A THREE-PHASE ALGORITHM FOR SOLVING A FLEET SIZE AND MIX VEHICLE ROUTING PROBLEM WITH TIME WINDOWS UNCERTAIN DEMANDS

Kusuma Soonpracha
Department of Industrial Engineering
Kasetsart University
E-mail : soonpracha@gmail.com

Assoc. Prof. Dr.Anan Mungwattana
Department of Industrial Engineering
Kasetsart University
E-mail : fenganm@ku.ac.th

Asst. Prof. Dr.Tharinee Manisri
Department of Industrial Engineering
Sripatum University
E-mail : tharinee.ma@spu.ac.th

บทคัดย่อ

งานวิจัยนี้มุ่งเน้นการศึกษาปัญหาใหม่ซึ่งเป็นปัญหาเฉพาะของปัญหาการจัดเส้นทางเดินรถขนส่งแบบมีรถหลายขนาดแบบทั่วไป โดยเพิ่มขอบเขตของข้อจำกัดด้านกรอบระยะเวลา และความต้องการของลูกค้าเป็นแบบไม่แน่นอน โดยขั้นตอนวิธีที่นำเสนอเพื่อใช้ในการแก้ปัญหา คือ ขั้นตอนวิธีแบบสามเฟส โดยเทคนิคหลักประกอบด้วย ขั้นตอนวิธีเชิงพันธุกรรมแบบปรับปรุง ขั้นตอนวิธีแบบสองขั้นโดยประยุกต์ใช้การสุ่มเพื่อทำการรวมและแยกเส้นทาง และขั้นตอนการตัดสินใจเพื่อหาคำตอบเชิงทนทานบนพื้นฐานของสถานการณ์ที่เลวร้ายที่สุด ทั้งนี้สมรรถนะของผลเฉลยเชิงทนทานใช้การประเมินโดยตัวชี้วัด คือ ต้นทุนเพิ่มเติม และความต้องการที่แท้จริง นอกจากนี้ผลเฉลยเชิงกำหนดที่ได้จากการแก้ปัญหาด้วยวิธีการที่นำเสนอ ได้นำไปเปรียบเทียบกับผลลัพธ์ของนักวิจัยท่านอื่นซึ่งชี้ให้เห็นความมีประสิทธิภาพของขั้นตอนวิธีที่นำเสนอ

คำสำคัญ: ความทนทาน ปัญหาการจัดเส้นทางเดินรถขนส่งแบบมีรถหลายขนาดภายใต้กรอบระยะเวลา ความต้องการไม่แน่นอน ขั้นตอนวิธีเชิงพันธุกรรมแบบปรับปรุง ขั้นตอนวิธีการค้นหาแบบแทรก

ABSTRACT

This paper is aimed at studying a new problem which is a specific problem of organizing the mixed-size vehicle routing system, with the additional variants of time windows constraint under uncertain customer demands. A methodology of three-phase algorithm is proposed for solving this particular problem. The major techniques consist of a modified genetic algorithm, a two-step of random route merging and splitting operation, and a robustness decision making based on the worst case scenarios operation. The performance of the robust solution is evaluated by using the extra cost, the unmet demand against the deterministic approach. Moreover, the deterministic solution obtained from the proposed scheme yields the good result after being compared with the previous outcomes presented by the other researchers.

KEYWORDS: Robustness, Fleet size and mix vehicle routing problem with time windows, Uncertain demand, Modified genetic algorithm, Insertion search algorithm.

INTRODUCTION

A vehicle routing problem (VRP) and its variants are still growing in research areas but the most interesting topics in which a lot of researchers put the effort to develop new methodology for solving a problem are a homogeneous vehicle fleet type, i.e. only one single type of vehicles with the same capacity, under the certain variables. In practice, the vehicle routing problem (VRP) deals with a heterogeneous vehicle fleets more than with a single fleet type, and is restricted by some business constraints and some transportation regulations such as the limited truck zones with special times, vehicle sizes, gross vehicle weights, etc. Moreover, the real world vehicle routing problems usually include the uncertain factors such as customer demands, travelled times, etc. that effect a route planning. These extensions make the problems more complex and are much harder to solve than the classical VRP.

