Multi-Objective Vehicle Routing Problem with Time Windows and Fuel Consumption Minimizing

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Abstract: Transportation often represents the most important single element in logistics costs and its reduction and finding the best routes that a vehicle should follow through a network is an important decision. the energy cost is a significant part of total transportation cost and it is important to improve the operational efficiency by decreasing energy consumption. Unlike most of the studies trying to minimize the cost by minimizing overall travelling distance, the energy minimizing which meets the latest requirements of green logistics, is considered in this paper. the customers' priority for servicing is considered as well. Besides, the model is interpreted as multi-objective optimization where, the energy consumed and the total fleet are minimized and the total satisfaction rates of customers is maximized. A new solution based on the evolutionary algorithm is proposed and its performance is compared with the CPLEX Solver. Results illustrate the efficiency and effectiveness of proposed approach.

1 INTRODUCTION

Transportation often represents the most important single element in logistics costs and to its reduction finding the best routes is an important decision problem. One of the most important and widely studied combinatorial optimization problems in this area is the vehicle routing problem with time windows (VRPTW). The literature of the VRPTW, due to its inherent complexities and usefulness in real life is rich in different models and solution approaches (Chiang & Hsu 2014, Blaseiro et al. 2011, Dhahri et al. 2014, Ghannadpour et al. 2014, Lin 2011, Mavrovouniotis & Yang 2015, Tan et al. 2006 and Feng & Liao 2014).

Although there are different forms of VRPTWs, most of them minimize the cost by minimizing the overall traveling distance or the traveling time. In fact, it is the amount of fuel or energy consumed, not the traveled distance that is the greater concern to transportation companies and meet the latest requirements of green logistics. Statistics show that energy cost is a significant part of total transportation cost (Xiao et al. 2012). in this regard, Tavares et al. (2008) took into account the effect of both road inclination and vehicle load on energy consumption in waste collection. Moreover, Bektaş and Laporte (2011) studied the pollution-routing problem (PRP) that in which the amount of pollution emitted by a vehicle is considered in depth. Minimizing the fuel consumption in VRPs is also considered by Gaur & Mudgal (2013) and Kara et al. (2007) with a new cost function and based on the results, the fuel consumption could be reduced by 5% on average. In this regards, Zhang et al. (2014) introduced an environmental vehicle routing problem (EVRP) with the aim of reducing the adverse effect on the environment and by using a hybrid artificial bee colony algorithm.

Besides, the proposed model in this paper is interpreted as multi-objective optimization problem. In real-life, for instance, there may be several costs associated with a single tour. For this reason, adopting a multi-objective point of view can be advantageous by determining the trade-offs between the objectives. In the multi-objective area, Tan et al. (2006) and Ombuki et al. (2006) proposed a hybrid multi-objective evolutionary algorithm (MOEA) for solving the multi-objective VRPTW. Tan et al. (2007) proposed a similar approach for VRP with stochastic demand. Ghannadpour et al. (2014) and Ghannadpour & Hooshfar (2015) solved Dynamic

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VRPTW as a multi-objective problem by GA. Other similar approach could be found in (Sivaram Kumar et al. 2014, Garcia-Najera & Bullinaria 2011 and Garcia-Najera et al. 2015). The remainder of this paper is organized as follows. Section 2 defines the model description. The structure of the solution technique is discussed in Section 3. Section 4 describes the computational experiments carried out to investigate the performance of the proposed method, and finally Section 5 provides the concluding remarks.

