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Dynamic scheduling of highway cargo transportation

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Abstract: Purpose. The purpose of this paper is the methodology improving of the schedule compiling, and its implementation regarding and increasing the requirements for their quality. Methodology. The main data of scheduling is the set of orders forecasted, and it allows us to reach the minimum delays of goods delivery. Prediction is given with time windows, which is a required tolerance due to uncertainty. However, many external factors are random, and they can break these tolerances. We used combined meta-heuristic methods of iterated local search with variables clustering for solving it. It has been applied a priory signs of optimality of schedules. Results. Thus, we have grounded the reason to classify received orders by compatibility, geographic location, arrangement and urgency. The article gives definitions, and proves the valuable importance of compatibility, as well as proposes the set of indicators of full or partial compatibility, and incompatibility of cargo transportation tasks. It has been proved that the most important property of orders is their organizational compatibility. It has been applied the optimization criterion of total duration of all scheduled vehicles is applied. Total delays and idle mileage of trucks, or their idle time also considered as the quality indicators. The algorithm of operational correction of the pre-scheduled decomposition with respect to external disturbance has been developed. So, it has been investigated the impact of planning horizon on scheduling efficiency. The theoretical contribution. Assessing of orders compatibility gives us the ability to integrate single orders into complex transport tasks within the time horizon of planning. This allowed one to achieve a guaranteed optimal schedule. Based on operational information request one can re-qualify the whole demand and make changes in the already developed schedule without changing its quality.
Practical implications. The algorithm leads to an approximated optimal solution of total duration of cargo transportation and its delays.

Keywords: cargo delivery, dynamic scheduling, time windows, multiple vehicle routes, orders batching.

1. Introduction

Long distance delivery of large groups of goods has become a very important resource in modern transport systems. This is due to the growth of cargo turnover, significant competition trucking companies, limited modes of operation of trucks, and their crews. On the other hand, the usage of intelligent transportation systems requires careful approach to intelligence analysis, decision making, and monitoring their implementation. The management of intercity highways road transportation has certain features, which increase the problem of fleet performance.

This is, firstly, a considerable distance from the points of departure to the acceptance of goods, in which the duration of the whole process depends on the time of departure, and arrival of the trucks to

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the place of delivery of the goods. Secondly, it is an idle mileage of trucks, which considerably raises the cost of transportation, so carriers can not afford it. And thirdly, it is a wide geographical distribution of cargo stations, and acquisitions of cargo flows, through which the development and compliance of the schedule have significant limitations. In this regard, designing methodology, and monitoring of their work scheduling requires special attention.

While designing schedules, one is using the orders prediction and reaches the minimum delays in the transport process based on this. As a rule, they are executed with time windows that are a certain reservation for uncertainty.

However, many external factors are random, which may violate these tolerances if there is an unfavourable coincidence of circumstances. First of all, these are unpredictable orders, arising on the planning horizon, and also cancellation of known orders that have already been included in the previously designing schedule. It is also impossible to reliably predict a change of cargo delivery operations duration, traffic congestion, and the reduction of the throughput capacity of highways, fails of vehicles, and their leaving of the routes too. Taking into account, or ignoring these factors, and making changes to the previous timetable can reduce the efficiency of transportation. The purpose of these studies was to improve the method of routes and timetables of vehicles constructing on the intercity network, taking into account the complication of circumstances, and requirements for the performance of transportation.

Scientists have been focusing on vehicles routing for over 50 years [1]. Solved by them problems became further gradually more complicated in order to get closer to the real conditions of transportation of passengers and goods. There was growing interest of dynamic routing problems in recent years, as well as the development of on-line schedules for transportation operators [2]. This is due to an increase in the amount of available data, at the same time, the improvement of the means of transmission and processing of information, which has become a driving factor of process management. The main intention of the researchers is to provide reliable and accurate solutions of routing, which have changes over time. The usage of information and telecommunication technologies has transformed the methodology of scheduling into a bottleneck, taking into account random factors. Thus, in particular, it has been shown that the use of a large number of sensors, parallelization of the process, and the introduction of cloud technologies in transport management significantly increases information flow of that is processed by outdated methods [15]. Therefore, the arrival of intelligent technologies in the transport is constrained by current methodology.

