Simulation and Optimization of Logistic Systems with Genetic Algorithms

Krisztián Bóna and Balázs Molnár
Budapest University of Technology and Economics
Department of Transportation Technology
Bertalan L. u. 2, 1111
Budapest, Hungary
E-Mail: {kbona; bmolnar}@kku.bme.hu

Abstract

The competition between manufacturers has increased since the developments in the information and communication technology and the globalization of the markets. In this new competitive environment, the companies try to keep and strengthen their position. This is only possible, if the companies' processes are effective and operated economically. The companies try to achieve optimum solutions, but processes must be continuously reevaluated because of the rapidly changing factors that determine competitiveness. Through logistics oriented analysis of the trends in industry, commerce and services (integration of customers, global networks, E-Business etc.) is it only possible to build successful strategies. Optimization problems that occur at the design and organization of logistic processes are usually multi-variable and complex problems with stochastic parameters. Traditional methods are not able or consume too much time to solve these problems, so designers and operators of logistic processes must apply other methods.

In this paper we will represent a possible classification of the search methods used in the optimization of logistic systems and processes. After a short description of the methods, the increasing importance of simulation will be discussed, and the possible cooperation of simulation and modern optimization methods will be demonstrated through two practical applications.

Optimization problems in logistic systems

The optimization of logistic systems often means that from a set of possible solutions the one must be selected, which entirely satisfies the – the previously defined – target function under –also previously defined – conditions. The set of possible solutions is called the *search space*. The dimension of the search space depends on the number of the parameters in the optimization. Another important property of the optimization problem is that the parameters are discrete or continuous. The length of the interval in which the feasible values of the parameters are located specifies the constrains of the optimization problem. However, in special cases other restrictive factors can also be considered. The objective function describes the target of the optimization, which is usually a minimization or maximization problem. In the field of logistics, the greatest effort must be devoted to the formation and the solution of the objective function. Because of the complexity of the logistic problems these often seem impossible. Logistic problems are even more complicated, since the variables are stochastic, and as a result of that, the optimization contains uncertainty. The optimum input values must be found as fast and as accurate as possible under the above mentioned circumstances. The classification of the available optimization methods is shown in Figure 1.

