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Customer satisfaction in dynamic vehicle routing problem with time windows

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The dynamic vehicle routing and scheduling problem is a well-known complex combinatorial optimization problem that drew significant attention over the past few years. This paper presents a novel algorithm introducing a new strategy to integrate anticipated future visit requests during plan generation, aimed at explicitly improving customer satisfaction. An evaluation of the proposed strategy is performed using a hybrid genetic algorithm previously designed for the dynamic vehicle problem with time windows that we modified to capture customer satisfaction over multiple visits. Simulations compare the value of the revisited algorithm exploiting the new strategy, clearly demonstrating its impact on customer satisfaction level.

1. Introduction

The vehicle routing problem with time windows (VRPTW) belongs to the class of the NP-hard combinatorial optimization problems [1]. Since heuristic methods often produce near-optimal solutions in a reasonable amount of computational time, most research so far focused on the design of heuristics and meta-heuristics [2–6]. The dynamic (real-time) vehicle routing problem with time windows (DVRPTW) in particular is still even harder to solve than the static problem since customer requests are generated or do occur dynamically, mainly during the execution of the problem-solving procedure. Work and surveys on DVRPTW may be found in [7–19]. From the various heuristic methods reported for the DVRPTW, tabu search and genetic algorithms techniques have demonstrated the best performance [11,13,19]. Although ant colony systems have been successfully applied to the dynamic vehicle routing problem (with no time window constraints) [10], comparisons for similar problems remain difficult. For a recent review on the conducted works, the reader can refer to [20,21].

Transportation service providers performing pick up/delivery increasingly strive to improve customer satisfaction. In the basic DVRPTW, servicing all customers in specified time windows is simply and naturally reinforced. This refers to the so-called VRPTW problem with hard time windows. Hard time windows refer to a strict time interval that a servicing vehicle can't violate when visiting a customer/site. In contrast, despite rigid structures governing transportation practices, there are a lot of cases where violated time windows may still lead to acceptable satisfaction service levels or problem-solving conditions. A solution with temporal service constraint violations characterizes DVRPTW with soft time windows, in which a penalty is incurred to reflect a measure of customer dissatisfaction. Soft time windows may by definition accommodate some constraint violations but subject to some additional cost. Accordingly, each customer has a desirable time window under which a service occurring over that interval would generate a high satisfaction level (customer satisfaction is maximum) as opposed to a degraded (penalized) customer satisfaction level if service takes place earlier or later than expected [22,23]. This problem is pervasive through many application domains and situations involving worldwide distributors such as newspaper delivery, postal delivery, and school bus routing. In other respect, there is widespread belief that transportation firms and businesses should focus on and improve quality of service to successfully meet customer satisfaction [24]. As world markets gradually become more competitive and service demand is steadily growing, the importance and relative weight of customer satisfaction is gaining momentum. Therefore, driven by changing market demands, logistic providers adapt new strategies to reduce costs and improve customer service in response to individual demands.

Dynamic changes in travel times due to traffic congestion and other nuisances typical of urban transportation, force customer satisfaction consideration to qualify multiple plans in the decision making model. To the best of our knowledge, the spectrum of customer satisfaction situations covered remains very limited.

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Current models barely reflect and unsatisfactorily capture uncertainty linked to customer satisfaction in cases where multiple service deliveries might be required. In this work, a new customer satisfaction model is introduced to achieve real-time planning and execution, extending single visit binary customer satisfaction to a satisfaction continuum building up over multiple rounds while accounting for possible uncertainty.

Customer satisfaction level closely relates to quality of service. As a result, customer satisfaction level may no longer simply stands as "good" or "bad" but may rather ranges over a whole continuum of contentment. In this work, we present a new approach to solve a DVRPTW focusing on customer satisfaction. The targeted problem being addressed is different from the split-delivery version of VRPTW (SDVRPTW) where known customer demand may be ultimately satisfied through multiple vehicle visits. A customer visit corresponds to a customer being serviced by a vehicle. Neither should the problem be confused with the vehicle routing problem with time windows and stochastic demands (VRPTWSD), in which customer demands characterized by probability distributions and total demand at customer location are known in advance. In this paper, an evolutionary approach is proposed to solve the dynamic or real-time version of VRPTW with multiple customer visits where the number of customer visits depends on previous visit outcomes (customer satisfaction). This situation occurs when partial customer satisfaction matters and full satisfaction cannot be guaranteed, as uncertainty on customer satisfaction level still persists naturally after service delivery. Cases where partial customer satisfaction deserves some attention include application domains such as large scale disaster management, differential diagnosis resulting from medical conditions, health care, forest fire handling and effect mitigation, service vehicle repair, real-time tactical reconnaissance military missions, or fluctuating customer demand intrinsically hard to accurately estimate by a bounded resource service provider. Based upon an original strategy to integrate anticipated future visit requests during plan generation to improve customer satisfaction level, the proposed approach uses a hybrid genetic algorithm to maximize the number of satisfied customers, while minimizing temporal constraint violation and total traveled distance. From a computational experiment, the value of the approach is assessed through a comparative performance analysis.