Overviews of various routing problems were done in publications [1, 2, 9, 10]. Vehicle routing problems (VRP) belong to combinatorial analysis, and they are divided by the probability and availability of information flow for static, dynamic, and stochastic. Static VRP has been sufficiently processed in previous works, but it solving loses relevance, according to that trucks dispatchers switch to use operative control methods [3]. In addition, many types of static VRP can not be solved by methods, which give sufficiently accurate and effective solution. Having solved the static VPR and scheduling in practice, carriers still have to apply the reserving of fleet capacity, and when faced with unforeseen circumstances, they suffer considerable economic losses.

Events occur during the transport planning process in modern production situations, or when the plan is in progress. The questions of whether to consider, or ignore them, and how to take into account new developments, affect the quality of the adopted plan, which further complicates the task of routing and leads to greater uncertainty. That is why, a class of dynamic routing problems has arosen, which is also so called on-line plan with real-time tasks, the content of which is to correct the previous designed operational plan in relation to changing circumstances. Such tasks were formulated and their initial review was made in the work of Psaraftis in 1988 for the first time [7]. In the works of Larsen and Madsen [10], Jaillet and Wagner, Schorpp and Pillac there were offered a variety of algorithms for solving dynamic routing and scheduling. However, they all applied methods which previously been used with varying success to static problems. There were the nearest neighbour method, the method of the taboo on a separate set of decisions [5] and meta-heuristic, other heuristic methods, which are discussed in detail at the work [9]. As the flow of information grows, dynamic routing techniques, taking into account the time factor, namely the time tolerances, the so-called time windows, proposed by Larsen and Wagner, become less effective. It was indicated by Larsen, that the growth of orders volume to fulfil, and unplanned increase in when the process is already in progress, fundamentally affects new solutions [10]. The size of the planning horizon in this case no longer plays such a key role, as for small orders and small fleets of vehicles. That is why, the researcher proposed to apply orders sorting, taking into account the urgency of their execution and time expenditures for this purpose. In his works, as well as, Karsten Lund and Rygaard [11], it was proposed to evaluate the routing and scheduling task in terms of rate of dynamism. This is an estimation of the flow of unscheduled events comparative to the planned ones. It can be successfully used to select the appropriate solution algorithm.

Stochastic VPR concern, mainly, random factors that lead to unexpected changes in the duration of travelling, idle time, and other delays. Essentially complete review of modern developments in the methodology of this direction was made in their research by Ritzinger U., Puchinger J., and Hartl R. F. [9]. The presence of random temporal factors does not change the planned route, or not update after implementation, in most cases, as stochastic routing optimization is often called a priori.

The category of dynamic and stochastic tasks of dynamic routing has led to an increase of scientific interests recent years. Thanks to the latest advances in information and communication technology, this new class of problems allows to more accurately process real data flows. The advantage is that besides the effective processing of dynamic events, stochastic knowledge of detected events is considered. Flatberg [16] reviewed the problems of this mixed type, but he focused on dynamic ones in particular, while Ritzinger and Puchinger [9] gave a review of Dynamic Vehicle Routing Problem (DVRP), but with an exclusive emphasis of the various hybrid methods applied to this direction.

There are several approaches to the classification of combinatorial optimization of DVPR. The main features are accuracy, type of space of solutions, structure of the computational scheme, etc. [1, 7]. As to accuracy, algorithms could be divided into precise ones which give a global solution, approximate, and heuristic. Approximate algorithms can be divided into actually approximating ones, which do not find only a solution with certain accuracy, but even allow one to get it certain estimates, and heuristic algorithms, which are based on probable reasons, although they do not give any estimates to the solution found [3]. Meta-heuristic are very promising methods among the modern approximate optimization methods, which give a solution of the problems of discrete optimization such as multi-route travelling salesmen. Meta-heuristics are hybrid methods of problems solving, built with combining known procedures, in which one acts as the leading role and the other (or several others) is subordinated. Certain known heuristics or other algorithms are usually performed as both, leading and subordinate procedures. We can select such a kind of algorithms as simple ones, hybrid algorithms, meta-heuristics, hybrid meta-heuristics, and hyper-heuristics by the complexity of the structure of the optimization of discrete structures.

The DVPR and a strategy for their solving based on the paradigm of Ant Colony systems considered in the paper of Montemanni R., Gambardella L., Rizzoli A., and Donati A. [8]. The method was evaluated by few tests, which were identified from a set of widely available problems. The results of the calculations confirm the effectiveness of the proposed strategy. However, such sets are not always available.

