Scientific Journal of Riga Technical University
Computer Science. Information Technology and Management Science
2011
Volume 49

An Integrated Approach to Product Delivery Planning and Scheduling

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***Abstract* – Product delivery planning and scheduling is a task of high priority in transport logistics. In distribution centres this task is related to deliveries of various types of goods in predefined time windows. In real-life applications the problem has different stochastic performance criteria and conditions. Optimisation of schedules itself is time consuming and requires an expert knowledge. In this paper an integrated approach to product delivery planning and scheduling is proposed. It is based on a cluster analysis of demand data of stores to identify typical dynamic demand patterns and product delivery tactical plans, and simulation optimisation to find optimal parameters of transportation or vehicle schedules. Here, a cluster analysis of the demand data by using the K-means clustering algorithm and silhouette plots mean values is performed, and an NBTree-based classification model is built. In order to find an optimal grouping of stores into regions based on their geographical locations and the total demand uniformly distributed over regions, a multiobjective optimisation problem is formulated and solved with the NSGA II algorithm.**

***Keywords* – tactical planning; vehicle scheduling; cluster analysis; optimisation; simulation**

I. INTRODUCTION

Nowadays a vehicle schedule optimisation task has a high commercial priority in transport logistics. This problem is relevant to the delivery task of multiple products from a distribution centre to a net of stores, when delivery time constraints are predefined. The problem has also specific stochastic performance criteria and conditions, as well as a high number of decision variables, which complicates the 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 also very time-consuming and requires specific knowledge and experience of planning staff in this domain. Moreover, in real-life situations a cluster analysis of the product demand data and potential tactical plans is not performed. But the most suitable product delivery plan could be defined as a result of such an analysis that would ensure high quality solutions to schedule optimisation problem and reduce computational costs of the problem solution.

The methodology proposed in the paper is aimed at selecting a product delivery tactical plan of the distribution centre for a week and optimising parameters of the corresponding vehicle schedule. The methodology integrates a cluster analysis that defines typical product demand patterns and identifies an appropriate demand cluster and tactical delivery plan, and simulation optimisation techniques used to optimise vehicle delivery schedules. Vehicle routing and scheduling optimization is based on the data from tactical planning of weekly deliveries. In practice, weekly delivery planning is based on data about the number of products to be delivered to stores and their allocation to geographical regions.

The paper is also focused on cluster analysis of the demand data by using the K-means clustering algorithm. To define an appropriate number of clusters, silhouettes plots are built and their mean values are estimated. As far as the demand is dynamic and variable, a classification model that assigns an appropriate demand cluster is presented by an NBTree, which induces a hybrid of decision-tree and Naive-Bayes classifiers. Finally, in order to find an optimal grouping of stores into regions based on their geographical locations and aimed to leverage the total product demand over regions, a multiobjective optimisation task is formulated, and the NSGA II algorithm is used to solve the problem.

II. PROBLEM STATEMENT

A methodology for product delivery tactical planning and scheduling to a net of stores is described below. The main task of the logistics department is to prepare an effective tactical delivery plan for the upcoming week.

The problem in the previous tactical and strategic planning method arose due to the fact that all schedules of deliveries were based on a single predefined weekly delivery plan or base plan, tuned and corrected for each new week. However historical data of store demands show that often the real demand can differ from the expected or average one, which is determined in the predefined or base plan. Thus significant changes should be made in the base delivery plan for each new week. The reasons for the demand variance can be demand seasonal effects or marketing events, and they are not further discussed in this work. This research focuses on the methodology that will allow reducing the affect of demand variation on the delivery planning process and avoid numerous time-consuming adjustments of the base plan.

The problem solution to be found is a detailed delivery plan where schedules, routes and goods to be delivered are defined with the condition that this delivery plan is the best for the defined input data.

Input data are data on the historical demand and location of the logistics department customers (i.e., stores), data on available vehicles for the product transportation and the existing delivery routes. Some additional input data are also used, in particular, time windows defined for product deliveries to stores.

An optimal delivery plan should satisfy the following criteria. The number of goods delivered to the stores should be equal to the demand of these stores for a particular day. Delivery costs have to be minimised. This implies sub-criteria such as the number of vehicles used to deliver all goods should be decreased, and transportation costs should be minimized, which can be achieved by optimal delivery routing and scheduling.