2 MODEL DESCRIPTION

The problem considered here is energy minimizing vehicle routing problem with time windows (VRPTW) as a multi objective optimization. VRPTW is given by a special node called depot, a set of customer $C = \{0, 1, 2, \dots, N\}$ to be visited and a directed network connecting the depot and the customers. Also a set of fleet $V = \{1, 2, \dots, K\}$ located at the depot is available. Each vehicle has a limited capacity (q_k) and each customer has a varying demand (m_i). A distance d_{ij} and travel time t_{ij} are associated with each arc of the network. On the other hand, any customer i must be serviced within a pre-defined time interval $[e_i, l_i]$. Each vehicle k is also supposed to complete its individual route within the total route time (r_k). The objective of the classical VRPTW is to serve all the customers such that the total distance traveled by the vehicles is minimized. But this paper, unlike most of the work those minimize the cost by minimizing overall traveling distance, tries to minimize the real cost of a vehicle traveling along a route. It has been recognized that the real cost of a vehicle in a network depends on many factors like load of vehicles, fuel consumption per mile, time spent or distance traveled up to visit a node, depreciation of vehicles, maintenance, driver costs and etc. Although energy consumption is largely determined by distance, other factors such as load also have a considerable impact on fuel costs. So, if the other factors are kept constant, the energy consumption then mainly depends on distance and load.

The classical cost function of VRPTW is as equation (1) and it should be modified as $Minimize\ f(Load, distance\ traveled)$ where *load* is the weight of the vehicle (tare plus the load of the vehicle) over each link (i, j).

$$Min\ \sum_{i=0}^{N} \sum_{j=0, j\neq i}^{N} \sum_{k=1}^{K} d_{ij} x_{ijk} \tag{1}$$

It should be noted that this cost function is mainly focused on energy consumption and it can be calculated based on the work done by a vehicle over a route (arc) of network. It is assumed the movement of vehicles is considered as an impending motion where the force causing the movement is equal to the friction force. So, a new objective function to minimize the work done by vehicles or the energy used (equivalent to fuel consumed by vehicles) is obtained and should be considered instead of classical cost function as follows:

$$Min\ \sum_{i=0}^{N} \sum_{j=0, j\neq i}^{N} \sum_{k=1}^{K} \left[\acute{\mu}_{ij} \times \left(u_i + tare_k \right) \times g \times d_{ij} \right] \times x_{ijk} \tag{2}$$

Where g is the acceleration of gravity ($9.81\ m/s^2$) and $\acute{\mu}_{ij}$ is the coefficient of friction on link (i, j). Moreover, u_i is the load of vehicle upon leaving customer i as follows: ($\forall\ j \in C \backslash \{0\}$)

$$\sum_{i=0, i\neq j}^{N} \sum_{k=1}^{K} \left(u_i + m_j \right) \times x_{ijk} = u_j \tag{3}$$

These new constraints and objective function are non-linear and should be approximated to liner equation. For this purpose a new variable u_{ij}^{k} is defined instead of u_i which means the load of vehicle k when moves from customer i to customer j. The linear formulation is described later.

The concept of customers' satisfaction proposed in our recent research (Ghannadpour & Hooshfar 2015) is also considered and developed here for different kinds of customers. In this paper the preference information of customers is represented as a fuzzy time windows as Fig.1. In this approach, every customers can be assigned by the expert to one of groups (e.g., important customers (C_C), casual (C_C) and etc.) where $C_C \cup C_I = C \backslash \{0\}$.

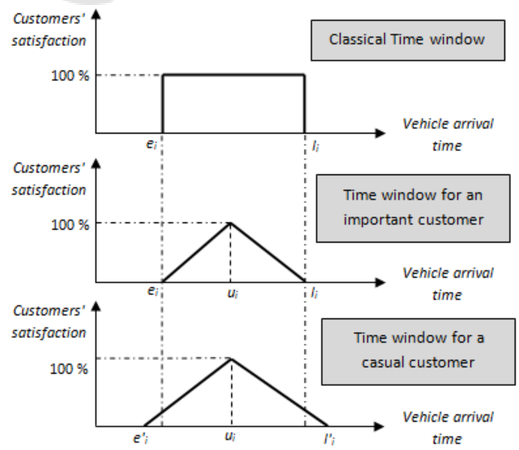

Figure 1: Conventional and fuzzy time window for each customer.