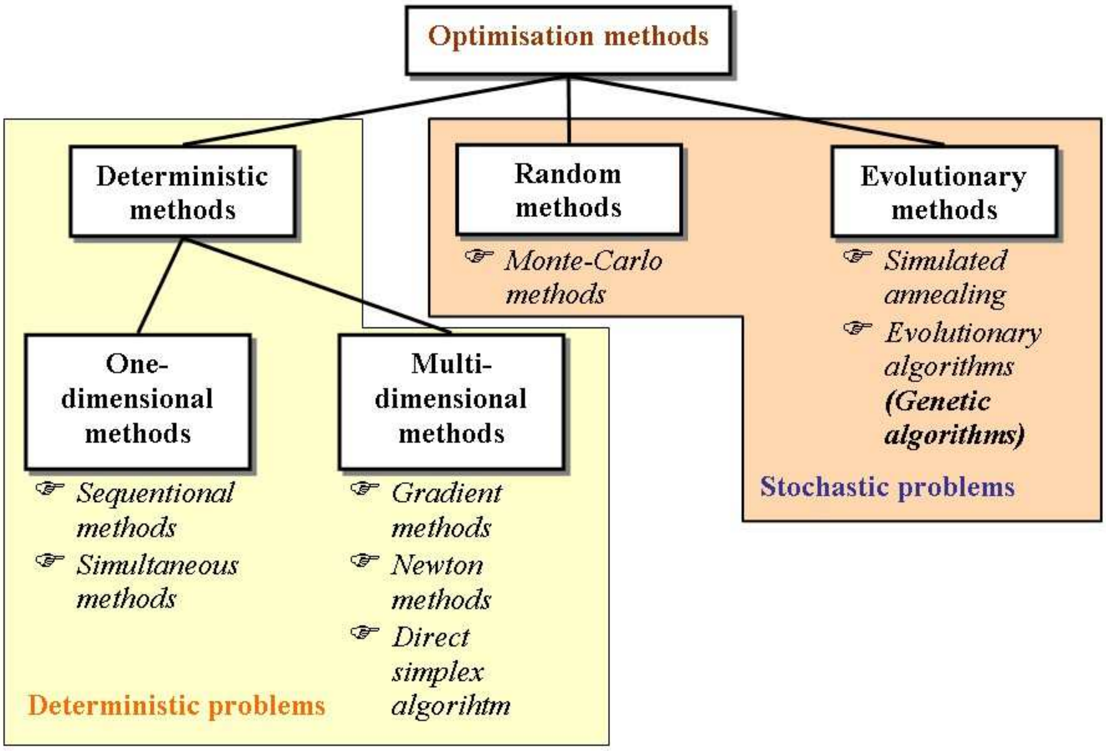

Figure 1: Classification of the optimization methods

Deterministic methods:

These methods are suitable to search optimum solution of non discrete, non-stochastic functions with no constrains. As a result of the applied algorithms, these methods not always find the global optimum, but converge to the closest local optimum. In case of logistic process optimization, these methods are applicable if simple analytical methods fail to bring any results (i.e. non-continuous derivative).

a.) *One-dimensional methods:* the most simple case, the objective function has one parameter (i.e. Total Cost = f(x)).

b.) *Multi-dimensional methods:* the objective function has more input parameters, the search space grows exponentially with the number of parameters (i.e. Total Cost = $f(x_1, x_2, \dots, x_n)$).

Random methods:

These methods change the input variables according to probability and not deterministic rules. Using of random decisions is practical, if deterministic rules do not provide satisfying solutions. The so called *Monte-Carlo methods* are used in very complex problems, where the points are selected with uniform probability and the values of the objective function are evaluated and the smallest (largest) is selected as optimum solution.

Evolutionary methods:

Considerable research is devoted to understand and apply the quasi-"perfect" systems in nature and the natural selection mechanism to solve technical problems. The elaborated methods that model the observed procedures in nature to find the optimum solution – named evolutionary methods – are derivative independent and are suitable to optimize problems with discrete and continuous parameters, even if these are stochastic. These advantageous features of evolutionary methods enable to solve complex problems in production and logistics (i.e. scheduling). The most popular and commonly used evolutionary methods are the genetic algorithms (GA). The first GA were developed by John Holland and his colleagues. The main properties of GA are the following:

- GA use the collective learning mechanism of the set of entities (*chromosomes*) – called *population* – to find the optimum solution, where each chromosome represents one point of the search space. The results achieved by each chromosome are available to the others.
- The offspring of the entities are created by operators using randomness. The *crossover* forms a new chromosome by using information from two or more entities. The other operator is *mutation,* which eventually creates a defected copy of the offspring.
- The ability of one entity to survive (fitness) is determined by an objective function. An entity with higher fitness will be selected with a higher probability to form an offspring by the selection method.

A basic question of the genetic algorithms is the representation technique of the chromosomes in the population. The most common techniques are: the binary, the real and the permutation representation methods. The next important question is that how the data are provided in the right quantity and quality to the optimization problem. This is the topic of the following part of the paper.