III. Proposed Methodology

Due to the high computational costs for the optimisation part of the tactical delivery planning, some suggestions and problem simplifications are made in this research to reduce the search space of possible solutions.

First, while keeping an existing planning procedure, where a delivery plan for the next week is made based on the predefined tactical plan, several tactical plans for different demand modes are introduced. It is assumed, nevertheless, that demand of the stores for each week could be different; it is possible to identify several typical demand patterns. Herewith all new demand patterns are related to these typical patterns. This simplification will reduce the work of adjusting a typical delivery plan to the current situation. Since there are now more typical delivery plans that are based on typical demand patterns, the work will be reduced to making a decision, which delivery plan should be used for the next week and small adjustments of it still maybe required.

Another suggestion is to group stores and assume that a vehicle from a distribution centre will deliver only to stores from a similar group. This simplification can significantly reduce the dimensionality of the final scheduling and routing problem, which will reduce the complexity and computational efforts required to solve the problem.

A. Detailed Description

The proposed scheme of the problem solution is depicted in Fig. 2. The main data flow in the solution process is as follows: from demand forecast input data to an optimal schedule and route output data, accomplished by additional actions. These actions, which should not be performed regularly, include identification of typical demand patterns, grouping of stores, and preparation of strategic delivery plans. First two actions are based on the historical demand data, and thus should be performed rather rare. Synthesis of a strategic delivery plan is based on the outputs of the previous two steps and is computationally time-consuming, but it is not a repetitive process as well. Also, these tasks are essential, as they can reduce the complexity of the following tactical and operational planning.

These methods will be applied in each procedure step:

- Building product dynamic demand patterns by clustering historical daily demand data for different weeks.
- Grouping of stores and assigning stores to regions is based on clustering embedding additional techniques, which will allow making groups of stores more homogeneous by the product demand per region.
- Strategic delivery planning is performed for each group of stores and each pattern demand by using combinatorial meta-heuristic optimisation techniques.
- Identification of demand patterns is based on the classification model created for typical demand patterns.
- Tactical delivery planning – currently is made with an adjustment of a strategic plan to a new or forecasted demand.
- Vehicle routing and scheduling by using scheduling optimisation meta-heuristics described in [1].

IV. Data Analysis and Clustering

A. Cluster Analysis of Planning Weeks by Product Demand

Vehicle routing and scheduling optimization is based on the data from tactical planning for a week delivery. At the moment, only one tactical delivery plan is being used as the base plan. As far as the product demand per store is dynamic and not deterministic, the product delivery plan has to be adjusted almost each week. It seems reasonable to specify typical patterns of dynamic daily demand for different planning weeks and introduce several base plans each representing an appropriate product delivery time table for a specific demand pattern. Thus this work is aimed to find a number of typical demand patterns and corresponding clusters or groups of weeks, and construct a classification model that will allow allocating any specific week to one of previously defined clusters. The historical data on daily number of delivered products for 52 weeks are used in the business case. The following two tasks are set to achieve the defined objective:

1. Finding a number of typical demand patterns by performing a cluster analysis of input data – weekly demand time-series each representing a sequence of points – daily number of the product deliveries for a specific week (see Fig. 1);
2. Constructing a classification model that for any week allows determining an appropriate demand pattern and correspondent product delivery plan.

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
2885	3390	3891	4115	4612	4687	3371
2831	3553	3859	3785	4432	4899	3527
2763	3548	4067	4631	4838	5057	3511
2951	3820	3987	4360	5075	[illegible]	3345
[illegible]	2731	3101	2988	[illegible]	3524	2643
3150	3459	4339	4377	5187	4956	3545
2934	3229	3643	3693	4018	4411	3583