This paper has been emphasized on developing a renew methodology to solve a fleet size and mix vehicle routing problem with time windows (FSMVRPTW) under uncertain customer demands. The FSMVRPTW is one of the specific problems of the classical vehicle routing problems in which more than the single kind of the vehicles are composed and the vehicle fleet has to be assigned to start the services within the time permissions. The route assignments have to be planned under the assumption of the demand uncertainty that causes the solutions for future are difficult to describe precisely. Therefore, the authors propose the robustness approach in robust decision making for solving this specific vehicle routing problem.

The further details of the problems, the literature review, the proposed methodology, the computation results, and the conclusions are discussed in next sections.

LITERATURE REVIEW

The previous work of Soonpracha et al. (2014) has been reviewed the heterogeneous vehicle routing problems and constructed an overview problem structure which puts a special emphasis on robustness approach. The problem variants of each VRP classification are presented in the table matrix. The abbreviations of the problems and the variants as shown in Table 1 - 2 are consisting of HFVRPs: heterogeneous fleet vehicle routing problems; FSMVRPs: fleet size and mix vehicle routing problems; RVRP: robust vehicle routing problem; RFSTF: Robust Fleet Sizing Transport Freight; SVRP: Stochastic vehicle routing problem; MD: Multi-depot; SD: Split deliveries; and TW: Time windows.

The problem objective depends upon the research scope of the researchers. The total transportation cost is the most favorite. The major cost components make compost of the fixed vehicle cost and the variable cost. The en route time travelled is focused when the problems deal with time windows constraint. The unmet demand and the total time delay are found in few studies in which the problems contain the non-deterministic data.

Resulting from the literature review indicates that most researchers put emphasis on seek the heuristic and metaheuristic algorithms to solve these specific problems. The summarization of the methodologies that are applied for the fleet size and mix vehicle routing problems and the variants, the heterogeneous fleet vehicle routing problems and the variants, and the stochastic and the robust vehicle routing problems, and the related research studies are summarized in the Table 1 - 2.

Manisri (2009) proposed the robust solution of a vehicle routing problem (VRP) with uncertain travel times. The probability scenario-based approach is used to find the robust solution. The results are strongly against perturbation of travel times but not cover on uncertain demands.

PROBLEM DESCRIPTION

The fleet size and mix vehicle routing problem with time windows (FSMVRPTW) is a specific problem of the classic vehicle routing problems. The problem formulations used in this paper are based on the models as proposed by Amico et al. (2007), Belfiore and Fแvero (2007), Bräysy et al. (2008) and Repoussis and Tarantilis (2010). The problem is initiated from the assumption that there are unlimited number of available vehicles (Baldacci et al., 2007). The fleet with different types of vehicles, are composed in order to serve all customers' uncertain demand di, that is particular for this paper.

Alike other general capacitated VRPs, each truck can carry a maximum of its capacity. Every route of the vehicle fleet must be started at the single depot, linked to the other assigned customer(s), and ended a loop by returning to the depot. The depot is determined the time interval restriction. When a truck arrives at a customer, it is allowed to begin the unloading services within the time windows of such customer. In the case of a truck arriving early, the useless activity is considered as waiting time (Dullaert et al., 2002).

In each route, two types of cost are considered for the total transportation cost, a fixed acquisition cost and a variable cost. The fixed acquisition cost is depended upon a vehicle of type. The variable cost is the cost of traveling between the destinations. The symmetry and deterministic properties are imposed for the travel distance and the travel time. Further, a unit of distance is assumed to be equaled to one and has the same unit of the travel time (Dullaert et al., 2002). The time windows are stated of being constrained in this case, assume the variable cost equals to the total time spending along the determined route. The total time spending is computed by considering three types of usage time consisting of 1) traveling time between a pair of nodes, 2) service times and 3) waiting time that can occur only if the truck arrives the customer before the permitted earliest time.

Table 1 Methodology approach for the fleet size and mix vehicle routing problems and the variants.

