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Multiobjective optimization in delivering pharmaceutical products with disrupted vehicle routing problem

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This paper is interested in pharmaceuticals distribution which is one of the most important activities and ensures the availability of drug products to a set of customers (pharmacies). The study introduces the Disrupted Vehicle Routing problem with Soft Time Windows since pharmaceutical distributors should respond to increased demands for products to ensure timely and efficient delivery to dynamic demands. We also propose an improved multiobjective local search (IMOLS), which uses methods of neighborhood search such as large neighborhood search (LNS) and variable neighborhood search (VNS) based on a hybrid approach in the optimization of vehicle routes. The algorithm is expected to achieve competitive results compared with previously published studies.

1. Introduction

The vehicle rounting problem with time window (VRPTW) is one of the most important variants of the vehicle routing problem (VRP), which has arisen due to the growing importance of time constraints in the modern societies. Different real world applications in the logistics problems such as school bus routing and delivery or collection of goods are solved by the approaches proposed to deal with the VRPTW problems (Affi et al., 2018). City logistics focuses on practical logistics applications, which are often set in soft time windows environment where late deliveries are possible at some penalty cost and in practice this can be due to several hazards like a traffic jam causing a delay in delivery. In the vehicle routing problems with soft time windows, a vehicle can arrive late within the maximum allowed time, so we can produce solutions that reduce the transportation cost using fewer number of vehicle through small violations of time windows. These conditions lead to the definition of the Vehicle Routing and scheduling Problem with soft Time Windows (VRPSTW). Due to the expanding global population, demand for drugs increased, so pharmaceutical distribution is one of the fastest growing sectors and has become much more important. Like any company distributing a product, pharmaceutical societies offer product delivery services to ensure efficient delivery to pharmacies and improve their competitiveness. But there is a difference between the pharmaceuticals distribution and the general product distribution system since pharmacies do not have a large surface area for storing large quantities of drugs, and there is also a high

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demand for pharmaceutical products, which forces each pharmacy to have several unexpected orders while the working day plan is in progress. In general, vehicle route planning can be interrupted by various disruptions, which are unanticipated event occurring during the execution of the routes, and the disruption management is destined for revising an operational plan in real time in order to provide quickly good solutions for the disrupted VRP. Where all new demand for product is received during the execution of the plan and must be incorporated into an evolving schedule in real time, here we introduce the disrupted vehicle routing problem which is a special case of dynamic VRP, and of course this dynamic aspect of the problem studied need the support of technology to detect the position of the vehicle and inform drivers of the revised plan.

Companies differentiate themselves by the quality of service they provide to customers, this is why pharmaceutical distributors should avoid any type of dissatisfaction among pharmacists using effective methods to deal with disruption in customer demand. So this paper proposes an approach to solve the disrupted vehicle routing problem with soft time window. In real world applications, the multi-objective optimization that aims to optimize multiple objectives simultaneously is very important since it considers all objectives with the same importance and allows obtaining a set of Pareto optimal solutions that represent the tradeoffs among the objectives. On the other hand, the evolutionary algorithms are well adapted for solving multi-objective optimization problems, so we use a hybrid method to initialize nondominated solutions. Concerning the pharmaceutical sector, some authors choose to transform multiple objectives into a single objective problem by allocating weights to each objective function component, and they propose an improvement heuristic (Fix-and-optimize (FO)) and the Variable Neighborhood Decomposition Search VNDS to solve this problem. For other authors, the problem is formulated and solved as a disrupted problem, they improve the quality of service to customers (evaluated by the delivery times to pharmacies), without significantly changing the current costs related to the driving distances.To solve the problem, they adopt a heuristic approach, structured in four phases. Recently, it is well known that local search methods provide very good results. Therefore, we propose an improved multiobjective local search method (IMOLS), which optimizes many objectives by using different local search procedures, for dealing with multi-objective disrupted vehicle routing problem with soft time windows. We aim to minimize the objective function composed of the transportation time and the delay time for each customer. We use methods of neighborhood search as large neighborhood search (LNS) and variable neighborhood search (VNS) in the optimization of vehicle routes. In view of the growing demand for pharmaceutical products, and to respond to repetitive daily orders from pharmacies, this research addresses the need to propose a method for dynamic planning, which takes the characteristic of this crucial sector. The problem is treated differently from the other works since we propose a multiobjective method for solving the problem studied, and there is also a novelty in the MOLS, such as the nondominated solutions are generated by the multiobjective hybrid method to initialize the archive.

This paper is organized as follows: section 2 presents a literature review, and section 3 introduces the multiobjective optimization and presents the problem formulation. Section 4 proposes the multiobjective algorithm based on a hybrid method for the disrupted VRPSTW. The experimental results are reported in Section 5. Finally, in Section 6 we make a conclusion of this research.

2. Literature review

The vehicle routing problems with time windows (VRPTW) are the most studied, because they are more practical in many industrial applications. The optimization of these problems allows especially a saving of time which ensure customer satisfaction, and represents a major objective for most modern societies. For a long time, older articles have been interested in the resolution of instances with customers related to time intervals, using exact methods, and heuristics (Desrochers et al.,1988; Golden & Assad, 1986; Golden & Assad,1988; Solomon & Desrosiers, 1988). VRPTW continues to draw the attention of researchers, that is why several recent articles propose new methods to solve this problem. Teodor

Dimitrov (2016) studied the vehicle routing problem with time windows (VRPTW) and aimed to optimize the vehicle routes in the distribution of goods from the distribution center to a set of customers in urban areas using two types of vehicles (capacity). They used Google's web map service to calculate the distance travelled and realed travel time measured by real urban street network to model the problem, and proposed an evolutionary optimization algorithm (imperialist competitive algorithm) to solve VRPTW. The paper of Sydneyta and Komarudin (2017) was interested in urban logistic and aimed to have a better planning for VRPTW, by minimizing total distance travelled , number of routes and total travel time. The proposed method is structured on 2 steps, first it generates initial solution, and second it improves the initial solution using heuristic methods which are local search and Lin Kernighan Helsgaun.

Many studies in the literature were concentrated in vehicle routing problem with hard time windows (Bettinelli et al., 2011; Yu et al., 2011), but others tried to treat more practical problems such as vehicle routing problem with soft time windows (Hashimoto et al., 2006; Chiang & Russell, 2004; Fu et al., 2008; Figliozzi, 2010). Figliozzi (2010) proposed an iterative route construction and improvement algorithm to deal with vehicle routing problem with soft and hard time windows. The solution method was divided into two phases: route construction and route improvement. The primary objective function for the VRPSTW was the minimization of the number of routes (NV). A secondary objective was the minimization of the number of time window violations (%HTW). A third objective was the minimization of total time or distance plus penalties for early or late deliveries. Another recent article that is interested in this type of time window belongs to Salani et al. (2014). This work proposed two exact algorithms to solve the vehicle routing problem with soft time windows. The first was based on standard branch-and-cut-and-price. The second algorithm used concepts of bi-objective optimization and was based on the bisection method. The soft time windows can be also divided into many types by the penalties calculation method, such as the penalties can be calculated for the outside both early and late of the limited time interval, and it can be calculated only for a late arrival, which is referred to as the semi soft time windows, as in the case of Setak et al. (2016). The solution to this problem is obtained through a CPLEX solver, a genetic algorithm, and a simulated annealing algorithm.

