Designing e-Commerce Transportation Network: Challenges and Solutions

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Keywords—e-Commerce transportation network, multimodal transport, service network design, stochastic programming

I. INTRODUCTION

Compared to the logistics for tranditional store retailing, transprotation service for e-commerce is extremely challening because of the enormrous freight varieties in types, package sizes, and geographical locations to be serviced. The complexity of the problem is futher increased by the uncertaities in vehicle travel time and service demand in both temporal and spatial dimensions. Building a multimodal consolidation based transportation network is therefore crucial for freight companies to mimimise the cost while maintaining high quality services. Figure 1 gives a schematic illustration of such a network with 5 nodes, including a hub and 4 transportation gateways. Each gateways is associated with a number of freight centers with dedicated feeder transports connecting them. The transportation between any pair of main nodes (gateways and the hub) can be done through air, rail, road, water or any combination of these different transport modes. With multimodal transportation networks, the goal is to fully exploit the advantages of different transport modes while limiting their drawbacks. However, optimising such a network has proved to be extremely challenging.

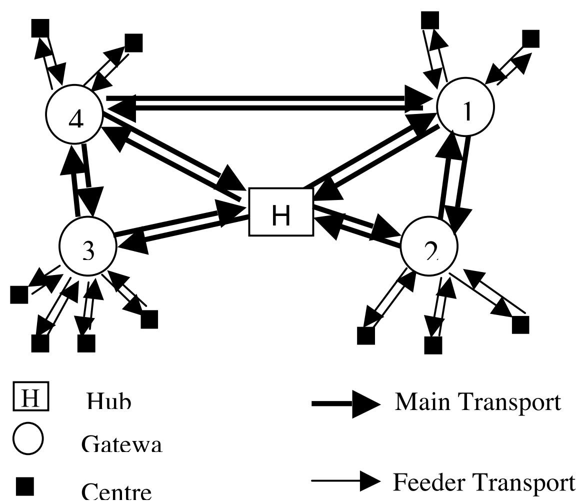

Figure 1: A multi-mode less-than-truckload transportation network

Service network design is used in less-than-truckload (LTL) transportation to address the selection, routing and scheduling of services, with the aim of making good cost-savings while rendering excellent service. Compared to the intensively studied vehicle routing problems (VRP), service network design provides is a better way to model the freight conslidation and transfers within a multi-mode transportation network. This is because, in service network desgin formulations, vehicle routes and commodity flows are modelled seperately using two set of variables. Other main advantages of service network design models include the presence of the vehicle balance constraints to ensure continunity of transportation services over time, ability to express bidirectional commodity flow over the network, and its ability to express non-linear transportation cost into an integer/linear model.

Despite these benefits, practical application of service network design models are still limited. In this research we indentify and discuss the main issues and challenges faced in using service network design formulations to tackle practical e-Commerce transportation network problems. We also discuss the possible solutions and directions to address these challenges.

II. CHALLENGES FOR PRACTICAL SERICE NETWORK DESIGN

A. Multimodal tranfer synchronisations

Although a multimodal transportation network can exploit the benefits and strengths of different transport modes in terms of speed, cost and reliability, synchronisation between different modes of transport can be very challenging. This is particularly difficult under uncertain service and vehicle travel times. Although the synchornisation techniques are reviewed in [5] for VRP problems, most of them are not directly applicable for a multimodal freight service network because of separate modelling of multimodal vehicle routes and commodity flows. Fortunately, considerable progress has been made in the synchronisation problem in airline network designs under uncertain travel and service times (e.g. [6]) and many approaches are more applicable for multimodal freight transportation network design. Nevertheless, more research efforts are required in this direction.

