Decision Support for Capacitated Arc Routing for Providing Municipal Waste and Recycling Services

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Abstract

This paper describes the design, development and initial evaluation of a decision support system (DSS) for capacitated arc routing. The research was motivated from a collaboration project with The City of Calgary business unit for Waste & Recycling Services (WRS). Their services cover residential waste collection for 306,000 residential homes. Intelligent decision support was needed to address the increasing business complexity and the need for higher efficiency and transparency of decision-making processes.

The proposed routing is incorporating seasonal trends of waste creation. The seasonal changes are between 10,000 (low) to 25000 (peak) tons per month for the whole city. Different arc routings apply for different amounts of waste. A prototype DSS was developed with several components including one for prediction of waste amounts and one for arc routing of trucks. The paper describes the methodology, the existing DSS-WRS prototype implementation and preliminary results from its case study implementation.

Keywords: capacitated arc routing, waste prediction, DSS prototype, case study.

1. Introduction

Intelligent decision support that is using advanced decision technologies and analytics methodology is becoming increasingly important in logistics and supply chain management [11]. With an existing portfolio of methods and techniques (see, e.g., [7]), the emphasis is on providing customized solutions for real-world application scenarios. Typically, to achieve this, customization of existing methods need to be done.

The capacitated arc routing problem is the problem of servicing a set of streets in a street network using a fleet of capacity constrained vehicles initially located at a central landfill. The objective of the problem is to minimize the total routing cost. Often several extra constraints must be taken into account.

The focus of this paper is on delivering a DSS which suggests practically applicable routes being based on hybrid waste prediction models. The main contributions of the paper are:
• Proposing a heuristic approach H-WRS for a special case of arc routing problems which improves an existing approach which is ignoring the varying amounts of waste;
• Application of a hybrid method for waste prediction;
• Evaluation of H-WRS for real world data form a case study project with The City of Calgary, and
• Presentation of a DSS prototype in which waste prediction, arc routing and route analysis are integrated.

The paper is subdivided into seven sections. Following the introduction, a discussion of related work is provided in Section 2. The prediction and routing component of the DSS are outlined in Sections 3 and 4, respectively. The design and implementation of the DSS prototype, integrating both components, is the key content of Section 5. Details of a real-world case study with The City of Calgary are reported in Section 6. The paper is wrapped-up in Section 7 by giving a summary and by outlining directions for future research.

2. Related work

The capacitated arc routing problem (called CARP in the paper) is a well investigated optimization problem defining routes serving all arcs of a given directed graph. CARP arises in a number of applications naturally whenever it is necessary to find a route covering a given set of arcs of a directed graph. Some of these applications can be found in mail delivery [21], snow removal [5] and street cleaning [1]. Another important application of CARP relates to intelligent waste management [22].

Many variations of the CARP exist. They deal with time windows, turn constraints and capacity constrained vehicles. In this paper, we consider capacitated arc routing in the presence of a landfill. Different algorithms relying on different assumptions and algorithmic ideas do exist. For an overview, see a
collection of articles around vehicle routing collected in [7].

Baniet et al. [2] introduced a DSS model used in assisting decision makers with GIS to be able to give robust prediction despite the inherent uncertainties of waste generation and the plethora of waste characteristics, and discussed optimal allocation of waste streams for recycling, incineration, landfill and composting.

A constructive heuristic which takes into account the environmental aspect as well as the cost is proposed in [1] to solve the routing aspect of garbage collection based on a look-ahead strategy which is enhanced by two additional mechanisms.

A decision support system, for urban waste management in a regional area, to be used for evaluating general policies for service organizations, is proposed in [8]. The decision support system allows the generation and evaluation of suitable alternatives with respect to salient features of the problem, especially environmental consequences. The paper describes the identification and collection of relevant information, the structuring of a database, the design of combinatorial optimization algorithms for solving the core location problem, the study of models for evaluating the different alternatives and their framing in a complete multi-criteria decision model.