Year	Researchers	Problem
1996	Osman and Salhi	FSMVRP
• Route perturbation procedure and tabu search		
1997	Salhi and Sari	FSMVRPMD
• A multi-level (p-level) composite heuristic		
1999	Liu and Shen	FSMVRPTW
• Modified combined savings and opportunity salvings		
1999	Gendreau et al.	FSMVRP
• Generalized insertion and unstringing and stringing, tabu search using sweep and adaptive memory procedure		
2002	Dullaert et al.	FSMVRPTW
• Adapted combine savings, adapted optimistic opportunity savings, adapted realistic opportunity savings		
2002	Renaud and Boctor	FSMVRP
• Sweep-based algorithm approach and suborders of 1-petal, 2-petal, petals selection procedures		
2002	Wassan and Osman	FSMVRP
• New variants of tabu search mixed with reactive tabu search concepts, variable neighborhoods		
2007	Amico et al.	FSMVRPTW
• Insertion-based parallel approach and the RR paradigm		
2007	Belfiore and Fávero	FSMVRPTW
• Scatter search approach		
2008	Bräysy et al.	FSMVRPTW
• Multi-restart deterministic annealing algorithm		
2009	Baldacci and Mingozzi	FSMVRP and FSMVRPMD
• Exact algorithm based on the set partitioning formulation		
2009	Belfiore and Yoshizaki	FSMVRPTWSD
• Scatter search approach		
2009	Brandäo	FSMVRP
• Deterministic tabu search algorithm (incorporating generalized insertion and some neighborhood reductions)		
2009	Bräysy et al.	FSMVRPTW
• Hybrid metaheuristic approach for 3-phase: an efficient and well-scalable metaheuristic		
2009	Liu et al.	FSMVRP
• GA based heuristic, applies a mutation local search		
2009	Prins	FSMVRP
• Two memetic algorithms:- genetic algorithms hybridized with a local search and distance measure		
2010	Repoussis and Tarantilis	FSMVRPTW
• Adaptive memory programming solution approach, semi-parallel construction heuristic, and tabu search		
2011	Penna et al.	FSMVRP
• Hybridized heuristic based on iterated local search with a random neighborhood ordering		
2011	Subramanian et al.	FSMVRP
• Iterated local search based heuristic and a set partitioning		

Table 2 Methodology approach for the robust and stochastic vehicle routing problems and the related research studies.

Year	Author	Problem
2009	Janssens et al.	VRPTWST
• Project network concept, time considering		
2009	Sӧrensen and Sevaux	RVRP
• Memetic algorithm with population management		
2009	Sungur et al.	RVRP
• Modified Miller-Tucker-Zemlin formulation wit exact algorithm		
2009	Yin et al.	Road Network under demand uncertainty
• Sensitivity based, scenario-based and min-max		
2009	Zhu et al.	RVRPTWSD
• Considering the minimax approach across all scenarios		
2010	Moghaddam et al.	RVRP
• Exact algorithm based on Miller-Tucker-Zemrin and branch and cut procedure for small problem size, ant colony optimization		
2011	Aguirre et al.	SVRP
• Exact formulation:- MILP-based approach		
2011	Manisri et al.	RVRPTW
• Push-forward insertion heuristic, local search and tabu search		
2012	Goodson et al.	SVRP
• Cyclic-order neighborhoods in a simulated annealing framework		
2012	Moghaddam et al.	RVRP
• Advanced particle swarm optimization algorithm		
2014	Janssens et al.	RVRPTW
• Push forward insertion heuristic, the λ-local search method		

In the general problem, not yet the robustness case, the objective function of the FSMVRPTW may consider three components, 1) fixed acquisition cost, 2) variable traveling cost and 3) waiting time and/or service time. In this paper, the FSMVRPTW is the total summation of the fixed cost obtained from vehicle fleet composition acquisition and the sum of total times spending including waiting times.