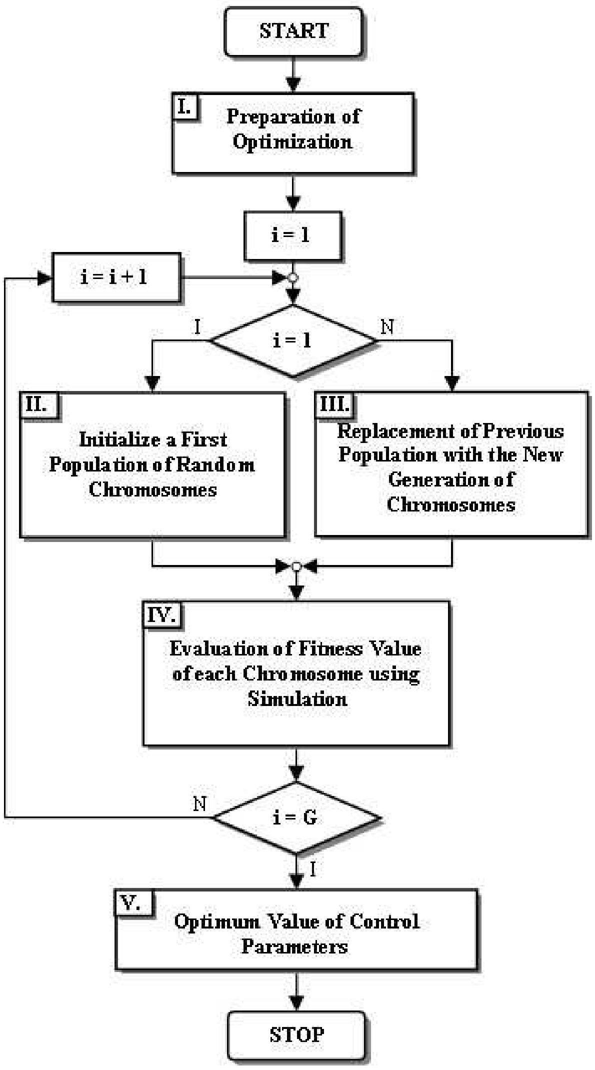

Figure 2: Optimization with Genetic Algorithm

Optimization with Genetic Algorithms:

1. The GA prepares an initial population of "n" chromosomes, where a chromosome represents a possible solution to the problem.
2. Evaluation of the fitness value of each chromosome.
3. Forming a new population, by repeating the following steps:
   3.1. Selection (Parents);
   3.2. Crossover (Offspring);
   3.3. Mutation;
   3.4. Analysis of the offspring, if it represents a feasible solution.
4. Replacement; substitution of the entities of the previous population, with the new formed offspring.
5. Checking the end condition.
6. Repeating the steps from Step 2. until the end condition is not satisfied.

Simulation

Recent developments in the field of simulation made it possible to the users to build an accurate, detailed, true-to-life model in a relative short time. The simulation is a virtual copy of the real system, which – based on the behavior of the components, our measurements and observations – enables the direct analysis of all the modeled properties of the system. Simulation is applied if the construction a mathematical model of the system, or experiments and analysis of the system are not possible or have high costs. Simulation is a tool, which is capable to handle the stochastic processes of the system based on statistical distributions and so avoids the pitfall of calculating with averages. In many real-life environments – like production processes or logistic systems – simulation is the only tool which is able to map the dynamics of the system into a model. A validated simulation model offers a whole range of what-if scenarios to support an objective and well-established decision. Figure 3. shows the different modeling and simulation methods, and the type of simulation that was used in the practical applications. In production and logistic systems, among many other problems, simulation is used to:

- Analyze the implementation of an equipment into the production line,
- Develop production capacity,
- Determine inventory levels,
- Decrease lead times,
- Develop planning methods,
- Determine effects of system failures,
- Find bottlenecks in the system, etc.