3. The prediction component

3.1 A hybrid prediction method combining k-means clustering and linear regression

Municipal waste management is an important area to apply predictive models. However, few attempts (such as [6], [20]) have been made to reach a high accuracy level with a high volume of data. In [15], a hybrid prediction method that addresses the above gap by combining k-means clustering and linear regression methods was proposed and evaluated. Therein, k-means clustering was used for creating clusters, each one containing the instances that are most similar to each other. In addition, linear regression was used to acquire the weights of the attributes for the similarity in k-means. After creating the clusters, linear regression was applied to create the final predictor for each cluster.

3.2 Evaluation

The proposed method has been evaluated through a real-world case study with the WRS of the City of Calgary in Canada. The dataset used in this study included 63,000 records on historical waste generation for the period of January 2006 to May 2009.

The attributes of the dataset represent two types of information for each record. First, information regarding the collection including 21 attributes, such as the waste volume, date, travelled distance of the collection trucks, number of trips etc. This information is updated on a daily basis. Second, information regarding the collection area (beat), including 80 attributes, which are mainly about the number of different types of housing, e.g. number of duplexes, number of apartments less than 4 units etc.

The results [15] showed that the proposed prediction model outperforms the k-means clustering or linear regression in isolation. Applying the hybrid prediction method to the beat designs of November 2010 – October 2011 resulted in the estimations shown in Figure 7, with the comparison to the actual waste amount for the whole city. The estimated waste was calculated through the following steps [14]:

1. The history data of January 2006 to May 2009 was used as the training set for building the prediction model. The clusters were generated (25 clusters) from applying linear regression.
2. The data of November 2010 to October 2011 was used as the test set.
3. The records in the test set were entered into the model one by one, and the closest cluster to each record was determined.
4. Linear regression was used to calculate the predicted waste amount for each cluster. The waste amount is predicted for each configuration of (beat, day) in a given month.

4. The routing component

4.1 Un-capacitated arc routing

The first class of problems is defined on a directed graph having arcs representing streets (and their direction). As most of the streets are bidirectional, we introduced bi-directional links between nodes. The set of arcs is subdivided into those representing service streets (with municipal waste to be collected) and the ones without having service requests. In addition, there

![Figure 1. Comparison of actual vs. estimated waste amounts for the period of Nov 2010 – Oct 2011 [14]](image-url)
is a landfill, which is the starting and ending node of the route to be determined.

Based on that, the un-capacitated arc routing problem UCAR is the question of finding a route which (i) starts and ends at the landfill node, (ii) is servicing all pre-selected streets, and (iii) is of minimum length.

**Definition:** Given a directed graph $G = (V, A, AS)$ with total set of arcs $A$ and a subset of arcs $AS$ representing streets to be served. With a singular node $v_0$ representing the landfill, a route is a directed path from $v_0$ to $v_0$ which includes all arcs from $AS$ (at least once).

**Definition:** Given a length function: $A \rightarrow \text{Real}^+$ assigning each arc $x$ of $G$ a length real value $\text{length}(x)$, the length of a route $R$ is defined as:

$$\text{Length}(R) = \sum_{x \in R} \text{length}(x) \quad (1)$$

**Definition:** The un-capacitated arc routing problem UCAR is to find a route of minimal length.

In [14], the heuristic provided by Thimbleby [23] is used and extended for the case of a network having a set of strongly connected sub-graphs.

**Definition:** A directed graph is strongly connected if there is a (directed) path from each vertex in the graph to every other vertex.

The idea used by Livani [14] was to apply Dijkstra’s shortest path algorithms [4] whenever moving from one component to another. The resulting algorithm called $H$-UCAR constitutes the baseline for the capacitated arc routing problem studied next.

### 4.2 Capacitated arc routing

Different types of constraints might occur on top of the above formulation UCAR. These constraints might result in truck capacity (weight, volume) or time constraints (working time constraints for the truck operators). In this paper, we consider weight and related capacity constraints.

