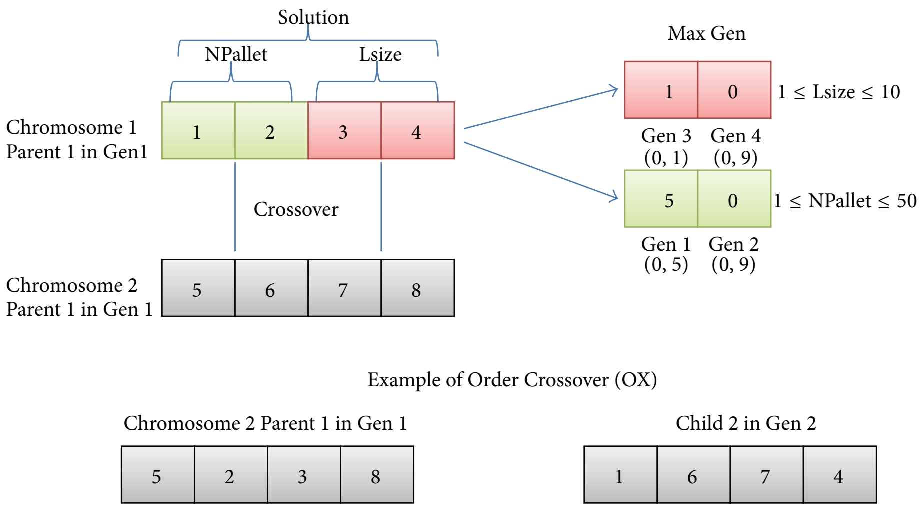

Figure 6: Satisfaction degrees in SA for two alternatives with NegExp supply in Source plants.

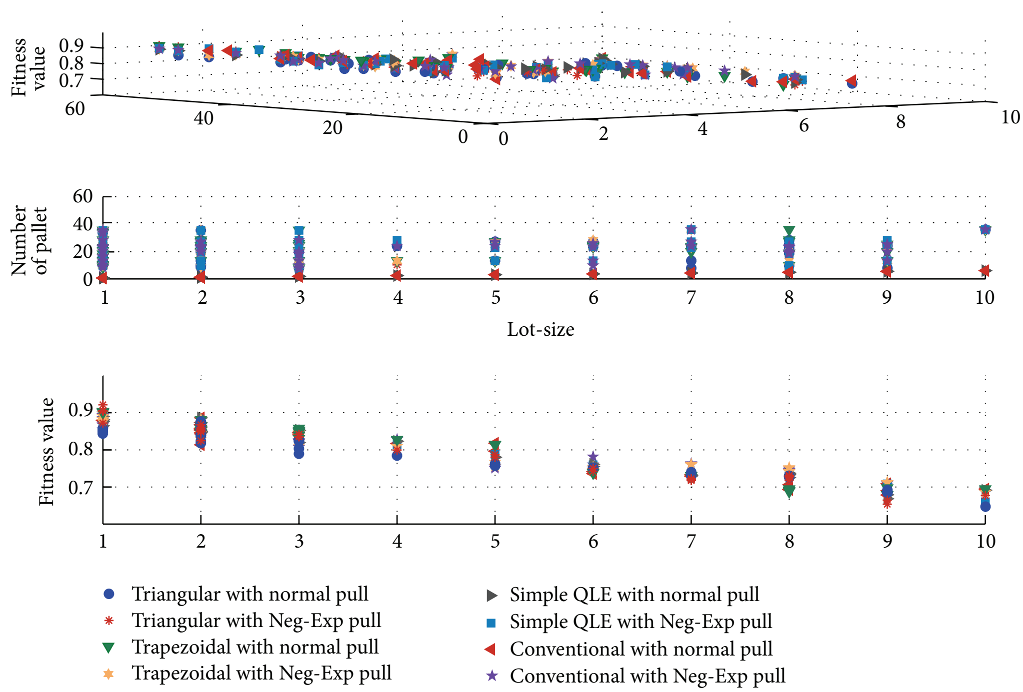

Figure 7: Fitness values of all eight alternatives from three views, showing normalized fitness values against various numbers of pallets and their lot sizes.

a professional manager is to define the best tradeoffs in accordance with the practical tolerances their organization can accept. There exists always a lower and an upper limit for a desired goal. This boundary builds a range for being satisfied with an achieved objective. Of course, the closer to their ideal value, the higher satisfaction can be obtained. However, this boundary may be applied to alternative goals differently by means of its function shape. On this basis, instead of optimizing some contradictory goals managers can subjectively optimize their multiobjective problems by converting them into a uniform problem (called a scalarized problem) of maximizing their satisfaction degrees for all objectives. Moreover, a very appropriate solution in operational research for solving multiobjective problems is the Pareto frontier. In general, the solutions of a multiobjective problem that any improvement in one objective results in decline of at least one other objective are called Pareto optimal solution. A set of these optimal solutions from different points of view is called Pareto optimal set. This is what the outputs of the satisfaction degree solution are going to depict in 3D figures. The drawn plot out of a set of Pareto optimal solution is called Pareto frontier.