The increased awareness in just-in-time supply systems and the apparition of new advances in communication and information technologies have recently lead researchers to focus on dynamic vehicle routing problem. One of the new papers interested in the disrupted VRP which is a special kind of DVRP is the work of Eglese (2018). His review introduced the disruption management in vehicle routing and scheduling for road freight distribution. He presented a set of papers, each proposing an approach according to the type of disruption addressed. Since there are many causes of disruption such as vehicle breakdown, traffic accidents, delays departures, new orders or cancelled orders, the author of each paper solved a specific disrupted VRP, for example Mu et al. (2011) focused on one type of the disrupted VRP, when the vehicle breaks down during the execution of the VRP plan, and they solved the problem by using two heuristic algorithms based on tabu search, where one of the two algorithms was based on a method intended to treat the open VRP. The objective was to minimize the number of vehicles used and the total distance travelled to deliver unserved customers affected by a vehicle breakdown. A disruption in customer demand was studied in the paper of Bouziyane et al. (2018). They treated the multiobjective problem as a monoobjective problem by using weights for each objective, and used discretization method based on the hybrid algorithm, which combined a genetic algorithm with the Variable Neighborhood Search (VNS). The demand uncertainty can also be a cause of disruption (Moghadam & Seyedhosseini, 2010), the authors solved this problem by the Particle Swarm Optimization (PSO), and they used their approach for real world case study of drug distribution. As in all cases where the disruption occurs, Dhahri et al. (2015) prepared a plan to minimize the negative impact of the nonavailability of a vehicle. They proposed a variable neighborhood search (VNS) metaheuristic to solve the vehicle routing problem with time windows with preventive maintenance (VRPTW-PM) by revising the plan in real time that minimizes the number of vehicles and the total traveled distance. To apply the VNS algorithm, they used the Nearest Neighbor heuristic to build the initial solutions, and then five moves were used to generate neighborhoods, and finally a local search method was applied to ameliorate the obtained solution. Affi et al. (2018) also chose the variable neighborhood search based on the VND algorithm to solve the green vehicle routing problem, and the results were compared with the existing literature.

Several sectors benefit from the recent developments in the vehicle routing problems. Among them there are pharmaceuticals distribution which is one of the most important activities. The paper of Campelo et al. (2019) treated the case of pharmaceutical distribution company that serve pharmacies and the problem was characterized by multiple daily deliveries and different service level constraints. The authors used consistent routes to improve driver efficiency, and proposed a method which combined Fix-and-optimize (FO) approach and the Variable Neighborhood Decomposition Search VNDS to tackle this problem. In other situations, pharmaceutical distributors should ensure timely and efficient delivery to dynamic demands, which was also studied by De Magalhaes and De Sousa (2006) where they introduced and studied the drug distribution problem to pharmacies, and the solution method was proposed for a cooperative distributor of pharmaceutical goods operating in the North and Centre of Portugal. The authors aimed to optimize the vehicle routes, in order to improve the quality of service without significantly changing delivery costs. This was accomplished by proposing a dynamic algorithm based heuristic to serve all demands arriving along the day. The heuristic approach adopted was structured in four phases: creation of a groups of clusters, construction of each route and selection of the route to be performed in the last phase. To evaluate the algorithm, they compared the results obtained with those produced by the manual procedure, based on two criterions: The distance (ratio between the total number of kilometres of the route and the total number of delivered orders) and the quality of service (average delivery time). This work, therefore, was characterized by a new proposition of a multiobjective method which takes into account the specific features of the pharmaceutical sector.

Most real problems have more than one objective function to be optimized and this is the case for the problem studied by Qiuyun et al. (2013), their research object was the dynamic vehicle routing problem with time windows for distribution goods, which takes into consideration the random demand and the dynamic network. The problem has many objectives: maximize the number of customer serviced, minimize customer waiting time and the total vehicle driving distance, it was treated as a multiobjective optimization problem. The resolution is based on dynamic hill-climbing local search operator and genetic hybrid algorithm, while a standard test data from Solomon were used for simulation experiment. Most multi objective optimization problems used genetic algorithm. One of the oldest known approach belongs to Deb et al. (2002), in which the concept of pareto dominance was present in the design of their method, because in the multi-objective optimization, a good solution refers to his ability to dominate others. Ombuki et al. (2006) used a genetic algorithm with pareto ranking technique to solve the multi objective VRPTW, the algorithm minimized the number of vehicles and total distance travelled and produced a set of unbiased solutions for both objectives against large number of standard benchmark instances. Other authors integrated the genetic algorithm in their approach of resolution: Ghoseiri and Ghannadpour (2010) derived a multi objective VRPTW, in which the total distance travelled and the number of vehicles used were minimized. They combined the genetic algorithm with goal programming approach for solving the problem. The algorithm was tested on huge number of Solomon's benchmark instances, and the results validated the effectiveness of the algorithm. The last example is for Kumar et al. (2014) who treated a multi objective VRPTW with three objectives namely total distance travelled, total number of vehicles used and route balance. To solve this problem, the authors used a genetic algorithm, with new specifications that characterized the proposed approach, and made it highly competitive, for example fitness aggregation approach to evaluate fitness function value for multiple objectives, and specialized genetic operators concerning selection, crossover and mutation. Not far from the principle of genetic algorithm, a novel multi-objective evolutionary algorithm was proposed by Najera and Bullinaria (2011), where the approach was based on Darwin's theory of evolution to solve the multi objective VRPTW. The specific feature of this proposed method was the use of similarity measure for maintaining population diversity by including the similarity measure in the recombination phase. For more powerful methods, the genetic algorithm is often combined with local search methods, for example Minocha and Tripathi (2011) developed a model for multi objective VRPTW, in which minimization of total distance travelled and number of vehicles used are the components of the objective function. The genetic algorithm with local search heuristics (replacing next neighbor and reinserting random customer) was introduced to solve the problem. The results showed that incorporation of local search heuristics improved the efficiency of the proposed approach.

