SIMULATION OPTIMISATION AND MONITORING IN TACTICAL AND OPERATIONAL PLANNING OF DELIVERIES

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ABSTRACT
Data mining, simulation, heuristic optimisation and monitoring techniques are applied to improve complex planning decisions at tactical and operational levels. The paper presents an integrated approach to product delivery planning and scheduling built on integration of these technologies. A business case in tactical and operational planning of deliveries is given in the paper. Cluster analysis of dynamic demand is described. The region clustering of customers is performed through multi-objective optimisation. Vehicle scheduling is introduced and performed for the routed solution.

Keywords: clustering, simulation, metaheuristics, optimisation, tactical planning, vehicle routing, scheduling

1. INTRODUCTION

To ensure the competitiveness, a modern business management requires application of a number of methods in the field of information technologies and operations research. To get the best solution of the problem, these methods must be highly integrated to complement each other.

In the paper, a business case for a logistics department of a distribution centre (DC) for a retail store network is discussed. Four core technologies, such as data mining, computer simulation, optimization and monitoring, applied for an integrated planning and control of deliveries are discussed (see Fig. 1).

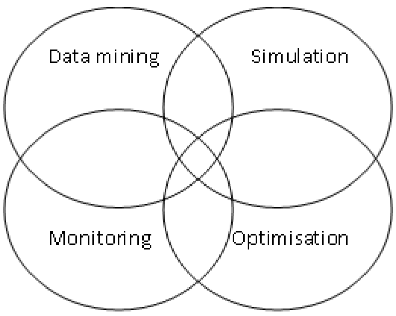

Figure 1: Technologies Integration

Here, data mining techniques are used to perform a cluster analysis in order to define natural grouping of input data, e.g., geographical locations of customers and their demand data in order to define various types of tactical delivery plans. Simulation provides evaluating of specific operational decisions in advance, e.g., while comparing vehicle routes and schedules. Simulation enhanced with metaheuristic optimization allows searching for the optimal solutions at an operational planning level. In particular, an integrated use of data mining, simulation and metaheuristic optimization techniques are described in Merkuryeva et al. 2011. Here, the scheme of integrated planning and control of deliveries is extended by including monitoring tasks.

Despite the fact that the main field of monitoring application is maintenance of already existing business processes, the monitoring may be also applied at the different stages of the business planning process.

2. MONITORING IN SIMULATION OPTIMISATION

Applications of monitoring at tactical and operational planning levels are illustrated in Figure 2. Here, a simulation model is interpreted as a representation of a real system, which input data is based on the data obtained from the real system.

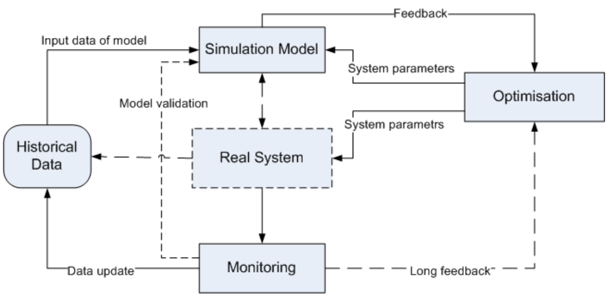

Figure 2: Role of Monitoring

Monitoring can be used already during the modeling phase or even before a simulation model is developed, in order to create a set of historical data. In the delivery planning problem, these data could be observations of customer demand, or data received from vehicles tracking in order to define more realistic simulation model for vehicle routing and scheduling tasks.

If a simulation model is already built and verified, monitoring is a key technique for its complete validation. In this case, monitoring data provides a good basis for the black-box validation and especially for the solution validation of the model. Here, solution validation means determining that the results obtained from the model of the proposed solution are sufficiently accurate for the purpose at hand (Robinson 2004). Continuous collection of observation data via monitoring provides adjustments for the existing model, and makes it adaptive for the changing and developing environment.

Within the optimisation stage of an integrated planning approach, a simulation model provides a feedback link to a parametric optimisation tool in order to test the proposed parameters of the investigated system (Fig. 2). Also, due to a relatively short-time response of the model, the meta-heuristic optimisation tool is effectively exploring system behaviour on the model. It is also worth considering that if the best found decision is applied for the real system, due to different simplifications and aggregations in a simulation model the behaviour of the system with this proposed solution may differ from expected.

Moreover, real-time monitoring in integrated planning and control is used in practice. Modern advantages in information and communication technologies allow managing a vehicle fleet in real-time. Vehicle tracking with GPS, information on the route and customer requirements can be applied for the rerouting and rescheduling of vehicles.

