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SIMULATION-BASED METAHEURISTIC OPTIMIZATION OF LOGISTICS SYSTEMS

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Simulation models are important for planing, implementing and operating logistics systems since they can depict their dynamic system behavior. In the field of logistics, discrete-event models are widely used. Their creation and computation is often very time and labor consuming. For this reason, the paper reviews optimization methods for simulation models to quickly and effectively execute analysis and planning tasks related to production and logistics systems. The paper reviews literature from 2008 to 2011 that describes the latest research in optimization methods for simulation models that are widely used. Most of those methods discussed in this paper are metaheuristics. Metaheuristics have a good trade-off between solution quality and computing time, especially for complex problems or large problem instances.

Key words: logistics systems simulation, optimization models

Introduction

Competitive manufacturing, creation and exploitation of logistics systems today are no longer possible without optimization. Research and analysis methods of systems flows are based on both analytical and simulation modeling. Simulation models are important for planning, implementing and operating logistics systems, and for describing the systems dynamic behavior. Simulation modeling has the capability to represent complex real-world systems in detail. The purpose of experiments with the model is to acquire new knowledge about objects or processes, which need to be explored. The input parameters can often be divided into two groups. We describe the variants of the system structure or variants of its exploitation scheme with the help of the first group of parameters. The second group of parameters is used to determinate the intensity of system input flows and performance times of individual operations. The final result of this model analysis in ideal should contain the input parameter combination that ensures a key indicator of system functioning extreme value. In logistics and industry discrete event models are widely used. The experiments with such models are often made in order to compare several structures of system variants and to choose the best of them, but automatic search for the optimal variant is not used very often.

Overview of Publications of the Winter Simulation Conference

In practice, one often has to deal with global optimization problems. A global optimal solution of a search algorithm can be used for solving system structure optimization tasks, as well as solving the ongoing processes in the system optimization tasks. Global optimization methods include a mechanism that allows escaping from local minima, while the local optimization method does not have such mechanism. Therefore, heuristic techniques to search for new areas of attraction are used in global optimization algorithms.

We also know that most of the optimization algorithms are used in combination with discrete event models and are based on the representation of the model as a "black box" which belongs to the class of metaheuristic algorithms. In case of a general "black box" model, global optimization is performed without prior knowledge of the criterion function surface – determined by criteria and constraints. The purpose of this publication is to analyze the current situation in the application of optimization techniques for simulation models of production and logistics processes.

In particular, the following questions should be answered:

1. Which indicators of logistics system functioning are determined by the use of simulation models?
2. What are the parameters of simulation models that are selected as variables in the search for optimal conditions for the logistics systems functioning?
3. What kind of optimization algorithms are used for work with discrete event models, in general, and with the models of production and logistics processes, in particular?

Answers to these questions are searched looking at the Winter Simulation Conference (WSC) publications and are reflected in Table 2. The WSC is the premier international forum for disseminating recent advances in the field of system simulation. In addition to a technical program of unsurpassed scope and quality, WSC provides the central meeting place for simulation practitioners, researchers, and vendors working in all disciplines in industry, service, government, military, and academic sectors.

The second column of the Table 2 indicates whether it is a production or a logistics system and their further fields.

Logistics can be defined in a number of ways, depending on one's view of the world; but in this paper it is taken to be the set of activities the objective of which is to move items between origins and destinations in a timely fashion. As we can see from the column two logistics involves the integration of information, transportation, inventory, warehousing, material handling and packaging. Logistics is a very wide field including procurement, production and distribution. Given services are performed by logisticians, the main fields of logistics can be broken down as it is shown in Table 1. Models division in groups such as production and logistics, shown in Table 2, is quite arbitrary, since the model type of production can almost always be attributed to a group of production logistics (see Table 1).

Table 1. Main fields of logistics

Logistics	Activities	Objective
Procurement Logistics	Market research, requirements planning, making or buying decisions, supplier management, ordering, and order controlling	Maximize the efficiency by concentrating on core competences, outsourcing while maintaining the autonomy of the company, and minimize the procurement costs while maximizing the security within the supply process
Production Logistics	Connects procurement to distribution logistics. Activities are related to organizational concepts, layout planning, production planning, and control	Use the available production capacities to produce the products needed in distribution logistics (ensure that each machine and workstation is being fed with the right product in the right quantity and quality at the right time)
Distribution Logistics	Order processing, warehousing, and transportation	Deliver the finished products to the customer

The third column of the Table 2 contains parameters of the systems performance, values of which have been estimated by using simulation models and have been used as the objective function in the implementation of the optimization processes. One part of these parameters has a physical nature (throughput rate, buffer allocation, setup time, etc.), and the other part is used to display the level of expenditure or income, for example, holding cost, ordering cost or shortage cost.

