Dynamic Vehicle Routing Solution in the Framework of Nature-Inspired Algorithms

Chapter · December 2015

DOI: 10.4018/978-1-4666-9720-1.ch003

Omprakash Kaiwartya
Nottingham Trent University

Sushil Kumar
Jawaharlal Nehru University

Mukesh Prasad
University of Technology Sydney

Designing and Implementing Global Supply Chain Management

Sudhanshu Joshi
School of Management, Doon University, India

Rohit Joshi
Indian Institute of Management IIM, Shillong, India

A volume in the Advances in Logistics, Operations, and Management Science (ALOMS) Book Series

BUSINESS SCIENCE Reference
An Imprint of IGI Global

Published in the United States of America by
Business Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Names: Joshi, Sudhanshu, editor. | Joshi, Rohit, 1975- editor.
Title: Designing and implementing global supply chain management / Sudhanshu Joshi and Rohit Joshi, editors.
Description: Hershey, PA : Information Science Reference, [2016] | Includes bibliographical references and index.
Identifiers: LCCN 2015042004| ISBN 9781466697201 (hardcover) | ISBN 9781466697218 (ebook)
Subjects: LCSH: Business logistics. | Business logistics--Data processing.
Classification: LCC HD38.5 .D4665 2016 | DDC 658.5--dc23 LC record available at http://lccn.loc.gov/2015042004

This book is published in the IGI Global book series Advances in Logistics, Operations, and Management Science (ALOMS) (ISSN: 2327-350X; eISSN: 2327-3518)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

All work contributed to this book is new, previously-unpublished material. The views expressed in this book are those of the authors, but not necessarily of the publisher.

For electronic access to this publication, please contact: eresources@igi-global.com.

Chapter 3
Dynamic Vehicle Routing Solution in the Framework of Nature-Inspired Algorithms

Omprakash Kaiwartya
Universiti Teknologi Malaysia, Malaysia

Sushil Kumar
Jawaharlal Nehru University, India

Pawan Kumar Tiwari
Jawaharlal Nehru University, India

Mukesh Prasad
National Chiao Tung University, Taiwan

ABSTRACT

Vehicle Routing Problem (VRP), a well-known combinatorial optimization problem had been presented by Dantzing and Hamser in 1959. The problem has taken its inspiration from the transport field. In real field environment, a lot of variants of the problem exist that actually belongs to the class of NP-hard problem. Dynamic Vehicle routing problem (DVRP) is one of the variant of VRP that varies with respect to time. In DVRP, new customer orders appear over time and new route must be reconfigured at any instantaneous time. Although, some exact algorithms such as dynamic programming methods, branch and bound etc. can be applied to find the optimal route of a smaller size VRP. But, These Algorithms fail to give the solution of existed model of VRP in real field environment under given real time constraints. Courier services, dial a ride services and express mail delivery etc. are the few examples of real field environment problems that can be formulated in the form of DVRP. In this chapter, A novel variants of DVRP named as DVRP with geographic ranking (DVRP-GR) has been proposed. In DVRP-GR, geographical ranking, customer ranking, service time, expected reachability time, customer satisfaction level have been optimized. A solution of DVRP-GR using seed based particle swarm optimization (S-DVRS-PSO) has been also proposed. The simulations have been performed using customized simulator developed in C++ environment. The data sets used in the simulations are OMK-01, OMK-02 and OMK-03 generated in real vehicular environment. The solution of the proposed algorithm has been compared with the randomized solution technique. Analysis of the simulation results confirms the effectiveness of the proposed solution in terms of various parameters considered viz. number of vehicles, expected reachability time, profit and customer satisfaction.

DOI: 10.4018/978-1-4666-9720-1.ch003

INTRODUCTION

Recently, Intelligent Transport System (ITS) has diversified the application area of Dynamic Vehicle Routing Problem (DVRP) enormously. E-commerce, print media, medical, public transportation, oil sector are only few examples (Golden, Raghavan, & Wasil, 2008). DVRP is an extension of traditional Vehicle Routing Problem (VRP) in terms of complexity. The traditional VRP can be symbolically stated on a connected network $N^C = \left(N_S, C_S, C_m\right)$, where $N_S = \left\{n_0, n_1, n_2, n_3, \ldots, n_n\right\}$ indicates the set of nodes; $C_s = \left\{\left(n_i, n_j\right), n_i, n_j \in N_s \ and \ i \neq j\right\}$ represents the set of connections and $C_m = C_m\left(i, j\right)_{\left(n_i, n_j\right) \in C_S}$ denotes communication cost matrix defined over C_S. Traditionally, the node n_0 is the central depot from where all the vehicles start and end their services. The remaining nodes of N_S denotes the customers spread over geographically distinct locations. The VRP is nothing but finding a set of routes for a given set of vehicles such that each vehicles visit the customers exactly once and overall travel cost of the vehicles should be minimum (Lin, Choy, Ho, Chung, & Lam, 2014). An example of traditional VRP has been illustrated in Figure 1. The central depot has four delivery vehicles to serve the demands of four customers. According to the availability of the routes, the routes for delivery vehicles have been planned.

Due to the recent technological advances in real time communication, the shape of VRP has been changed as DVRP (cf. Figure 2). A number of variants of VRP have been explored as DVRP by incorporating different set of constraints in traditional VRP (Pillac, Gendreau, Guéret, & Medaglia, 2013). The most common variants have been illustrated following.