The methodology of genetic algorithm (GA) of DVRP model solving is presented in a large number of papers, in particular Hanshar F., Ombuki-Berman B. [12]. The effectiveness of the proposed algorithm is estimated using a set of indicators found in the literature. The author proposed a GA methodology that performs better functions of minimizing travel costs in comparison with the taboo search approach, implemented in the above-mentioned works. However, the use of GA requires a large amount of training data and their use is restrained by the need for training cycles.

A review of well-known publications demonstrates the advantage of adaptive methods for DVRP compared to non-adaptive approaches. If the data stream is pre-processed, then such a decision-making approach yields an average improvement of 0-5%, while RA-based methods receive up to 10% improvement. However, the approaches to online solutions are beneficial [9].

Taking into account the performed review, we can argue that adapting incoming data and its clustering is the best direction of dynamic optimization of vehicle fleet routes algorithm improving and it can provide a higher quality solution to the DVPR.

2. Materials and Methods

Normally dynamic routing is based on the fact that the forecast of orders for cargo transportation on the given transport network is done for some period T_{pr}. Then one makes a scheduling of their implementation that is a set of the moments of vehicle arrival at the stations of loading and unloading, taking into account the random location of the trucks on the network, after that. It is known the parameters of orders. If there are more vehicles than available for a travels in the planned period, then the timetable should include the next loading station after the previous delivery of the goods. The route of each vehicle is planned continuously, taking into account the efficiency of the entire fleet capacity. The following criteria of optimal scheduling are used, as the minimum of total guaranteed transportation lasting of all cargoes (most often for perishables goods), the minimal of transportation expenses, and the maximum of total incomes. But the criteria of the minimum of travel distance and the minimum of idle time are often used for long-distance large consignment transportation instead. The main transport network of road freight transport has such properties, that a departure point of some cargoes may be a destination point for others. This happens at random moments of time. Therefore, trucks are idly waiting for a long time, very often, for possible orders, while avoiding a futile mileage. The last two indicators for a single process are not contradictory. If the number and size of scheduled transportation on the planning horizon are stable, then such a problem is considered as static. One solves it by the mentioned methods of mathematical programming, heuristic, or meta-heuristic methods. Orders, which are scheduled to be executed, are characterized by having a station of departure, and delivery of goods. The duration of each of them is a random variable that is estimated by mathematical expectations $\overline{t_i}$ and a known deviation. Each order has also the permissible time delay of their execution called as a time windows. Time window lower border $t_{b.i}$ is the earliest time point, before which it can not be executed and upper border $t_{e.i}$ is the latest moment, after which this order must be executed. The size of the time window is, preferably, wider, than the maximum deviation of the time of execution of the order itself. The solutions of the static problem found were previously met by the dispatching services of the carrier for accuracy and reliability. The maximum number of planed scheduled orders does not exceed 100-120 in practice, which makes it possible to design an approximation of the optimal scheduling, and estimate its deviation.

Consequently, the previous optimal schedule is a set of moments $t_1, t_2, \ldots t_n$, for N_a vehicles, the amount $N_{a.1}$ of which is involved in the transport process. Other vehicles are reserved. Minimum project execution time is T_1, $T_{pr}>T_1$. There are unforeseen circumstances, among which the following events are possible, when the project is executed at some point of time from the zero reference $0<t< T_{pr}$:

a) new orders are received with time windows that intersect with the planning horizon;

b) previous planned order is cancelled;

c) estimated transportation time t_{ij} has increased / decreased, where i, j, respectively, are the point of departure and receipt of the cargo;

d) a vehicle failed and descended from the route.

The presence of such events changes the static routing problem into a dynamic one. Such events are of a random nature and, according to research, are subject to the Poisson law [10]. The reaction to such events by carriers may be one that is accepted or rejected by one of the possible solutions:

a) to refuse an acceptance of new orders;

b) to ignore cancelled orders;

c) to change the sequence of orders;

d) to change the number of vehicles on the routes, including the reserve.

In this article, we tried to solve two topical issues. Firstly, it will be the changes of the previous order affect the quality that it has achieved before? Secondly, how the process of constructing / correction of optimal timetable and routes is influenced by the availability of information about the properties of scheduled and new orders.