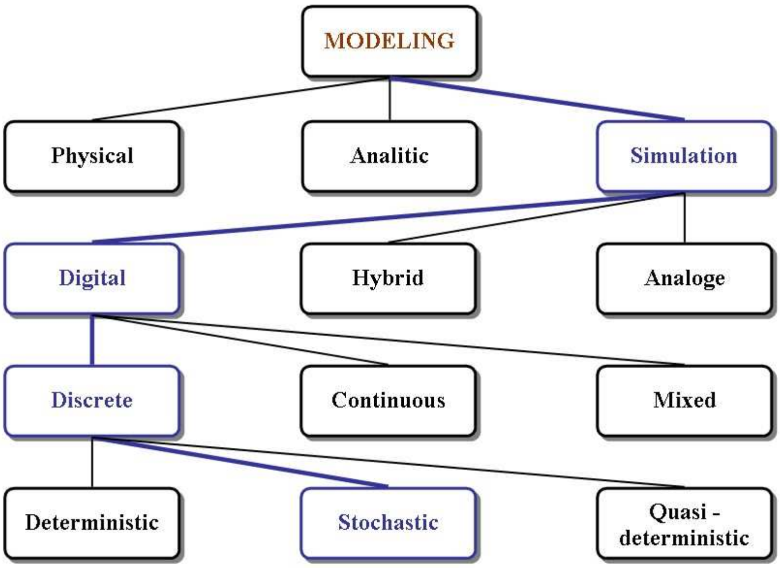

Figure 3: Modeling and Simulation

Simulation Optimization

Optimization and simulation are both tools that support decision making. Optimization uses fix input data, avoids uncertainty and details. Optimization models simplify the complexity of the real system and some factors are even not considered. In the best case, the optimization will find an optimum solution to the 'simplified' model, but not the real problem. Simulation is not creative like optimization, but can cover uncertainty and complexity of dynamic systems in detail.

The combination of optimization and simulation (simulation optimization) can be defined as the process of finding the best set of input variables without evaluating each possibility. The objective of simulation optimization is to minimize the resources spent (i.e. time) while maximizing the quality of information gained in the experiment. The schematic model of simulation optimization is shown in Figure 4.

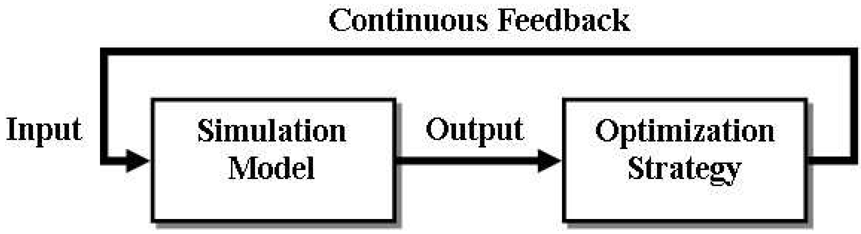

Figure 4: Simulation and Optimization

In the future, labor intense logistic processes (i.e. order picking), scheduling problems and control and planning systems (i.e. inventory control) may be the subjects of simulation optimization. Two practical examples will be described in the next chapter.

Case 1: Simulation Optimization in Inventory Control

Optimization of inventory control processes means that in a time period the costs related to the inventory processes are minimum and/or the probability of customer order satisfaction is maximum. The optimization must find the values of the control parameters so that the above mentioned costs and reliability indicators tend to the right direction. There are two basic questions to be answered in inventory control optimization:

(1.) What control parameters are necessary to optimize the process according to the above described aspects?

(2.) How the values of the control parameters are determined dynamically in order to reach the optimum?

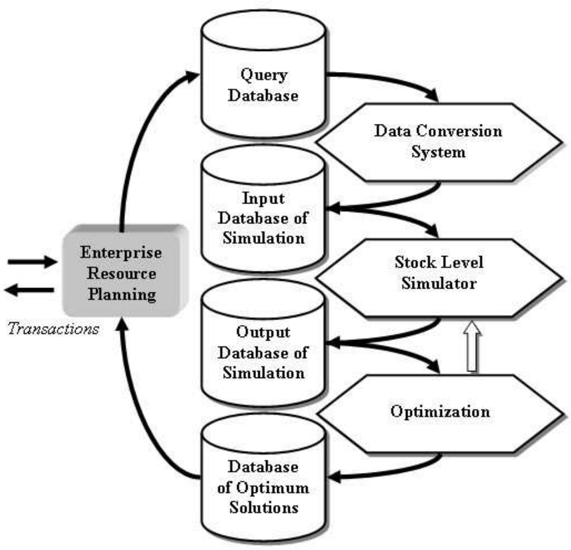

Figure 5: Inventory Control Process

The different inventory mechanisms and inventory models may be applied to the exact answers of these questions. The applied inventory strategies define unequivocally the parameters, and an optimization algorithm is used to calculate the optimum value of the parameters. The model of the inventory control system is described in Figure 5. The two core elements of the control system are: the stock level simulator and the optimization part. The discrete event simulator of the system provides the continuous information flow into the optimization module. The Genetic Algorithm implemented in the optimization module uses binary representation of the chromosomes to find the optimum values of the parameters of the applied inventory control strategy. In the followings, the mechanism of the GA will be described. The numbers in the brackets refer to the steps depicted in Figure 2. Before optimization starts, the following parameters must be set (I.):