In this paper, the term "robustness" refers to the solution robustness in which the obtained solution remains close to optimal for all scenarios. The specific definition of the robustness is applied the definitions as definited by Kouvelis and Yu (1996), Manisri et al. (2011), and Moghaddam et al. (2010). A scenario is a set of customer demands realizations, Ud. A whole system S is a combination of individual scenario s_n where $\forall s \in S$. A scenario s_i is a representation of a system in which the customers' demands are uncertain by the impact of individual customer's behavior based on risk aversion $(\beta^s \alpha^s)$. In this work, a scenario is a set of uncertain customers' demands Ud, modeled as $Ud_i = (1+\beta^s \alpha^s)\, d_0$ where i = 1, 2,..., n; d_0 is an expected demand of customer i, and s $\in$ S. A mathematical formulation for the RFSMVRPTW belongs to the FSMVRPTW but the customer demand (d_i) is replaced by the set of uncertain demand (Ud) model as modified (Moghaddam et al., 2010).

As presented in the robust handbook of Kouvelis and Yu (1996), this concept is applied in some research such as Zhu et al. (2009) and Manisri et al. (2011). In this research, the robust decision making framework is adapted the concept of Kouvelis and Yu (1996) but the final result is evaluated against the deterministic approach (Sungur et al., 2008). Thus it can balance between the expensive cost when a robust approach is applied and the unmet need when the deterministic approach has to suffer if the worst case happens. Even this research assumption considers the uncertain input variables, the robust discrete optimization is suggested by using the minimax criterion to reduce the complexity of the problems. The minimax criterion is one of the worst case approaches (Kouvelis and Yu, 1996).

The proactive robustness approach is focused in this paper that is to benefit in long run planning by hedging against all scenarios. The absolute robustness is one of the proactive robustness approaches that is applied for RFSMVRPTW. The absolute robust decision is defined as the one that minimizes the maximum total cost, among all feasible decisions over all realizable input data scenarios.

The main uncertainty to this RFSMVRPTW concentrates on the customer demands. The demands vary over a pre-specified planning horizon. Thus, the fleet and routing designs are decided over a long period of time for reducing the impact on the system effectiveness. It means that the solutions obtained from the decision making are good enough for a variety of future operating scenarios and this is referred to the robustness term (Janssens et al., 2009). The objective function of RFSMVRPTW is to minimize the maximum total cost of FSMVRPTW is in placed by the absolute robustness as shown in Equation (1). The robust objective function is subject to the constraints as common used in the fleet size and mix vehicle routing problems where the total summation of the fixed cost obtained from vehicle fleet composition acquisition and the sum of total times spending including waiting times are demonstrated in the first and second term, respectively. The comprehensive meaning of the robust optimization objective is to obtain a solution of the total transportation cost that is good for all possible data uncertainty and hedge against the worst case.

$$ZA(RFSMVRPTW) = min_{X,Y} max_{s \in S} (\sum k \in K \, fk \sum j \in N x_{0j}^{k})$$
$$k \in Kyn + 1, k - y0, k \qquad (1)$$

SOLUTION APPROACH

In this paper, the RFSMVRPTW under uncertain demands has been solved using three major phases of heuristic and metaheuristic algorithms. The first phase is to build an initial solution. A solution improvement is performed in the second phase. The last phase is a process of the robustness decision making in which based on worst case scenarios.

Phase I: Initial solution construction.

In this first phase, an initial solution of the FSMVRPTW is constructed using a modified genetic algorithm (mGA) hybridized the route insertion operation. A population is constructed by generating gene for each chromosome based on random permutation. The lower bound of VRPTW fleet cost is calculated and used for guiding the program to build the multi-tour. The total cost fitness function which is composed by two main components, i.e. the sum of total fixed cost obtained from vehicle fleet composition acquisition and the sum of total times spending including waiting times. If any single route of the FSMVRPTW tours is violates the time windows or the vehicle capacity constraints, then the operation of local insertion search is activated.

In the evolution operation, the population pair is matched by random permutation. The fitness of the pair genes are compared and selected the better performance as to be the parents and child for producing a new generation. The genetic operation consists of two major processes, crossover and mutation. The crossover operation is performed with order-based one-point crossover. The procedure of the mutation operation is designed to generate a random number for selecting a pair-gene index to perform swap operation. By believing that the best solution can heal the weak cells, the program applies the elitism concept by memorizing the best solution. After the solutions have been generated for several generations, the best solution will take place either a randomized solution or the worse solution. According to this assumption, the next generation result will be improved by then.