Figure 1. The traditional Vehicle Routing Problem (VRP)

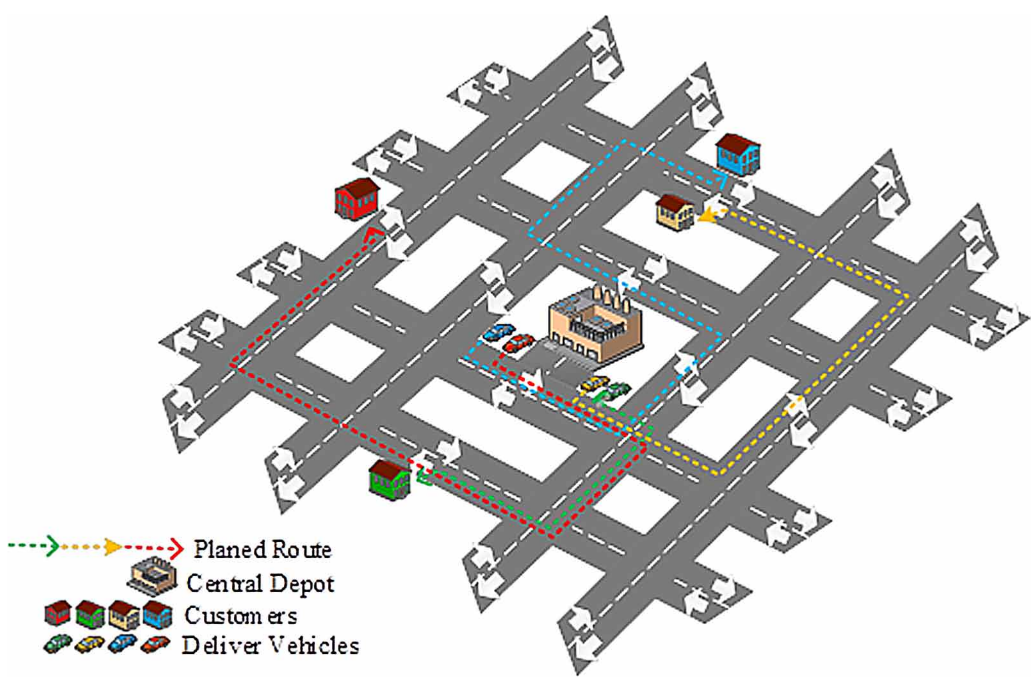
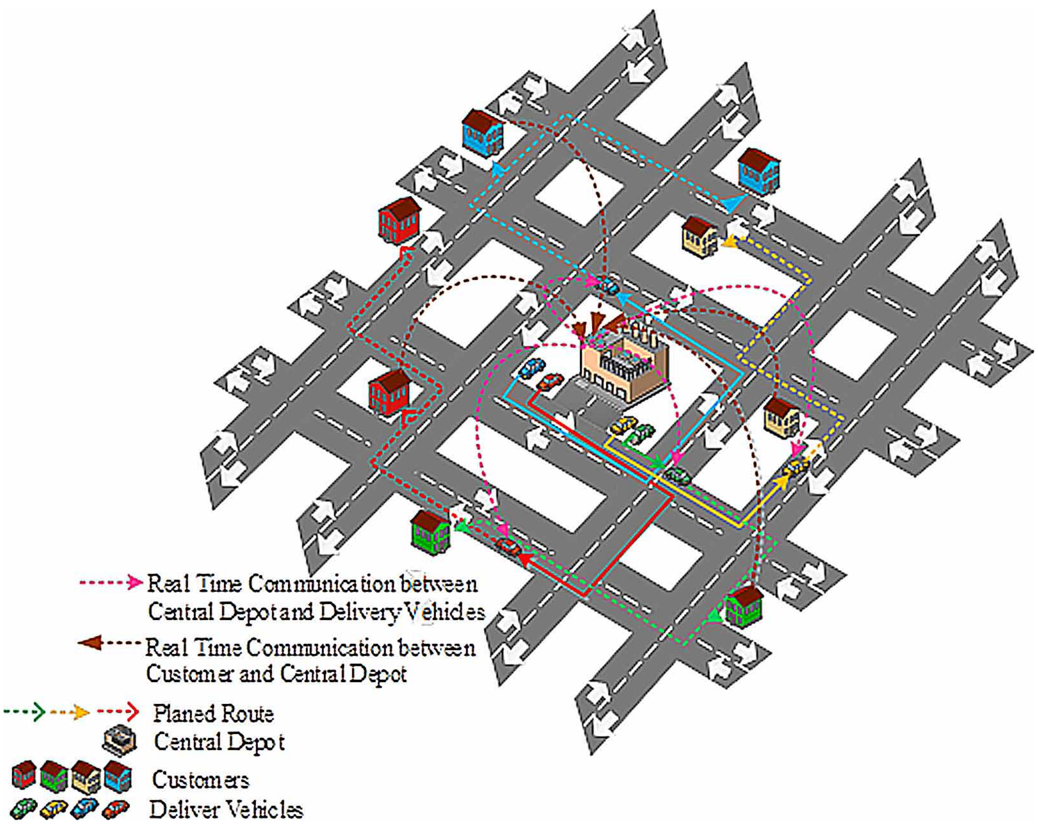


