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THE CASE STUDY OF IMPLEMENTING THE DELIVERY OPTIMIZATION SYSTEM AT A FAST-MOVING CONSUMER GOODS DISTRIBUTER

ABSTRACT

Using new optimization methods and information-communications technology has become the key issue in the competition among the distributers of fast-moving consumer goods. Introducing a delivery optimization system instead of manual routing enables significant cost savings. The prerequisites for optimization are stable information system and efficient company management. The rich vehicle routing problem model is discussed and the effects of implementing the delivery optimization system are presented. For four years of continuous utilisation, the system has helped the distributer to reduce the overall distribution costs. It also made possible to close down several depots and handle more customer requests without investing in the vehicle fleet. The developed optimization system enabled the distributer to adapt to the new distribution schedule and react to first indicators of recession very fast.

KEY WORDS

vehicle routing problem, optimization, two-echelon vehicle routing problem, delivery, distribution

1. INTRODUCTION

During the last decade, the competition among the Croatian distributers of fast-moving consumer goods in the commercial logistics sector has increased. New technologies such as delivery optimization and fleet management software emerged as the key advantage in competition of distributers. Transportation costs can be reduced significantly if manual delivery planning process is entirely replaced or augmented by some kind of optimization software. In logistic business, the transition from manual dispatching routines to computer aided dispatching system, which incorporates automatic route optimization and planning, can produce a domino effect of positive changes. The first prerequisite for efficient transition is a flexible and stable information system of the distributer company, and the second one is a competent company management on operational level. Management should have clear mission to deploy the new dynamic schedules and time-critical protocols for drivers and warehouse crew.

Computer aided delivery planning is relatively a new practice in logistics, but at its core it is an old scientific combinatorial problem. The development of cheap computing power during the last two decades has enabled the practical application of combinatorial optimization methods and techniques in the logistics sector. In addition, the availability of affordable fleet tracking software can help dispatchers to supervise distribution in real-time and to control the transport costs. Also, integration of optimization and car navigation system can assist drivers to follow the calculated routes without specific knowledge of the geographic area. The use of computerized methods for transportation can result in savings ranging from 5% to 20% of the total costs [1].

This paper presents the effects of implementing a delivery optimization system in case of a distributer of fast-moving consumer goods. The distributer's delivery process is analysed and appropriate Rich-VRP model is presented in Section 2. Section 3 is the main part of the paper where the optimization process for delivery planning and route optimization is explained. In the same section the algorithms for each solver and used scenario are described. In Section 4, the effects of implementing the delivery planning and optimization system are analysed. In Section 5 a new optimization scenario is suggested. In the last Section the conclusions are drawn.

2. PROBLEM DESCRIPTION AND MODELLING ISSUES

The Vehicle Routing Problem (VRP) is one of the most significant problems in distribution management [2]. Recently, in the scientific community the focus has moved from improving solutions of VRP test problems [3-5] to the development of more robust algorithms which are flexible enough to allow easy addition of some real-life constraints [2, 5, 6]. This change is a direct influence of logistic commercial sector on the scientific community. Scientific attractiveness of VRP has been constantly growing since Dantzig and Ramser formulated VRP in 1959 for the real-life truck dispatching problem [7]. There are more than 900 papers connected to Vehicle Routing Problem available in academic journals just in INSPEC database [6].

2.1. Standard VRP models

VRP is an NP-hard problem defined by the task of determining the optimal set of routes to be performed by a fleet of vehicles to serve a given set of customers [1]. The solution of VRP is a set of routes beginning and ending in the depot, where all customers are served only once. VRP is a combinatorial optimization problem on the graph. Let $G=(V,A)$ be a fully connected graph with a set of vertices $V=\{0,\ldots,n\}$. Vertex with index 0 is a depot, while other vertices have indices $i=1,2,\ldots,n$ and represent customers. Each edge