In the real-world scenario motivating this research, the region of the whole city is subdivided into areas called beats. A beat can be defined as an area of the city or a set of streets that should be serviced by a single truck in one day. These beats are constructed keeping in mind the capacity of a truck and the time constraint. Trucks are pre-assigned to certain beats (and serving on a particular day of the week). This allows us to decompose the problem from handling the whole city area by just looking at each beat in isolation.

**Definition:** Given a load function $\text{load}: A \rightarrow \mathbb{Z}^+$ assigning each arc $x$ an integer load value $\text{load}(x)$, the load of a route $R$ is defined as:

$$\text{Load}(R) = \sum_{x \in R} \text{load}(x) \quad (2)$$

A truck used for the routing has a limited capacity denoted by $\text{cap}$. In case of larger beats and in case of peak season, one route determined from UCAR might violate the capacity constraint (3) and thus is not feasible.

$$\text{Load}(R) \leq \text{cap} \quad (3)$$

The capacitated arc routing problem CAR is looking for a route $R$ of minimum length which might include several returns to the landfill in order to ensure that (3) is never violated.

The problem is illustrated in Figure 2. The route starting at the landfill is serving sub-beats (strongly connected components) A, B, C, D, and E. At this point, the truck has achieved (or is close to achieve) its capacity limit. Consequently, it needs to return to the landfill. After disposal, a second directed path is taken serving F, G, H, I, and J.

The key idea of our proposed approach is to consider the predicted amount of waste from the very beginning and to monitor the actual usage of truck capacity for determining the route optimization. A more detailed description of the solution approach called $H$-CAR is provided in the subsequent section.

**Figure 2. Illustration of CAR**

### 4.3 Heuristic H-CAR

H-CAR extends the shortest path computation by another parameter reflecting the degree of utilizing the capacity of the truck and the distance of the sub-beat from the landfill. When the truck starts (or is far below capacity), it should select the sub-beat which is closest to its current position and as the trucks nears getting
filled, H-CAR guides to move to sub-beats closer to the landfill.

In order to balance between the two considerations, we assign weights for each of the criteria to select the next sub-beat. The weights are being dynamically updated. This process can be explained by the following steps:

**Actual capacity utilization:** For a given route R, after servicing the i-th sub-beat, the total amount collected by the truck is \( SL(R,i) \), and the fraction of total capacity utilized \( FL(R,i) \) in the truck is computed as

\[
FL(R,i) = \frac{SL(R,i)}{cap} \quad \text{for all sub-beats } i = 1, 2, \ldots
\]  
(4)

**Distance computation:** For a given route R, after servicing i-th sub-beat, distances are computed as follows:

a) Distance from next sub-beat (DS): We compute the distance from the last serviced sub-beat (i-th sub-beat) in R to the next sub-beat (j-th sub-beat) using Dijkstra’s shortest path algorithm [4]. Let this be denoted by \( DS(R,i, j) \).

b) Distance from the landfill (DL): We compute the distance of the next sub-beat (j-th sub-beat) from the landfill using shortest path computation. Let this distance be denoted by \( DL(j) \).

**Computation of weights:** We assign weight functions to these two factors to combine them to form one metric. Weight function for DL is computed from the fraction of space left in the truck as follows:

\[
w_1(R,i) = 1 - FL(R,i)
\]  
(5)

Similarly, the weight function related to DS is computed as follows:

\[
w_2(R,i) = FL(R,i)
\]  
(6)

**New Metric computation:** For a given route R, the weighted sum of distance \( DM(R,i,j) \) for comparison between two sub-beats i and j, is defined as follows:

\[
DM(R,i,j) = w_1(R,i) \cdot DL(j) + w_2(R,i) \cdot DS(R,i,j)
\]  
(7)

For a given beat i, we compute DM for all sub-beats that have not yet been covered by the existing route R. Out of these, the sub-beat with minimum value of DM is selected to be traversed next. A real-world case study evaluation of this heuristic is presented in Section 6.