There are always some challenges to solve a multiobjective problem, among them is scalarizing the multiobjectives and

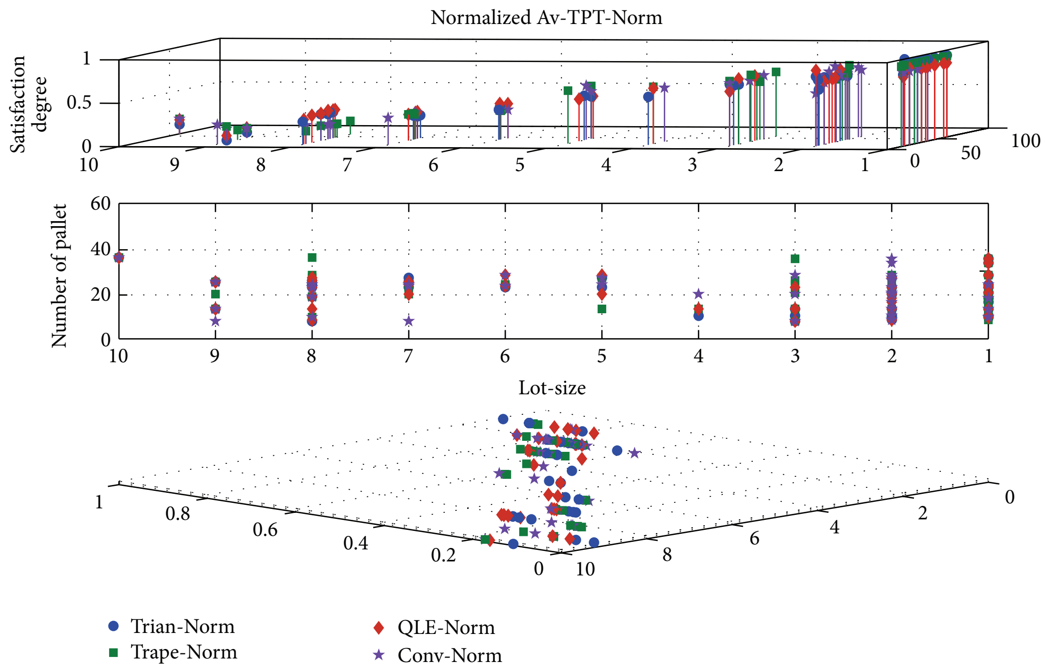

FIGURE 8: Satisfaction degrees of normalized average TPT (global and local TPT) with demands following normal distribution.

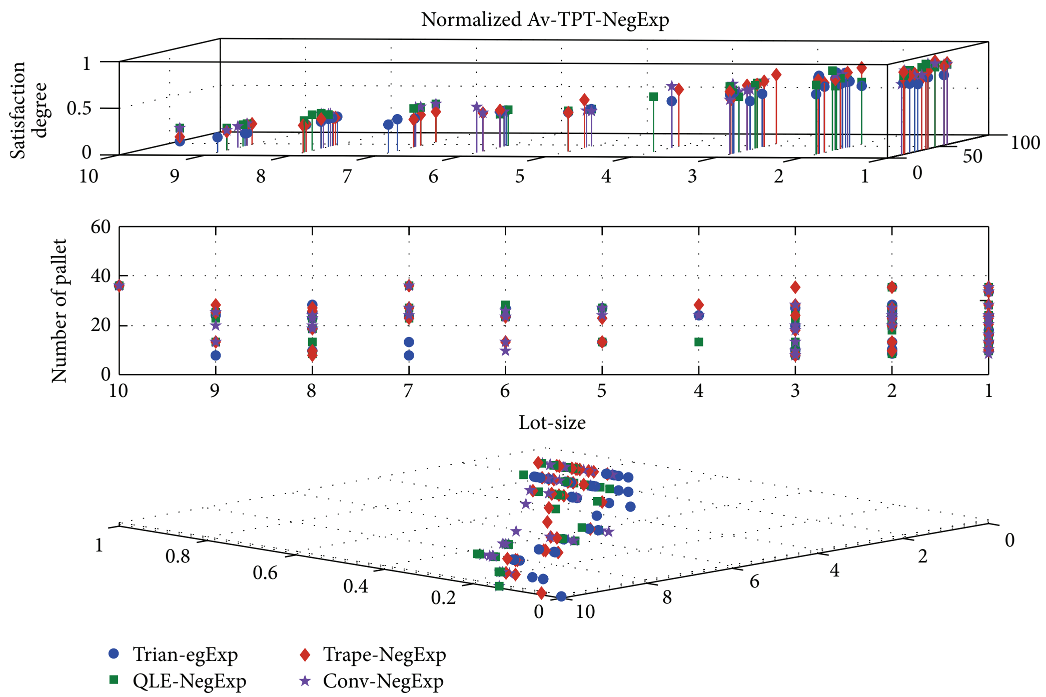

FIGURE 9: Satisfaction degrees of normalized average TPT with demands following negative exponential distribution.

