Lecture 3. Logistic Network Scenario

The main objective of lecture is to consider the logistic Network Scenario

1. General Structure
2. Problem Statement
3. Simulated Annealing
4. Problem Formulation (Solution)

1. General Structure

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.

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. 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.

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 min and 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.

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. Therefore, further synthesis is required to achieve a uniform objective equation. This is broadly explained in the solution section: 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. 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.

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. 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.

3. 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 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, is the least temperature, and denotes the cycle number in the loop. For more information about different strategies in SA see also:

Fuzzy set theory is considered as a powerful set theory for characterizing ill-defined, uncertain, and stochastic nature of practical operations in complex systems, like vagueness in logistics. 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. 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.

Desirably, fuzzy sets can directly assist the solution of normalizing multiobjective problems 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.

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. 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 as defined by (5); see Figure 4. While is the lower bound and is the upper bound of the fuzzy number with membership degrees of zero is the modal point (middle range) with membership degree of one. However, the other simple function to be used in manufacturing operations is trapezoidal.

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. 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 can be calculated by the following equation:

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

4. 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 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.