- The inventory control strategy ([t;q] – [t;S] – [s;q] – [s;S]),
- The upper and lower bounds of the parameters to be optimized (A_{min}; A_{max}), (B_{min}; B_{max}),
- The number of simulation runs (N),
- The number of generations (G),
- The number of chromosomes in a population – (E_G),
- The number of offsprings in a generation (U_G),
- The crossover (p_k) and the mutation probability (p_m) and
- The power in the fitness value evaluation (k).

At the initialization of the first generation (II.) of the „E_G" chromosomes, the "A" parameter is coded in the upper A^{bit} bits and the "B" parameter is coded in the lower B^{bit} bits in binary form of each chromosome. The connection between the stock-level simulator and the optimization module is created by the fitness value evaluation (IV.). The fitness values are evaluated based on the Total Cost values belonging to each entity with the Power Law Scaling technique with the parameter "k".

The expected value of the Total Cost is evaluated by the stock-level simulator during the "N" runs. After the ordering of the entities according to their fitness value, the replacement (III.) of the previous population, the formation of the „U_G" new offspring, is performed by the following GA operators: Roulette Wheel Selection, Four-point Crossover and Mutation. The Parents are selected randomly and crossover is performed, if Random(0;1)<p_k is satisfied. The new formed Offspring is mutated, if Random(0;1)<p_m is satisfied. This ensures the continuous evolution of the chromosomes towards better solutions and the diversity of the combinations (not to stick at a local optimum). After "G" number of runs, where "G" is set by the user at the beginning, the algorithm selects the best solutions of the parameters (A_o;B_o) from the last generation and decodes these.

Case 2: Planning of Order Picking Processes

In profit-oriented environments, such as warehousing, the minimization of labor costs, and thus the flexibilization of labor force is an increasingly important issue. Such an operating policy requires effective capacity planning methods to determine the number of personnel and equipments per activity and scheduling procedures to define the sequence of tasks by considering their strict deadline. In the following, the use of a discrete event simulation model for multi-criteria scheduling optimization of order picking activities in a warehouse with genetic algorithm (GA) is presented. The operative planning system consists of a database, a discrete event simulation model, an application for capacity estimation and a scheduling algorithm. The system was designed to support operative warehouse management personnel in order picking process scheduling and planning.

Order picking – retrieval of products from storage to meet customers' demand – is often the most labor intense activity in a warehouse. Therefore, the costs of order picking may amount to about half of the operational costs in a warehouse, so any improvement in this field may result in significant cost reduction (Van den Berg 1999).

The Model

The object of the developed model is to determine on the one hand the number of order pickers, on the other hand the sequence of the retrieval of the pick lists so that the total cost of order picking is minimal.

The objective function describing the optimization problem consists of the following three terms:

- Minimization of the labor costs;
- Minimization of earliness/tardiness costs;
- Maximization of resource utilization.

The labor costs are determined by the number of order pickers and the specific labor costs which may vary per each shift. The pick lists must be ready for shipping by the internal deadlines calculated by the tour-planning module of the WMS based on delivery dates of the customers' orders. Deviation from these cut off times induces incidental expenses. If the orders are prepared earlier, then these must be stored temporarily, so storage costs occur and in addition, useful space is occupied from other warehousing activities. Although if the trucks must wait because the orders are not picked on time, then transports may arrive late to customers, service level of delivery declines and extra labor and other costs may occur.