The formulation of the problem is as following. The scheduled time T_{pr} is set, which can be changed depending on the desired forecasting range. There is also a known set of orders for carrier company, $P=\{1,2,\ldots,p\}$, which have to be executed with minimal delay in one or more truckloads that are originally located on the transport network in a random way. The content of each order is to deliver a unitary group of goods $Q_{i.j}$ from some point g_i to another g_j, $i,j=1 \ldots n$, $n<p$. It was accepted that there is a path between any two station on a given transport network (the network is strongly connected), so the distance between them is known, but for convenience, it is evaluated indirectly by the travelling time $t_{i.j}$ at a known steady average operating speed. Since the problem relates to trunk transport (intercity, international), then the main criterion for a carrier here is, preferably, the maximum useful mileage during a given period. Otherwise, this is the minimum time of idle mileage.

Since a time, $\bar{t}_i \leq T$, then during each planning period, each truck can execute several orders. To start the first one the vehicle must be submitted to the point, where the order is formed no later, than the policy moment of the time $t_{e.i}$. Consequently, it is necessary to take into account the duration of initial mileage, as well as the travelling time between *i* and *j* stations – $t_{i.j}$. To perform each subsequent order the vehicle must be submitted for loading to the adjacent transport facility, where there is a corresponding request, or download at the same place where the previous unloading took place.

The feature of this problem is that there are no finite restrictions for all orders of set *P* for the period T_{pr}. This problem is associated with a time ordering of operations and their assignment to the available vehicles. That is why, it can be associated also with known classification features, as tasks of cyclic unitary schedules compiling for streaming project operations by several operators [3]. When planning the transportation execution, it is necessary to develop, on the one hand, the shortest route for each vehicle that will be involved in the process, and on the other hand, the best schedule for orders executing for a combination of trucks with minimal unproductive downtime in the presence of time constraints, i.e. without delays. Such a problem should also be attributed to optimization, considering the structure and properties of a typical transport process of medium and large transport systems [5].

Developed problem relates to NP complex one in strong sense by the complexity of optimal solution, that is, there is a non-deterministic algorithm for finding a successful exact, or approximate solution for polynomial time. The method of mixed graph ordering is used for its development [17].

According to it the whole set of known orders represents the oriented mixed graph $A(G,U,V)$, where *G* is the set of vertices $\{g_1 ... g_p\}$ where $g_2 ... g_{p-1}$ symbolizes the moments of their execution starting. The vertex g_1 is fictitious, representing the formal moment of the beginning of the whole project. The vertex g_p is fictitious too symbolizing the end of a scheduled cycle of duration T_{pr}. *U* is the set of arcs each of them represents communication time $a_{i.j}$ between the moments of the start of the execution of the i-th and j-th orders by the same vehicle. Arc of graph *A* are weighted. If there is an order, it is reflected in the graph *A* with the arc of the weight $a_{i.j} > 0$. The requirement must be fulfilled:

$$-a_{j.i} \leq t_{o.j} - t_{o.i} \leq a_{i.j} \tag{1}$$

where $t_{o.j}$, $t_{o.i}$ – the moments of the *i*-th and *j*-th orders execution start, respectively.

Arcs $a_{1.i}$ are earliest moments of the possible start of each order. Arc $a_{i.R}$ is the time communication, or "pure" duration of the execution of the *i*-th order, matches the event as if, a vehicle does not spend a time for zero mileage, before it begins the loading in the *i*-th station. Obviously:

$$a_{i.P} \leq a_{i.j} \tag{2}$$

Condition (2) must be fulfilled for any *i* and *j*. The arc with a negative weight, $-a_{i.j}$ represents the time limit for the execution of the order. For example, $-a_{p.1}$ is the allowed time to execute all known orders (as a rule, it coincides with the T_{pr} period). Arcs $-a_{p.i}$ reflect deadlines of the most late-end of *i* orders. All other non-existent or insignificant connections of the graph are represented by arcs with $-\infty$ weight.

There is also given a set of edges in the model of the disjunctive (mixed) graph *A*, each of which [*i*, *j*] corresponds to the pair of weights $a_{i.j}$, $a_{j.i}$. If there is an edge between vertices *i* and *j*, this means, then, their temporal independence, and the corresponding operations of *i*-th and *j*-th orders will be executed simultaneously or with partial overlap.