Fig. 1. Sample input data

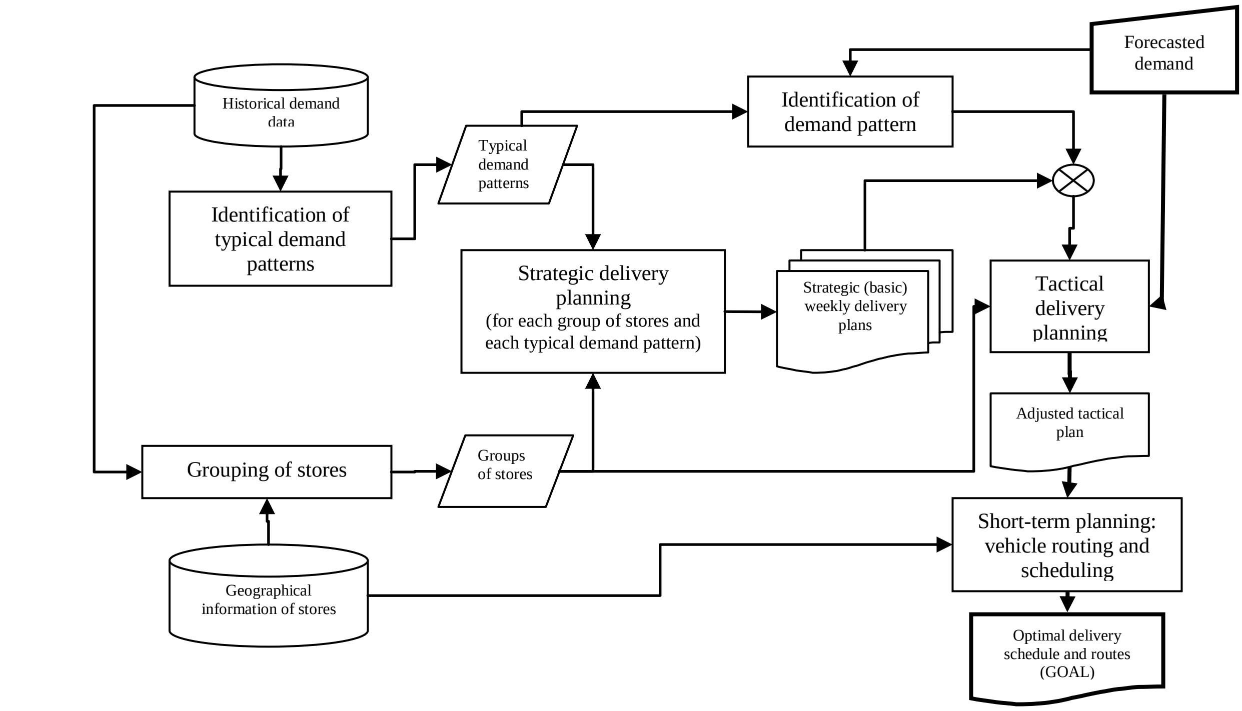


Fig. 2. Scheme of integrated solution

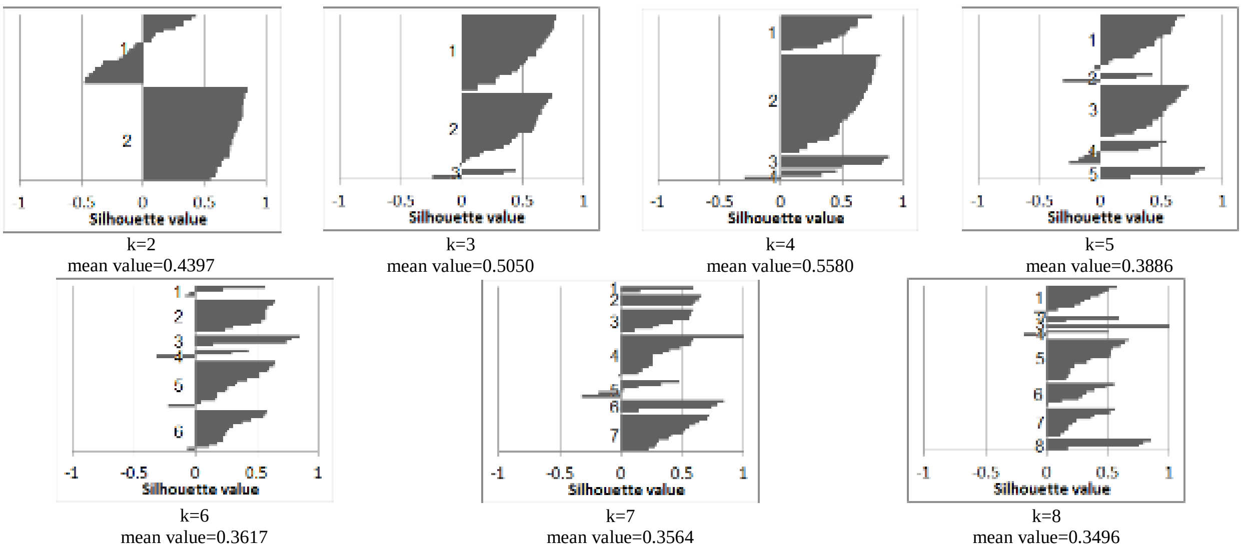


Fig. 3. Silhouette plots and mean value for the number of clusters from 2 to 8

Cluster analysis is a way to examine similarities and dissimilarities of observations or objects when characteristics of objects in the same cluster are similar but the characteristics of objects in different clusters are dissimilar [2]. Here, a cluster analysis of input data provides an opportunity to divide a variety of planning weeks into clusters and to find the number of clusters that represent weeks with specific demand patterns. It also gives information for a construction of the classification model in order to decide which weekly delivery plan would be preferable for the next week.

The K-means clustering algorithm is used in the paper. It is a partitional clustering that 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 [3] representing cluster centroid. The result is a set of clusters that are as compact and well-separated as possible. Here, an appropriate number of k clusters, or typical demand patterns is defined by using silhouette plots [4]. This method provides a numerical measure of how close each point is to other points in its own cluster compared to points in the neighbouring cluster. It is defined as follows:

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

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. Higher mean values of silhouettes show better clustering results that determine better clusters giving the best choice for a number of clusters.

In the research, 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 (Fig. 3).