selecting the best solution. There are different approaches and mathematical solutions for solving these challenges, for example, using a decision maker (like satisfaction degree), no decision maker (like no preference methods), a priori methods, a posteriori methods, interactive methods, and hybrid methods [56]. These all solutions are not covered by this paper, since the intention here is to introduce a simple and practical solution for practitioners to solve their multiobjective problems in a quick time. Nevertheless, the satisfaction degree solution is not distinct from Pareto frontier solution, the difference may be the exact formulation of the scalarized problem which can be also adopted by satisfaction degree and the later improvement iterations by decision maker which can be adopted as well.

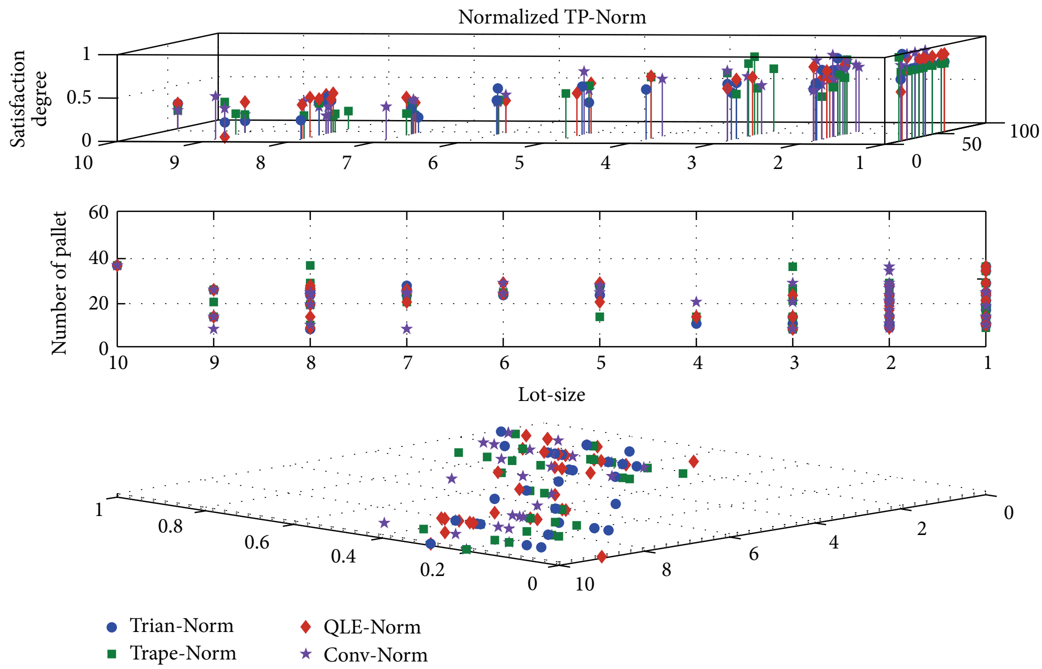

Figure 10: Satisfaction degrees of normalized throughputs with demands following normal distribution.