The paper is outlined as follows. In Section 2, the dynamic vehicle routing problem is first described. The customer satisfaction function is then introduced. Section 3 presents the proposed problem-solving approach whereas Section 4 conveys the main concepts of the revisited hybrid genetic algorithm reported in [25], capturing customer satisfaction possibly resulting from multiple visits. The basic principles and features of the problem-solving process and the underlying algorithm are described in details. Section 5 reports on the results of a computational experiment and discusses comparative performance with alternate methods. Finally a summary of the findings and future research directions are given in Section 6.

2. Problem description

The classical VRPTW involves customers with known demands to be serviced by a homogeneous fleet of vehicles with limited capacity. Each customer provides a time interval during which a particular task must be completed such as loading/unloading the vehicle. Routes are assumed to start and end at a central depot. The objective is to minimize the number of tours or routes, and then for the same number of tours, to minimize total traveled distance, such that each customer is serviced within its time window and the total vehicle load associated with a given route does not exceed vehicle capacity. In this paper, a new DVRPTW is being introduced. It is a variant of the static problem in which customer requests are generated dynamically during the construction of the solution.

In the targeted DVRPTW [11] under consideration, the temporal distribution of service requests is assumed to be unknown. Even if some requests are known in advance, most customer requests occur at run-time, making partial route construction an evolutionary process, interleaving plan construction and plan execution. Temporal problem attributes such as travel time, service time and time windows for servicing customers are assumed deterministic, making service request distribution the sole source of uncertainty. Time window constraints at each customer location can be violated. If a vehicle arrives at a destination too early it must wait before carrying out its service. Conversely, if it shows up too late, a penalty cost is imposed for lateness. The objectives consist in maximizing number of satisfied customers while minimizing temporal constraint violation and total traveled distance, subject to the following constraints:

- A hard time window (time window of depot) to initiate and complete (deadline) all solution tours,
- A maximum or fixed number of vehicles from the depot (fleet size),
- Limited vehicle capacity constraint,
- A hard route-time constraint, and
- Soft time window constraints on delivering customer service.

Vehicles have identical maximum weight capacities and maximum route-time (vehicle travel time) constraints. Maximum route time-length constraint is an additional feature to the standard DVRPTW. The duration of the trip for any vehicle should be shorter than the maximum allowed routing time (maximum route length). In the current dynamic problem setting, we assume the next vehicle destination (intended) to be communicated to the crew by the dispatching system at each service location, on or after customer service completion. The next destination is determined according to the best computed solution available. The dispatching system may advise of any new destinations during the problem-solving process as necessary. It is also assumed that for any planned visit that involves waiting time, crews stay at their current service location expecting a decision from the dispatching system. It should be emphasized that a vehicle traveling to its next destination is fully committed to visit its target. Consequently, aspects such as route diversions for a moving vehicle have not been considered.

2.1. Satisfaction function

Customer may require several visits to reach a satisfaction level threshold (e.g. detection or diagnosis problems). Each customer visit request is characterized by a service time and a service time window. Each customer shows an initial satisfaction level to be further updated on a visit basis. A visit outcome can be a success or a failure, defining s success and l–s failures over a given number of visits l, respectively. Based on probabilistic cumulative evidence emerging from multiple visits, the proposed customer satisfaction function/model is inspired from Bayesian probability update resulting from repeated visits, in which belief is replaced by user satisfaction level. The larger the number of successful visits (cumulative evidence) the larger the satisfaction level. As customer satisfaction depends on local visits being conducted, the satisfaction of customer c after l visits, $S_{c,l}(s)$, is defined as follows:

$$S_{c,l}(s) = \frac{1}{1 + \mu_c^s \delta_c^{l-s} \left[\left(1/s_{c,o} \right) - 1 \right]} \qquad (1)$$

where $S_{c,0} \in [0,1]$ refers to the initial satisfaction level of customer c. A customer satisfaction of 1 (0) means absolute satisfaction (total