Decision variables, displayed in the fourth column of Table 2, are characterized by a very large variety, since they are closely related to the physical processes occurring in the analyzed systems. Typical are the cases where the decision variables represent the system resources or the sequence of events planning variants. Almost all decision variables depicted in Table 2 are discrete variables.

The main conclusion based on the analysis of optimization algorithm types (see fifth column of Table 2) lies in the fact that almost all of these algorithms belong to the class of metaheuristics. A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms. Metaheuristics are often able to offer a better trade-off between solution quality and computing time, especially for complicated problems or large problem instances. Mostly metaheuristics are used for combinatorial optimization in which an optimal solution is sought over a discrete search-space. A complete list of metaheuristic optimization algorithms can be seen in Fig. 1, which displays the view of experts (Johann Dréo and Caner Candan), represented by them in 2011 [19]. Only the algorithms described in [6], [11] and [16], do not belong to the class of metaheuristics.

Table 2. Examples of simulation-based optimization of logistics and production systems

Paper	The modeled logistics or production system	Objective functions of optimization problems	Decision variables of optimization problems	Types of optimization algorithms
[1]	Production (buffer allocation problem)	Maximization of throughput rate, minimization of total buffer allocation	Buffer, server and work allocation	Stochastic components of genetic algorithms: roulette wheel, linear ranking and tournament selection
[2]	Production (industrial scheduling)	Fitness function: throughput, shortage, target levels, stopped in advance, setup time	Dispatching rules, sequence order	Direct, indirect and hybrid genetic representation
[3]	Logistics (barge transportation)	Total solution cost: total penalty cost, variable transportation cost, the total inventory holding cost	Reorder points and maximum capacities at each demand point in the system	Scatter search, an evolutionary heuristic approach
[4]	Logistics (mail transportation)	Quality of a transport solution: total cost, number of tardy mail, total amount of carbon dioxide emissions	Transport solutions with attributes: start point, start time, and end point	A hybrid of two evolutionary algorithms: evolution strategies and genetic algorithms
[5]	Logistics (multi-location transshipment problem)	Minimizing the total inventory, backorder and transshipments costs	Transshipment and replenishment quantities of each stocking location	OptQuest (scatter search, tabu search, integer programming and neural networks)
[6]	Production (inventory management)	Minimizing the total costs (holding cost, ordering cost and shortage cost) or maximize customer satisfaction	Values of reorder point, maximum inventory level	Response surface approach, kriging metamodeling
[7]	Production (supply chain)	Minimizing the required inventory subject to achieving some target customer service level	Reorder point and lot size decision variable settings at different lot setup time and delivery service levels	OptQuest (scatter search, tabu search, integer programming and neural networks)
[8]	Logistics (vehicle routing problem)	Minimizing the total costs.	Number of customers, number of vehicles, average demand, spread, capacity of vehicle, distance.	Neighborhood search embedded adaptive ant algorithm.
[9]	Logistics (cooperative transportation planning problem)	Smallest cost for tour plans	Created tour plan	An ant colony optimization, greedy heuristic
[10]	Logistics (supply chain)	Maximizing expected profit of supply chain members	Supplier production quantity, order quantities of supply chain, retail prices and others	OptQuest (scatter search, tabu search, integer programming and neural networks)
[11]	Production (testing area of an assembly line)	Maximizing the monthly profit per shift	Inter-arrival time, yield, and testing process time	Regression analysis for metamodeling purposes, generalized reduced gradient algorithm
[12]	Logistics (container operations in marine logistics)	Demand fulfillment rate, profit, container utilization, and operating cost	Fleet size, contractual waiting time, service level, proportion of high priority customers	OptQuest (scatter search, tabu search, integer programming and neural networks)
[13]	Production (scheduling jobs in semiconductor manufacturing)	Minimization of the make-span. Minimization of the maximum lateness. Minimization of the total weighted tardiness	Generated schedules	Simulated annealing algorithm to generate the schedules