Another strategy is to use only local search methods to solve the multi objective problems. Tricoire (2012) proposed a new algorithmic framework for multi-directional local search; the idea consists of selecting a solution, searching around it in each direction then updating the archive. For this reason, the author used different local searches, each of them working on a single objective. To treat the multi-objective generalized consistent vehicle routing problem, Kovacs et al. (2015) proposed two exact solution approaches based on the ε-constraint method, and a metaheuristic algorithm referred to as MDLNS. This approach combined two methods: the variable neighborhood search algorithm and the multi directional local search framework. This last method consists in iteratively improving the solutions by using a local search algorithm for each objective. In this work, the non-dominated set of solutions was initialized by using the construction heuristics, while in our algorithm, we initialize the solutions by applying a hybrid method, and this is among the most important novelties of our paper. The last paper studied introduce another metaheuristic for the multiobjective optimization, Kaiwartya et al. (2015) proposed a time seed based solution using particle swarm optimization (TS-PSO) to deal with the multiobjective dynamic vehicle routing problem (M-DVRP) with five objectives, namely, geographical ranking of the request, customer ranking, service time, expected reachability time, and satisfaction level of the customers. To solve the problem, they partitioned the time horizon into smaller size DVRPs, then they used the particle swarm optimization to solve the time seed, which is the result of repartition of each smaller size DVRP.

3. Problem description

This section briefly reviews the basic concepts of a multiobjective optimization problem (MOP), and presents the mathematical model of the problem (Bouchra et al., 2018).

3.1. Multiobjective optimization

A MOP is a problem in which two or more objectives contribute to the final result. A problem of multiobjective optimization is defined by:

$$\min F(x) = \{f_1(x), f_2(x), \ldots\ldots, f_m(x)\}$$

y Pareto-dominates x if and only if:

$$f_i(y) \le f_i(x) \forall i = 1,\ldots,m$$
$$f_j(y) < f_j(x) \exists j = 1,\ldots,m$$

y is a Pareto optimal solution if there is no solution z that dominates y.
The Pareto front contains all solutions which are not dominated by any solution, as shown in Fig. 1:

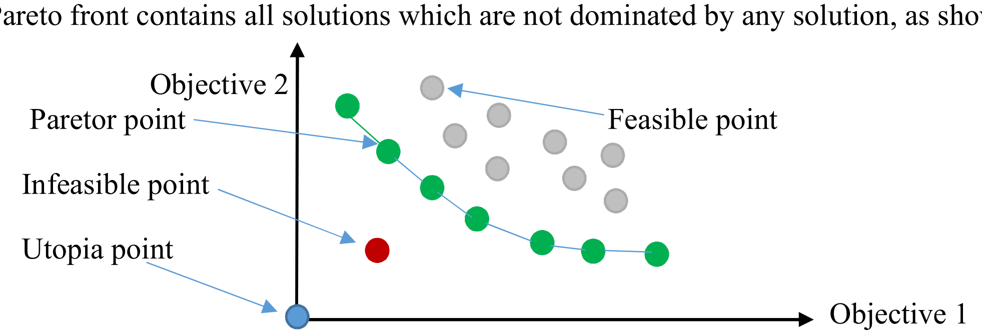

Fig. 1. Pareto front for minimizing two objectives

3.2. Mathematical formulation

We define the initial problem which is the Vehicle Routing Problems with soft Time Windows (VRPSTW), as finding a planning that minimizes the total traveling time and the total delay time simultaneously. This problem can be described as follows: Let $G=(V,A)$ be a graph, where $V=(v_0,.....,v_N)$ is a vertex set. $A=\{(v_i,v_j):i\neq j\wedge i,j\in V\}$ is an arc set. Vertex v_0 denotes a depot at which the routes of K identical vehicles of capacity Q start and end. The set of vertices $\{v_1,...v_N\}$ specify the location of a set of *N* customers. Each vertex in *V* has an associated demand $q_i>0$, a service time $s_i\geq 0$, and a service time window $[e_i,l_i]$. Each arc (v_i,v_j) has an associated constant distance $d_{ij}\geq 0$ and travel time $t_{ij}(t_{ij}=d_{ij}/v)$, v is the speed of the vehicle. *T* is the length of the working day. The arrival time of a vehicle at customer i is denoted A_i, its departure time D_i and the goods quantity in the vehicle k visiting the customer i is denoted by y_{ik}.

The decision variables are defined as follows:

$$x_{ijk}=\begin{cases}1 & \text{If there is travel from } i \text{ to } j \text{ by the vehicle } k\\ 0 & \text{otherwise}\end{cases}\qquad x_{ijk}=\begin{cases}1 & \text{If the vehicle } k \text{ visits the customer } i\\ 0 & \text{otherwise}\end{cases}\qquad x_{ijk}=\begin{cases}1 & \text{If the vehicle } k \text{ deviates from the customer } j\\ 0 & \text{otherwise}\end{cases}$$

The problem can be formulated as:

$\min f(x)=(f_1(x),f_2(x))$ where $f_1=\frac{1}{v}(\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N}d_{ij}x_{ijk})$ and $f_2=\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N}\max(0,A_j-l_j)x_{ijk}$.

In this paper, we consider a variant of VRPTW, in which the disruption involves new orders that arrive when the working day plan is in progress, and we propose a formulation for a multi-objective optimization to the disrupted VRPTW. The problem consists of finding new feasible vehicle routes that respect the capacity constraint after the insertion of new orders while their time windows are soft and can be violated. When the disruption occurs, we try to create a new feasible vehicle routes that integrates the new orders by adjusting the original plan reflecting the constraints and the objectives, so the objective of the problem studied is to minimize the total distance travelled by all vehicles and the delay time for all customers, and also to minimize the deviation from the original planning. When the vehicle deviate from the position *j*, new order is inserted in the position *j*+1, and the set of customers who have been already planned in position (*j*+1,*j*+2…., *n*) are rescheduled to positions (*j*+2,*j*+3,…., *n*+1).We define R_k as the set of customers served by the vehicle k ,rescheduled after the insertion of new order. The deviation costs include the additional distance which is due to the insertion of new order, and the increase in the delays for rescheduled customers.We suppose that the vehicles leave the depot with full load and serve a set of customers by limiting the delivering to one product type. Now, we give the mathematical formulation of the studied problem, based on the formulation of multiobjective VRPTW (Bouziyane et al., 2018).