K vehicles may be involved in the carriage process. They should work synchronously, each executing several orders in sequence. This means that one needs to select *k* chains in the graph *A*, which start at the vertex g_1, pass through some vertices of the graph, which are related to existing orders, and finish at the vertex g_p. We are looking for the minimum useless run in this variant of the problem, with minimal delays of the process. Therefore, the desired chains must pass through those vertices for which $q_{x.y}>0$. If the chain reaches the vertex y, and then there is no path in the graph A with an integral or nonzero weight, then the chain goes to the vertex g_p. The transport cycle for these vehicles will be considered as complete, despite the fact that there is a spare time to fulfil other, not yet executed orders. The problem in this formulation is similar to the typical task of several salesmen routing. The algorithm for solving this problem for a relatively small number of orders is based on the method of branches and boundaries and its development is described in previous studies [18]. If we consider a certain mixed graph, the sense of the problem is to replace or remove all its edges and arcs, which cause the presence of contours of positive weight (Fig. 1).

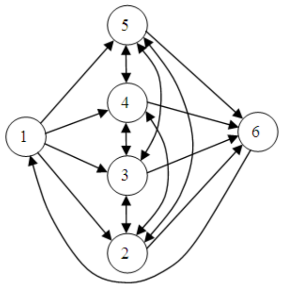

Figure 1. Test model for scheduling the execution of orders for the carriage of goods: $a_{i.j}$ – weight of the corresponding arcs

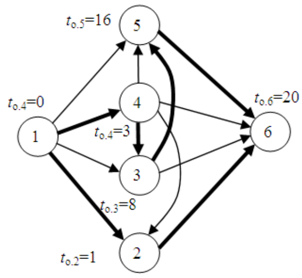

Figure 2. Results of the ordering of the mixed initial graph in the presence of deadlines for orders completion, the number of cars m=2

If all orders are independent, then the edges exist between each pair of vertices. Therefore, the complexity of the combinatorial search algorithm is measured by the number of search options from 2^{2n-1}, where n is the number of vertices of the initial graph. The duration of the algorithm at 100 vertices exceeds the permissible expectations and the search for a complete overload is complicated. Therefore, a heuristic based on the expression is used, and serves to select a conflict edge from the whole set of given:

$$h_{ij} = t_{e.j}\left(G,U\right) + \vartheta_j\left(G,U\right) + a_{i.j} - \vartheta\left(G,U\right), \tag{3}$$

where $\vartheta_j\left(G,U\right)$ – the maximum weight of the path in the graph $A\left(G,U\right)$, starting at the vertex g_j; $\vartheta\left(G,U\right)$ – the total longest path in the graph $A\left(G,U\right)$.

The searching of the most conflicting edge of all conflicting of set $V\left(\alpha_i\right)$ is based on the value $\min\left(h_{i.j}, h_{j,i}\right)$ calculation. The edges with this value found is the largest, is the most conflicting one. The ordering of the mixed graph leads to the construction of the oriented one (Fig. 2), in which there are no contours of positive weight, and which uniquely represents the optimal after speed schedules and routes, for two cars in this sample. The values $t_{0.i}$ marked at the vertices of the oriented graph are the moments of time, when the execution of the i-th operation should be started. However, when the number of orders increases as a result of incoming of additional operational information, then the presented model will contain only the edges that associate the new vertices with the available ones. Therefore, the optimal solution will be local and the quality of the new schedule may be worse. Therefore, to improve the algorithm we applied a grouping of orders, which is executed on the basis of the proposed classification.

Several features have been applied for the classification some of them are more significant for ordering the time graphic model. We will distinguish one-time, periodic, and permanent orders by frequency. This classification sign refers to the relationships of orders objects, one of which is the sender, and another is the consumer of goods. One-off order occurs once upon all planning periods. Periodicity orders are characterized by the fact that between the moments of their reception there is an idle time, which is, in general, a random variable. Permanent orders are characterized by the fact that they always exist at the point of departure of goods, regardless of the time of arrival of the vehicle for loading.

The order Z_1 and Z_2 will be divided into fully compatible, partially compatible, and incompatible. We will call such orders i, j a quite compatible, if whose execution in the sequence $i \rightarrow j$ with one vehicle is characterized by a complete absence of useless mileage and idle pending loading (Fig. 3). Partly compatible are such kind of orders, the execution of which leads to a futile run and / or idle in anticipation of the next boot (Fig. 4). Incompatibility of orders means that it is impossible to execute them in one flow with one vehicle. Incompatibility of orders Z_1 and Z_2 excludes their execution in one thread in one track due to the presence of overlapping time windows. Models of fully compatible and partly compatible transportation orders are shown in Fig. 3, 4.