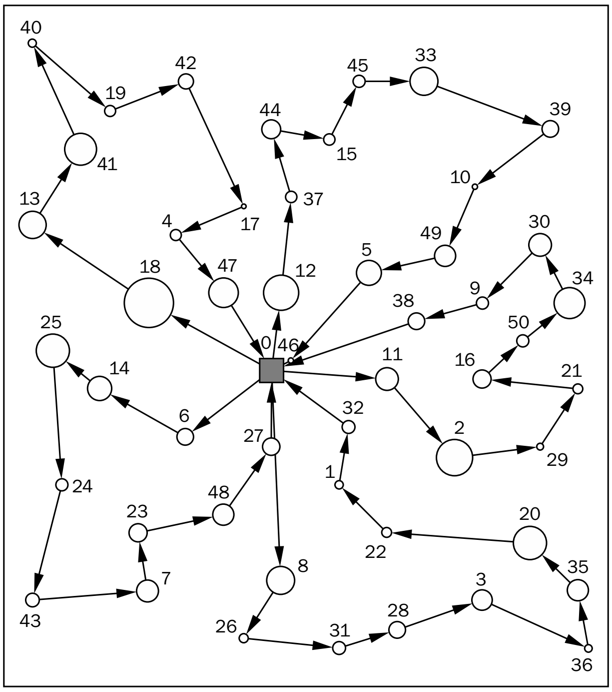

Figure 1 – Capacitated Vehicle Routing Problem

(i,j) from the set of edges A has non-negative transportation cost c_{ij} which can represent the cost of travel distance or time. In the case when one-way streets exist in a street topology, the asymmetric graphs are used where costs in one direction are not equal as in the opposite direction, $c_{ij} \neq c_{ji}$. The homogeneous fleet of K vehicles is available in the depot and each vehicle is used only for one route which begins and ends in the depot. If there are capacity constraints in the problem it can be treated as Capacitated Vehicle Routing problem (CVRP), *Figure 1*.

Each customer has a non-negative demand m_i while each vehicle k_i is limited by maximal capacity q_i. The basic VRP model can be extended by additional constraints. If customers request delivery within a specific time window, the problem can be modelled as a Vehicle Routing Problem with Time Windows (VRPTW) [8]. The service of each customer has to start within time window $[e_i,l_i]$, where e_i is the earliest and l_i the latest possible time when service must begin. If the vehicle arrives before opening of the time window it has to wait. It is forbidden to start service after the closing of time window l_i because it would produce an infeasible solution. The depot has also a time window that represents its opening and closing time. The primary objective in solving VRPTW is to find the minimal number of vehicles that can accomplish the delivery tasks in a way that each route satisfies all time and capacity constraints and each customer is served only once. The secondary objective is to minimize the overall travelled distance or time [9].

Another important linear programming model applicable in the presented case study is the Mix Fleet Vehicle Routing Problem (MFVRP) which involves the construction of a set of minimum cost routes originating and terminating at a central depot, for a fleet of heterogeneous vehicles with different capacities q_i, fixed costs and variable costs to serve a set of customers with known demands. The objective of the MFVRP is to determine the optimal mix of heterogeneous vehicles and their associated set of feasible routes that minimises the total variable and fixed cost subject to vehicle and customer restrictions [10, 11].

Well-known generalization of the VRP is the Multi-Depot Vehicle Routing Problem (MDVRP). The MDVRP extends the CVRP by introducing multiple depots [5, 12, 13]. In this extension each customer can be visited by a vehicle originating from one of several depots.

2.2. The Rich-VRP

A real-life freight delivery model for distributers of fast-moving consumer goods almost never directly fit in a mathematical linear programming model like VRPTW or some other extension of original VRP. The term Rich-VRP has been introduced recently to describe VRP problems when some special constraints have to be controlled by the algorithm. The linear programming model is a mathematical form which precisely defines the problem and all constraints, but do not solve the problem *per se*. Some heuristics, like Pisinger and Ropke's one, are robust enough to obtain high quality solutions for more than one modification of VRP [5]. Most of real-life heuristic techniques deal with some kind of Rich-VRP.

2.3. Case study modelling issues

In this case study, the fast-moving consumer goods distributer needs to deliver on the average 1,400 orders per day. There are more than 6,000 delivery locations that made at least one order in the last two years. A single delivery location may have several orders in one day and the distributer expects about 1,400 orders generated from 700 delivery locations per day on the average.