$$\min f(x)=(f1(x),f2(x))$$

$$f_1=\frac{1}{v}(\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N}d_{ij}x_{ijk}+\sum_{j=0}^{N}(d_{nj}+d_{nj+1}-d_{jj+1})Y_j)$$

$$f_2=\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N}\max(0,A_j-l_j)x_{ijk}+\sum_{k=1}^{K}\sum_{j=1}^{R_K}u_j$$

$$if(A_j>l_j)\rightarrow u_j=r=\frac{1}{v}(d_{nj+1}+d_{nj+1}-d_{jj+1})$$

$$if(A_j<l_j)\rightarrow u_j=A_j+r-l_j$$

subject to

$$\sum_{k\in K}\sum_{i\in N} x_{ijk} = 1 \qquad j \in N \tag{2}$$

$$\sum_{j\in N} x_{ijk} = \sum_{j\in N} x_{jik} \qquad i \in N, k \in K \tag{3}$$

$$\sum_{i\in N} x_{i0k} = \sum_{j\in N} x_{0jk} = 1 \qquad \forall k \in K \tag{4}$$

$$\sum_{j\in N} y_j z_{jk} \le Q \qquad \forall j \in N, \forall k \in K \tag{5}$$

$$y_{ik} = y_{jk} z_{jk} + q_i x_{ijk} \qquad \forall i, j \in N, \forall k \in K \tag{6}$$

$$D_j = [\max(A_j, e_j)] + s_j \qquad \forall j \in N \tag{7}$$

$$A_j = \max(A_{j-1}, e_{j-1}) + s_{j-1} + t_{j-1\,j} \qquad \forall j \in N \tag{8}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ijk} t_{ij} + \sum_{i=1}^{N} z_{ik} s_i \le T \qquad \forall k \in K \tag{9}$$

$$x_{ijk}, z_{ik}, Y_j \in \{0,1\} \qquad \forall i, j \in N, \forall k \in K \tag{10}$$

Function f_1 aims to minimize the transportation time for a set of requests received in advance before the start of the planning horizon and the additional time due to the insertion of the new request. It is the same for f_2 to minimize the delay time. This is stated by constraint (1). Constraint (2) restricts the assignment of each customer to exactly one vehicle route, and constraint (3) is a flow conservation constraint. Constraints (4) ensures that each vehicle starts and ends at the depot. Constraint (5) indicates the capacity constraint of the k^{th} vehicle. Constraint (6) updates the vehicle load. Constraints (7) and (8) update the depart time and the arrival time at each position. The maximum route duration is limited by (9). Finally, decision variables are defined as binary in constraint (10).

4. The Proposed Approach

The effectiveness of the multi-objective hybrid methods applied in several articles, and the strength of the multiobjective local search algorithms gave us the idea to combine the two approaches in order to propose a more powerful method, which is a multiobjective locale search and uses methods of neighborhood search such as LNS and VNS, where the starting point is a set of nondominated solutions, obtained by the application of a multiobjective hybrid method.

4.1 Disrupted VRPSRW for pharmaceutical distribution

The problem studied can be described as follows: we receive new requests after vehicles leave the depot to serve a set of customers according to the original optimal plan, the objective is to minimize the impact of these new orders by adjusting the original plan. In the original optimal plan, some customers are serviced on time (i.e $A_j < l_j$), and other with a delay time when $A_j > l_j$. When disruptions happen, and the new order is inserted in the routes, it may have influence on customers, it is the deviation of the starting service time ($\max(e_j, A_j)$) in the new solution which might imply a further delay. The disruption management is called to find an effective strategy that minimizes the impact of disruption, caused by new orders, when the original optimal plan becomes infeasible. The distribution of pharmaceutical products can be modelled as the disrupted vehicle routing problem, because they have several orders during the day after execution of the plan, and they require short delivery time. Given the specificity of the pharmaceutical sector, re-optimization is not practical for this case, so, in this work we propose an effective method to find the original optimal solution and we use information of this plan to insert new requests by a local search method, in order to ensure rapid response to pharmacies.

By considering this plan, we take advantage of the effectiveness of the method used for planning tours, and we can solve rapidly the problem in a reasonable computing time. As indicated by the mathematical formulation, we are interested in multiobjective optimization and we try to provide a good non-dominated front.

4.2 The multiobjective hybrid approach for the resolution of the problem

The proposed approach consists of three main steps: in the first, we apply the multiobjective genetic algorithm that improves the initial population, composed of static customers. Secondly, the VNS explore efficiently promising areas, and finally, a multiobjective local search procedure (objectivewise local search) is designed for each objective. In this way, the plan named as original provides near optimal solutions and it will be used after adjustments to include new orders. Here a new plan has to be computed very quickly for changing problem.

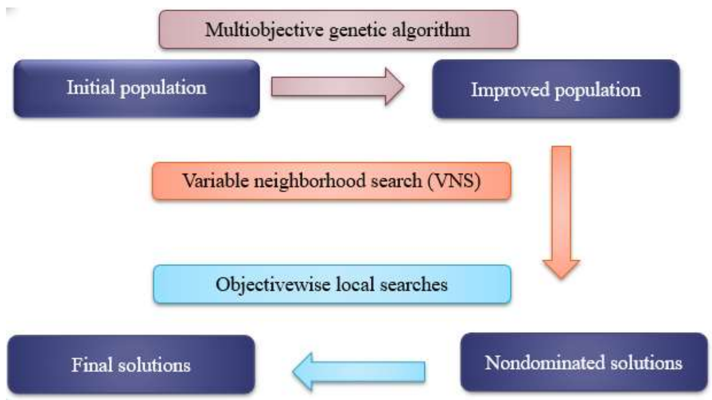

Fig. 2. Steps of the proposed approach

This approach allows combining the advantages of a hybrid multi-objective evolutionary algorithm and a multi objective local search**.**

4.2.1 Multiobjective Genetic Algorithm

The first two steps allow exploiting a hybrid method to generate non-dominated set of solutions, in order to provide good approximation of the Pareto front. In what follows, we detail the specific features of the first part of this hybrid approach: the genetic algorithm.

Initialization phase

Each solution in the initial population is the permutation of *n* positive integers, such that each integer is corresponding to a customer. We use a single line to represent each solution; it is a representation of several tours served by a set of vehicles.

We use a greedy constructive heuristic to generate a 50% of the initial population, the greedy method starts with one customer and move systematically to the nearest customer that has not yet been visited. The rest of the population is generated randomly with the aim of converting the entire search space. Among all the solutions of the initial population, we seek the nondominated solutions, we keep them in the A1 set. We use the Split method which was originally introduced by Beasley (1983) for the CVRP. It uses the shortest path heuristic algorithm for the second phase of a “route-first, cluster-second" approach. To illustrate the transition from a solution in the form of a line to a solution in the form of tours, we present an example with seven customers, each with a request q_i . Knowing that the capacity of the vehicle is 20, so the chromosome may be broken into three parts. Customers are listed in their order of visitation (0 is the depot):

Customer i	1	3	2	7	5	6	4
q_i	10	7	2	12	6	5	11

The solution can be presented as follows figure:

Vehicle 1	0	1	5	2	0
Vehicle 2	0	7	3	0	
Vehicle 3	0	6	4	0	

Fig. 3. An example of encoding of a solution

Fitness assignment

To evaluate them, every individual in the population must be assigned to fitness. In this paper, we are interested in multiobjective problems, so we use the non-dominance sorting criterion of Deb et al. (2002). This approach consists of distributing the population according to several fronts, based on the concept of Pareto dominance. The first front contains the best solutions, called the non-dominated solutions in the case of minimization of f1 and f2.