Figure 2. Dynamic Vehicle Routing Problem (DVRP)



1. **VRP with Pick and Delivery (VRP-PD):** A given set of goods have to be transported from some pick-up locations to the delivery locations. It means, no central depot for vehicles is required.
2. **Capacitated VRP (C-VRP):** Vehicles with pre-specified but same goods carrying capacity.
3. **Heterogeneous VRP (H-VRP):** Vehicles with pre-specified but different goods carrying capacity.
4. **VRP with Last-In-First Out (VRP-LIFO):** The items that have been picked up most recently must be the items that have to be delivered in the next delivery locations.
5. **VRP with Time Window (VRP-TW):** Each delivery locations must be visited during a pre-specified time interval.
6. **Open VRP (O-VRP):** The vehicles are not required to return to the central depot after visiting all the assigned customers.
7. **Dial A Flight VRP (DAF-VRP):** Public transport through airline has been also studied as one of the variants of VRP.
8. **Dial A Ride VRP (DAR-VRP):** The normal public transport problem.
9. **VRP with Multiple Trips (VRP-MT):** The vehicles can take more than one delivery tour once it finishes the assigned tour.

An example of DVRP has been illustrated in Figure 2. Due to real time communication among central depot, new customers and delivery vehicles, the VRP of Figure 1 has been converted into DVRP. The planned route of all the four delivery vehicles depicted in the VRP (cf. Figure 1) has been changed dynamically due to real time communication of dynamic request.

Considering large number of customers, the optimal solution of the above mentioned DVRPs cannot be obtained within reasonable time due to NP-hard nature of the problems (Savlesbergh, 1985). In the last ten years, various nature inspired meta-heuristic techniques have been applied to solve the customized instances of the above mentioned DVRPs. Genetic Algorithm (GA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PCO) are the most commonly used techniques for the solution of the above DVRPs (Lau, Chan, Tsui, & Pang, 2010; Xing, Rohlfshagen, Chen, & Yao, 2011; Goksal, Karaoglan, & Altiparmak, 2013). Nowadays, these techniques have been also gaining popularity in Vehicular Adhoc Networks (VANETs) (Kaiwartya, & Kumar, 2014) and high performance computing (Tiwari, & Vidyarthi, 2014). These techniques have been described below in terms of algorithmic steps.

1. **Genetic Algorithms Based Solution [10]:**
   a. Population of size N is created from the search space through a random process.
   b. Each member of the population represents a solution and is termed as chromosome in traditional GA.
   c. Fitness of each chromosome is evaluated in the reference of our concerned objective function.
   d. Best chromosomes are selected from the population for producing the off-springs, which transfers the best genetic properties of population to next generation. The process of production of off-springs is termed as cross-over in GA.
   e. Generate new members through mutation process.
   f. Repeat the steps 3 to 5 till the termination criteria is not satisfied
2. **Ant Colony Optimization Based Solution [11]:**
   a. Deploy a random number of ants in the concerned system, whose solution is required.
   b. Each Ant travels in the system for constructing the solution. Move of each step of ant is determined by some probabilistic rule. A complete path of an ant represents a solution. The probabilistic rule combines the prior and posterior information in the journey of ants
   c. Evaluate the fitness of the path constructed by the ants in reference to the objective function
   d. Ant secrets pheromone while travelling through a route. The route, used by more ants have higher amount of pheromones.
   e. Utilize the best experiences of ancestors by adjusting the amount of pheromones.
   f. Repeat the steps 2 to 6 till the termination criteria is not satisfied
3. **Particle Swarm Optimization Based Solution [12]:**
   a. Generate N random solutions in the search space termed as particles. Each particle is represented by a vector of two components. The first component of the vector represents position of the particle and second component represents velocity of the particle.
   b. Evaluate the fitness of each particle in reference to the objective function.
   c. Update the position and velocity of particles through the rules optimization.
   d. Repeat the step 2 to 3 till the termination criteria is not satisfied.

In this chapter, a new variation of DVRP has been proposed by incorporating a novel constraint Geographic Ranking (GR) of requests in customer request vector. The proposed DVRP with geographic ranking (DVRP-GR) has request vector with four components namely urgency, profit, geographic ranking and delivery time window. Divide and conquer approach has been used to solve DVRP-GR. Each request of the customer has been processed by evaluating the four components of the request vector.

The rest of the sections of the chapter are organized as follows. In section 2, some early and recent developments in VRP and DVRP have been described. The details of DVRP-GV and it seed based solution approach has been discussed in section 3. In section 4, performance evolution and result analysis has been presented. Finally, we conclude the work presented in this chapter in section 5.