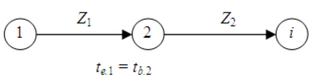

Figure 3. Model of fully compatible orders

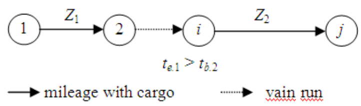

Figure 4. Model of partially compatible orders

The compatibility or partial compatibility ratio is not reversed. Moreover, if the indicated *com* relations are completely compatible, *inc* are incompatible, *pc* are partially compatible, then the following logical expressions can be written, which follow the notation for orders *a, b, d*.

1. If *a com b,* then *b inc a.*
2. If *a com b,* and *b com d,* then *a pc d.*
3. If *a com b,* and *a com d* then *b pc d.*
4. If *a pc b,* and *a inc d*, then *d pc b.*

These are basic logical dependences, on the basis of which, using logic algebra, one can write other logical expressions that combine orders into logistic chains.

If there are several orders that can be included in a single stream in the aggregate, then the entire set can be estimated by quantitative indicators such as:

- order of compatibility ratio, which we define as:

$$K_{com} = \frac{n_{com}}{n_{\Sigma}}, \tag{4}$$

where n_{com} is the number of compatible orders (events) in the array ordered, n_{Σ} – the total number of events.

According to the definition of compatibility, the maximum value of K_{com} = 0,5. That is, if a maximum of half of orders is a compatible, then second half of this relationship is not mirrored;

- the coefficient of partial compatibility is determined from the expression:

$$K_{p.com} = \frac{n_{\Sigma} - n_{\max.flows}}{n_{\Sigma}}, \tag{5}$$

where $n_{\max.flows}$ – the maximum number of flows (with ruptures), which can be designed in the initial graph. The numerical value of the partial compatibility factor may lie within the range of 0..1;

- the coefficient of incompatibility of orders (events) is determined from the expression:

$$K_{inc} = \frac{n_{inc}}{n_{\Sigma}}, \tag{6}$$

where n_{inc} is the number of incompatible events in the entire set of them. This coefficient can reach a maximum of 1.0, since orders can be located on the network, and demanded so, that none of them can be executed by the same vehicle.

Using the compatibility signs, one can divide the orders into such groups, which will be executed in the same flow at the stage of the initial scheduling. Returning to the previous example of a static problem, we can mark in the initial graph arcs and their ratio of the full compatibility between the vertices, or the absence of an arc or edge as the complete incompatibility (Fig. 4).

If one compares the given in Fig. 5 model with initial one on Fig. 1, the full compatibility of orders 4-3 and 3-5 can be seen, as well as the incompatibility of orders 2-3 and 3-2. Such a batching greatly simplified the optimization of the design of the decomposition, and led to the same result that in Fig. 2. If the number of orders increases, then we can assume that the quality of the constructed schedule will be better, than applying the above heuristic algorithm without classification and grouping of objects.

If unplanned orders are received during the planned horizon, then, taking into account their time parameters, they can also be classified. In order to get the optimal solution for the order of performing unplanned tasks, it is necessary to rebuild the disordered mixed graph, taking into account that there will already be no edges connecting the vertices, which at the moment of receipt of new orders are already excluded from the current schedule, because the events they represent has gone. The complexity of arranging a new graph will not be higher than the previous one, since new vertices have established compatibility links, and some vertices are already excluded from the review. Let us consider an example of the model above with four orders and two cars. Previously, it was well-ordered and looked like Fig. 2. At time $t_{o.7}$=9 hours from the beginning of the plan of transportation implementation, two trucks began to move around the network. One of them at the time $t_{o.4}$=3 hours has completed the order 4 and has been sent to the next item for the order 3, which, according to the schedule, was completed at the time $t_{o.3}$=8 hours.

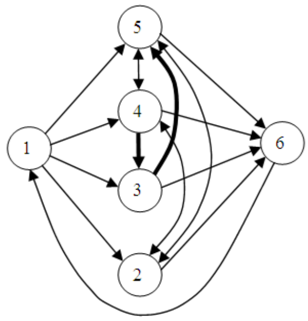

Figure 5. A model of schedule design with the terms of full orders compatibility (continuous solid arrows) marked on them

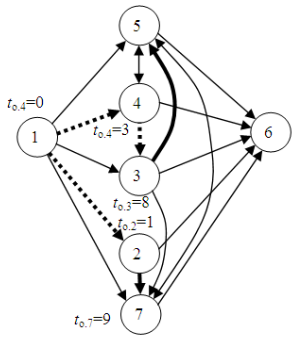

Figure 6. Model for adjusting the schedule after reception of unplanned order 7; the number of vehicles is *m*=2

Another vehicle has already completed order 2 and, according to the previous timetable, should complete whole transportation plan. The new order 7 is fully compatible with order 2 after its parameters evaluated before. Therefore, the next re-optimization results change the schedule, according to which second track has to execute a new order 7 after the execution of order 2. In this case, the total duration of the project does not increase, but the performance of both vehicles increases.