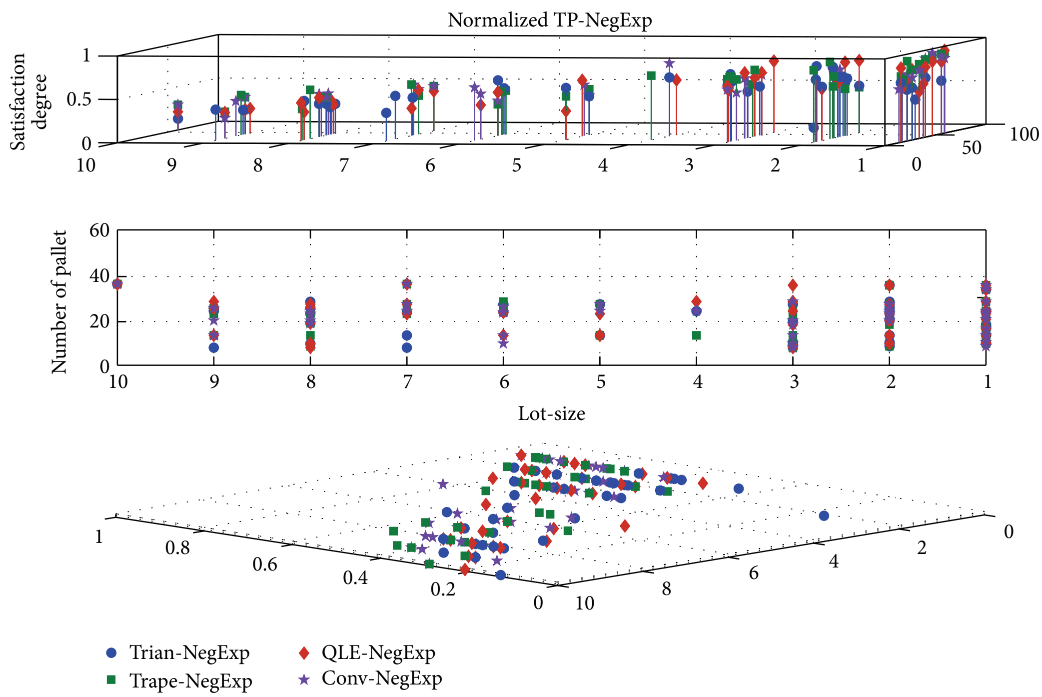

Figure 11: Satisfaction degrees of normalized throughputs with demands following negative exponential distribution.

For this purpose, all objectives together can simply be mapped into maximization of a linear membership function which takes the aggregation of every satisfaction degree within the range of [0 1]. Mapping of a real objective into the normalized satisfaction degree is a subjective process that can be applicable just by defining the lower (b) and upper (e) bounds, that is, [b e], of the corresponding objective by decision maker. Indeed, the boundaries are selected by the decision maker according to the system performance and his/her satisfaction from the operations. Explanation of this transformation process can better be illustrated by Figure 5. For this procedure, (17)–(20) hold true. It is noticeable that (17) $\mu_{\tilde{a}}$ reflects the satisfaction degree of the minimization objective of TPT, (18) calculates the satisfaction degree $\mu_{\tilde{b}}$ of minimization of WIP, and (19) defines the satisfaction degree $\mu_{\tilde{c}}$ of maximization of TD. Then either by configuring some fuzzy rules, the minimum operator (16), or simply using the average aggregation operator for the satisfaction degrees, one unique linear satisfaction degree, representing all objectives, can be achieved:

$$\text{maximize } f = \text{Min}\left(\mu_{\tilde{a}}, \mu_{\tilde{b}}, \mu_{\tilde{c}}\right), \tag{16}$$

$$\mu_{\tilde{a}} = \begin{cases} \left\{\dfrac{e - x_1}{e - b}\right\} \xrightarrow{\text{if}} b < x_1 < e, \\ 0 \xrightarrow{\text{if}} e \leq x_1, \\ 1 \xrightarrow{\text{if}} x_1 = b = 0, \end{cases} \tag{17}$$

$$\mu_{\tilde{b}} = \begin{cases} \left\{\dfrac{e - x_2}{e - b}\right\} \xrightarrow{\text{if}} b < x_2 < e, \\ 0 \xrightarrow{\text{if}} e \leq x_2, \\ 1 \xrightarrow{\text{if}} x_2 = b = 0, \end{cases} \tag{18}$$

$$\mu_{\tilde{c}} = \begin{cases} \left\{\dfrac{x_3 - b}{e - b}\right\} \xrightarrow{\text{if}} b < x_3 < e, \\ 0 \xrightarrow{\text{if}} x_3 \leq b, \\ 1 \xrightarrow{\text{if}} e \leq x_3, \end{cases} \tag{19}$$

where

$$\begin{aligned} x_1 &= \sum_P \text{AGTPT}_p + \sum_P \text{ALTPT}_p, \\ x_2 &= \sum_P \text{WIP}_p, \\ x_3 &= \sum_T \sum_P \text{TD}_{tp}. \end{aligned} \tag{20}$$

In addition to the first application of fuzzy set theory, it can also contribute to the material flow control inside shop floors by means of self-controlled pallets. Each autonomous pallet is able to watch the size of parallel queues in front of parallel stations. This gives the pallet the ability to estimate the waiting time for each station (by aggregating the uncertain processing times of all waiting products in a queue) and to choose the one with the least waiting time [32]. This kind of autonomous control for pallets is called QLE. However, if the waiting and processing time of stations are not deterministic, this ambiguity leads to imprecise estimation of the waiting times in queues. Thus, the fuzzy set theory can assist the estimation process as follows.