EARLY AND RECENT DEVELOPMENTS IN VRP AND DVRP

The VRP was first proposed by Dantzig and Ramser in 1959. The authors optimized the routing of a fleet of gasoline delivery trucks between a bulk terminal and a large number of service stations supplied by the terminal. They have used linear programming formulation for obtaining near optimal solution (Dantzig, & Ramser, 1959). After the induction, VRP has been one of the challenging are of research that has witnessed consistent attention of the researchers from industries and academia. The research contribution can be categorized into two dimensions: probabilistic optimization and static optimization. In probabilistic optimization, the components of the problem such as demand, number of customer, service time are considered as future events and probabilistic models have been used to predict the future behavior of these components. In static optimizations, available information about the components has been considered without including future behavior of the components. Some of the most recent works in DVRP have been studied following. Multi objective dynamic vehicle routing problem with fuzzy travel times and customers' satisfaction in supply chain management has been suggested in (Ghannadpour, Noori, & Tavakkoli-Moghaddam, 2013). The authors have investigated fuzzy time window and fuzzy travel time in depth for the VRP. The travel distance, number of vehicles and waiting time of vehicles has been minimized as well as the satisfaction rate of customers has been minimized. A set based discrete particle swarm optimization approach for optimizing vehicle routing problem (S-PSO-VRPTW) with time window has been described in (Gong, Zhang, Liu, Huang, Chung, & Shi, 2012). The solution approach selects an optimal subset from the universal set and subsequently solves the selected subset problem. The authors have derived new mathematical formulations for velocity and position update in discrete PSO. A fitness function for candidate solution evaluation has been also formulated. The line haul feeder vehicle routing problem with virtual depots has been presented in (Chen, Chou, Hsueh, & Ho, 2011). Feeder vehicle and virtual depot concepts have been introduced by the authors. Travel distance and waiting time for vehicles have been minimized using heuristic cost sharing methods. A patrol routing algorithm has been constructed in (Steil, Pate, Kraft, Smith, Dixon, Li, & Parrish, 2011) for police, ambulance and taxi services. The algorithm has been explored in terms of expression, execution, evaluation and engagement. A Domain Specific Language (DSL) Turn has been used to express the algorithm. PatrolSim, a custom simulator has been used for the execution of the algorithm. Response time, network coverage and hotspot coverage metrics have been used for the evaluation of the algorithm. A web based Geographic Information System (GIS) portal, CAPS Maps has been used for end user engagement of the algorithm. Multi depot Capacitated Arc Routing Problem (MCARP) has been introduced in (Xing, Rohlfshagen, Chen, & Yao, 2010). An evolutionary approach has been constructed by integrating some classical heuristics into a canonical evolutionary framework. The near optimum MCARP solution has been used to learn two distinct kinds of heuristic information. The evolutionary process has been guided by this heuristic information. Arc guided evolutionary algorithm for solving vehicle routing problem with time window has been developed in (Repoussis, Tarantilis, & Ioannou, 2009). In the population, individuals have been represented using arcs so that evolution strategy can be adapted to the VRP-TW.

Ruin and recreate principle has been used for mutation process. A trajectory local search algorithm has been developed to minimize distance. A route elimination procedure has been also suggested. Moreover, VRP has always been in the full attention of researchers. Salvelsbergh shows that even Vehicle routing problem with time window (VRPTW) problem with a fixed number of vehicle is a NP-complete problem (Savlesbergh, 1985).

DVRP WITH GEOGRAPHIC RANKING AND SEED BASED SOLUTION

In this work, a different aspect of DVRP has been considered by incorporating a novel constraints geographical ranking of request. The proposed DVRP with Geographic Ranking (DVRP-GR) can be symbolically presented as a connected network $N^C = \left(N_S, C_S, C_m, C_v\right)$, where $N_S = \left\{n_0, n_1, n_2, n_3, \ldots, n_n\right\}$ indicates the set of nodes; $C_s = \left\{\left(n_i, n_j\right), n_i, n_j \in N_s \ and \ i \neq j\right\}$ represents the set of connections, $f_4 = Max \sum_{l=1}^{N_C} SL\left(ERT_j\right) \cdot CPF_l^{wt}$ denotes communication cost matrix defined over C_S and constraint vector $C_v = \left\{C_1, C_2, C_3, C_4\right\}$ is the four constraints attached with each request. The DVRP in this consideration is nothing but finding a set of routes for a given set of vehicles such that optimizes both C_m and C_v. In some of the earlier VRP it has been assumed that each customer wants their corresponding service in strict hard time window and as a consequence of this the customer provides its satisfaction values in binary digit i.e. 0 or 1. This means that either the customer is fully satisfied or he rejects it in totality. But it is not seen practically in real time scenario. As well as, this assumption has also been seen as a big hurdle in DVRP. For creating a mathematical model for DVRP we will seek some kind of flexible Time window, in which a customer will be ready to accept the delivery by saying that it's all right in relaxed time window. Basically as soon as a customer enters in the system he sends its relevant information to the central depot through VANETs communication technology (Rao, Soni, Singh, & Kaiwartya, 2014; Kumar, Kumar, Shukla, Raw, & Kaiwartya, 2014; Kaiwartya, & Kumar, 2014 ; Gupta, & Kaiwartya, 2014; Kaiwartya, & Kumar, 2014; Kaiwartya, Kumar, & Kasana, 2013; Kaiwartya, & Kumar, 2013; Kaiwartya, Kumar, Lobiyal, Abdullah, & Hassan, 2014; Kaiwartya, & Kumar, 2015). Each customer request is a vector length five as given in Table 1.

Once a request reaches to the central depot system, it will immediately generate a new order vector for each customer request of length six. The order vector is given in Table 2.

The description of each of the component of order vector is as follows.