3. Results

The proposed algorithm was applied to a large array of sample data. It has been considered the order for the carriage of goods between cities on the transport network was considered, which presents L'viv region of Ukraine, which is approximately 150×150 km. The average travel time between the cities is about 6,5 ± 3,5 hours. The fleet of vehicles is initially located in the regional centre. Its number is 40 trucks. The same is the maximum initial number of orders. In other words, there is the possibility to distribute existing orders between the available fleet, so that each vehicle will be occupied with one order execution. The transportation of goods is carried out by the pendulum kind of routes, however if the point of consumption and the point of departure of the goods coincide, then the possible version of the circular route with the breakdown of the traffic flow exists. The maximum planning horizon was 195 hours of continuous time that is approximately 8 days. Each order is characterized by the average duration of its execution as well as time windows. Thus, in the set of orders, the relationship between the couple of events was established.

The ratio of their full compatibility is $K_{com}=0,1$, partial compatibility is $K_{p.com}$ = 0,5, ratio of incompatibility is $K_{inc} = 0,2$. All orders are periodic and they are located on the specified geographical area, so that from all 44 cities of the region 10 are involved in the project, and approximately 20% from the total 31.5 thousand km length of regional roads can be used for the execution of all orders. During the planning period, new orders are received by the carrier, which can be described by the Poisson process with the intensity $\lambda=0.09$ orders per hour. The new requirements for carriage are such that they do not change the previously accepted compatibility metrics. It was assumed that the volume of transportation corresponds to the cargo capacity of each of the available vehicles of the fleet.

The initial optimization of known orders was carried out with a variable horizon of 20...195 hours. The dependence of the duration of forecasting from the number of planned orders is reflected in Fig. 7. These data were obtained from the transport and logistics company on the basis of the application information. The number of random orders received in the allocated planning period is shown in Fig. 8.

The properties of orders and location of vehicles at the initial moment remained stable, when designing schedules and routes with different horizons of planning. This was related to their time windows, medium duration, and others. Tables 1-3 show the optimization results in two methods:

applying the proposed classification of orders and grouping them, and using the heuristic algorithm " branch-and-bound" [17]. In the first case, the initial model is subject to limitations, but they are such of kind that make the best decisions.

As it can be seen from the results and their comparison, the proposed algorithm shows a higher level of quality scheduling and routing. This is especially noticeable in terms of unproductive idle vehicles, due to the fact that the execution of the order is discordant. It may occur when the vehicle has already executed a pre-order, and the next can not be started, or when all current orders are already executed, or distributed, and there are no new accepted orders. Three tables show clear that the idle time is especially relevant at large planning horizon.

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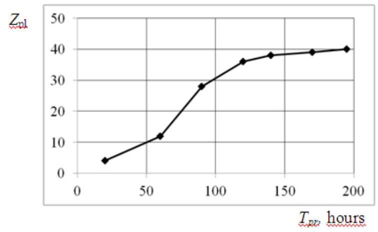

Figure 7. Dependence of the number of planned orders from the duration of the planning horizon

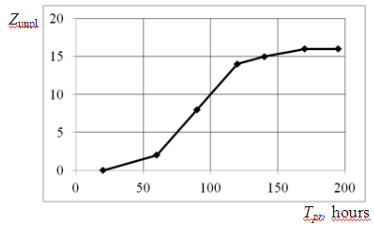

Figure 8. Dependence of the number of unplanned orders from the duration of the planning horizon

Table 1. Indicators of quality of designed dynamic schedules at the initial planned quantity of orders 40

Indicator, unit of measurement	Methodology		Level of new algorithm %
	branch-and- bound, without orders classifying	branch-and- bound with the previous classification of orders	
Planning horizons. hours	195	195	0.0
The number of actually executed orders	33	36	+9.1
Number of actual unscheduled orders	14	16	+14.3
The number of actually involved vehicles	38	36	−5.3
Minimum guaranteed project duration. hours	22.2	19.5	−12.2
Mileage duration of all vehicles with cargo. hours	312	346	+10.9
Duration of useless mileage of vehicles. hours	112	94	−16.1
Duration of idle time of all vehicles. hours	84	47	−44.0