Particularly, two alternatives as triangular and trapezoidal functions are considered for the fuzzy sets which approximate the waiting and processing times of products in queues and stations. In alternative one (Trian), the triangular fuzzy numbers for approximating the processing times of stations are considered as *1:48*, ***2:00***, *2:12; 2:06*, ***2:20***, *2:34;* and *2:24*, ***2:40***, *2:56* for the three product types. Here, the (mean $*$ 0.05) can be considered as standard deviation of the normal distribution $N \sim (\text{mean}, (\text{mean} * 0.05)^2)$. These values are exerted to recognize uncertain waiting times and, thereupon, choosing the best route with the least waiting time. This calculation happens by knowing the number and types of products in each parallel queue to choose the corresponding values for the triangular sets. In other words, the pallet adds the fuzzy set of its content to the fuzzy sets of all existing products in the queue as well as the successor station, by mean of the addition operator (7). After calculating the waiting times of all three parallel stations then by means of ranking criteria, say (9), (10), and (11), the pallet chooses the station with the least waiting time.

For the second alternative (Trape), the trapezoidal fuzzy numbers are differently calculated to the triangular ones. Since just the mean times (modal points in triangles) are given, they are taken as the reference values to estimate trapezoidal functions for each product type. The quadruple of each type are calculated as (mean − 2 (mean $*$ 0.05), mean − 1 (mean $*$ 0.05), mean + 1 (mean $*$ 0.05), mean + 2 (mean $*$ 0.05)), which means: *1:48, 1:54,* ***2:00***, *2:06, 2:12; 2:06, 2:13,* ***2:20***, *2:27, 2:34*; and *2:24, 2:32,* ***2:40***, *2:48, 2:56*, respectively, for each type on parallel stations. The process of waiting time estimation is comparable to the alternative one; again the pallet adds the trapezoidal set of its content to the fuzzy sets in the queue as well as the successor station by using (8) to achieve the entire waiting time. Accordingly, by means of the criteria (15) and (14) the least waiting time of parallel queues can be approximated.

Furthermore, the developed GA for this problem is supposed to optimize the fitness value, which is a maximization function. This importance is done by means of the following procedure. The fitness values (called observation too) for each individual, in the first generation, are originally calculated by (5). Then by means of (1) the selection's probabilities for each individual can be found. Derived from the probability values, ten individuals have to be randomly chosen for crossover and mutation operators. In the next generations the procedure is repeated the same until the termination value (sixth generation) is reached. Basically, GA by using (1) defines selection probabilities for individuals and then based on probabilities takes each successful couple of individuals to breed two children, by means of crossover and then mutation. In this experiment, the first created generation is configured by 10 individuals. The crossover operator (Figure 6) and mutation operators are applied according to their probability values as 0.8 and 0.1, respectively. Nevertheless, from the second generation to the last one, the populations are combined out of 20 individuals to cover a broader scope of the solution space. In the second generation, again 10 individuals with higher probabilities are selected to become parents for breeding new children. This repetitive procedure runs up to the termination value, which is set as six generations. All individuals in a new generation are evaluated; unless they have been seen in the previous generations. Universally, for seeking the excellent performance of the system, within the range of pallets number (*NPallet* = [10 60]) and lot size (*Lsize*