Table 1. Customer request

Q	PLDT	PUDT	STIL	STIU	ECPUT

Q= Quantity of Item.
PLDT= preferred lower limit for delivery time.
PUDT= preferred upper limit for delivery time.
STIL= Satisfactory time interval for PLDT.
STIU= Satisfactory time interval for PUDT.
ECPUT=Extra cost on per-unit item paid by the i-th customer.

Table 2. Order vector

GR	CR	ST	ERT	SL	PF

GR=Geographical ranking of the system.
CR=Customer Ranking .
ST=Service time of the request.
ERT=Expected Reachability Time .
SL=Satisfaction level of the request.
PF=Profit from the request.

Geographical Ranking of the Customers

The geographical ranking is not only dependent on the distance (Dist.) of the customer from the central depot but it is an implicit complex functions of many variables such as facility of Road Networks (RN)/ Average Density of Request (ADR)/ Safety and Reliability (SR) of the area. A vector of length four is associated with each request by central depot. The components of the geographical ranking (GR) vector and corresponding weighting parameters have been described in Table 3.

Consideringα as weighting parameter, the constraint $\sum_{i=1}^{|v_{GR}|} \alpha_i = 1$ always holds. The GR of a request can be calculated as

$$Gr = \frac{\sum_{i=1}^{4} \alpha_i r_i}{|v_{GR}| - 1} \tag{1}$$

and thus, each request has been geographically ranked between 0 to 1.

Customer Ranking

The customers can be categorized into the following categories: Very Important Customer (VIC), Important Customer (IC), Regular Customer (RC) and Casual Customer (CC). The system provides a minimum guaranteed satisfactory level for requested service to VIC considering the profit factor offered to the system by VIC. Consequently, VIC always demands the service in very strict time window. Although the IC also has smaller time window but the system can provide the service in the maximum possible relax-able time window to IC. RC is usually beneficial to the system in long run, so system also tries the best possible service in flexible time window. CC comes to the system randomly and their demands are not credible to the system. Based on their doubtable credibility, the system delivers the demands of CC whenever they have been found on the route of other customer's categories. The categorization of customers, their ranking and guaranteed satisfactory level (GSLS) has been described in Table 4.

Table 3. Geographical ranking vector

ADR	Dist.	RN	SR
(0.5)	(0.2)	(0.1)	(0.2)

Table 4. Guaranteed satisfactory levels

Types	VIC	IC	RC	CC
Rank	4	3	2	1
GSLS	1	.75< and <1	.5< and <.75	0=< and <.5

Service Time

The quantity of demand and type of items are the two major factors for service time of a request from the customers. Once the order of demands has been reached to the customer, the time spent on delivering the order to the customers is known as service time of the request. Service time has been determined by the central depot system on the receipt of a request from the customers in real time fashion.

$$ST = \sum_{i=1}^{N_{item}} \frac{q_i^n I_i}{S_i^r} \tag{2}$$

q_i^n is the quantity if item and I_i is the type of item and S_i^r is the service rate of item.

Expected Reachability Time

The average time required to reach an on-road delivery vehicle to the requested customer is called Expected Reachability Time (ERT). It depends on a previously defined components namely, GR of the order vector. If the customer belongs from the highly ranked geographical area then the ERT will be less. ERT of a request can be calculated as

$$ERT = \frac{\left|GP_{curr}^{v} - GP^{C}\right|}{S_{avg}^{v} GR_{wt}} \tag{3}$$

where, GP_{curr}^{v} is the current geographical position of vehicle, GP^{C} is the geographical position of customer, S_{avg}^{v} is the average speed of vehicle and GR_{wt} is the weightage of geographical ranking.

Satisfaction Level

The delivery of service up to the customer's expectation is the notion of satisfaction level (SL) for a particular request. It is function with domain ERT and range [0,1]. It is expressed as

$$SL(ERT) = \begin{cases} 0, (ERT < PLDT - STIL) or (ERT > PUDT + STIU) \\ 1, PLDT << ERT << PUDT \\ \dfrac{ERT - (PLDT - STIL)}{STIL}, (PLDT - STIL) < (ERT < PLDT) \\ \dfrac{(PUDT + STIU) - ERT)}{STIL}, PUDT < ERT < (PUDT + STIU) \end{cases} \tag{4}$$

Now, all the components of order vector has been defined and formulated. The objective function of the proposed DVRP-GR has been expressed as

$$Max\left(\frac{1}{f_1},\frac{1}{f_2},f_3,f_4\right) \tag{5}$$

where, each of the functions is defined as follows.

$$f_1 = Min\left(N_v\right) \tag{6}$$

$$f_2 = Min\sum_{i=1}^{N_v}\sum_{j=1}^{N_C}\sum_{k=1}^{N_C} ERT_{jk}\chi_{jk}^{i} \tag{7}$$

$$f_3 = Max\sum_{j=1}^{N_C} PF_j \tag{8}$$

$$f_4 = Max\sum_{j=1}^{N_C} SL(ERT_l)\cdot CPF_l^{wt} \tag{9}$$

where, N_v is the number of vehicles and N_c is the number of customers. The χ_{jk}^{i} is the characteristic function expressed as

$$\chi_{jk}^{i} = \begin{cases} 1, i^{th}\ vehicle\ goes\ from\ j^{th}\ customer\ to\ k^{th}\ customer \\ 0, otherwise \end{cases} \tag{10}$$