3. BUSINESS CASE

In real-life applications the delivery planning and scheduling problem has different stochastic performance criteria and conditions. Optimisation of transportation schedules itself is computationally time-consuming task which is based on the data from tactical planning of weekly deliveries. This research focuses on the methodology that will allow reducing the affect of the demand variation on the product delivery planning and scheduling, and avoid numerous time-consuming planning adjustments and high computational costs.

In the distribution centres, this problem is related to deliveries of various types of goods to a net of stores, in predefined time windows, taking into account transportation costs and product demand variability. The problem has also a high number of decision variables, which complicates the problem solution process. Heuristic methods and commercial software that are usually applied could lead to non-effective solutions, high computational costs and high time consumption.

In practice, product demand from stores is variable and not deterministic. As a result, the product delivery tactical plan that is further used for vehicle routing and scheduling has to be adjusted to real demand data, and product delivery re-planning supervised by a planner is often required. This task is time-consuming and requires specific knowledge and experience of planning staff in this domain. Moreover, in practice a cluster analysis of the product demand data and potential tactical plans is not performed. But the most suitable delivery plan could be defined as a result of such an analysis that would ensure high quality solutions to schedule an optimisation problem and reduce computational costs of the problem solution.

The paper presents an integrated approach to product delivery planning and scheduling built on a cluster analysis, simulation optimisation and monitoring techniques.

4. INPUT DATA CLUSTERING

First, a cluster analysis is applied to process input data and select an effective product delivery tactical plan for the upcoming week. Then, it is used to group customers into groups, based on their geographical location and average weekly demand.

4.1. Cluster Analysis of Dynamic Demand Data

Here, a cluster analysis (Seber 1984) is aimed (Merkuryeva, Bolshakov, Kornevs 2011): 1) to find a number of typical dynamic demand patterns and corresponding clusters of planning weeks; and 2) to construct a classification model that for any week allows determining an appropriate demand pattern, allocating a specific week to one of previously defined clusters and determining the correspondent product delivery plan. In the business case, the historical data on daily number of delivered products for 52 weeks are used and specified by weekly demand time-series each representing a sequence of points – daily numbers of product deliveries for a specific week.

The K-means clustering algorithm (MacQueen 1967) is used. It aims to divide *n* observations into a user-specified number *k* of clusters, in which each observation belongs to a cluster with the nearest mean representing a cluster centroid. The result is a set of clusters that are as compact and well-separated as possible. An appropriate number of *k* clusters, or typical demand patterns is defined by using silhouette plots (Kaufman and Rousseeuw 1990). Higher mean values of silhouettes show better clustering results that determine better clusters giving the best choice for a number of clusters. In this method, a numerical measure of how close each point is to other points in its own cluster compared to points in the neighbouring cluster is defined as follows:

$$s_i = \frac{b_i - a_i}{\min(a_i, b_i)}, \qquad (1)$$

where s_i is a silhouette value for point i, a_i is an average dissimilarity of point i with the other points in its cluster, and b_i is the lowest average dissimilarity between point i and other points in another cluster.

K-means clustering experiments have been performed for the number of clusters from 2 to 8. Then for each clustering experiment, silhouette plots have been built, and mean values of silhouettes per cluster have been calculated. Analysis of silhouettes mean values leads to the conclusion that the best cluster separation could be done at k=4 with a silhouette mean value equal to 0.558. Clusters 1 to 3 seem to be appropriately clustered. Dynamic patterns received for clusters from 1 to 3 are presented in Fig. 3.

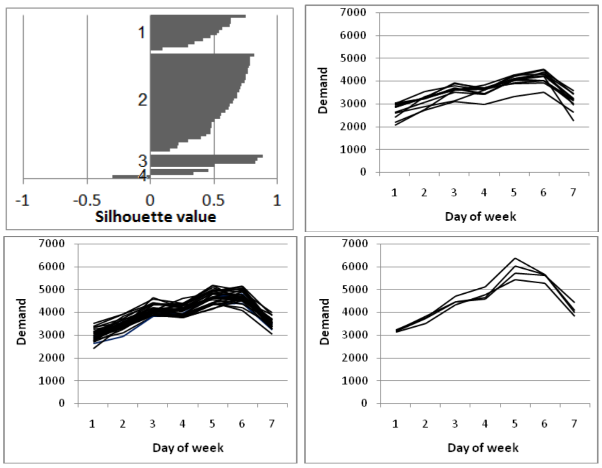

Figure 3: Silhouette Plot for the Number of Clusters k=4 and Demands Patterns with a Mean Value Greater than 0.5 (Merkuryeva et al. 2011)