Each customer has a time window during which the delivery has to start. For minor number of customers the initial time windows had to be modified due to some practical reasons. For example, if a delivery location is crowded with vehicles of other distributers that had come earlier, the distributer's vehicle has to wait in a queue before it unloads the ordered goods. If the time window closes before unloading begins, the customer will not accept the delivery so the distributer will pay certain penalties. The uncertainty of unload waiting time is resolved by shifting lower and upper bound of time window by an average waiting time in queue at a location instead of using contracted time window. Such modification ensures early arrival and completion of the delivery.

The fleet size varies between 50 and 60 vehicles of various sizes and types. The drivers have a maximum working time of 8 hours. At the end of a working day a certain part of the vehicle fleet does not return to the depot. There are 5 geographical regions, 4 depots and 4 satellites (cross-docks). At some areas the neighbour regions overlap and the depots can compete for delivery, see *Figure 2*. For instance, the delivery locations in the area near to Šibenik can be served either from the Split or Zadar depot. Depending on the geospatial and temporal characteristics of each delivery day the optimization system determines the best depot for serving customers in the overlapping area.

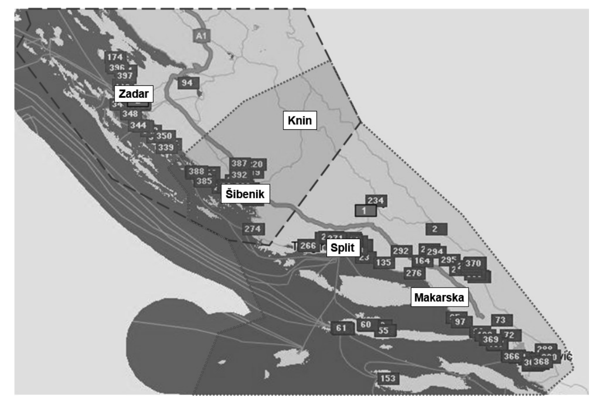

Figure 2 – Overlapping area

In urban areas it is very difficult to predict the service time of a particular customer. The problem arises in downtowns where time needed to park the vehicle and manually carry goods across the pedestrian zone increases. Therefore the calculation of the service time in this Rich-VRP model is based on the geographical position of customers, the volume of order and on specific remarks of delivery locations such as using elevator, paper work, etc.

Some vehicles have compartments which are temperature-controlled because some commodities need to be cooled. The commodities that do not have to be cooled can be delivered by any vehicle, even in a cooled compartment if it is necessary. Two-commodity constraints [14, 15] are also included in our Rich-VRP model. In the presented case study the model can be described as mix fleet multi depot VRPTW with multi-commodity [16].

3. OPTIMIZATION PROCESS

During the last four years of everyday software utilization different optimization scenarios have had to be considered. Different scenarios have different objectives and constraints. For example, sometimes it is useful to solve the problem with fixed number of vehicles in order to reduce the working time of drivers or to handle peak days using the whole fleet. If there are not enough drivers it can be useful to eliminate one route after the initial solution is obtained by putting its orders into routes of other vehicles. In such scenario the problem is relaxed by allowing drivers to work overtime. The relaxation of constraints and acceptance of infeasible solutions during the optimization is one of the frequently used techniques in heuristic approach. By using a penalty function for infeasible solutions as part of the optimization objective, infeasible solutions can lead toward feasible ones that satisfy all constraints. When such approach is used the objective function is balanced between two goals. The one is to reduce cost through distance and time measure, and the other one is to satisfy all constraints and eliminate penalties, if there are any. Balancing of driver workloads can also be set as part of the optimization objectives. The dispatcher can change the priorities of optimization objectives to suit the company needs at the time. Driver overtime and delayed arrivals to customers produce most of the extra costs. Therefore, the most critical constraint in the presented case study is time limitation.