According to Fig. 1, the classical time window is changed to the triple $[e_i, u_i, l_i]$ and $[\acute{e}_i, u_i, \acute{l}_i]$ for important and casual customers. $\mu_i(t_i)$ is the membership function of customer i and shows the grade of satisfaction when the start of service time is t_i. The start time of service for each customer i is as $t_i = at_i + w_i$ where at_i and $w_i$are arrival and waiting time at customer i. Therefore a new objective function should be considered as $Max\ \sum_{i \in C \setminus \{0\}} PR_i \times \mu_i(t_i)$ where, PR_i is the importance degree of customer i.

The mathematical formulation of the proposed model is as follows:

$$Min\ \ f_1 = \sum_{j=0}^{N} \sum_{j=0, j \neq i}^{N} \sum_{k=1}^{K} (tare_k \times x_{ijk} + u_{ij}^k) \times d_{ij} \tag{4}$$

$$Min\ \ f_2 = \sum_{k=1}^{K} \sum_{j=1}^{N} x_{0jk} \tag{5}$$

$$Max\ \ f_3 = \sum_{i=1}^{N} PR_i \times \mu_i(t_i) \tag{6}$$

S.t:

$$\sum_{k=1}^{K} \sum_{j=1}^{N} x_{ijk} \leq K \qquad \forall\ i = 0 \tag{7}$$

$$\sum_{j=0, j \neq i}^{N} x_{ijk} = \sum_{j=0, j \neq i}^{N} x_{jik} \leq 1 \qquad \forall\ i \in C,\ \forall\ k \in K \tag{8}$$

$$\sum_{k=1}^{K} \sum_{i=0, i \neq j}^{N} x_{ijk} = 1 \qquad \forall\ j \in C \setminus \{0\} \tag{9}$$

$$at_0 = w_0 = f_0 = \mu_0(t_0) = t_0 = 0 \tag{10}$$

$$at_i + w_i + f_i + t_{ij} - (1 - x_{ijk})\, M \leq r_k \qquad \forall\ i \in C/\{0\},\ \forall\ k \in K,\ j = 0 \tag{11}$$

$$at_i + w_i + f_i + t_{ij} - (1 - x_{ijk})\, M \leq at_j \qquad \forall\ j \in C \setminus \{0\},\ \forall\ i \neq j \in C,\ \forall\ k \in K \tag{12}$$

$$\mu_i(t_i) = \left(\frac{(at_i + w_i) - e_i}{u_i - e_i}\right) * (1 - y_i) + \left(\frac{l_i - (at_i + w_i)}{l_i - u_i}\right) * y_i \qquad \forall\ i \in C_I \tag{13}$$

$$\mu_i(t_i) = \left(\frac{(at_i + w_i) - (e_i - \delta)}{u_i - (e_i - \delta)}\right) * (1 - y_i)\ + \left(\frac{(l_i + \delta) - (at_i + w_i)}{(l_i + \delta) - u_i}\right) * y_i \qquad \forall\ i \in C_C \tag{14}$$

$$(u_i - (at_i + w_i)) * y_i + ((at_i + w_i) - u_i) * (1 - y_i) < 0 \qquad \forall\ i \in C \setminus \{0\} \tag{15}$$

$$e_i \leq (at_i + w_i) \leq l_i \qquad \forall\ i \in C_I \tag{16}$$

$$e_i - \delta \leq (at_i + w_i) \leq l_i + \delta \qquad \forall\ i \in C_C \tag{17}$$

$$\sum_{j=0, j \neq i}^{N} \sum_{k=1}^{K} u_{ij}^k - \sum_{j=0, j \neq i}^{N} \sum_{k=1}^{K} u_{ji}^k = m_i \qquad \forall\ i \in C \setminus \{0\} \tag{18}$$

$$u_{ij}^k \leq q_k \times x_{ijk} \qquad \forall\ j \in C, \forall\ i \neq j \in C, \forall\ k \in K \tag{19}$$

$$x_{ijk} \in \{0,1\},\ u_{ij}^k \geq 0 \qquad \forall\ i, j \in C,\ \forall\ k \in K$$

Formulas (4-6) are the objective functions Formula (4-5) minimize total energy consumed and the total number of vehicles and formula (6) maximizes the total satisfaction rates of customers.