B. Integrating with crew scheduling

In classic arc-node service network design formulation[1] below, decision variable y^f_{ij} defines the number of vehicles of type f that covers an arc (i,j), however, it does not explicitly define the actual routes for the vehicles.

$$\min \sum_{f\in F}\sum_{(i,j)\in A} h^f_{ij} y^f_{ij} + \sum_{k\in K}\sum_{(i,j)\in A} c^k_{ij} x^k_{ij} \tag{1}$$

s.t.

$$\sum_{k\in K} x^k_{ij} \le \sum_{f\in F} u^f y^f_{ij}\ ,\ \forall (i,j)\in A \tag{2}$$

$$\sum_{j\in N} x^k_{ij} - \sum_{j\in N} x^k_{ji} = b^k_i\ ,\ \forall i\in N\ ,\ \forall k\in K \tag{3}$$

$$\sum_{j\in N} y^f_{ij} - \sum_{j\in N} y^f_{ji} = 0\ ,\ \forall i\in N\ ,\ \forall f\in F \tag{4}$$

[1] Due to limited space, we do not give the definition of the notations.

$$x_{ij}^{k} \geq 0,\ \forall k \in K,\ \forall (i,j) \in A \quad (5)$$

$$y_{ij}^{f} \geq 0 \text{ and integer},\ \forall f \in F,\ \forall (i,j) \in A \quad (6)$$

To translate the solution obtained from above model to practical decisions, we have to extract vehicle routes that are legally and practically feasible and then assign them to drivers. This would lead to a crew scheduling problem with various constraints related to shifts, maximum working hours, preferred rest places, etc. Recently out research team has looked at this problem and proposed a practical decomposition method [7]. More research is required in this direction.

C. Solving large scale stochastic SND problems

As was discussed earlier, e-comerce transportation network design is subject to various uncertainties, amongst which the demand uncertainty is of particular importance. In the literature, stochastic programming is widely consdiered as an appropriate framework for modeling service network design with uncertainties, which is also referred to as stochastic service network design [1]. The uncertain demand is often expressed in continuous probability distributions or discrete distributions with large numbers of outcomes. The most widely applied approach to this problem consists of approximating these distributions as a limited number of discrete outcomes (scenarios), each with a known probability of occurrence. As the uncertain demand unfolds over time, these outcomes are organized into a hierarchical tree-like structure, termed the scenarios tree. The two-stage stochastic program based on scenario trees can be formulated into what is referred to as the extensive form [2] or deterministic equivalent, which is essentially a large-scale deterministic model. Unfortunately, directly solving the resulting model within acceptable computing time is typically beyond the capability of existing commercial solvers.

Various decomposition procedures have been developed to divide the extensive form into smaller, more manageable subproblems. As a scenario-based decomposition method, the progressive hedging algorithm (PHA) lends itself well to stochastic service network design where individual scenario problems can be solved efficiently. After decomposing the extensive form by scenarios into single-scenario subproblems, the PHA iteratively solves each subproblem and aggregates solutions of these subproblems into an overall solution that is implementable. This continues until a consensus solution amongst all of the subproblems is obtained or other stopping criteria such as time limit are met. Although the desirable theoretical property of convergence to a global optimum in the convex case [3] does not hold in the context of stochastic service network design, the PHA can be effectively used as a heuristic to find high-quality solutions within reasonable time.

The performance of the PHA can be enhanced by replacing the preceding scenario decomposition with bundle decomposition [2, 4], where individual scenarios are combined into bundles and the extensive form is decomposed using scenario bundles into multi-scenario subproblems. At the heart of bundle decomposition is the method for scenario bundling. Here we presents a novel fuzzy c-means (FCM) based method to partition the scenario set into bundles, which is distinctly different from existing scenario bundling methods to our knowledge.

III. Fuzzy C-Means-Based Scenario Bundling

Fuzzy c-means (FCM) is a data clustering algorithm that allows a data point to have membership in more than one cluster. FCM-based scenario bundling computes a fractional membership score to measure the degree to which a scenario belongs to a bundle. The membership scores for all of the scenarios across all of the bundles can be organized into a matrix Δ called the fuzzy partition matrix, with the elements representing the degree of membership for a scenario in a given bundle. FCM-based scenario bundling decides the bundle centers and the membership scores by minimizing the sum of distance between a scenario and a bundle center weighted by that scenario's membership score over all possible scenario and bundle center pairs.

We evaluate the proposed scenario bundling method on a number of problem instances of different sizes. We take the objective function value obtained by *k*-means as the reference value. We found that 80% of solutions obtained by FCM are of better quality than those found by *k*-means. Amongst the inferior solutions yielded by FCM, the worst one has a relative difference of 2.1%, desmonstraing the promising soft bunding techniques for secnrio decompositions.

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