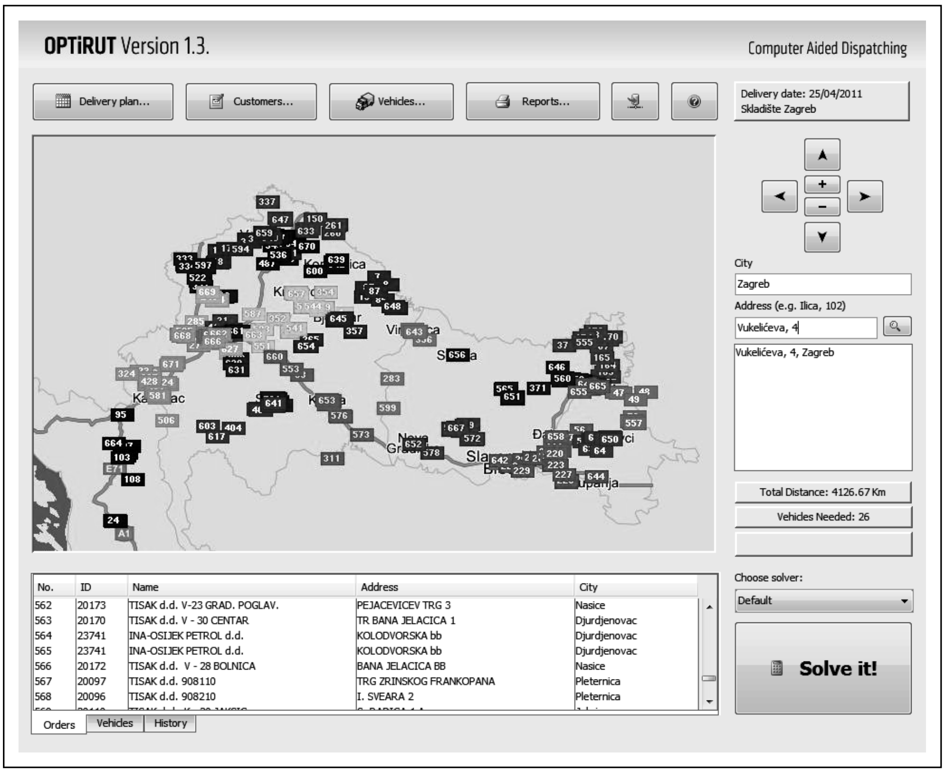

Figure 3 – The developed optimization system

3.1. Manual and automatic routing

Although the developed optimization system (shown in *Figure 3*) is capable to automatically solve the described Rich-VRP model, it is more suitable to put the dispatcher in the central position where one can choose the most suitable optimization solver. The developed scenarios describe the most common situations that are periodically repeated. The pattern can be seen in the day-by-day operation, and solvers are tailored for different scenarios, so that the dispatcher can choose the most suitable one.

During every day work it has become clear that one automatic solver of any kind is not the best solution and that manual routing should not completely disappear. The dispatcher's experience can be valuable because some delivery locations have special treatments which are hard to include or impossible to predict in the model. Sometimes the driving time to very far customers and back lasts longer than the driver's working time. In such case, the dispatcher can isolate a single vehicle and manually create its route and increase driver working time by a necessary amount of time. Slight deviation in working time or relaxation of some other minor constraints should always be a human decision. Drivers are paid for overtime work, but the distributer can reduce overall expenses if the dispatcher decides not to send more than one vehicle to the very far delivery locations. Those situations are detected and handled using visual tools. The group of very far delivery locations is assigned to the suitable vehicle that has enough capacity. The route is then constructed by solving the Travelling Salesman Problem with Time Windows (TSPTW) [17] with depot closing time set to infinite. In addition, every vehicle can have its own starting time. In the described case the dispatcher can decide that such a route should start earlier than others so that the closing time window of each customer on the route can be satisfied. In order to cover all the distributer's requests and needs, it can be beneficial to include the manual routing possibility as a part of optimization tool set.

Each day there is a certain number of very large orders which are treated separately because big and small orders are rarely transported together by the same vehicle. The multiple trips of a single vehicle are not allowed due to working time limitations. Eventually, the dispatcher can outsource vehicles with large capacity to deliver very big orders. Outsourced vehicles may have multiple trips if it is necessary. By isolating very big orders the occupancy of vehicle cargo space becomes an easier constraint in comparison to time.