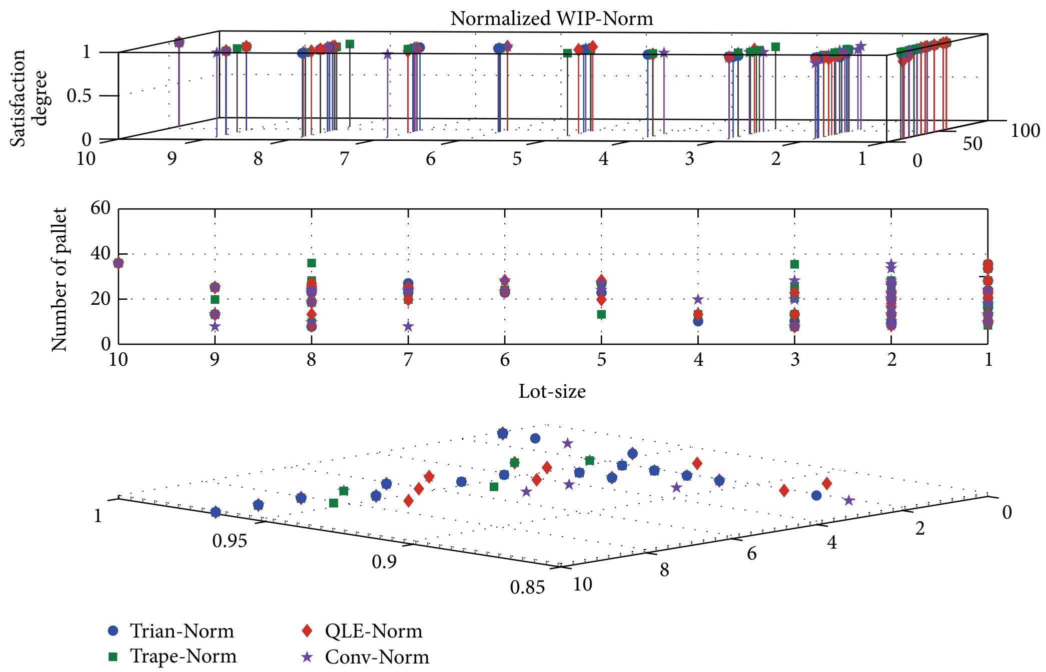

Figure 12: Satisfaction degrees of normalized WIP with demands following normal distribution.

= [1 10]), GA evaluates 110 individuals, that is, $(1 \times 10 + 5 \times 20 = 110$ out of $50 \times 10 = 500)$, see Figure 6 for more illustrations.

In general, two alternative pull-flow scenarios are considered to be experimented against four material flow control systems. In the first alternative, demands are triggered by following the negative exponential distribution (NegExp), whereas in the second alternative demands follow the normal distribution (Norm). Additionally, four variants are developed for material flow control as QLE with triangular fuzzy set (Trian), QLE with trapezoidal fuzzy set (Trape), QLE with crisp values (QLE), and conventional flow control (Conv). These alternatives and variants together configure eight experiment alternatives in the simulation which are presented in the next section. Moreover, to define the performance of each alternative some indicators are evaluated as throughput time (TPT), number of output products (TP), and work-in-processes (WIP).

8. Experimental Results

The eight alternatives include applying different fuzzy sets against conventional crisp numbers in estimation of waiting times for parallel queues are compared by scatter and surface graphs. Figure 7 shows a variety of values for fitness function in GA experiments against the two optimization factors. As it can be seen in different cases the fitness values of each alternative vary. This proves the compatibility of every control system for a specific flow circumstance. Additionally, the surface graphs in the appendix look smoother in case of using fuzzy sets than using crisp values in conventional and QLE control alternatives. Indeed, these results justify that when the system has high pressure of flow regarding number of pallets, lot size, and demand rate; besides existing some uncertain factors using fussy numbers brings more reasonable performance.

For better representation of the control alternatives against each performance indicator they are solely displayed in Figures 8, 9, 10, 11, 12, and 13. There, the alternatives against each performance indicator are easily analyzable for managers to decide over their flow control system.

Finally, application of metaheuristics gives the opportunity to decision maker for adapting its system to optimality through a broad range of available searched values. Moreover, to justify the performance of GA in seeking the near-optimum solutions, SA is employed as well. The results in Table 3 out of SA are quite comparable with those from GA; therefore, both are applicable for this problem with authenticity. However, because of SA essence, just the continuously improving results are shown to the simulator, according to the temperature and cooling system. Nevertheless, SA like GA requires several tunings to bring desirable results. Since GA has several operators (e.g., crossover or mutation probabilities) as well as SA (e.g., definition of step function) to proceed their evolutionary approaches towards optimum solutions there is no guarantee for such heuristics to get the global optimums. Therefore, tuning of the operator factors requires more efforts and experience. However, there lots of studies which aimed for tuning the factors of heuristics that can be directly applied for tuning. The tuning of the factors is subjective and may vary for alternative problems.

9. Summary and Discussion

In summary, the beginning sections of the paper gave some information about material flow control strategies. The strategies complying with material pull and material push