Genetic algorithm operators

The performance of genetic algorithms is affected by genetic operators, we present thereafter the crossover and mutation operators applied to the initial population. But before that, we use Binary Tournament Selection for selecting parent individuals from the population. The first of two parent is chosen from the nomdominated solutions A1, and the second is randomly selected from the population. Every two parent candidates are compared using Pareto dominance in order to keep the parent who participates in the recombination process. To perform this process, a random swath of consecutive customers from parent P1 are copied into the offspring S1, and the remaining values are placed in the child S1 in the order which they appear in parent P2. To get a second child S2 from the two parents, we flip Parent P1 and Parent P2. The crossover operator is described in Fig 4. A further stochastic change or mutation is applied to the offspring to avoid premature convergence of the algorithm to a local optimum.

For the permutation encoding already used, we apply order changing which select two customers (customer 5 and customer 1 for example) and exchange them, the two chosen customers may belong to the same route, as they may belong to two different routes. After we apply the crossing and mutation, we must determine the individuals who will be present in the following population. At each iteration, we compare the new individual (offspring) with the nondominated solutions A1, if he dominates at least one solution, the offspring is inserted in the set of the nondominated solutions A1. The process is repeated until a fixed number of iterations. At the end, all the solutions of the set A1 are compared with each other to keep only the nondominated solutions A2.

P1	2 (2)	5 (6)	7 (12)	6 (5)	1 (10)	4 (11)	3 (7)

T1: 0-2-5-7-0 T2: 0-6-1-0 T3:0-4-3-0

P2	1 (10)	2 (2)	5 (6)	6 (5)	4 (11)	3 (7)	7 (12)

T1: 0-1-2-5-0 T2: 0-6-4-0 T3:0-3-7-0

P3	5 (6)	4 (11)	7 (12)	6 (5)	1 (10)	3 (7)	2 (2)

T1: 0-5-4-0 T2: 0-7-6-0 T3:1-3-2-0

Fig. 4. Recombinaison process (order crossover operator)

4.2.2 Implementation of Multiobjective VNS algorithm

The second part of the proposed approach improves the solutions obtained by the genetic algorithm. This part is based on a metaheuristic called variable neighborhood search (VNS), where the principle is the change of neighborhoods during the search. Our algorithm based on VNS to solve the problem is inspired from the work of Geiger (2004), who presents a Multiobjective Variable Neighborhood Search Algorithms for a Single Machine Scheduling Problem with Distinct due Windows (MOVNS). In our algorithm, we use the nomdominated solutions from the set A2 as initial solutions, and we use tree neighborhood structures for generating neighbor solutions by swap operator, interchange operator and insert operator. At the beginning, we randomly choose a solution X from A2, then, at each iteration, a neighbor X1 is generated using the neighborhood structure N1, and we apply 2 opt on X1 to get X2. If X2 is a dominant solution, we will insert it into A2, and we evaluate another neighbor generated by the same neighborhood structure. Otherwise, we move to another neighboor generated by the other neighborhood structure, up to a maximum number of iterations. This process is repeated *n* times with change of X which is randomly selected from set A2. The procedure of VNS applied to our problem is detailed in the following paragraphs. The description consists of building an initial solution, shaking phase, local search method, and acceptance decision.

Building an initial solution: The initial solution is an element of the set of nondominated solutions A2.

The shaking phase: We use tree neighborhood structures, one by generating neighbors using the insertion method, this is accomplished by inserting a customer chosen randomly from the permutation in a new position also chosen randomly. In the other neighborhood structure, two randomly selected customers are simply swapped.

Local search method: This paper selects 2 -opt as a local search operator in order to obtain a new nondominated solutions in a short period.

The acceptance decision: If the new solution dominate elements of the set A2, the latter is updated by adding the new solution, and we continue the search with the same neighborhood structure. Otherwise, we move to another neighborhood structure. The pseudocode description of the steps of VNS, obtained by taking tree neighborhoods structures is done in Algorithm 1:

Algorithm 1

```
A2 <--Set of nondominated solutions
N← Maximal number of iterations
Repeat
   i=i+1
  select randomly a solution X from A2
  while StoppingCriterion=False
        select a neighborhood structure Ni
        generate a solution X1 using Ni
        X2<--2-opt applied on X1
        Evaluate X2
        If   X2 is a nondominated solution then
             Update A2
   End while
Until (i=N)
Return A2
```

The set A2 is then sorted to keep only the nondominated solutions obtained after application of the multiobjective variable neighborhood search (MOVNS), the new set is named A3.

4.3 Multiobjective locale search

In this paper, the idea of MOLS was inspired from the paper of Wang et al. (2016) in which the method of resolution is based on a single –objective local search. Therefore, we adopt the same strategy of resolution, by applying two local search algorithms, each search in one direction at a time to minimize one objective. In the third part of the application of the proposed method, we add another objective to try to minimize the number of vehicles used. Set A3 of non-dominated solutions is initialized by using a multiobjective hybrid method, then we select one of the solutions and we apply a local search strategy for each objective. The update of the archive is done by adding new efficient solutions, and the algorithm stops when the maximum number of iterations is reached. The algorithm that describes this third step of the proposed algorithm is presented in algorithm 2:

Algorithm 2

```
Initialize Archive A3
  While (iteration number < maximum iteration number) do
        X=randomly select a solution from archive A3
        for obj=1 to 3 do
              perform objectivewise local search
              update archive A3
        End for
  End while
```

This part tries to optimize three objectives of a given solution in parallel. Archive A3 is initialized by the set of nondominated solutions obtained by application of MOVNS.

Objectivewise Local Search for minimizing the total distance

In this step there are two cases: If all orders are received before the beginning of the planning horizon, we remove a random customer from a route, which is randomly selected and we try to reinserts it into the position which makes the resultant solution after insertion have the lowest total distance. If a disruption occurs, we do not remove any customer, but we try to insert the new customer into the best position.

Objectivewise Local Search for minimizing the number of vehicles (MOLSV)

To minimize the number of vehicles, first, the route which has the fewest customers is selected. Then, we enumerate all customers in the selected route to try to insert them into other possible routes. So, one vehicle can be reduced if customers in the selected route are inserted into other routes successfully.

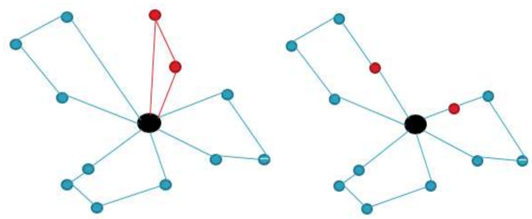

Fig. 5. minimizing the number of vehicles

According to the above example, one tour has disappeared, so we have been able to minimize the number of tours from 4 to 3. This is the route whose number of customers served is the smallest, and the customers are re-entered into existing tours.