And CPF_l^{wt} is weight of preference of customer expressed as

$$CPF_l^{wt} = \frac{GR_l + CR_l}{Max\left\{GR_l + CR_l, i = 1,2,3\ and\ j = 1,2,3,4\right\}} \tag{11}$$

The various constraints of the multi objective optimization functions have been listed below. The vehicle constraint states that only one vehicle can be assigned to a customer. The vehicle constraint can be expressed as

$$\sum_{i=1}^{N_v}\sum_{j}^{N_C}\chi_{jk}^{i} = 1, k = 1,2,3,\ldots,N_C \tag{12}$$

The capacity constraint states that each vehicle has a given capacity and a vehicle could not deliver the demands of customers excessing its capacity. The capacity constraint can be expressed as

$$\sum_{j}^{N_C}\sum_{k}^{N_C}\chi_{jk}^{i}\cdot d_k^{C} << C_h, i = 1,2,3,\ldots,N_v \tag{13}$$

The reachability constraint states that the difference of ERT between two successive customers must be greater than or equal to the sum of service time of the previous customer and the travel time between the customers. The reachability constraint can be expressed as

$$\chi_{jk}^{i}\left(ERT_{j}^{i}+t_{jk}+ST_{r}\right)<<\chi_{jk}^{i}\cdot ERT_{j}^{i},r,s=1,2,3,\ldots,N_{C}\ and\ i=1,2,3,\ldots,N_{v} \tag{14}$$

A novel approach, Seed based Dynamic Vehicle Routing Solution (S-DVRS) has been proposed for solving the above discussed DVRP-GR. In S-DVRS, the complete DVRP has been divided into number of smaller and feasible component DVRPs. Consequently, the complete time horizon of the each DVRP has been divided into number of smaller time seeds. The duration of time seeds in a particular DVRP is based on degree of dynamism in a given component DVRP. Higher degree of dynamism in DVRP requires smaller time seeds. The above solution approach can be represented as

$$N^{C}=\begin{cases}Connection\ Component\left(N_{i}^{C},i=1,2,3,\ldots,n\right)\\ and\ time\ horizon\ of\ ith\ component\ T_{i}=\sum_{j=1}^{S}t_{j}^{S}\end{cases} \tag{15}$$

The each $N_{dr}^{i}=\left(0-N_{C}^{i}\right)$, *i*=1, 2, 3,…, *n* has been solved using time seed based Particle Swarm Optimization division method (S-DVRS-PSO). For each time seeds set of demand vector is created that represents a particle in PSO. The set of demand vector is optimized by using optimization function Equation (5) as fitness function of the proposed PSO. The complete algorithm is shown in Algorithm 1.

Algorithm 1. Algorithm-S-DVRS-OPS

Notations:
N^C: Connected network graph
Nv: Number of vehicles
Nsr: Number of static request
CRV: Customer request vector
OV: Order vector
GR: Geographical ranking
CRK: Customer ranking vector
N_i^C : Number of customers in i^{th} partition of network
N_{dr}^i : Number of dynamic request in i^{th} partition of network
gbest: Global best solution in terms of OV
lbest$_i$: Local best solution in i^{th} partition of network
Input: $N^C\left(N_S,C_S,C_m,C_v\right),N_v,N_{sr}$
Process:
1. ***Initialize*** a connected network $N^C\left(N_S,C_S,C_m,C_v\right)$.
2. $N_v=r\ and\ (100-200)\ and\ N_C=N_S\ and\ N_{sr}=r\ and\left(0-N_C\right)$

continued on following page

Algorithm 1. Continued

3. ***For*** i=1 to N_{sr}
4. ***Generate*** CRV (Q, $PLDT$, $PUDT$, $STIL$, $STIU$, $ECPUT$) randomly
5. ***End for***
6. Generate population of particles as OV
7. ***For*** i=1 to N_{sr}
7. ***Generate*** GR vector (ADR, $Dist.$, RN, SR) randomly and calculate Gr using equation (1)
8. ***Generate*** CRK vector (VIC, IC, RC, CC) randomly and assign weight according to ranks
9. ***Calculate*** ST using equation (2)
10. ***Calculate*** ERT using equation (3)
11. ***End for***
11. $gbest=OV$
12. ***Partition*** $N^C\left(N_S, C_S, C_m, C_v\right)$ into k subgraphs as $N^C = \bigcup_{i=1}^{k} N_i^C$
13. **For** i=1 to k
14. $N_{dr}^i = \left(0 - N_C^i\right)$
15. ***Generate*** N_{dr}^i number of dynamic request vector (Q, $PLDT$, $PUDT$, $STIL$, $STIU$, $ECPUT$)
16. ***Generate*** population of particle as order vector OV
$lbest_i=OV$
17. ***While*** (time horizon for f_4 does not elapse)
18. ***Update*** position and velocity by updating values of each element of OV
19. ***Check*** fitness of particles using optimization function equation (5)
20. ***Update*** $gbest$ by comparing $lbest_i$
21. ***End while***
22. ***End for***
23. ***Return*** $gbest$

Output: $gbest$.