3.2. Solvers and algorithms

The whole optimization process including manual modifications takes about 30 minutes on the average and is done once a day in the afternoon hours. The block diagram of the optimization process is shown in *Figure 4*. The process begins with importing orders

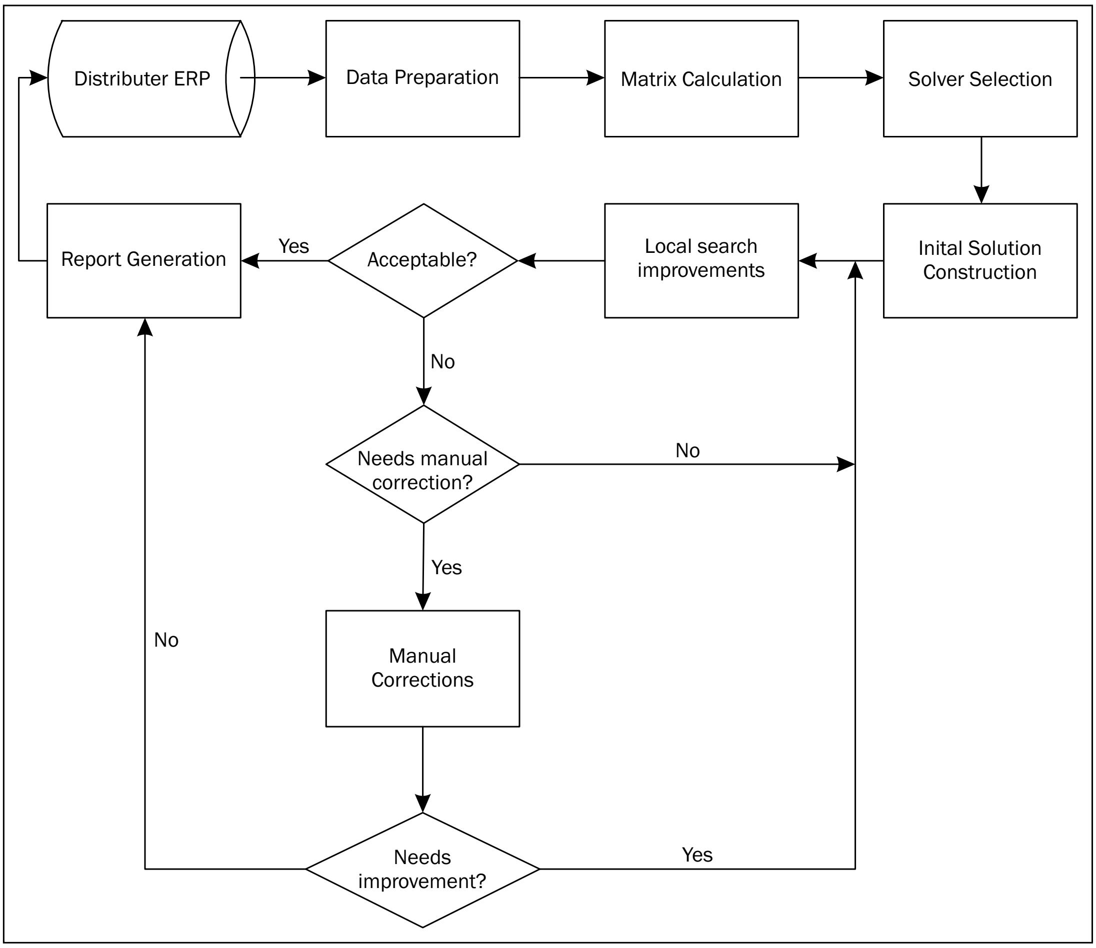

Figure 4 – The optimization process

from the distributer's Enterprise Resource Planning (ERP) software. Data needed for optimization (such as position of delivery location on digital map, volume of order or number of articles) is prepared. The incorporated Geographic Information System (GIS) needs a certain amount of time to calculate distances between all possible pairs of locations using the navigation map of Croatia [18]. The dispatcher can choose from several optimization solvers tailored for typical scenarios. The most used solvers are the default solver and the "fixed" solver with primary objective to use a fixed number of vehicles. The calculation always begins with an initial solution. Improvements are made by a local search improvement mechanism described further in this section. After the first solution that can be applied directly, the dispatcher takes control and makes additional tuning. The dispatcher can make manual corrections on routes and can try to improve the solution again. When the solution is good enough, the reports are generated and the plan of delivery is sent back to the ERP like a product of optimization phase. The default solver is capable to solve a problem with 1,000 orders in about 5 minutes. The solver execution time can be changed by the dispatcher if it is necessary.