Constraint (8) secures maximum size of fleet. Constraints (8) and (9) define that every customer node is visited only once by one vehicle. Constraint (11) is the maximum travel time constraint. Constraints (12-17) define the arrival time, and the time windows for different kinds of customers. Constraints (13-15) compute the satisfaction level of each customer Constraints (13-15) are non-linear and they have relaxed to linear constraints. Constraint (18) indicates the load of vehicle after it visits a customer. Constraint (19) limits the maximal load carried by the vehicle and force u_{ij}^k to zero when $x_{ijk} = 0$.

3 SOLUTION METHOD

This section designs an efficient evolutionary method for tackling the proposed model that in which objectives are met and the constraints are satisfied. The proposed model is based on the conventional VRPTW which is NP-hard and should be tackled by heuristics. The evolutionary algorithms like GA have many advantages in finding an easy way of the solution representation and in implementation for multi objective models and ability of incorporation with the different operators that improve the solutions.

3.1 Representation

In this method each chromosome which is a solution to the problem, is represented by an integer string of length N. This string of customer identifiers represents the sequence of deliveries that must be covered by vehicles during their routes.

3.2 Pareto Ranking Procedure

The Pareto ranking procedure (Ghannadpour & Hooshfar 2015) which tries to rank the solutions to find the non-dominated solutions is used for evaluation of each chromosome. In this approach, chromosomes assigned rank 1 are non-dominated, and inductively, those of rank *i* +1 are dominated by all chromosomes of ranks 1 through *i*.

3.3 Population & Initialization

In this paper the method of PFIH (originally proposed by Solomon (1987)) is used to create the first chromosome. PFIH method defines the relation of $c_i = \alpha d_{0i} + \beta l_i + \gamma((p_i/360)d_{0i})$ to find the first customer in each new route where; d_{0i} is the distance from customer i to the central depot; l_i is the latest time and p_i is the polar coordinate angle of the customer i. Once the first customer is selected for the current route, the heuristic selects from the set of unrouted customers the one customer which minimizes the total insertion cost between every edge in the current route without violating the time and capacity constraints.

3.4 Selection

This paper uses a standard k-tournament selection where a tournament set of size *k* is randomly drawn from the population and the chromosome with a lower rank is selected and will then be recombined via the recombination operators to create potential new population.

3.5 Recombination

This paper uses the modified best cost-best rout crossover (BCBRC), which selects a best route from each parent and then for a given parent, the customers in the chosen route from the opposite parent are removed. The final step is to locate the best possible locations for the removed customers in the corresponding children.

3.6 Local Search

The local search (LS) is employed as mutation to the child chromosome with a probability $p_{mutation}$. This paper uses a λ-interchange mechanism as local search method that moves customers between routes to generate neighborhood solution for the proposed. Given a feasible solution for the model represented by $S = \{R_1, \dots, R_p, \dots, R_q, \dots, R_k\}$ where R_p is a set of customer served by vehicle route p. A λ-interchange between a pair of routes R_p and R_q is a replacement of subset $S_1 \subseteq R_p$of size $|S_1| \leq \lambda$ by another subset $S_2 \subseteq R_q$ of size $|S_2| \leq \lambda$, to get the new route sets $\acute{R_p}$, $\acute{R_q}$ and a new neighbouring solution $\acute{S} = \{R_1, \dots, \acute{R_p}, \dots, \acute{R_q}, \dots, R_k\}$ where $\acute{R_p} = (R_p - S_1) \cup S_2$ and $\acute{R_q} = (R_q - S_2) \cup S_1$. The neighbouring $N_\lambda(S)$ of a given solution S is the set of all neighbors $\{\acute{S}\}$ generated by the λ-interchange method for a given λ. In one version of the algorithm called GB (global best), the whole neighborhood is explored and the best move with lower rank is selected. In another version, FB (first best), the first admissible improving move is selected if exists; otherwise the best admissible move is implemented. In this paper 1-interchange (FB) or 2-interchange (GB) is employed to the child chromosome with the special probability.