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. As a result, an appropriate number of product demand patterns and corresponding clusters of observed weeks is defined by 4 (Fig. 4). Clusters 1 to 3 seem to be appropriately clustered. Here, winter weeks particularly belong to cluster 1, autumn and spring weeks are mainly in cluster 2, while summer weeks are allocated to the clusters 2 and 3. However, silhouettes values for a cluster 4 are negative. Theoretically, weekly demands assigned to this cluster could be better allocated to another cluster. These (i.e., for Midsummer, Christmas and New Year's event weeks) weeks are unlike in the demand dynamics and in specific days, where demand peaks are observed.

Reallocation of 'unlike' weeks avoids receiving negative silhouette values (see Fig. 4). However, this does not provide an increase in the silhouette mean value as might be expected. In this case, 'unlike' weekly demands behave as a 'noise' in their 'native' clusters, decreasing silhouette values. Then, clustering experiments have been performed with 49 weeks, where three 'unlike' weeks have been excluded from a cluster analysis. This has allowed us to increase the silhouette mean value up to 0.5822 while getting the same groups of data clusters 1-3.

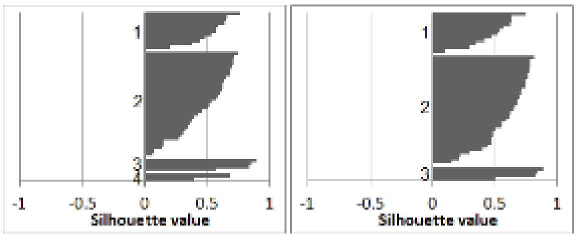


Fig. 4. Silhouette plots for the number of clusters *k*=4 with reallocation of 'unlike' weeks and for the number of clusters *k*=3 and 49 sample weeks

As a result, the number of clusters is fixed and set equal to *k*=4. Dynamic demand patterns received are presented in Fig 5. Correspondent average daily number of delivered products per cluster is defined by 3474, 3938, 4528, 4030 rolls, correspondingly. It is worth noting that a tactical weekly delivery base plan could then be defined for a cluster with a silhouette mean value greater than 0.5. In this case, a tactical product delivery base plan is selected, adjusted or built for the first three clusters, and not analysed for the last one.

A classification model that assigns an appropriate demand cluster is represented as 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 [2].

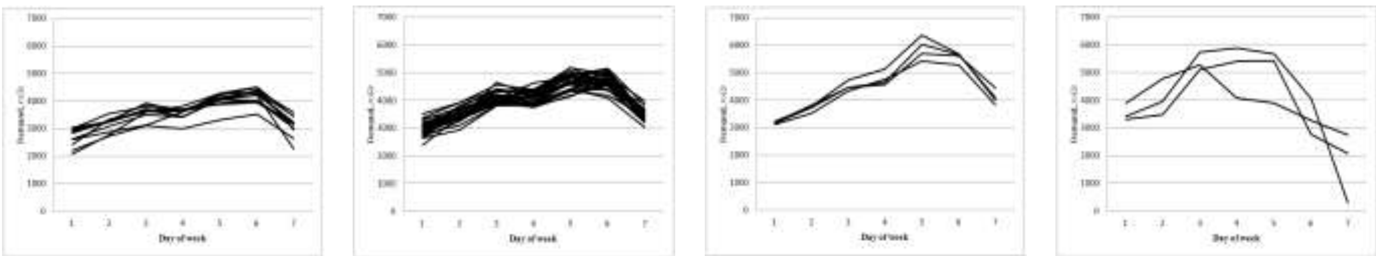
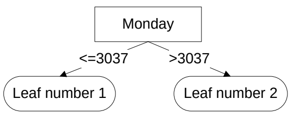