The default solver generates an initial solution by using Solomon's construction algorithm I1 [3, 19]. Since each day can have different spatial and temporal characteristics, it can be reasonable to use a different parameter λ which emphasises those characteristics. The route is initialized with the seed customer that is farthest from the depot or has the smallest latest arrival time depending on the aforementioned parameter λ. Other customers are selected based on the same criterion and inserted until it is possible, and if there are some customers left out, another vehicle is initialized until all customers are served. The described Solomon's I1 solves VRPTW problems. A modification of the algorithm was necessary in order to solve Rich-VRP with additional real-life constraints.

The default solver uses a two-phase approach. In the first phase an attempt is made to construct a feasible solution that uses a minimal number of vehicles using an ejection pool mechanism [20]. Starting from the initial solution a vehicle that seems easiest to eliminate is selected. Its route is deleted and assigned customers are added to the ejection pool and then inserted into other routes while trying to satisfy all given constraints. If the ejection pool gets empty the procedure is repeated until all possible vehicle reductions are done or time limit for route reduction phase is reached. Since it is quite important to reduce the number of routes, the first phase of the algorithm uses 50% of time provided for calculation. In the second phase the total time is minimised. Sometimes it can happen that the construction algorithm is unable to insert all customers into routes. The ejection pool mechanism is suitable for such scenarios and instead of removing one vehicle, none of them is removed from the solution and un-routed customers are added to the ejection pool. If all customers from the ejection pool are successfully routed at some point of the first phase, an attempt is made to reduce the routes.

The second-phase algorithm is based on Variable Neighbourhood Search (VNS) [21] which controls the local search operators. Implemented local search operators are: relocate, exchange and 2-opt, 2-opt* and cross exchange. VNS is combined with Large Neighbourhood Search (LNS) [5] when the local optimum is reached. The default solver always works with feasible solutions and it is used as a basic optimization tool.

The fixed solver can be used for peak days (i.e. days before holidays or peak of tourist season) instead of the default one. While the default solver always attempts to generate a feasible solution, the fixed solver will use all available vehicles but some constraints may be relaxed if a feasible solution cannot be constructed. The fixed solver penalizes violation of customer time windows, vehicle overloading and drivers' overtime. Violation of vehicle capacity constraint is highly penalized and can happen only if the total delivery quantity is higher than the total capacity of fleet or when the dispatcher decides to do so by manually routing the vehicles. It is worth mentioning that relaxations are not encouraged by the algorithm and are used only if the dispatcher approves them. In this case the study capacity constraints are always feasible, but time constraints can cause unfeasibility of the solution. The fixed solver has different objectives from the default solver. The main objective is to reduce penalties if there are any. But if there are no penalties in the solution, the reduction of total time becomes the objective.

4. EXTENSION TO 2-ECHELON VRP

In the very beginning the distributer had eight depots. One year after deploying optimization, it became clear that the model should be extended as a Two-Echelon Vehicle Routing Problem (2E-VRP) [22] in order to further reduce the costs. The 2E-VRP is characterized by a single depot and a given number of satellites.

The first level routing problem addresses the depot-to-satellites delivery, while the satellite-to-customer delivery routes are built in the second level. The goal is to ensure an efficient and low-cost operation of the system, where the demand is satisfied on time and the