4 COMPUTATIONAL ANALYSIS

In this section, since there is no any prior work on the proposed model, a set of complete randomly generated instances with different size (N) is considered as numerical examples. In the first step, the validity of new mathematical formulation for small and medium instances are implemented by CPLEX Solver separately (with a time limit of 2 hours) and the results are analyzed. Finally, the quality of proposed evolutionary method is evaluated. In this step the instances with larger size are considered and the results obtained by the proposed method and CPLEX Solver are analyzed.

4.1 Mathematical Modelling

Table 1 presents a summary of results obtained by CPLEX Solver when the single objective energy minimizing VRPTW is considered. The column labeled “with classical cost function” gives the findings of VRPTW when it tries to minimize the total distance travelled by vehicles (distance oriented); column “with new cost function” gives the findings of model when it tries to minimize the total energy consumption (fuel oriented). For each instance, the vehicles' total traveling distance (indicated by Dis.) and the related fuel consumption (indicated by Related FC) are calculated when the distance-oriented model is implemented. Moreover, the fuel consumption (FC) and the related traveling distance (Related Dis.) are also obtained by fuel-oriented model. The times marked with an asterisk show the time limit of 2 hours for the CPLEX Solver and the solver is interrupted after this time. For some instances there is no integer solution up to this time limit.

It can be observed from Table 1 that for the small/medium – scale instances, the FC obtained by fuel oriented model is on average 5.6% lower than the obtained by distance oriented model but with a 10.6% increase in distance traveled. In other words, by 10.6% increase in distance traveled, the fuel cost which is a significant part of total transportation cost can be reduced by 5.6%. It should be noted that the choice of any solutions (fuel & distance oriented) depends on the DM's preference.

Table 1: VRPTW with fuel consumption by CPLEX Solver.

Instance	N	With classical cost function		
		Dis.	CPU t. (Sec.)	Related FC.
1	4	115.3760	0.2030	2847.909
2	5	140.1070	0.2180	2427.428
3	10	226.6523	2.8750	4392.852
4	12	303.2485	13.359	6106.863
5	15	321.6250	37.765	9817.879
6	20	497.100	7200*	14827.87
7	30	--------	7200*	--------
8	40	--------	7200*	--------
Ave.		221.4018		5118.586
Instance	**N**	**With new cost function**		
		Dis.	CPU t. (Sec.)	Related FC.
1	4	2438.131	0.0541	138.152
2	5	2393.459	0.0620	156.523
3	10	4382.368	2.0150	228.777
4	12	5933.309	17.357	340.049
5	15	9220.890	69.531	376.166
6	20	--------	7200*	--------
7	30	--------	7200*	--------
8	40	--------	7200*	--------
Ave.		4873.631		247.9334
Dev. (%)	FC dev. : -5.57 / Dis dev. : 10.64			

4.2 Analysis of Proposed Method

In this section, the quality of proposed evolutionary method is evaluated. In this step the instances with larger size are considered and the results obtained by the proposed method and CPLEX Solver are analyzed. The results of Mathematical Model are found by using the weighting method as follows:

$$Minimize \quad w^1 \times \left(\frac{f_1}{f_1^{max}}\right) + w^2 \times \left(\frac{f_2}{f_2^{max}}\right) - w^3 \times \left(\frac{f_3}{f_3^{max}}\right) \qquad (20)$$

Where, w^i is the weight of objective function f_i estimated by DM and$\sum_i w^i = 1$ and the objective functions f_i are calculated according to relations (4-6). The proposed heuristic is coded and run on a PC with Core 2 Duo CPU (3.00 GHz) and 2.9 GB of RAM. Moreover, the model is implemented under parameters of Population size = 30 - 100, Generation number = 500-1000, Crossover rate = 0.80, Mutation rate = 0.40, Selection rate of improvement operators = 0.5. It must be mentioned that the population size and the generation number is adopted with the problem size.