Phase II: Solution improvement

Two steps are proposed in the solution improvement phase, i.e. route merging and re-construction with insertion and permutation operation (IPO), and random inter-route merging and splitting. The first step is to generate the set of random numbers which is used for selection the route orders and the nodes of the randomized tours. Resulting from the random generation, an initial solution can be divided into two majors groups; random and nonrandom groups. The random route contains two subgroups that are the groups of random and nonrandom nodes. These groups are programmed to merge into a new route and re-construct a new route with insertion and permutation operation (IPO). Eight operations including recalculate process, merge into a single route process, and merge and reprocess by using IPO are assigned for all groups. Each operation result is compared with the previous solution. The maximum solution improvement is selected, and sent to the next process to perform inter-route neighborhood search operation (INSO). If the current solution is better than the previous result, it is replaced by then.

The insertion and permutation operation (IPO) is proceeded by inserting next remaining customer into the last position based VRPTW ordered. After inserted, all possible permute route solutions are constructed and computed the en route time travel including matching with the minimum vehicle capacity. Only the best solution from the candidate lists is selected. The process is performed re-run until the setting iteration number is reached. The inter-route neighborhood search operation (INSO) starts the process by relocating a node of the first move-out route into the right position respecting to time windows of the first move-in route. The solution is always updated by the best result, i.e. minimum total cost, if it can be obtained. After all nodes of the first move-out route have been inserted, then do the same operation with the second move-in route, and repeat until all move-in routes are performed. When the first iteration is done, update the solutions by replaced with the best result obtained from pairwise (move-in and move-out routes) operations. The operation is terminated once the setting iteration number is reached, or no feasible solutions can be calculated.

The second step is the random inter-route merging and splitting operation. In this step, only random routes are performed inter-route search. The procedure begins with assigning the operation of splitting or merging to the groups of random and nonrandom nodes of the random routes. All new assignment tours are recalculated and selected the maximum solution improvement. Next, the best solution is used for reprocessing by applying IPO, INSO, and the insertion using ordered waiting time based greedy search (WTGS). The outcomes of all operations are compared and updated if the current solution is better than the previous obtain.

Phase III - Robustness decision making

As described in the previous section, the complexity of uncertain customer demands is reduced by converting to deterministic scenario-based approach. A single scenario is a representation of a set of input data uncertainty to the decision model, and all total assumed cases represent a whole system. The number of realizable scenarios over a pre-specified planning horizon normally depends upon a person who takes charge of the strategic planning task or a person who gets involved in managing the customers' demands information. The scope of this research does not involve finding the potential number of scenarios, so several numbers of scenarios will be assumed to be the representations of realistic situations. The first and second phases are processes until all scenarios are completely solved. All results are passed through the last phase for finding the robustness solution.

The scenarios of the input uncertain customer demand are created in phase I. The previous process seeks for a solution of each run for each scenario. The robust solution is evaluated using the absolute difference robustness criteria. That is to select the maximum solution among all decisions of each scenario and to perform the calculation among the formulation (1).

In this research, the evaluation of the robust solution results uses the extra cost comparison and the unmet demand indicators (Sungur et al., 2008). The extra cost performance measurement indicator (ratio x) quantifies the relative extra cost of the robust with respect to the cost of the deterministic. If the deterministic approach is purposed, this extra cost is not suffered. The extra cost ratio is calculated using the Equation 2.

$$Extra\ cost\ ratio, x = \frac{(Z_{RFSMVRPTW} - Z_{FSMVRPTW})}{Z_{FSMVRPTW}} \qquad (2)$$

$$Unmet\ demand\ ratio, u = maxUd / \textstyle\sum_{i \in C} d_{io} \qquad (3)$$

The unmet demand denoted by the ratio u is a performance indicator used to measure the demand when facing with the worst case, it quantifies the relative maximum unsatisfied demand (max Ud) of the uncertainty based scenarios with respect to the total expected demands of the deterministic problem. The unmet demand ratio is calculated using the Equation 3. The unmet demand of the robust decision making is equaled to zero. The additional performance measurement is compared with some benchmark problem sets. Due to the non-existence of recent published papers on the RFSMVRPTW, the solutions resulted from some FSMVRPTW research works, for example, Belfiore and Fávero (2007), Dullaert et al. (2002), and Liu and Shen (1999), are used to examine the competitive performance obtained from the proposed methodology.