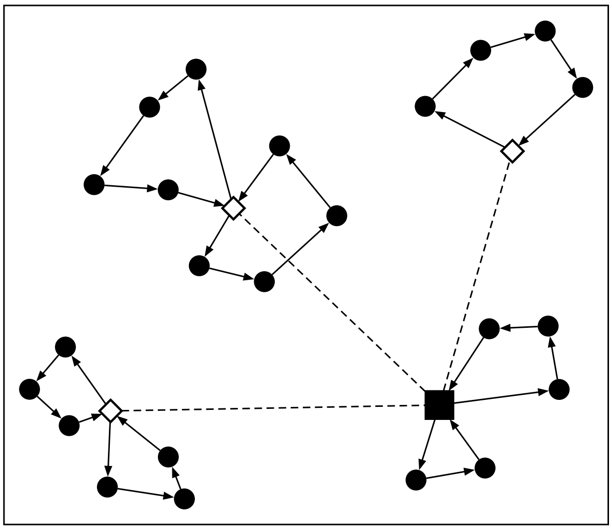

Figure 5 – Example of Two-Echelon Vehicle Routing Problem without inter-satellite communication

total cost of the traffic on the overall transportation network is minimized [23]. Satellites represent locations where goods are transferred from large vehicles coming from the depot to smaller outbound vehicles that are used for delivery in the surrounding territory. There was no need to solve this problem as original 2E-VRP because inter-satellite communication was not needed, see *Figure 5*, due to the geographical shape of Croatia and because inter-satellite communication would hardly give any advantage. This new moment gave the distributer a possibility to close four small remote depots and replace them by satellite locations with no inventory holding facilities at all. Closing down of four depots produced extra savings and did not cause any major disturbance to company's distribution practice.

The centralization of the delivery planning system reduced also the number of dispatchers as a result of closing unnecessary depots. Through using GPS car navigation system with uploaded delivery routes any driver can do any delivery. The specific driver knowledge about the geographic location of a particular delivery area has become less important. The computer aided optimization system has served as decision-support system for company's management during the last four years of utilization. Improved fleet management and well established strategic decisions are also positive effects of system implementation.

5. NEW OPTIMIZATION SCENARIO

During the first two years of utilising the optimization system, the delivery deadline was 24 hours after an order had been received. Because of economic recession the entire business model had to be changed. The customers started to order smaller amounts of goods but at the same time they placed orders more

Figure 6 – Customer clusters

frequently. The response of the distributer was very pragmatic. The new business model with weekly delivery enabled the distributer to cluster customers geographically. The north part of Croatia has two depot locations and two satellite (cross-dock) locations.

To each depot or cross-dock location five polygons are assigned with equal number of customers in each polygon. The polygons are shown in *Figure 6* and are marked by numbers 1-5 representing the five working days in a week. After switching to new delivery schedule the distributer started to serve its customers according to the calculated clusters. For example, on Mondays the vehicles deliver only orders of customers that are geographically located on polygons marked by 1. Each customer has to wait for the assigned weekday to get the ordered goods. The longest response to order is now set to seven days. To calculate the effects and possible savings of the new schedule, the impacts of clustering were simulated with historical data in June 2011. The comparison of real-driven and simulated routes is given in *Table 1*.

Through using the new once-a-weekday delivery schedule the average savings were 26% in distance, the number of tours dropped by 15% and overtime working hours dropped by 78%. One can notice obvious savings by comparing two delivery days shown in *Figure 7*, the one with 24 hours response and the other with 7 days response.

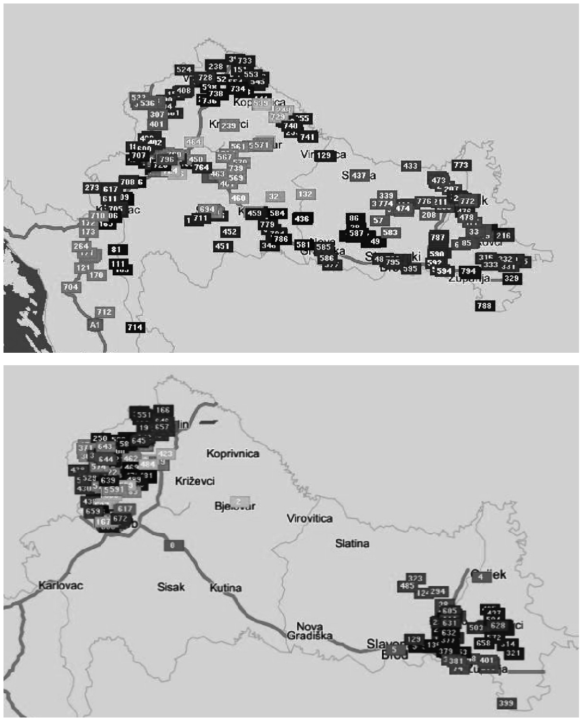

Figure 7 – Effect of clustering on a single day (above – before clustering, below – after clustering)