A classification model (Merkuryeva, Bolshakov, Kornevs 2011) that assigns an appropriate demand cluster is presented by an NBTree, which induces a hybrid of decision-tree and Naive-Bayes classifiers. This algorithm is similar to classical recursive partitioning schemes, except that leaf nodes created are Naive-Bayes categorizers instead of nodes predicting a single class (Seber 1984). For a specific week, an NBTree allows identifying an appropriate cluster and then choosing weekly tactical delivery base plan corresponding to this cluster. Then, selected weekly delivery plan is used for optimisation of parameters of vehicle schedules.

4.2. Region Clustering Through Multi-Objective Optimisation

In practice, weekly delivery planning is done based on data about store allocations to geographical regions. In the business case, all stores are grouped into 12 regions. However, this grouping has been made manually and seems not to be effective. Additionally, rearranging of regions is required when a new store is opened. Also, it is desirable to get regions with a uniform total weekly demand.

Here, the region clustering task is formalised as a multi-objective optimisation problem. Input data contains the number of stores n, the number of regions k, two geographical coordinates x_i and y_i for each store i, $i = 1,..., n$ defined in the Cartesian coordinate system and the total weekly demand d_i for each store i.

Decision variables are defined that for each store i assign a region (or cluster), i.e.

$$a_i \in \{1,2,...,k\};\ i = 1...n. \qquad (2)$$

Two objective functions are introduced in the problem. The first one determines how good generated regions from the geographical location point of view are, while the second objective function defines if the total demand is equally distributed among these regions. Both objective functions are minimized as follows:

$$f_1 = \sum_{j=1}^{k} \sum_{i \in A_j} r(i, j) \to \min, \qquad (3)$$

$$f_2 = \sum_{j=1}^{k} \left| \sum_{i \in A_j} d_i - \frac{\sum_{i=1}^{n} d_i}{k} \right| \to \min, \qquad (4)$$

where f_1 defines the sum of distances $r(i, j)$ between centroids i of the regions and stores j assigned to them, and f_2 is the sum of variances of the total demand for each region and the average demand per region. No additional constraints are defined in the optimisation problem.

To solve the problem, a multi objective optimisation Nondominated Sorting Genetic Algorithm II (NSGA-II) (Deb 2002) implemented in HeuristicLab optimisation framework (Wagner 2009) is applied. The optimization problem itself is implemented as a multi-objective optimisation problem plug-in of HeuristicLab with integer encoding of solutions and their evaluation by two mathematical functions (3) and (4).

In experiments with NSGA-II, the following operators were applied: a discrete crossover operator for integer vectors (Gwiazda 2006); an uniform one position manipulator (mutation operator) (Michalewicz 1999); and a crowded tournament selector (Deb 2002). A termination criterion is defined by a number of generations, i.e. 10000 generations in this case.

Selected solution in the middle of the Pareto front (see Fig. 4) obtained with the NSGA-II algorithm has compact clusters or regions. Moreover, these results show that only two regions demands are much lower than others. Further leveraging of the region demand could make worse the geographical location of regions with higher priority.

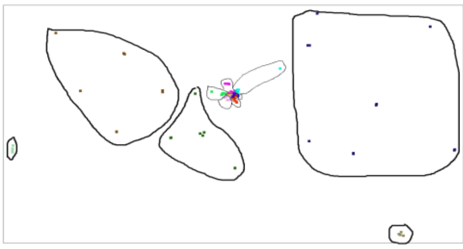

Figure 4: Solution in the Middle of the Pareto Front

5. VEHICLE ROUTING AND SCHEDULING

Within the proposed integrated delivery planning and scheduling approach, vehicle routing and scheduling tasks are solved at the operational planning level. Data from a delivery tactical plan, which description is out of the paper scope, are transferred. For each planning day, vehicle routes and schedules are defined to minimize their transportation costs.

5.1. Vehicle Routing with Time Windows

Classical statement of the vehicle routing problem with time windows (VRPTW) is applied (Cordeau et al. 2001). Input data includes a set of customers, and data about their geographical locations and demand. Each customer has to be served by one vehicle and only once within a planning horizon. For each customer time window when it has to be served is defined. Vehicles routes start and end in DC. Shortest routes for a fleet of homogenous vehicles with limited capacity have to be found.