Objectivewise Local Search for minimizing the total delay time

We select the route which has the longest delay time, and we apply the Large Neighborhood Search (LNS), in order to obtain new solution with lowest total delay time. LNS metaheuristic was first proposed by Shaw (1998) for solving vehicle routing problem with time windows (VRPTW). The main idea aims to explore a large neighbourhood of the current solution by using two heuristics: the removal heuristic selects a number of customers to remove from the vehicle routes, and the repair heuristic reinserts these customers in order to improve the solutions. The basic structure of a large neighborhood search (LNS) is shown in algorithm 3:

Algorithm 3

```
Initialize a feasible solution X
Xb=X;
repeat
    X'=r(d(X))
    X=X'
    If c(X')<c(Xb) then
        Xb=X'
    end if
until stop criterion is met
return Xb
```

Pseudo code for the LNS is shown in details in algorithm 3, in which we define Xb as the best solution, X as the current solution and X' as the temporary solution. We initialize the best solution by a feasible solution, then we apply the destroy method d(x) and the repair method r(x) to obtain a new solution. This solution is evaluated to only accept improving solutions and update the best known solution, and finally, this process is repeated until a stopping criterion is met. A very simple destroy method would select the customers to remove randomly. But in this paper we use the worst removal heuristic (Ropke & Pisinger, 2006) which removes customers inducing high cost to serve it in the current route planning, and we use a greedy heuristic to rebuild the destroyed solution by inserting the one whose insertion cost is the lowest and repeat inserting until all customers have been inserted. The algorithm considers the three objectives one after the other in the loop for. By improving one of these objectives, we try to find better solutions without deteriorating other objectives. Otherwise, we keep these solutions because they represent the entire pareto front.

5. Computational results

The proposed method was coded in C and executed in an Intel (R) Core(TM) i5 Processor 2.67GHz with 4 Go of RAM. The genetic algorithm parameters were set to the following suitable values determined by:

popSize = 5000 (the number of individuals in the population)
γ = 1.0 (probability of recombination)
μ = 0.05 (probability of mutation)
numGen = 500 (number of generations)
Tsize = 2 (tournament size)

5.1 Results on small size instances

The proposed algorithm has been tested for a series of small example problems, and the mathematical model has been implemented using Cplex. Cplex is not able to solve multi objective optimization problem. However, we use weighted sum single objective formulation to obtain solutions for the randomly generated instances. To simplify programming in Cplex, the objective function must find the minimal solution, after the insertion of the dynamic customers, without minimizing the deviation compared to the original planning. We use linear scalarization of the multiobjective optimization problem, where the weights of the objectives are equal:

$$\textbf{min} \quad f = 0.5 * f1 + 0.5 * f2$$

$$f1 = \sum_{k \in K} \sum_{i,j \in N+} t_{ij} x_{ijk}$$

$$f2 = \sum_{k \in K} \sum_{i,j \in N+} \max(0, A_j - l_j) x_{ijk}$$

N+: sum of static customers plus the dynamic customers. The results of comparing the proposed method to the CPLEX are shown in Table 1:

Table 1
Results for small seize instances

IS-SZ	DY-CU	Cplex cost	Cplex Time	IMOLS distance	IMOLS delays	IMOLS Time	GAP
6	0	134.8	0.18	135.1	0	0.20	0.002
6	1	157.1	0.18	172	0	0.20	0.094
6	1	157.6	0.18	170	0.49	0 .22	0.096
8	1	148.5	0.23	149	0	0.23	0.003
8	1	148.4	0.28	148	1.56	1.71	0.070
8	2	158.1	0.26	150	1.71	1.92	0.010
8	3	174.1	0.6	151	6.71	1.71	0.060
15	0	227.2	38	233.3	0	11.9	0.02
15	1	238.4	35	274	0.24	16.9	0.14
15	2	241	31	255	0.37	15.4	0.07
15	3	257	197	259	0.07	17.43	0.010

The column Cost IMOLS is the total distance travelled by all vehicles, Retard IMOLS is the sum of delays for all customers and column Time IMOLS is the computing time in seconds for the proposed multiobjective method.The column IS-SZ is the size instances, and DY-CU is the number of dynamic customers. The column Cost Cplex is the solutions computed with Cplex, which represents the sum of the travel time and the delay time. The column Time Cplex is the computing time of Cplex in second. The relative deviation from the optimal results found by the CPLEX is done by:

Gap = (Cost IMOLS−Cost Cplex) / Cost Cplex.

The average gap is 0.04% for the 11 instances when the total number of customers is less than 15, and the number of dynamic customers is less than 3. The computing time for the two methods is about the same for instances of size 6. It became small for the MOLS method compared with the Cplex method for instance of size 15. The results obtained by our method affirm our objectives of responding more quickly to the dynamic demands while minimizing the distance and the sums of the delays (average delays=1min).

5.2 Results for the 100 customer instance

The results that illustrate the distance and the average of delay time after application of each step of the proposed method are shown in the following table (Table 2):

Table 2
Improvement of the results by the proposed method

Initial results		Genetic algorithm		Hybrid method		Local search	
2885.13	129.33	2719.76	14.56	1782.18	1.79	1511	1.04
2869.62	129.51	2682.04	26.71	1769.06	1.81		
2888.15	109.71	2553.33	35.38	1735.70	1.82		
2773.48	135.15	2653.52	31.54				
2891.09	94.37	2828.11	12.54				
3022.76	76.76	2674.77	29.49				
3023.92	76.76	2734.89	13.73				
		2745.85	13.61				
		2812.73	13.07				
		2725.95	13.80				

According to Table 2, we can note the improvement of the set of solutions nondominated after each step. Initial solutions are the set of nondominated solutions while generating the initial population. The Culumn Genetic algorithm select the nondominated solution by applying the multiobjective genetic algorithm, then the multiobjective VNS is used, and solutions are shown in the hybrid method Column. Among these solutions, the user can choose the most suitable solution for him, to be improved by the multiobjective local search method, this is done by the local search Column.