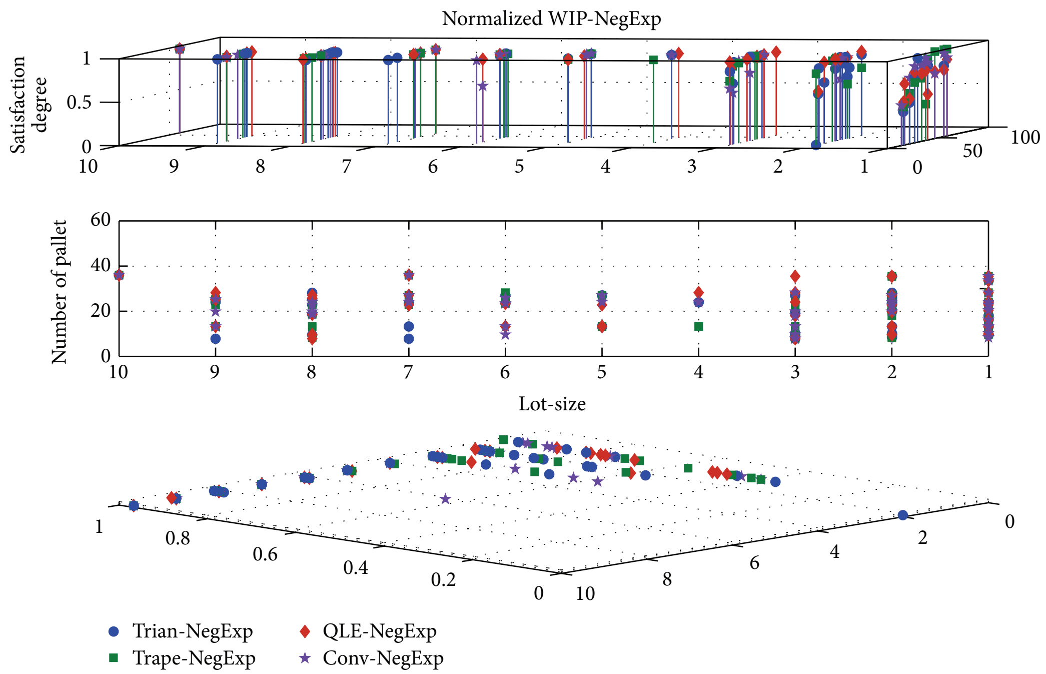

Figure 13: Satisfaction degrees of normalized WIP with demands following negative exponential distribution.

Table 3: Fitness values out of SA in three dimensions.

Lot-size	Number of pallet	Trape_ Norm	Conv_ NegExp	Trian_ NegExp	Trian_ Norm	QLE_ Norm	QLE_ NegExp	Trape_ NegExp	Conv_ Norm
		Fitness values out of SA results in a three dimension form							
5	45	0.84	0.78	0.78	0.78			0.76	0.80
4	22	0.85				0.81		0.79	
3	33		0.82	0.79			0.77		0.84
3	17		0.79	0.83	0.84		0.81	0.83	
2	45	0.88	0.85	0.86	0.82	0.83	0.89	0.84	0.86
2	22	0.83		0.81	0.88	0.82	0.83		0.82
1	27	0.90	0.87	0.85	0.91		0.88	0.88	
1	16	0.92		0.84	0.85	0.86	0.90	0.88	0.87

were briefly explained and some theoretical examples were mentioned for them. The main emphasis in the conceptual sections was on the advantages of applying a hybrid control system out of push and pull concepts to exploit the advantages of both. This was inspired by Polca, CONWIP, Leagility, and other comparable hybrid systems to control a smooth and robust flow of material in dynamic systems (regarding uncertainty and fluctuating demands). In order to reflect the applicability of the recommended thesis on supply networks, an exemplary model is simulated with a discrete-event approach. The specifications of the model were given as well. After justifying the importance of coordinating (optimizing WIP and waiting time at) the collision point of push and pull flows, GA and SA as global optimization heuristics were concisely described and their procedures to get the optimum solution were defined. However, both methods may bring different results in case of varying their adjustment factors (e.g., crossover, selection function, cooling schedule, etc.). Later, a brief review is done on the application of fuzzy set theory in normalizing multiobjectives optimization problems and in defining uncertain processes. It was explained that by means of satisfaction degree of decision maker all single objectives can be converted into the range of [0 1] with a common unit to homogenize the heterogeneous multiobjectives. Moreover, the application of fuzzy sets in compensating uncertainty and ambiguity of processes, for example, processing and waiting times, by means of alternative membership functions was described and practiced. Correspondingly, triangular and trapezoidal fuzzy numbers with their selected ranking methods were elaborated.

It was shown that heuristic methods (e.g., GA, SA, and Tabu search) can be employed to find optimum values for coordinating factors (here number of pallets and lotsize) of stochastic flows (i.e., push and pull). Following the conceptual