Fig. 5. Typical demand patterns for the number of clusters *k*=4



Leaf number: 1 Naive Bayes Classifier

Class	Monday	Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
		(-∞-3298.5]	(3298.5-∞)	(-∞-3798.5]	(3798.5-∞)	(-∞-3731]	(3731-∞)	(-∞-4315.5]	(4315.5-∞)	(-∞-4521.5]	(4521.5-∞)	(-∞-3213]	(3213-∞)
1 0.400	1.000	0.786	0.214	0.786	0.214	0.857	0.143	0.929	0.071	0.929	0.071	0.643	0.357
2 0.600	1.000	0.200	0.800	0.050	0.950	0.050	0.950	0.150	0.850	0.200	0.800	0.050	0.950

Leaf number: 2 Naive Bayes Classifier

Class	Moday	Tuesday	Wednesday		Thursday			Friday		Saturday			Sunday		
			(-∞-4924.5]	(4924.5-∞)	(-∞-4485.5]	(4485.5-5268]	(5268-∞)	(-∞-5313]	(5313-∞)	(-∞-4081.5]	(4081.5-5218.5]	(5218.5-∞)	(-∞-2895]	(2895-3989.5]	(3989.5-∞)
1 0.682	1.000	1.000	0.941	0.059	0.889	0.056	0.056	0.941	0.059	0.056	0.889	0.056	0.056	0.889	0.056
2 0.182	1.000	1.000	0.833	0.167	0.143	0.714	0.143	0.167	0.833	0.143	0.143	0.714	0.143	0.286	0.571
3 0.136	1.000	1.000	0.200	0.800	0.333	0.167	0.500	0.400	0.600	0.667	0.167	0.167	0.667	0.167	0.167

Fig. 6. NBTree classification model

For a specific week and demand time-series, a cluster is identified by determining a proper leaf number C based on the number of product deliveries on Monday. When the leaf number is known, a cluster is estimated by a formula:

$$C = \underset{c_j = C}{\arg\max}\, P(c_j)\prod_{i=1}^{m} P(a_i \mid c_j) \tag{2}$$

where $P(c_j)$ defines the probability that weekly demand belongs to cluster c_j, and $P(a_i / c_j)$ defines a conditional probability that demand for a day a_i belongs to cluster c_j. Probabilities $P(c_j)$ are calculated from clustering results, while $P(a_i / c_j)$ are defined from the Naive Bayes classifier according to the above determined leaf number (Fig. 6). Then a cluster with highest probability value $P(c_j)\prod_{i=1}^{m} P(a_i \mid c_j)$ is assigned.

The model is validated by 10-fold cross-validation that separates data into 10 sets. In iteration the NBTree is trained on nine datasets and tested on one dataset. This is repeated 10 times and the average of correctly classified instances is counted. Preferably, an error value should be less than 5%. In this case study, 98.08% of all instances are classified correctly.

For a specific planning week, an NBTree allows identifying an appropriate cluster and then choosing weekly tactical delivery base plan corresponding to this cluster. The decision tree allows making a decision about a proper delivery base plan for the next week.

To improve the accuracy of cluster analysis and performance of the correspondent classification model, the number of weeks has been increased up to 156 weeks. Two demand time-series have been generated for each planning week by uniformly changing its daily number of delivered products by ±5%. In a similar way, input data for another 52 weeks have been generated and used to validate a classification model itself. Built on this data the NBTree-based classification model is given in Fig. 7. In this case, 10-fold cross-validation showed that only eight weeks have not been classified correctly, which produced an error value of about 5%.

```
FRI <= 4294.5
|   TUE <= 3380.5: 1 cluster
|   TUE > 3380.5: NB 3
FRI > 4294.5
|   TUE <= 3700.5
|   |   MON <= 3062: 2 cluster
|   |   MON > 3062
|   |   |   THU <= 4368.5: NB 8
|   |   |   THU > 4368.5: NB 9
|   TUE > 3700.5: NB 10
```