To solve the problem, a coarse-grained island genetic algorithm with offspring selection (IOSGA) (Affenzeller et al. 2009) was applied. IOSGA parameters are defined as follows: a proportional selector; 5 islands; 200 individuals in population; ring mutation each 20 generations with 15% rate: random individuals are replaced with best from the neighbouring island. Maximal selection pressure was set to 200, and mutation was applied with 5% rate. Mutation operators provided in HeuristicLab framework were involved.

A set of optimisation experiments were performed in order to define which of crossover operators provides most relevant results (see Fig. 5). These results were obtained with GVR crossover (Pereira et al. 2002) and with edge recombination (ERX) and maximal preservative (MPX) crossovers for solutions encoded in Alba encoding (Alba and Doronso 2004). Application of the ERX crossover provided the best results in terms of the total distance and preserved the defined number of available vehicles. However, the results obtained for Alba encoded solutions were worse in terms of the capacity constraints violation. In turn, application of GVR crossover although provides solutions with an overflow of number of vehicles, nevertheless the capacity constraints are satisfied in most cases.

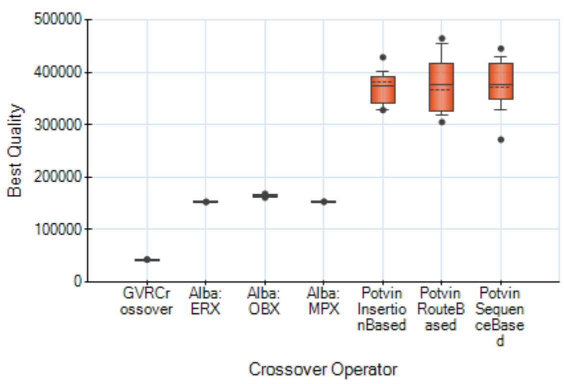

Figure 5: Performance of Crossover Operators in VRP

Finally, a crossover operator which works with an unlimited number of vehicles, but provides best results in terms of keeping routes not overloaded such as GVR crossover was selected. To minimize a number of required vehicles later, the vehicle scheduling problem is introduced in the next paragraph.

5.2. Vehicle Scheduling for the Routed Solution

While solving the classical VRPTW it is assumed that any vehicle may perform only one route in the planning horizon. Each route starts and ends in the depot of the distribution centre, and defines the sequence of the customers served.

In the business case, all routes are shortened by the capacity of vehicles. Both routing and scheduling tasks are performed each day, and planning horizon is defined by 24h. This leads to ineffective solutions, where each vehicle generally performs only one short task of a few hours long and most of the day this vehicle is idle.

This problem can be formulated as Vehicle Scheduling Problem with Time Windows (VSPTW) and solved with methods and tools developed in (Merkuryeva and Bolshakov 2012). Here, the routes correspond to the trips in the VSPTW task and are assumed to be independent from vehicles; and vehicles may perform any fair number of routes during the day.

As far as the final solution of the VRPTW task is feasible for the capacity and time window constraints, it could be optimised by combining and compacting routes to increase vehicle utilization. As a result, during the day each vehicle can perform a sequence of the predetermined routes. Application of the vehicle scheduling for the solution of vehicle routing problem allows reducing a number of required vehicles.

Here, the problem statement described in (Merkuryeva and Bolshakov 2012) has been modified. Routing was performed for each group of delivered goods. Furthermore, for all customers time windows and service times were introduced, which made the problem definition more flexible. Input data used in the vehicle routing task is transferred to the vehicle scheduling one. The vehicle loading time is replaced by a service time in DC.

Let note that for the unification with a VRPTW, a sequence of stores in trips in a new statement was defined as route. Correspondingly, moving times in a trip were interpreted as transportation times in a route. Finally, a vehicle capacity is not involved in the problem, as in the VRP all vehicles have same capacity, and no route of feasible VRP solution will exceed this value.

5.3. Route Scheduling

To implement a solution for vehicle scheduling problem, a problem plug-in in HeuristicLab optimisation framework was developed. Input data are defined as follows:

- Ready time for each customer, in minutes;
- Due time for each customer;
- Service time for each customer;
- List of routes (obtained in VRP solution);
- List of route transportation times, which includes times for vehicles to move between

sequential points of routes (obtained in VRP solution);
- Estimated number of vehicles.

Solution fitness evaluator in the plug-in simulates a schedule of a solution candidate and identifies time windows mismatches, evaluates idle times and the total usage time for each vehicle. Two types of soft constraints are introduced:

1. Number of times when a vehicle arrives to a customer after due time defined by N_{ad};
2. Number of vehicles with working hours more than 24 h defined by N_{ot}.