It should be noted that the Repetition of experiments is 10 runs. Table 2 presents the average and best values (among the non-dominated solutions) of proposed method over 10 runs and to the finding of CPLEX Solver.

Table 2: Average and best results over 10 experiments.

N	h – ave			h – best		
	$\overline{FC}$	$\overline{K}$	$\overline{Sat}$	FC^b	K^b	Sat^b
10	4424.69	6.0	25.20	4382.37	6	26.00
15	9845.04	6.6	33.20	9308.00	6	36.00
20	14520.1	8.1	49.50	14345.3	8	54.00
30	19150.3	12	78.40	18009.1	12	79.00
40	29308.4	16.8	103.8	25542.8	16	105.0
70	59805.0	15	117.0	50231.1	15	120.0
100	83063.7	18.6	260.5	75654.6	18	270.0

N	Deviation (%)					
	$D^{\overline{FC}}$	$D^{\overline{K}}$	$D^{\overline{Sat}}$	D^1	D^2	D^3
10	0.960	0.00	3.08	0.0	0	0
15	5.450	9.09	7.78	0.9	0	0
20	1.200	1.23	8.33	-1.6	0	0
30	5.960	0.00	0.76	---	---	---
40	12.85	4.76	1.14	---	---	---
70	16.01	0.00	2.50	---	---	---
100	8.920	3.23	3.52	---	---	---
Ave.	7.340	2.62	3.87	-0.2	0	0

The column labeled "$h-ave$" gives the total average findings of proposed heuristic over 10 runs and it is divided into three columns where the each of them represents the average of each objective function (indicated by $\overline{FC.}$, $\overline{K}$ and $\overline{Sat}$); column " $h-best$ " gives the best results of each objective function obtained by proposed heuristic over 10 experiments (indicated by FC^b, $K^b$and Sat^b). Deviation between the average and best results of proposed heuristic are listed in the columns labeled $D^{\overline{FC}}, D^{\overline{K}}$ and $D^{\overline{Sat}}$. Moreover, D^i $(i=1,2,3)$ represents the deviation between the best value of objective function f_i obtained by proposed heuristic over 10 runs and the best value found by the CPLEX Solver. It should be noted that the listed values of deviations represents the amount of difference between the best and average results of proposed method over 10 experiments and could illustrate the consistency and reliability of results. Moreover the deviations between the best results of proposed method and CPLEX Solver represents the quality of obtained results and the negative value represent the amount of improvements obtained by the proposed approach.

According to this table we can see the results obtained from proposed method are rather consistent and the average deviations over 10 experiments are lower than 8%. Moreover, the average difference between the best values of proposed method and CPLEX Solver illustrates the improvement of 0.2% in the first objective for the first three instances and for the others the CPLEX Solver cannot find any solution in a reasonable amount of computational time.

In general, the relationship between these defined objectives is unknown until the problem is solved in a proper multi-objective manner. These objectives may be positively correlated with each other or they may be conflicting to each other. According to the results, the customers' satisfaction rate is improved as the total fuel consumed is deteriorated. Moreover, the waiting time imposed on vehicles is increased in these instances due to get the better satisfaction rate of customers. These behaviours for the 7th instance of Table 6 are illustrated in Fig.2.