PERFORMANCE EVALUATION AND RESULT ANALYSIS

The customized simulator developed in c++ environment has been used to evaluate the performance of S-DVRS in solving DVRP-GR. In order to test the performance of our proposed algorithm we have generated three random data sets viz. OMK-01, OMK-02 and OMK-03. These dataset can be found in (Kaiwartya, www.kaiwartya.com). The time horizon considered for the data sets is twenty three hours (6 AM to 5 AM in the next morning). In other words we can say that time horizon lies in the closed time interval [0, 1380] minutes. In this chapter, we have only considered whether the Pareto based solution generated by the proposed algorithm covers the solution achieved by randomized algorithm considering only one objective function while keeping others as constant. In the Table 5, comparison of our proposed S-DVRS with randomized algorithm has been depicted.

Table 5. Simulation results

Data Set	Function	S-DVRS-PSO	Randomized Solution			
			$N_v^R = N_v^{SDP}$	$N_v^R = \lceil 1.5N_v^{SDP} \rceil$	$N_v^R = \lceil 1.8N_v^{SDP} \rceil$	$N_v^R = \lceil 2N_v^{SDP} \rceil$
OMK-01	f_1^{-1}	0.024	0.024-	0.016	0.014	0.012
	f_2^{-1}	0.00095	0.00072	0.00072	00072	0.0010
	f_3	105U	15U	25U	40U	28U
	f_4	0.71	0.23	0.35	0.49	0.72
OMK-02	f_1^{-1}	0.018	0.018	0.012	0.010	0.009
	f_2^{-1}	0.00117	0.00078	0.00088	0.00105	0.00116
	f_3	137U	52U	72U	85U	65U
	f_3	0.74	0.43	0.53	0.58	0.67
OMK-03	f_1^{-1}	0.036	0.036	0.024	0.020	0.018
	f_2^{-1}	0.00082	0.00072	00072	0.00072	0.00081
	f_3	86U	8U	13U	21U	40U
	f_4	0.66	0.19	0.27	0.36	0.58

The results depicted in Table-1 show that the solution provided by the proposed algorithm is found to be competitive enough as compared to the solution provided by the randomized algorithm. It is also noteworthy that our algorithm considers all the objective functions of DVRP-GR model concurrently whereas single objective has been considered in other algorithms. This can be attributed to the fact that a lot of dynamic features such as GR, CR, Dynamic traffic hazards and so forth have been considered in the proposed S-DVRS model that could not be tested with the existing VRP or modified-VRP data sets. Additionally in randomized solution, by increasing number of vehicles two time $N_v^R = \lceil 2N_v^{SDP} \rceil$ as compared to S-DVRS-PSO, the randomized solution come close to the proposed solution in terms of SL but the profit earned by the proposed model is far better than the compared randomized solution. In near future, the full capability of our proposed algorithm will be rigorously tested and compare with recent nature inspired algorithms.

CONCLUSION AND FUTURE WORK

In this chapter, a novel variation of DVRP has been developed by incorporating geographical ranking. The proposed DVRP is called DVRP with Geographical Ranking (DVRP-GR). The seed based particle swarm optimization solution S-DVRS-PSO for the proposed DVRP-GR has been also proposed. DVRP-GR along with its solution S-DVRS-PSO could be useful in various delivery services such as logistics, courier, e-commerce and so forth. The proposed S-DVRS-PSO provides better solution the considered DVRP-GR in terms of number of vehicles, expected reachability time, profit and user satisfaction level as compare to the randomized solution.

In future research, the authors will incorporate enhance the customized simulator developed for DVRP-GR. The incorporation of Geographical Ranking (GR) module to other existing DVRP will also be a challenge for us. The comparison of other DVRP integrated with GR with the proposed DVRP-GR will be also performed.

REFERENCES

Chen, H. K., Chou, H. W., Hsueh, C. F., & Ho, T. Y. (2011). The Line haul Feeder Vehicle Routing Problem With Virtual Depots. *Automation Science and Engineering*. *IEEE Transactions on*, *8*(4), 694–704.

Colorni, A., Dorigo, M., & Maniezzo, V. (1991). Distributed Optimization by Ant Colonies. In *Actes de la première conférence européenne sur la vie artificielle* (pp. 134–142). Paris, France: Elsevier Publishing.

Dantzig, G. B., & Ramser, J. H. (1959). The Truck Dispatching Problem. *Management Science*, *6*(1), 80–91. doi:10.1287/mnsc.6.1.80

Ghannadpour, S. F., Noori, S., & Tavakkoli-Moghaddam, R. (2013). Multiobjective Dynamic Vehicle Routing Problem With Fuzzy Travel Times and Customers' Satisfaction in Supply Chain Management. *Engineering Management*. *IEEE Transactions on*, *60*(4), 777–790.

Goksal, F. P., Karaoglan, I., & Altiparmak, F. (2013). A hybrid discrete particle swarm optimization for vehicle routing problem with simultaneous pickup and delivery. *Computers & Industrial Engineering*, *65*(1), 39–53. doi:10.1016/j.cie.2012.01.005

Golden, B. L., Raghavan, S., & Wasil, E. (2008). *The vehicle routing problem: latest advances and new challenges*. Springer Publication. doi:10.1007/978-0-387-77778-8

Gong, Y. J., Zhang, J., Liu, O., Huang, R. Z., Chung, H. S. H., & Shi, Y. H. (2012). Optimizing the Vehicle Routing Problem With Time Windows: A Discrete Particle Swarm Optimization Approach. *Systems, Man, and Cybernetics, Part C: Applications and Reviews*. *IEEE Transactions on*, *42*(2), 254–267.