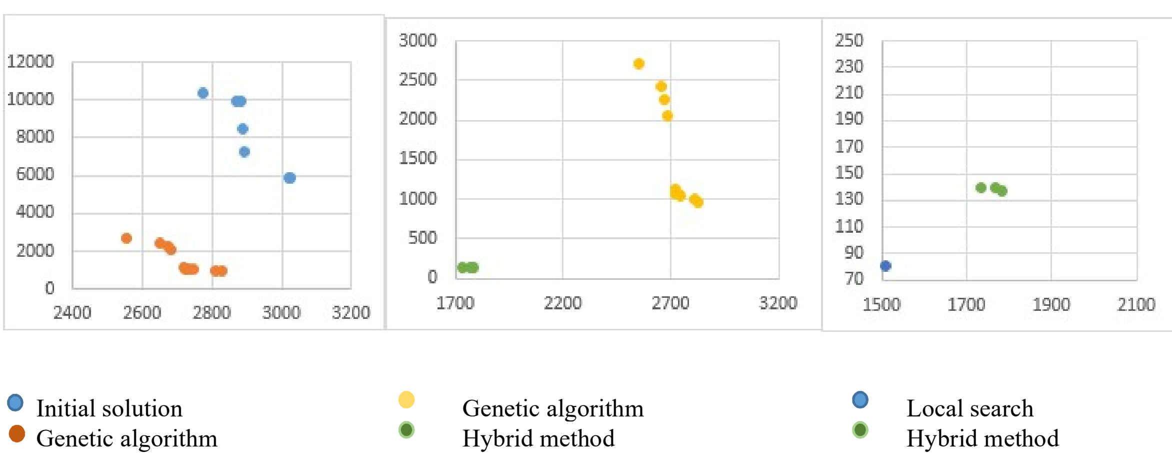

Fig. 5. Nondominated solutions improvements

Fig. 5 illustrates the improvement between each 2 step of the method: IS (Initial population), GA (multiobejctive genetic algorithm), HM (multiobjective VNS) and LS (multiobjective local search). In this problem, we integrate dynamic customers directly after its appearance given the urgent nature of pharmaceutical demands. The proposed method has been tested on the problem set C1. Table 3 presents some results generated by the proposed method:

Table 3
Results of the proposed method

		IMOLS				IMOLS	
Instances	dod	D	Delay	Instances	dod	D	Delay
C102	10	1389	3	C103	10	1254	4
	30	1551	9		30	1444	2.19
	50	1607	6		50	1601	0
	70	1620	3		70	1508	0.28
	90	1505	10		90	1612	0.18
C104	10	1329	0.39	C105	10	1229	4
	30	1396	0.37		30	1627	12
	50	1547	0.19		50	1370	5
	70	1529	0.03		70	1640	1.30
	90	1440	0.12		90	1210	2
C106	10	1502	7	C107	10	1200	0
	30	1112	11		30	1340	0.8
	50	1660	12		50	1209	8.3
	70	1419	10		70	1287	1
	90	1643	7		90	1506	3
C108	10	1572	2	C109	10	1765	1
	30	1693	8		30	1388	0.2
	50	1587	2		50	1392	0
	70	1506	1		70	1559	8
	90	1400	5		90	1320	0.73

dod (degree of dynamism): The ratio between the number of dynamic requests and the total number of requests.

D: The total distance traveled by all the vehicles used.

Delay: The average of delay time.

Using 10 vehicles, the results are calculated for 5 degree of dynamism (10%,30%,50%,70% and 90%).

The results achieved meet the objectives aimed by pharmaceutical distributors, whose first is to directly serve dynamic customers as soon as possible, thus allows to meet the expectations of pharmacies by reducing the delay time. Therefore, the delays of dynamic customers are lower than the static customers, and in general the average of these delays is very small (less than 12 min), and the average of delay time for all the instances tested is 3.7 min. The other objective concerning the travel time, related to the distance, is also minimized for the vehicles used in the routes planning. In what follows, we compare our results to those of the ACSLNS method, which is a proposed approach to solve the VRPHTW (Messaoud et al., 2013), it combines two methods: Ant Colony Algorithm (ACS) for minimizing the number of vehicles (ACSNV) and Large Neighborhood Search (LNS) for minimizing the total distance. Their tests were carried out with 10 vehicles by treating 5 degrees of dynamics (dod), which are 10%, 30%, 50%, 70% and 90%.

According to Table 4, compared to the distance in the case of application of the ACSLNS –DVRPHTW, our approach was able to reduce this distance, with an average of 4.6 min of delay.

Table 4
Comparison between ACSLNS and IMOLS results

Instances	ACSLNS			IMOLS	
	dod	D	PCS	D	Delay
C102	30	1571	98	1551	9
C102	90	1520	95	1505	10
C103	10	1386	99	1254	4
C103	30	1769	100	1444	2.19
C103	50	1786	100	1601	0
C103	70	1810	99	1508	0.28
C103	90	1732	100	1612	0.18
C104	10	1454	100	1329	0.39
C104	30	1478	100	1396	0.37
C105	70	1687	98	1640	1.30
C106	30	1302	98	1112	11
C106	70	1608	95	1419	10
C107	50	1372	100	1209	8.3
C108	90	1404	98	1400	5
C109	70	1692	100	1559	8

PCS: The percentage of customers served within their time window.

For all these instances, we were able to serve all customers, with a small average delay, and a smaller distance, which allowed the time required to reduce the travel time. In addition, the specificity of the pharmaceutical sector has been taken into consideration. The proposed method is very effective to meet urgent demands, by minimizing the appearance time of the dynamic requests and the start time of service. There is an improvement in results, the distance has been minimized compared to results of ACSLNS.

6. Conclusion

The total volume of medicines consumed globally will increase by about 3% annually through 2021. So, the pharmaceutical industry is of great interest and it must find new ways to keep this important industry growing. This paper has introduced a multiobjective variant of VRPSTW. The choice of treating the problem according to a multi-objective approach is due to their advantage to manage a vector of constraints, and to envisage an optimization according to several objectives. We have used the Pareto approach to solve the studied problem, which has the advantage of finding diversified solutions along the Pareto front. The proposed approach to solve the problem is based on a multiobjective local search, such that the solutions in the initial archive were obtained by the hybridization of the genetic algorithm and the VNS, which allowed to design a more powerful method. This paper took into consideration the characteristics of the studied problem, so, it can enrich the contributions in the pharmaceutical sector. Computational results show that the goals have been, by reducing the distance travelled and responding to dynamic customers as quickly as possible.

References

Affi, M., Derbel, H., & Jarboui, B. (2018).Variable neighborhood search algorithm for the green vehicle routing problem. *International Journal of Industrial Engineering Computations, 9*(2),195-204 .

Beasley, J.E. (1983) . Route-_rst cluster-second methods for vehicle routing. *Omega, 11*(4),403-408.

Bettinelli, A., Ceselli, A., & Righini, G. (2011). A branch-and-cut-and-price algorithm for the multi-depot heterogeneous vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies*, *19*(5), 723-740.

Bouziyane, B., Dkhissi, B., & cherkaoui, M.(2018). Solving a dynamic vehicle routing problem with soft time windows based on static problem resolution by a hybrid approach. *International Journal f Supply and Operations Management*, *5*(2), 134-151.

Bouchra, B., Btissam, D., & Mohammad, C. (2018, April). Multiobjective local search based hybrid algorithm for vehicle routing problem with soft time windows. In *International Conference on Big Data, Cloud and Applications*(pp. 312-325). Springer, Cham.