Fig. 7. Detailed NBTree classification model

B. Cluster Analysis for Assigning Stores to Regions

In practice, weekly delivery planning is performed based on data about store allocations to geographical regions. In this case a proper region separation and introducing rules assigning stores to a specific region are very important. At the moment all stores are grouped into 12 regions. However, grouping of stores in regions has been made manually and rearranging regions in case a new store is added may be required. Also, it would be desirable to have separation of regions with a similar weekly total demand.

The use of cluster analysis allows dividing stores into regions according to their location. The following experimental scenarios are performed in the research. The number of regions is fixed and equal to the current number of regions (scenario 1) or the number of regions is variable and has to be optimized (scenario 2). Input data for analysis are geographical coordinates of each store in Cartesian coordinate system LKS 92 (scenario 1a and scenario 2a), for example, East – 503819; North – 310956 or in polar coordinates (scenario 1b and scenario 2b, correspondingly) that define an angle from a fixed direction and a distance from a fixed direction, for example, θ – 63° and r – 2570.

To find the best number of regions for scenario 2a and 2b, K-Means clustering is performed with the number of clusters from 6 to 15. For each case silhouette plots are built, and mean values of silhouettes for each cluster are calculated. Analysis of silhouettes mean values determines that the best cluster separation would be done at $k=7$ for scenario 2a (with mean equal to 0.78) and at $k=13$ for scenario 2b (with mean equal to 0.7081).

However, the analysis of these results shows that a clustering method does not provide improvements of the current regional distribution of shops. Also, it does not allow getting the total product demand equally distributed between these regions.

V. Region Clustering with Multiobjective Optimisation

A. Problem Formalisation

Input data of a region clustering problem contains the number of shops n, the number of regions k, two geographical coordinates – x_i, y_i of each shop i, $i = 1,\ldots,n$ in the Cartesian coordinate system and its total weekly demand d_i.

Decision variables define a region (or cluster) a_i to which a shop i is assigned, i.e.,

$$a_i \in \{1,2,\ldots,k\};\ i = 1\ldots n \tag{3}$$

Additional intermediate variables are introduced:

$$A_j = \{b \mid a_b = j\} \tag{4}$$

where A_j is a set of shops that are assigned to each region, and

$$r(i,j) = \sqrt{\left(x_i - \dot{x}_j\right)^2 + \left(y_i - \dot{y}_j\right)^2} \tag{5}$$

where $r(i, j)$ define an Euclidean distance from shop i to the centroid of cluster j and $\dot{x}_j$ and $\dot{y}_j$ are mean values of coordinates of all shops in cluster j:

$$\dot{x}_j = \frac{\sum_{i \in A_j} x_i}{|A_j|},\ \dot{y}_j = \frac{\sum_{i \in A_j} y_i}{|A_j|} \tag{6}$$

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

$$f_1 = \sum_{j=1}^{k} \sum_{i \in A_j} r(i,j) \to \min \tag{7}$$

$$f_2 = \sum_{j=1}^{k} \left| \sum_{i \in A_j} d_i - \frac{\sum_{i=1}^{n} d_i}{k} \right| \to \min \tag{8}$$

where f_1 defines the sum of distances between centroids of the regions and shops 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 for the optimisation problem.

B. Decision Variable Encoding

To define a vector of decision variables a_i values in one chromosome, an integer encoding is used. Correspondingly, a chromosome is defined as a string of *n* integers and formalised as a vector (a_1, a_2, a_n), where $a_i \in [1, k]$.

This allows applying in the optimisation process GA operators for the integer encoding.

C. Implementation of the Problems Solution Algorithm

To solve the problem, a multiobjective optimisation Nondominated Sorting Genetic Algorithm II (NSGA-II) [5] implemented in HeuristicLab optimisation framework [6] is applied. The optimization problem itself is implemented as a multiobjective optimisation problem plugin of HeuristicLab with integer encoding of solutions and their evaluation by two mathematical functions (7) and (8).

Input data are defined as follows:

- Coordinates of shops as an integer matrix where the first row indicates coordinates of a distribution centre (DC) and others define two Cartesian coordinates for each specific shop;
- Total weekly demand of each shop as a double array, in which the first element corresponds to the DC and thus always has demand equal to 0, and
- The number of regions is fixed and equal to 12.