COMPUTATIONAL RESULTS

The proposed methodology of three-phase algorithm using a modified genetic algorithm (mGA) hybridized the route insertion operation for creating an initial solution by setting the population size, number of iteration, mutation rate, and elitism rate equal to 80, 300, 0.8, and 20, respectively. The second step is applied a two-step of 1) route merging and re-construction with insertion and permutation operation (IPO), and 2) random inter-route merging and splitting for improving a solution. A 75% of total tours are setting for performing the randomized operation. The third phase is a robustness decision making for obtaining the robust solutions including robustness performance has been coded in MATLAB and has ran on an Intel(R) Core(TM) i5-3337U CPU@1.80GHz 8.00GB-RAM.

The method has been applied to test on the data set with 100-customer, 29 problems including R1, C1, and RC1 which is proposed by Solomon (1987), These problem sets have a short scheduling horizon and allow only a few customers per route. The cost structure of vehicle fleet a, b, and c is referred to Liu and Shen (1999), thus the test problems become 87 instance sets in total. The algorithm is tested for ten runs per problem. The best result is selected as the FSMVRPTW solution as shown in Table 4 which is compared with (A) Belfiore and Fแvero (2007), (B) Dullaert et al. (2002), and (C) Liu and Shen (1999). These authors use the techniques of a scatter search, an adapted savings insertion, and a modified realistic opportunity savings, respectively. Dullaert et al. (2002) reports the result by using the total schedule time excludes the service time and the fixed cost, Liu and Shen (1999) uses the total fixed cost and total schedule time excludes the service time, and Belfiore and Fแvero (2007) demonstrate both cost functions. The percentage gap (Δ) obtains from the difference outcomes between the three-phase algorithm and the other. The negative value means the cost is reduced. According to the report, it indicates that the three-phase algorithm yields the schedule cost reduction of 3.10%, 6.16%, and 4.03%, and the total transportation cost reduction of 1.34%, and increased by 0.69% and 1.35%in average of the result comparisons against the previous two author groups when applied to solve the problem R1, C1, and RC1, respectively.

Table 4 The results obtained from the 3-Phase algorithm compares with the methods of Belfiore and Fแvero (A), Dullaert et al. (B), and Liu and Shen (C)

Compare with Belfiore and Fávero (A) and Dullaert et al. (B)					
Set	(A)	(B)	3-Phase	Δ A%	Δ B%
R1a	1430.84	1548.53	1644.04	14.90	6.17
R1b	1432.57	1557.38	1390.40	-2.94	-10.72
R1c	1432.57	1557.85	1298.42	-9.36	-16.65
R1	1431.99	1554.59	1444.69	0.86	-7.07
C1a	1004.42	1166.09	1217.20	21.18	4.38
C1b	1001.33	1126.01	969.90	-3.14	-13.86
C1c	1003.85	1155.45	829.81	-17.34	-28.18
C1	1003.20	1149.18	1072.30	0.24	-12.55
RC1a	1568.96	1665.04	1601.63	2.08	-3.81
RC1b	1574.27	1680.55	1557.04	-1.09	-7.35
RC1c	1576.48	1689.92	1516.79	-3.79	-10.25
RC1	1573.24	1678.50	1558.48	-0.93	-7.13

Compare with Belfiore and Fávero (A) and Liu and Shen (C)					
Set	(A)	(C)	3-Phase	Δ A%	Δ C%
R1a	4210.36	4398.00	4244.04	0.80	-3.50
R1b	1937.52	2054.00	1992.40	2.83	-3.00
R1c	1640.64	1700.00	1626.42	-0.87	-4.33
R1	2596.17	2717.33	2621.35	0.92	-3.61
C1a	7421.33	8007.00	8123.50	9.46	1.45
C1b	2394.70	2485.00	2439.90	1.89	-1.81
C1c	1670.94	1705.00	1629.81	-2.46	-4.41
C1	3828.99	4065.67	4064.40	2.96	-1.59
RC1a	5130.44	5184.00	5021.63	-2.12	-3.13
RC1b	2190.39	2235.00	2319.04	5.87	3.76
RC1c	1790.12	1849.00	1852.79	3.50	0.20
RC1	3036.98	3089.33	3064.48	2.42	0.28