Table 2. Indicators of quality of designed dynamic schedules at the initial planned quantity of orders 36

Indicator, unit of measurement	Methodology		Level of new algorithm %
	branch-and- bound, without orders classifying	branch-and- bound with the previous classification of orders	
Planning horizons, hours	120	120	–
The number of actually executed orders	27	32	+18.5%
Number of actual unscheduled orders	12	14	+16.7%
The number of actually involved vehicles	30	26	−13.3%
Minimum guaranteed project duration, hours	22.2	19.5	−12.2%
Mileage duration of all vehicles with cargo, hours	265	246	−7.2%
Duration of useless mileage of vehicles, hours	87	84	−3.4%
Duration of idle time of all vehicles, hours	24	17	−29.2%

The application of the classification algorithm gives up to 44% reduction in the downtime of all vehicles with an actual number of 36 scheduled and 16 unscheduled orders, which were accepted. The number of actually executed scheduled orders is 32, and unplanned – 14 with a smaller scheduled horizon of 120 hours. Although the volume of execution of orders decreased slightly, but in this case, the idle time was shortened not so much, only for 29,2%. This is due to the fact mainly, that the duration of the project has not totally changed; therefore the algorithm has led to a thickening of the schedule with a slight decrease in the actual work performed.

Reducing the planned horizon does not significantly affect the quality of the schedule. After all, the relation between the planning period T_{pr} and the guaranteed duration of the project is 1: 8.8 and 1: 5.4, that is, the projected time exceeds the design by at least 5.5 times. If we analyze the data in Table 3, then it becomes obvious that the optimization algorithm with the previous classification is ineffective. But routing and scheduling is a static process, in fact, since there are no unplanned orders.

Table 3. Indicators of quality of designed dynamic schedules at the initial planned quantity of orders 4

Indicator, unit of measurement	Methodology		Level of new algorithm %
	branch-and-bound, without orders classifying	branch-and-bound with the previous classification of orders	
Planning horizons, hours	20	20	–
The number of actually executed orders	4	4	0
Number of actual unscheduled orders	0	0	0
The number of actually involved vehicles	2	2	0
Minimum guaranteed project duration, hours	19.6	19.4	−1.0%
Mileage duration of all vehicles with cargo, hours	30.2	30.2	0
Duration of useless mileage of vehicles, hours	5.2	4.4	−15.4%
Duration of idle time of all vehicles, hours	1.4	1.2	−14.3%

4. Discussion

The influence of the number of vehicles engaged in the process of transportation on the length of execution of a fixed number of orders is also investigated (Fig. 9). There are 40 scheduled and 12 non-scheduled orders. If the number of vehicles increase from 14 to a maximum of 40 units, then the length of the process will be reduced, but nonlinear. The research establishes the condition, that all 52 orders must be fulfilled. As one can see at Fig. 9, the increase in the number of cars over 31 does not lead to shorter project duration, because all operations will be distributed among existing trucks, and their performance will be reduced.

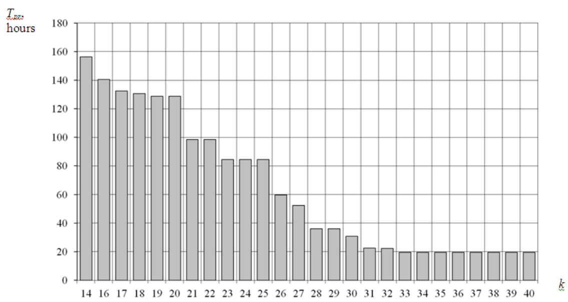

Figure 9. Dependence of the minimum durability of the project with the size of 40 planned + 16 unscheduled orders from the number of involved vehicles

5. Conclusions

The analysis of known routing and scheduling techniques showed that they become ineffective in terms of quality of results with increasing number of orders, especially unscheduled. The application of the previous classification is a way that improves the result. The corresponding algorithm, which is based on the ordering of mixed graphs, uses purpose-oriented restrictions in the form of oriented relationships between orders of one class. Classification of orders, in fact, has to be provided on the basis of time compatibility, taking into account time windows.

While applying the developed methodology for dynamic routing and scheduling, it has been found that it provides a significant improvement in the quality of the schedule by idle. But such an effect is achieved with a large planning horizon and large volumes of orders.

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