Campelo, P., Moreira, F.N., Amorim, P., & Almada-Lobo, B. (2019). Consistent vehicle routing problem with service level agreements: A case study in the pharmaceutical distribution sector. *European Journal of Operational Research, 273*(1), 131-145.

Chiang, W. C., & Russell, R. A. (2004) . A metaheuristic for the vehicle-routing problem with soft time windows. *Journal of the Operational Research Society,* 55, 1298–1310.

Deb, K., Pratap,A., Agarwal, S., & Meyarivan, T.(2002). A fast and elitist multiobjective genetic algorithm:NSGA-II . *IEEE Transactions on Evolutionary Computation*, *6*(2), 182-197.

Desrochers, M., Lenstra, J.K., Savelsbergh, M. W. S., & Soumis, F. (1988). Vehicle Routing with Time Windows: Optimization and Approxinmation, In B. Golden and A. Assad (eds.) *Vehicle Routing: Methods and Studies*, Amsterdam: Elsevier Science Publishers.

Dhahri, M., Zidi, k., & Ghedira, K. (2015). A Variable neighborhood search for the vehicle routing problem with time windows and preventive maintenance activities. *Electronic Notes in Discrete Mathematics*, *47*, 229-236.

Eglese, R., & Zambirinis, S. (2018). Disruption management in vehicle routing and scheduling for road freight transport: a review. *Top*, *26*(1), 1-17.

Figliozzi, M. A. (2010). An iterative route construction and improvement algorithm for the vehicle routing problem with soft time windows. *Transportation Research Part C: Emerging Technologies*, *18*(5), 668-679.

Fu, Z., Eglese, R., & Li, L. Y. (2008). A unified tabu search algorithm for vehicle routing problems with soft time windows. *Journal of the Operational Research Society*, *59*(5), 663-673.

Geiger, M.J. (2004). Randomized variable neighborhood search for multi objective optimization, *4th EU/ME: Design and Evaluation of Advanced Hybrid Meta-Heuristics*, 34-42.

Ghoseiri, K., & Ghannadpour, S. F. (2010). Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. *Applied Soft Computing*, *10*(4), 1096-1107.

Golden, B. L., & Assad, A. A. (1986). OR forum—perspectives on vehicle routing: exciting new developments. *Operations Research*, *34*(5), 803-810.

Golden, B. L., & Assad, A. A. (1988). *Vehicle Routing: Methods and Studies*. Amsterdam: Elsevier Science Publishers .

Hashimoto, H., Ibaraki, T., Imahori, S., & Yagiura, M.(2006). The vehicle routing problem with flexible time windows and traveling times . *Discrete Applied Mathematics*, *154*, 2271–2290.

Kaiwartya, O., Kumar, S., Lobiyal, D. K., Tiwari, P. K., Abdullah, A. H., & Hassan, A. N. (2015). Multiobjective dynamic vehicle routing problem and time seed based solution using particle swarm optimization. *Journal of Sensors*, Article ID 189832, 14 pages.

Kovacs, A. A., Parragh, S. N., & Hartl, R. F. (2015). The multi-objective generalized consistent vehicle routing problem. *European Journal of Operational Research*, *247*(2), 441-458.

De Magalhaes, J. M., & De Sousa, J. P. (2006). Dynamic VRP in pharmaceutical distribution—a case study. *Central European Journal of Operations Research*, *14*(2), 177-192.

Minocha, B., & Tripathi, S. (2011). Solution of time constrained vehicle routing problems using multi-objective hybrid genetic algorithm. *International Journal of Computer Sciences and Information Technologie*s, *2*, 2671-2676.

Moghadam, B.F., & Seyedhosseini, S.M. (2010).A particle swarm approach to solve vehicle routing problem with uncertain demand:A drug distribution case study. *International Journal of industrial Engineering Computations,1*(1),55-64.

Mu, Q., Fu, Z., Lysgaard, J., & Eglese, R. (2011) . Disruption management of the vehicle routing problem with vehicle breakdown. *Journal of the Opeational Research Society, 62*(4),742-749.

Najera , A.G., & Bullinaria, J.A. (2011). An improved multi-objective evolutionary algorithm for the vehicle routing problem with time windows. *Computers & Operations Research, 38(1*), 287-300.
Ombuki, B., Ross, B. J., & Hanshar, F. (2006). Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence*, *24*(1), 17-30.
Qiuyun, W., Wenbao, J., & Gang,Z. (2013). A novel model and algorithm for solving dynamic vehicle routing problem on goods distribution. *Journal of Applied Sciences, 13*(22), 5410-5415.
Ropke, S., Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickuo and delivery problem with time windows. *Transportation Sciences, 40*(4),455-472.
Salani, M., Battarra, M., & Gambardella, L. M. (2016). Exact algorithms for the vehicle routing problem with soft time windows. In *Operations Research Proceedings 2014* (pp. 481-486). Springer, Cham.
Setak, M., Azizi, V., Karimi, H., & Jalili, S. (2017). Pickup and delivery supply chain network with semi soft time windows: metaheuristic approach. *International Journal of Management Science and Engineering Management*, *12*(2), 89-95.
Shaw, P. (1998, October). Using constraint programming and local search methods to solve vehicle routing problems. In *International conference on principles and practice of constraint programming* (pp. 417-431). Springer, Berlin, Heidelberg.
Kumar, V. S., Thansekhar, M. R., Saravanan, R., & Amali, S. M. J. (2014). Solving multi-objective vehicle routing problem with time windows by FAGA. *Procedia Engineering*, *97*, 2176-2185.
Solomon, M. M., & Desrosiers, J. (1988). Survey paper—time window constrained routing and scheduling problems. *Transportation Science*, *22*(1), 1-13.
Sydneyta, V., & Komarudin, (2017) . Optimization of distribution route and schedule with vehicle routing problem with time windows (VRPTW) . *Proceedings of the 2017 International Conference on Industrial Design Engineering*, 121-126.
Teodor Dimitrov, B. (2016). A vehicle routing planning system for goods distribution in urban areas using google maps and genetic algorithm. *International Journal for Traffic & Transport Engineering*, *6*(2), pp 159-167.
Tricoire, F. (2012). Multi-directional local search. *Computers & Operations Research*, *39*, 3089–3101.
Wang, J., Zhou, Y., Wang, Y., Zhang, J., Chen, ,C. L. P ., Zheng, Z. (2016). Multiobjective Vehicle Routing Problems With Simultaneous Delivery and pickup and time windows: Formulation, instances, and algorithms. *IEEE Transactions on Cybernetics*, *46*(3)**,**582 – 594.
Yu, B., Yang, Z.Z., & Yao, B.Z.(2011). A hybrid algorithm for vehicle routing problem with time windows. *Expert Systems with Applications*, *38*, 435–441.