In this test, the algorithm has been operated to handle three scenarios. The first scenario uses the expected demands using the original given demands of the benchmark problem set. The second scenario assumes that the demands are patterned as the uniform distribution of the risk averse $(\beta^s \alpha^s)$, and the last scenario has the same characteristic but using the normal distribution instead. In this paper, the R1c is used as a pilot test to demonstrate the robustness decision making approach. The robust solution (ZRFSMVRPTW) of the total transportation cost is obtained from the whole scenarios and the deterministic solution (ZFSMVRPTW) equal to 1687.43 and 1626.42, respectively. The extra cost ratio of 3.75 percentages is on top of the normal case. The maximum uncertain demand as equals to 1609 is selected from the whole runs that the program has generated based on the uncertain demand model. The total value of the expected demands, i.e. 1,458, is the base case based on the data set as determined in the benchmark problem. The result of unmet demand ratio is equal to 1.10. It indicates that if the deterministic solution is chosen, it has to plan for suffering the unknown demands with such extra ratio of the expected demand that might be occurred in some periods of time.

CONCLUSION AND FUTURE WORK

The three-phase algorithm is developed and proposed to solve the robust fleet size and mix vehicle routing problem with time windows under uncertain demands. The test results of the deterministic solution indicate that the proposed technique is well performed especially when the fixed vehicle costs are not considered. Anyhow, the other problem sets of the well-known benchmark problem have to be tested and the experiment of this developed methodology should be performed and implemented in the real business cases to ensure that the proposed technique is more efficient and competitive

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Table 5 The results obtained from the 3-Phase algorithm under uncertain demands across three scenarios

Instance	Scenario-1			Scenario-2			Scenario-3			MaxC1	MaxC2
	DM	C1	C2	DM	C1	C2	DM	C1	C2		
1	1458	1300	1628	1609	1390	1746	1463	1332	1652	1390	1746
2	1458	1299	1627	1520	1376	1687	1468	1318	1654	1376	1687
3	1458	1298	1626	1555	1363	1705	1471	1343	1674	1363	1705
Min		1298	1626							1363	1687

DM: Demand, C1: Total transportation cost (Fixed cost and schedule time excludes the service time), C2: Total schedule time excludes the service time and the fixed cost

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>> Kusuma Soonpracha

Kusuma Soonpracha graduated the M.Eng and B.Eng in Industrial Engineering from Chulalongkorn University and Suranaree University of Technology, respectively. She is currently progressing in her studies toward a doctorate in Industrial Engineering at Kasetsart University. Her research interests are in the areas of Supply Chain and Logistics Management and Maintenance Management System.

>> Assoc. Prof. Dr.Anan Mungwattana

Associate Professor Dr. Anan Mungwattana graduated the Ph.D. in Industrial and Systems Engineering from Virginia Polytechnic Institute and State University, USA, the M.S. in Industrial Engineering from Auburn University, USA, and the B.Eng in Industrial Engineering from Kasetsart University, Thailand. He is an expertise in Logistics and is the Industrial engineering faculty's lecture at Kasetsart University. His research interests are in the areas of Lean Manufacturing, Supply Chain and Logistics Management, Production Planning and Control, Facility Design and Layout, and Manufacturing System Design and Operations.

>> Asst. Prof. Dr.Tharinee Manisri

Tharinee Manisri received the M.Eng. degree from Kasetsart University, Thailand, in 2003, and the D.Eng in Industrial Engineering from Kasetsart University, Thailand, in April 2009. She is an instructor in the department of Industrial Engineering, at Sripatum University, Thailand. Her research interests are in the areas of developing algorithms for complex, real-world logistic problems using heuristics and meta-heuristic techniques. She is also interested in simulation modeling and analysis. It is important to her that her research is directly applicable to practical problems. Currently she is working in the areas of developing algorithms in vehicle routing problem.