Table 1 – Simulation of clustering impacts

	Used Vehicles			Overall Distance [km]			Overtime [hh:mm]		
	real	sim.	savings	real	sim.	savings	real	sim.	savings
week 1	160	130	19%	27,140	19,136	29%	115:58	38:30	67%
week 2	148	127	14%	24,632	19,136	22%	118:05	26:20	78%
week 3	143	123	14%	25,614	18,514	28%	141:44	27:39	80%
week 4	145	126	13%	25,101	18,973	24%	102:21	12:49	87%
$\sum_{month}$	596	506	15%	102,487	75,760	26%	478:09	105:18	78%

One may find the drivers' reduced overtime as an unexpected optimization result but it was a product of dispatcher's decision to relax the working time limits by less than one hour per vehicle on average. The simulation has shown that beside significant additional savings in travelled distance and in the number of vehicles used, the difference is also noticeable in overtime savings which dropped to 10 minutes per vehicle on average.

6. CONCLUSION

The presented case study of a distributer of fast-moving consumer goods could be modelled like a mix fleet multi depot VRPTW with multi-commodity. Additional real-life constraints give this model the so-called "rich" attribute. The developed computer-aided system for optimization has been used in delivery planning every working day without exception for more than four years. The savings that the distributer had gained were not only the savings in the number of necessary vehicles, reduction of overall total time for delivery and fuel consumption. The better organization of transport gave clear picture to the management, and many other aspects of transport organisation started to change. Two-Echelon Vehicle Routing Problem and cross-docking without inventory holding facilities has been introduced into the delivery planning process. Such modification enabled the replacement of four physical depots by cross docks. The driver's knowledge about geographic location became less important and each driver now can work in any region. The number of dispatchers was also reduced and the efficiency of vehicle fleet has grown significantly. With the new optimization scenario the distributer can easily adapt to the new distribution schedule in order to react to the first indicators of recession in time.

Optimization of delivery was not only a question of buying and deploying the software. The true willing of the company management to force the dispatching crew to start thinking differently and use software tools instead of their own experience was an important factor of successful implementation. The scientific knowledge of heuristic methods powered by new technology was transferred to the industry. The engineering skill to mix old routines with new tools was very important too, because the interactive use of manual and automatic routing arises like a winning combination in practice. The experience of the team, that had more than ten pilot projects before this implementation, has also played an important role in this project.

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SAŽETAK

STUDIJA SLUČAJA IMPLEMENTACIJE SUSTAVA ZA OPTIMIZACIJU DOSTAVE ROBE ŠIROKE POTROŠNJE

Primjena novih optimizacijskih metoda i informacijsko-komunikacijskih tehnologija postaje ključna pretpostavka za konkurentnost među distributerima robe široke potrošnje. Uvođenje računalnog sustava za optimizaciju ruta dostave umjesto prakse ručnog rutiranja omogućuje značajno smanjenje troškova. Preduvjet uvođenja računalne optimizacije u poduzećima je pouzdani informacijski sustav i efikasna upravljačka struktura poduzeća. Prezentirani su efekti uvođenja sustava za optimizaciju dostavnih ruta, te je provedena diskusija o modelu proširenog problema usmjerava vozila. Tijekom četiri godina neprekidnog korištenja prezentiranog sustava, smanjeni su ukupni troškovi distribucije. Korištenje sustava stvorilo je pretpostavke za smanjenje broja skladišta i usluživanje većeg broja korisnika bez investiranja u nova vozila. Razvijeni sustav omogućio je distributeru da se brzo prilagodi recesiji i ostvari novi raspored distribucije prilagođen novim uvjetima.

KLJUČNE RIJEČI

problem usmjeravanja vozila, optimizacija, dvo-stupanjski problem usmjeravanja vozila, dostava, distribucija

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