Fitness function f summarizes vehicle idle times, when a vehicle waits to fit the time window, and a number of constraint violations are multiplied by penalty values:

$$f = \sum_{i \in V} t_i + k_{ad} N_{ad} + k_{ot} N_{ot} \to \min , \qquad (5)$$

where t_i is the total idle time of vehicle I; V defines a set of available vehicles; k_{ad} and k_{ot} are the penalty coefficients for late arrivals and overtimes, correspondingly, and k_{ad}, k_{ot} are assumed to be significantly greater than 1.

A chromosome for solution candidates is encoded as the permutation which consists of integer values. Integers that are larger than the number of routes encode gaps in the chromosome, where for a vehicle a new sequence of routes starts. Other integers define corresponding routes in sequences. The encoding used is similar to one described in Alba and Dorronsoro (2004) for a vehicle routing problem. Application of permutation based encoding allows easy usage of different recombination and mutation operators.

For the schedule optimisation purpose, an Evolution Strategies algorithm implemented in HeuristicLab (Wagner 2009) is applied.

5.4. Experimental Results

Various series of optimisation experiments were performed to determine a suitable algorithm for the VSPTW. Following algorithms were examined: evolution strategies (ES), genetic algorithm (GA), island genetic algorithm with 5 islands (IGA) and offspring selection genetic algorithm (OSGA) (Affenzeller et al. 2009). Maximal preservative crossover and insertion manipulator were defined as genetic operators for all algorithms. To determine a suitable algorithm, numbers of solution evaluations performed to obtain candidate solutions of the equal fitness were compared on hard instances, with a low number of vehicles and short time windows. Results of optimisation experiments for a single instance are shown in Figure 6.

The results of comparisons show that same instance is solved with ES and OSGA in shortest time, while GA without modifications demonstrated the worst results. This behaviour of optimisation algorithms can be explained with potentially small effectiveness of the crossover operator against a mutation operator. The evolution strategy was chosen as most suitable as it has ability to provide globally optimal results of VSP with fewer evaluations.

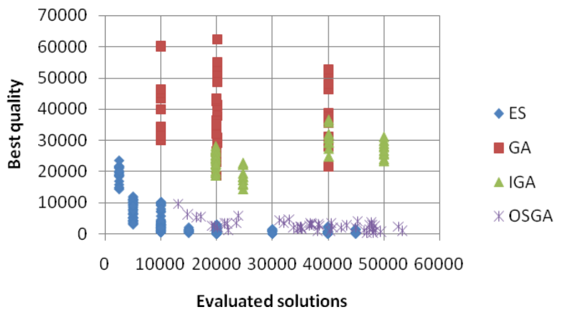

Figure 6: Productivity of Different Optimisation Algorithms for VSPTW

Following, a sample experiment based on one day plan and specific demand data for 53 stores is described. Time windows for most stores are defined from 6:00 a.m. to 9:00 p.m. Some stores can be served in any time.

Application of IOSGA for VRP has given 34 routes in the best found solution (see Figure 7). Most of the vehicles in the solution have very short routes due to a small vehicle capacity. But, due to long time windows of customers it is possible to combine these routes.

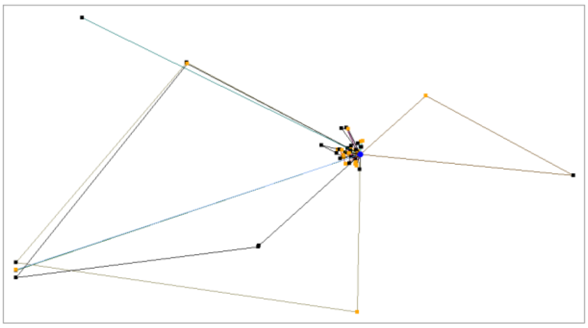

Figure 7: VRP Solution of the Case Instance

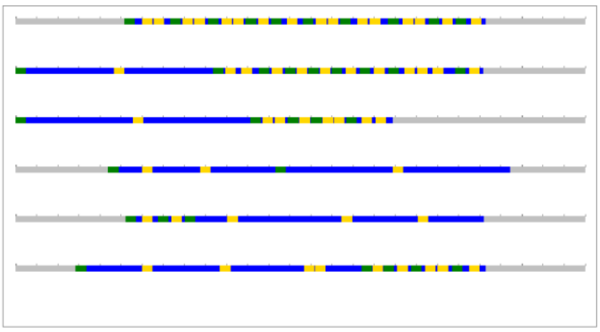

Figure 8: VSP Solution of the Case Instance

Finally, evolution strategies (100+20) were applied for the data obtained in VRP. A number of available vehicles in input data were varied. As a result, it was concluded that the problem instance had globally optimal solutions with all constraints satisfied if at least

6 vehicles are available. The correspondent Gantt chart is shown in the Figure 8. Green lines in the figure correspond to the loading times in DC and define beginning of routes from the VRP solution, blue ones to transportation times, and yellow lines define unloading times at stores.