In experiments with NSGA-II, the following operators have been applied: 1) Discrete crossover for integer vectors [6]; 2) Uniform One Position Manipulator (mutation operator) [8]; and 3) Crowded Tournament Selector [5]. GA parameters finally applied in the optimisation experiments are given in Table I. A termination criterion is defined by the number of generations, i.e. 10000 generations in this case.

TABLE I
PARAMETERS OF NSGA-II

Parameter	Value
Population size	200
Crossover rate	90%
Mutation rate	5%
Selected parents	400

D. Experimental Results

Pareto fronts for a different number of generations with a population size of 200 solutions are shown in Fig. 8. It can be seen that the increase in the number of generations improves the Pareto front of non-dominating solutions decreasing values of objective functions. However, when the number of generations exceeds 2000, these improvements become smaller. The Pareto front obtained at the 5000th generation provides good clustering results for regions from two perspectives, i.e. from geographical perspective and demand uniform distribution between regions. Further improvements seem to be very small.

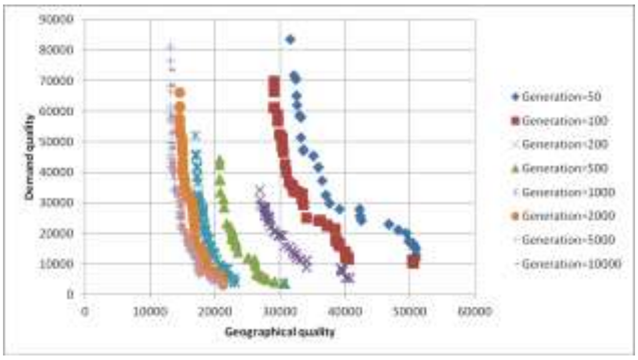


Fig. 8. Pareto fronts for a different number of generations

The visualization of the obtained results shows that two borderline solutions are not very good from the point of view of a decision maker as far as they give worse results for one of objective functions. Thus, a solution in the middle of the Pareto front is selected (see Fig. 9, where different regions with the shops assigned are shown). The corresponding values of objective functions are equal to f_1 = 14144 and f_2 = 33012. The total demand distribution is given in Table II.

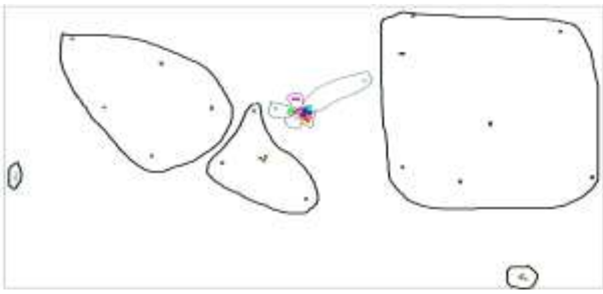


Fig. 9. Solution in the middle of the Pareto front

TABLE II
THE TOTAL DEMAND DISTRIBUTION

Region	Regions demand	Region	Regions demand
1	28443	7	25328
2	21429	8	21552
3	23440	9	21787
4	21687	10	12152
5	23583	11	14722
6	23101	12	21860

From Table II it can be seen that corresponding solution obtained with the NSGA II algorithm has compact clusters or regions. Moreover, these results show that only two regions have demand that is much lower than others. Further leverage of the region demand could worsen the geographical location of regions that have a higher priority.

VI. Conclusions

The proposed integrated approach to product delivery tactical planning and scheduling allows identifying typical dynamic demand patterns and corresponding product delivery tactical plans, as well as finding the optimal parameters of vehicle schedules. Here, cluster analysis provides an efficient tool for searching typical dynamic demand patterns and corresponding clusters for planning weeks, and gives information for construction of a classification model that allows identifying an appropriate tactical product delivery plan. Multiobjective optimisation with the NSGA II algorithm copes well with grouping of shops into regions with a similar demand. Identifying demand pattern and an appropriate delivery plan will ensure more qualitative solutions to the optimisation task and cut down its computational costs.

Acknowledgements

This work has been supported by the RTU research project FLPP-2011/06 "Simulation-Based Cluster Analysis and Optimisation of Vehicle Schedules".