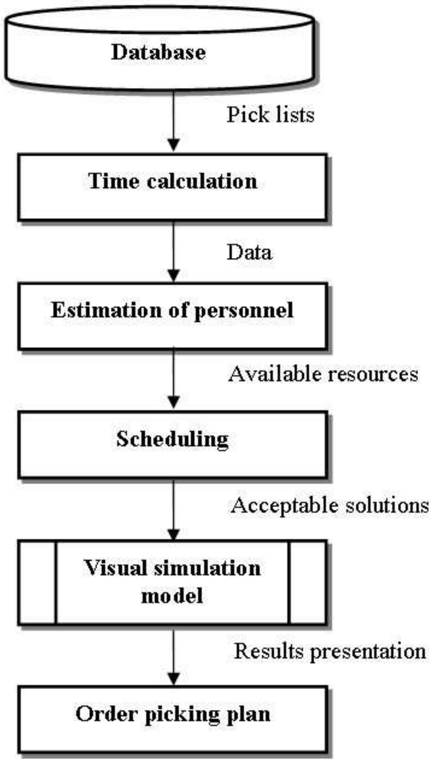

Figure 6: Scheduling and decision support process for order picking planning

In order to convert the objective function into a minimization problem, the maximization of resource utilization is formulated as the minimization of idle times. The model determines the optimal sequence of the completion of the pick lists in three phases:

- Experiment;
- Estimation;
- Optimization.

In the first phase the time needed to pick each list is evaluated. Based on the mean times, the number of required order pickers is estimated for each shift. In the third phase, the optimal schedule can be produced (Figure 6).

Optimization

In case of permutation problems, like scheduling, the best representation technique is to use the indexes of the tasks in the permutation, and so is one chromosome a sequence of integer numbers. The chromosomes of the GA in the Optimization phase represent the order, in which the pick lists are released to the order pickers to be retrieved from storage. The simulation model evaluates each chromosome in a population separately, calculates the time difference between the cut off time and the actual finish time of every pick lists and stores the idle times of the pickers and determines the objective value of the chromosomes. The objective value is mapped into a fitness value, by the Power Law Scaling method, where the actual fitness value is taken as a specific power of the objective value. The selection technique selects two parents at a time and employs the Roulette Wheel Mechanism. After selecting two parents, the offspring is formed by applying the Order Crossover (OX) technique. The Offspring is mutated with a mutation probability – which also can be set at initialization – using the Inversion mutation technique (Man 1997).

The offspring is placed into the new generation and the new generated population is used in the further run of the algorithm. The creation of new populations is repeated until the end condition is not satisfied. From the last generation the best solution is returned. The best solution represents the optimal sequence of releasing the orders to the order pickers.

Conclusion

The nature of the optimization problems in the logistic systems unequivocally determine the optimization algorithms that can be applied for the solutions. Practice shows, that deterministic problems with simple parameters and exact function can be effectively solved with the classic methods. But for more complex, stochastic problems it is remunerative to use besides the analytical methods, the advantages of computer technology, like simulation and computer aided modeling, in the search for the optimum solution. There is a trend to use these derivative independent, iterative, well-algorithmizable techniques to also solve complicated deterministic problems. In the future these methods will play an accentuated role in the development and application of optimization algorithms.

References

[1.] Goldberg, D.E. 1997. *Genetic algorithms in search, optimization & machine learning.* Addison Wesley.

[2.] Man, K.F.; Tang, K.S.; Kwong, S. 1999. *Genetic Algorithms, Concepts and Design.* Springer Verlag, Berlin.

[3.] Kljajić, M.; Bernik, I.; Breskvar, U. 2002. „Production Planning using Simulation Model and Genetic Algorithms“. In Proceedings of the IASTED International Conference, (Marina del Rey, CA, USA, May 13-15.). ACTA Press, Anaheim, 54-58.

[4.] Derhán D. 2002. Optimalizáló eljárás készítése genetikus algoritmus alkalmazásával. M.S. thesis, Budapest University of Technology and Economics.