Similar experimental results were obtained also for another problem instances. Better vehicle utilization was achieved for the instances with larger time windows.

5.5. Monitoring

Here, monitoring provides a long feedback link to an optimization tool at the operational and tactical levels of planning (Fig. 2). After the best solution found in the optimisation is applied in a real life, a new state of the system observed in monitoring is used to adjust parameters of the simulation model. In turn, an adjusted model is applied in further simulation optimisation experiments. And, despite the increasing a time factor, a simulation optimiser is applied to find benefits of a real-life system, and more realistic solutions will be received.

6. CONCLUSIONS

Combination of data mining, simulation, optimisation and monitoring techniques provides the powerful integrated planning approach that ensures effective decisions on various stages and levels of the delivery planning process. A cluster analysis of the input data reasonably reduces the dimensions of the tactical planning tasks and complexity of planning tasks at the operational level. The proposed vehicle scheduling method that complements vehicle routing ensures effective route and schedule solutions for a short-term delivery planning. This method can be applied for vehicle routing and scheduling tasks, where routes are very short in comparison with a planning horizon.

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REFERENCES

Affenzeller, M., Winkler, S., Wagner, S., Beham, A., 2009. Genetic *Algorithms and Genetic Programming: Modern Concepts and Practical Applications*. Chapman & Hall/CRC.

Alba, E., Dorronsoro, B., 2004. Solving the vehicle routing problem by using cellular genetic algorithms. *Proccedings of EvoCOP 2004*, pp. 11–20. April 5-7, Coimbra, Portugal.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), pp. 182-197.

Cordeau, F., Desaulniers, G., Desrosiers, J., Solomon, M.M., Soumis, F., 2001. VRP with Time Windows. In: Toth P., Vigo D., eds. *The vehicle routing problem*. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, pp. 157–193.

Gwiazda, T.D., 2006. *Genetic algorithms reference Vol. I. Crossover for single-objective numerical optimization problems*. TOMASZGWIAZDA E-BOOKS.

Kaufman, L., Rousseeuw, P.J., 1990. *Finding Groups in Data: An Introduction to Cluster Analysis. Hoboken*, NJ: John Wiley & Sons, Inc.

MacQueen, J. B., 1967. Some Methods for Classification and Analysis of MultiVariate Observations. *Proc. of the 5th Berkeley Symposium on Math. Statistics and Probability*, Vol. 1, pp. 281–297.

Merkuryeva, G., Bolshakov, V., 2012. Simulation-based Fitness Landscape Analysis and Optimisation for Vehicle Scheduling Problem. In: Moreno D.R., et al., eds. *Computer Aided Systems Theory – EUROCAST 2011, Part I, LNCS 6927*, pp. 280–286.

Merkuryeva, G., Bolshakov, V., Kornevs, M., 2011. An Integrated Approach to Product Delivery Planning and Scheduling. *Scientific Journal of Riga Technical University, 5 (49)*, pp. 97–103.

Michalewicz, Z., 1999. *Genetic Algorithms + Data Structures = Evolution Programs. Third, Revised and Extended Edition*. Spring-Verlag Berlin Heidelberg.

Pereira, F.B., Tavares, J., Machado, P., Costa E., 2002. GVR: A New Genetic Representation for the Vehicle Routing Problem. *Proceedings of the 13th Irish International Conference on Artificial Intelligence and Cognitive Science (AICS '02)*, pp. 95–102. September 12-13, Limerick, Ireland.

Robinson, S., 2004. *Simulation. The Practice of Model Development and Use*. John Wiley & Sons, Ltd.

Seber, G.A.F., 1984. *Multivariate Observations. Hoboken*, NJ: John Wiley & Sons, Inc.

Wagner, S., 2009. *Heuristic Optimization Software Systems - Modeling of Heuristic Optimization Algorithms in the HeuristicLab Software Environment*. PhD Thesis. Institute for Formal Models and Verification, Johannes Kepler University Linz, Austria.