The different behaviour is observed for the total fuel consumption and the required fleets. They are positively correlated with each other in some instances like instance #3 and they are conflicting to each other in others (like instance #2). By adding a vehicle to the schedule, the load of vehicles could be decreased along a route but the total distance travelled by vehicles may be increased or decreased and it is related to the geographical location and time windows of customers [15]. So by increasing the number of vehicles the load of vehicles is decreased and when the distance cost of solution is changed in the opposite direction, the total fuel consumed by vehicles is decreased. On the other hand, in the instance 3, although adding a vehicle provides a schedule with a lower load of vehicles for each route, the distance cost is much higher than that of the basic model. Therefore the total fuel consumed by all fleets is increased.

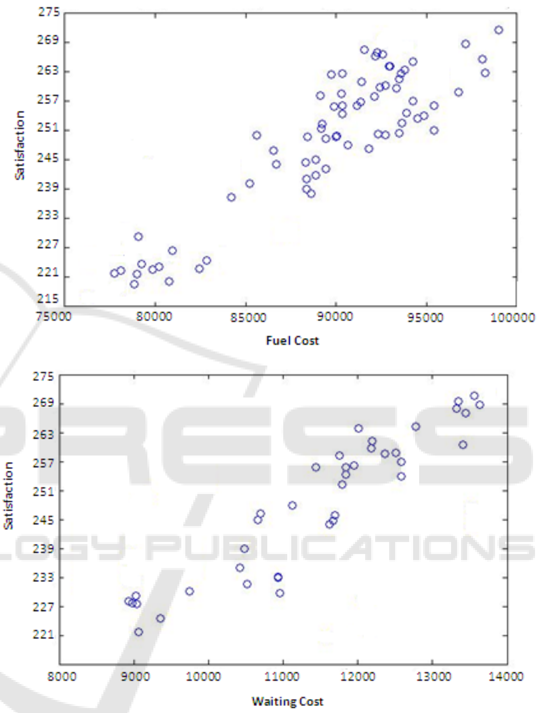

Figure 2: Population distribution of the 7th instance.

5 CONCLUSION

This paper presented a new model and solution for the multi-objective vehicle routing and scheduling problem with considering the fuel consumption rate. Moreover, this paper considered the customers' priority according to customer-specific time windows, which are highly relevant to the customers' satisfaction level.

Besides, the proposed model was interpreted as multi-objective optimization problem and a new solution based on the evolutionary algorithm was proposed. the performance on several completely random generated instance problems was compared with the CPLEX Solver. The results show the efficiency and effectively of proposed method.

It should be noted that the proposed model is very compatible with the constraints of reality and it is under implementation for locomotives routing and assignment for railway transportation division of MAPNA Group. In this model the trains are considered as customers and they are made up at different stations of network and they need to receive locomotive based on the time table of train scheduling. Moreover, the locomotives are located at some central depots and they depart toward the trains to move them from their origins to their destinations based on the train scheduling plan. One sample of train scheduling plan is illustrated in Fig.3. In this case, the trains with low priorities are considered to be having the classical time windows. Moreover, the trains with highly priority have the fuzzy time windows and the desired time is nearest to the earliest dispatching time of each train.

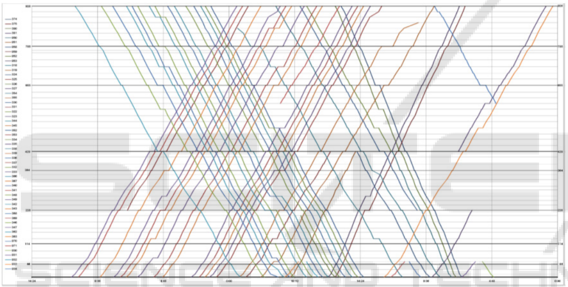

Figure 3: Typical train scheduling plan.

Moreover, the detailed schedule of each locomotive including the departure time, trains in its commitments, planned routes, waiting times, fuel consumption cost and etc is corresponding to the routes found by the proposed VRPTW and they are identified for this route.

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