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Gaļina Merkurjeva, Vitālijs Boļšakovs, Maksims Kornevs. Integrēta pieeja produktu piegādes plānošanai un grafika sastādīšanai
Produktu piegādes plānošana un piegādes grafika sastādīšana ir augstas prioritātes uzdevums transporta loģistikā. Sadales centros šī problēma ir saistīta ar dažādu tipu preču piegādi klientiem definētos laika logos. Praktiskos gadījumos problēmai var piemist vairāki gadījumrakstura izpildes kritēriji un nosacījumi. Pati par sevi piegādes plānu un to piegādes laika grafika optimizācija ir laikietilpīga un tai ir nepieciešama ekspertu zināšanu piesaistīšana. Rakstā ir piedāvāta integrēta pieeja produktu piegādes plānošanai un to laika grafika optimizācijai. Tā ir balstīta uz veikalu pieprasījuma datu klasteru analīzi tipisku dinamiskā pieprasījuma šablonu identifikāciju un attiecīgi vairāku produktu piegādes taktisko plānu iegūšanu. Tālākajā operācijas līmeņa plānošanā ir paredzēta imitācijas modelēšanā bāzētas optimizācijas metožu pielietošana transportlīdzekļu kustības grafika parametru atrašanai. Piemērotākais piegādes plāns nodrošinās kvalitatīvu risinājumu optimizācijas uzdevumā un ļaus samazināt to skaitļošanas laiku. Uzmanība rakstā ir pievērsta arī pieprasījuma nedēļas dinamikas datu klasteru analīzei ar K-means algoritmu, novērtējot iegūto klasteru silueta grafiku vidējās vērtības, kas ļauj noteikt pieprasījuma nedēļas dinamikas šablonu skaitu. Piemērotākā piegādes taktiskā plāna noteikšanai pamatojoties uz prognozētā pieprasījuma datiem, rakstā ir apskatīta NB-koka klasifikācijas modeļa konstruēšana. Papildus, pieejā ir definēts apakšuzdevums, saistīts ar optimālo veikalu grupēšanu reģionos pēc to ģeogrāfiskās atrašanās vietām, nolīdzināšot kopējo pieprasījumu šajās grupās. Tas ir formulēts kā daudzkritēriju optimizācijas problēma, kas ir veiksmīgi atrisināta ar NSGA II algoritma palīdzību. Manuskriptā apskatītā integrētā pieeja ļauj pamatotāk un ar mazākiem laika un ekonomiskajiem zaudējumiem iegūt preču piegādes grafiku loģistikas sadales centram.

Галина Меркурьева, Виталий Большаков, Максим Корнев. Интегрированный подход для планирования и составления расписания доставки товаров
Планирование и составление расписания доставки товаров является важной задачей в транспортной логистике. Для распределительных центров эта проблема связана с доставкой товаров в магазины в предустановленные временные окна. На практике таким проблемам могут быть присущи разнообразные стохастические критерии производительности. Составление же таких планов и последующая оптимизация их расписаний доставки является затратной по времени, а также требует привлечения экспертных знаний. В статье рассматривается интегрированная методика для составления плана доставки товаров и оптимизации его расписания. Подход основывается на анализе кластеров данных по динамике спроса для выявления типичных шаблонов спроса и создании на их основе нескольких тактических планов доставки. На последующих этапах операционного планирования предполагается применение оптимизации на основе имитационного моделирования для нахождения оптимальных параметров перевозки и расписания транспортных средств. Наиболее подходящий тактический план доставки обеспечивает качественное решение задачи оптимизации и позволяет снизить вычислительные затраты по его поиску. Также в работе детально рассматривается кластеризация динамики недельного спроса с применением алгоритма K-means и оценка средних значений силуэтных графиков полученных кластеров для определения количества шаблонов недельного спроса. Далее рассматривается построение NBTree модели классификации для выбора наиболее подходящего плана доставки на основе прогнозируемого спроса. Следующая из рассматриваемых в статье подзадач, рассчитанная на уменьшение размерности задачи оптимизации, связана с разделением магазинов на регионы по их географическому местоположению, уравнивая суммарный спрос по регионам. Для нахождения оптимального разделения на регионы, в работе сформулирована задача многокритериальной оптимизации, решенная с помощью алгоритма NSGA II. Рассмотренный подход позволяет более обоснованно и при этом с меньшими временными и экономическими затратами получить график доставки товаров для логистического распределительного центра.