Gupta, K., & Kaiwartya, O. (2014). Dynamic Ad Hoc Transport Protocol (D-ATP) for Mobile Ad Hoc Networks. In *Proceedings Confluence 2014*. IEEE.

Holland, J. H. (2007). *Adaptation in Natural and Artificial Systems*. University of Michigan Press.

Kaiwartya, O. (n.d.). *Wireless Communication Research lab*. Retrieved from www.kaiwartya.com

Kaiwartya, O., & Kumar, S. (2013). Enhanced Caching for Geocast Routing in Vehicular Ad-Hoc Networks (ECGR). In *Proceedings International Conference on Advanced Computing, Networking, and Informatics (ICACNI)*. Springer.

Kaiwartya, O., & Kumar, S. (2014). GeoPSO: Geocasting through Particle Swarm Optimization in Vehicular Adhoc Networks. In *Proceedings of Information Systems and Design of Communication (ISDOC)*. ACM.

Kaiwartya, O., & Kumar, S. (2014). Cache Agent based Geocasting (CAG) in VANETs. *International Journal of Information and Communication Technology*.

Kaiwartya, O., & Kumar, S. (2014). Geocast Routing: Recent Advances and Future Challenges in Vehicular Adhoc Networks. In *Proceedings of Signal Processing and Integrated Networks (SPIN)* (pp. 291–296). IEEE. doi:10.1109/SPIN.2014.6776965

Kaiwartya, O., & Kumar, S. (2015). Guaranteed Geocast Routing Protocol for Vehicular Adhoc Networks in Highway Traffic Environment. *Wireless Personal Communications*, *83*(4), 2657–2682. doi:10.1007/s11277-015-2562-4

Kaiwartya, O., Kumar, S., & Kasana, R. (2013). Traffic light based time stable geocast (T-TSG) routing for urban VANETs. In *Proceedings Contemporary Computing (IC3), Sixth International Conference on*. IEEE.

Kaiwartya, O., Kumar, S., Lobiyal, D. K., Abdullah, A. H., & Hassan, A. N. (2014). Performance improvement in geographic routing for vehicular Ad Hoc networks. *Sensors (Basel, Switzerland)*, *14*(12), 22342–22371. doi:10.3390/s141222342 PMID:25429415

Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings of IEEE International Conference on Neural Networks IV*. doi:10.1109/ICNN.1995.488968

Kumar, R., Kumar, S., Shukla, D., Raw, R. S., & Kaiwartya, O. (2014). *Geometrical Localization Algorithm for Three Dimensional Wireless Sensor Networks. In Wireless Personal Communications*. Springer. doi:10.1007/s11277-014-1852-6

Lau, H. C. W., Chan, T., Tsui, W. T., & Pang, W. K. (2010). Application of Genetic Algorithms to Solve the Multidepot Vehicle Routing Problem. *Automation Science and Engineering*. *IEEE Transactions on*, *7*(2), 383–392.

Lin, C. H., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2014). Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications*, *41*(4), 1118–1138. doi:10.1016/j.eswa.2013.07.107

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, *225*(1), 1–11. doi:10.1016/j.ejor.2012.08.015

Rao, R. S., Soni, S. K., Singh, N., & Kaiwartya, O. (2014). A Probabilistic Analysis of Path Duration Using Routing Protocol n VANETs. *International Journal of Vehicular Technology,* 10.

Repoussis, P. P., Tarantilis, C. D., & Ioannou, G. (2009). Arc-Guided Evolutionary Algorithm for the Vehicle Routing Problem With Time Windows. *Evolutionary Computation*. *IEEE Transactions on*, *13*(3), 624–647.

Savlesbergh, M. (1985). Local search for routing problem with time windows. *Annals of Operations Research*, *4*(1), 285–305. doi:10.1007/BF02022044

Steil, D. A., Pate, J. R., Kraft, N. A., Smith, R. K., Dixon, B., Li, D., & Parrish, A. (2011). Patrol Routing Expression, Execution, Evaluation, and Engagement. *Intelligent Transportation Systems*. *IEEE Transactions on*, *12*(1), 58–72.

Tiwari, P. K., & Vidyarthi, D. P. (2014). Observing the effect of interprocess communication in auto controlled ant colony optimization-based scheduling on computational grid. In *Concurrency and Computation: Practice and Experience*. Wiley.

Xing, L., Rohlfshagen, P., Chen, Y., & Yao, X. (2010). An Evolutionary Approach to the Multidepot Capacitated Arc Routing Problem. *Evolutionary Computation*. *IEEE Transactions on*, *14*(3), 356–374.

Xing, L. N., Rohlfshagen, P., Chen, Y. W., & Yao, X. (2011). A Hybrid Ant Colony Optimization Algorithm for the Extended Capacitated Arc Routing Problem. *Systems, Man, and Cybernetics, Part B: Cybernetics*. *IEEE Transactions on*, *41*(4), 1110–1123.