The continuation of Table 2

Paper	The modeled logistics or production system	Objective functions of optimization problems	Decision variables of optimization problems	Types of optimization algorithms
[14]	Production (pull manufacturing system, inventory system)	Maximizing the average profit. Minimizing the average total cost: average holding cost, order cost and shortage cost	Number of machines in each work station, the number of positions in each buffer. Reorder level and the maximum inventory level	OptQuest (scatter search, tabu search, integer programming and neural networks). Witness Optimizer (adaptive thermo-statistical simulated annealing)
[15]	Production (production of machined components)	Maximizing the total slack (difference between the due time and completion time for each work order)	Sequences of orders	OptQuest (scatter search, tabu search, integer programming and neural networks)
[16]	Production (production facilities for food and pharmaceutical packaging)	Leanness performance: cycle time, work in process and staff utilization	Demand management, preventive maintenance, labors capacity and product flow	Response surface methodology: mesh surface of three responses functions
[17]	Production (planning in semiconductor manufacturing)	Minimizing the total costs: the holding cost for work in process, the inventory holding cost, and the backlog cost	Number of lots of each product type released in given period	Controlled elitist genetic algorithm
[18]	Logistics (scheduling of railway network)	Minimizing travelling time of all trains in the rail network and finding the best station to stop for refueling and praying	Trains time table	Genetic meta-heuristic algorithm

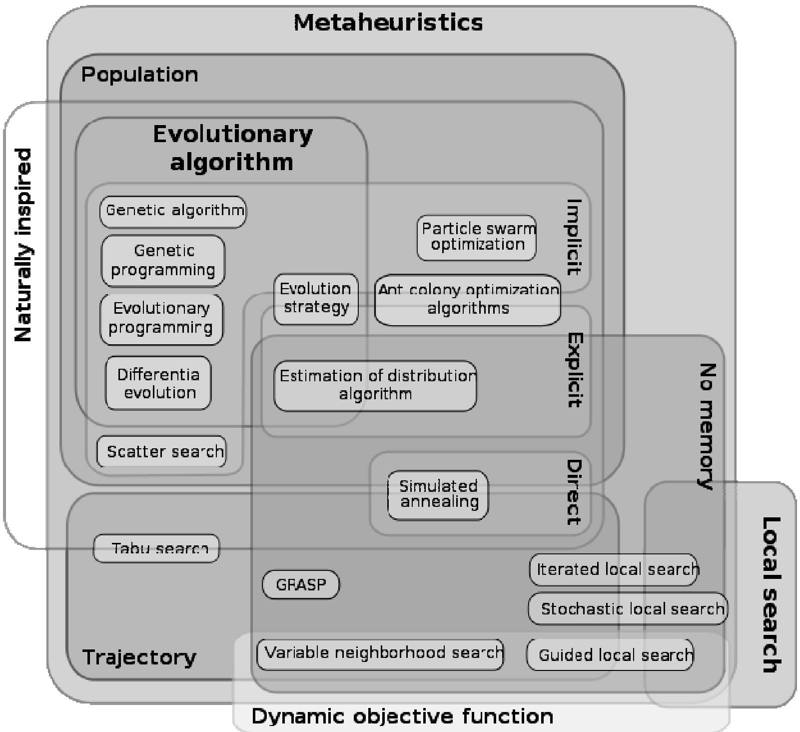

Figure 1. Metaheuristics classification [19]

Conclusion

In general, simulation-based optimization is the process of searching for the best set of model specifications, i.e. input parameters and structural assumptions, where the objective value is the output performance of the simulation model for the underlying system. Simulation-based optimization has been widely used in different fields including manufacturing systems, project management, operations scheduling, inventory systems and supply chains. Contemporary trends contributed to the appearance of a new class of complex processes in the field of optimization. These tasks are characterized by various objective functions and conditions, and a large number of variables that make the solving process more complex. Often, the analyst has to deal with a multi-function logistics system design case. There is no consensus about what types of optimization techniques one needs to apply to simulation-related research projects to ensure the effectiveness of searching in problem position space and in its separate regions with minimal computational costs. The paper presented the literature sources that describe the latest trends applied to this new class of models and the means by which it is possible to implement them.

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