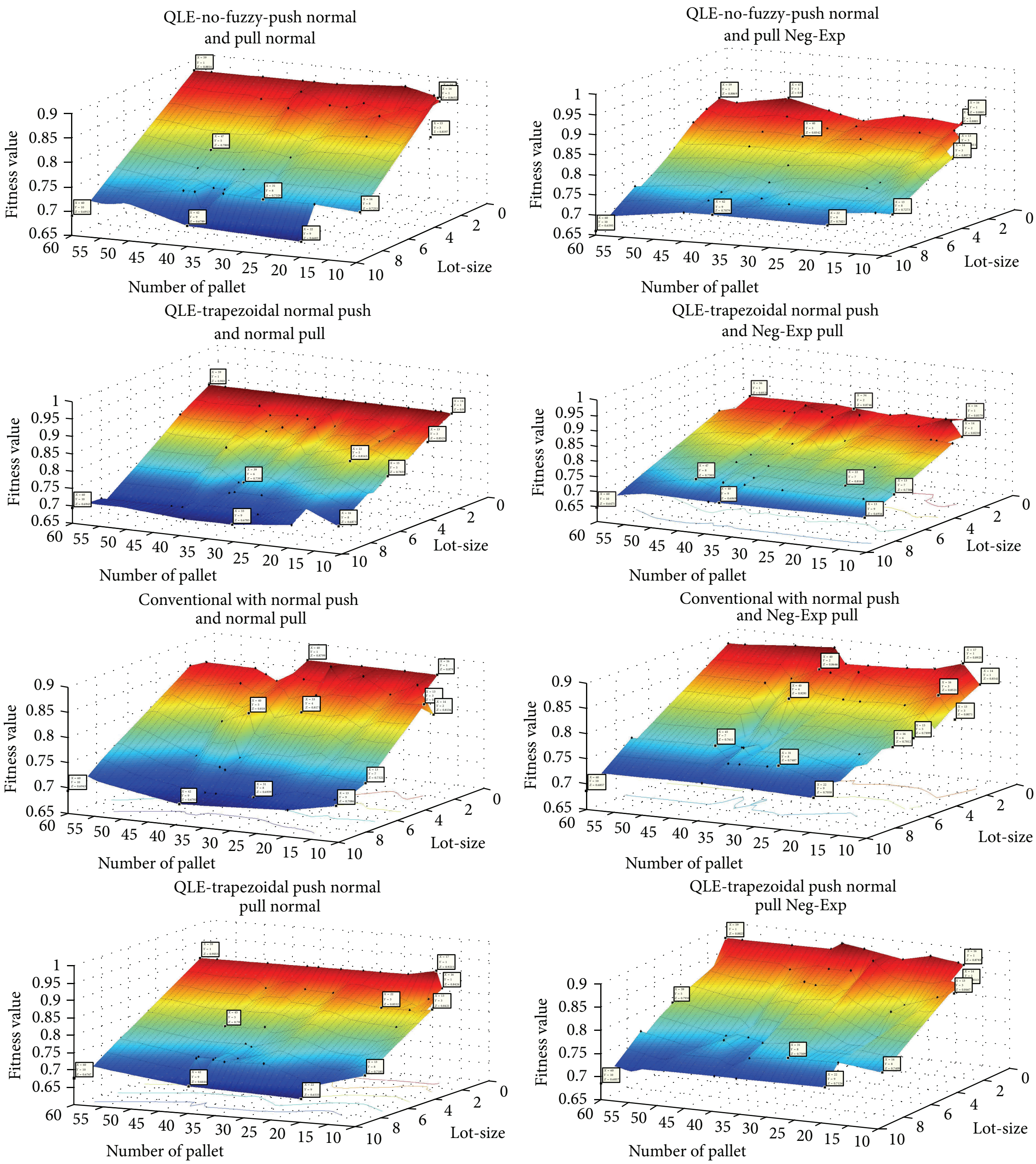

FIGURE 14

sections, the solution formulation for the simulated problem was fairly described. The results of the simulation experiments with alternative pull flows were depicted at the end. Conclusively, the enhancement of material flows with the assistance of fuzzy sets in alternative cases was proved against some performance indicators. Indeed, the graphs displayed a broad range of performances in case of alternative values for the two factors. The better flow of materials by use of fuzzy numbers was partially apparent in the graphs. However, in some cases the other alternatives as QLE and Conv without using fuzzy numbers outperformed the fuzzy sets. This fact reflects the necessity of adjusting the fuzzy sets to each specific simulation case. Moreover, the broad range of performances gives the opportunity to decision makers to fit their constraints to each performance circumstance in practice. Optimization of material flows throughout supply networks (inbound as well as outbound) is a challenging task of practitioners. Experimental results showed that employment of optimizing factors in metaheuristics and using simulation contribute to the solution of complex flow controls. The broad scope of solution space investigated by heuristics gives the opportunity to managers to observe a broad range of single solutions (Pareto solutions) and exert those which suit the best to their constraints and requirements.

A very appropriate solution in operational research for solving multiobjective problems is the Pareto frontier. The precision of this solution is reflected by its strong mathematical models for finding the scalarized problem and solving them. This approach is considered to be experimented and compared against the applied approach in this paper (satisfaction degree) as further works in similar case studies. Moreover, in this study the optimization procedure was not run in real time of flows, but with the assistance of offline simulation's experiments. In further works, employment of some intelligent methodologies for example, data mining, artificial neural network (ANN), and Lamarckian learning for improving GA [35] are to be explored. Some learning methodologies can directly be assigned to distributed flow objects, so that they get the capability to locally control and improve their routes and decisions locally and globally in real time [32, 57].

Appendix

See Figure 14.

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