5. Decision support prototype DSS-WRS

5.1 Overview

The DSS-WRS (Decision Support System for Waste and Recycling Services) prototype combines technical components based on customized techniques of prediction, optimization, Bayesian belief network analysis and simulation with necessary components on data and project administration. Here, we only describe the DSS business use cases such as Data Administration, Waste Prediction, Waste Prediction Analysis, Vehicle Routing, and Vehicle Routing Analysis that are related to this paper. The use cases are visible in the Graphical User Interface presented in Figure 3. In this paper, we focus on business use cases and solutions that are related to vehicle routing and waste prediction.

In Program Data Administration, all the information of the street network can be uploaded. Beat designs and waste prediction for the designed beats are available in Beat Design Administration and Waste Prediction, respectively. In the current version of the prototype [5], the results of five different prediction analyses are shown. Traveled length of near optimal routes inside the designed beats can be calculated using Traveled Length Calculation. For the calculated route length, a portfolio of analyses has been implemented. These analyses provide the users with the ability to investigate:

a. Traveled length
b. Traveled length across districts
c. Traveled length across days of the week
d. Traveled length histogram

The amount of waste for every beat can be seen in Waste Amount per Beat. From there, we can find the beats having predicted waste amount lower or higher than their truck capacity. The results of vehicle routing can effectively determine how the beat boundaries should be adjusted to optimize route length while we are trying to utilize trucks capacity. Alternatively, the configuration of trucks and the trucks fleet size can be adjusted based on the analysis of routing and the amount of predicted waste.

5.2 Implementation of DSS-WRS

The prototype is implemented as a client-server application on three tier architecture and it is publicly available on the Internet [5]. The presentation layer is based on JSF 2.0 [13] utilizing the library of Primefaces [19]. The middle tier, business logic layer, is pure Java code, and finally, the data layer is implemented using Hibernate 3.0 [10]. MySQL 5.0 [17] is applied as RDBMS. The software architecture is shown in Figure 4.

5.3 Implementation of H-CAR

The proposed heuristic was implemented in Java. We used the existing JGraph library [12] for basic graph algorithms and data structures. For solving the small size UCAP sub-problems on the strongly
connected sub-graphs, we re-used the code presented and offered by Thimbleby [1]. The implementation includes visualization of the suggested route on Google map.

**6. Case study**

An illustrative case study was conducted to check the validity of the method proposed and how it can be applied to real world problems. We provide some background information of the case study and details of the case study design in the following sub-sections.

**6.1 Background information**

In total, the service area of region of The City of Calgary is subdivided into three districts. Each district is a composition of regions called beats. For black cart waste collection, there are 470 beats, 88 vehicles (in 2012), and four collection days (Tuesday to Friday). From these 470 beats, 136 belong to district 1, 211 to district 2, and 123 to district 3. Besides black carts, The City of Calgary has introduced blue cart recycling. Most recently, green cart organics and yard waste collection has been initiated in a few communities.

Waste collection is done on four days of a week (Tuesday, Wednesday, Thursday, and Friday). There are different landfills for each district and the trucks start and end at the landfills. It may also be possible
that a truck has to travel twice to landfill in a single day in response to high load exceeding capacity.

6.2 Case study design

The City Of Calgary has more than 5000 named streets. We computed the route for some of the beats. Given a city street network and beat design, we are looking for an optimal path for each truck at the beat assigned to it. Optimality is targeted in terms of minimizing the distance travelled.

For three beats of the city network belonging to the ones of high total amount of waste, we performed a comparison of results obtained from procedure UCAR (see Section 4.2) with the ones from procedure CAR taking into account the actual truck capacity utilization as a parameter for determining the route.

6.3 Case study analysis

Results of the comparative analysis are presented in Table 1. For different amounts of waste, the extra distance traveled to landfill is reported for both solutions. We observe that CAR reduces the extra distance in almost all cases (one exception). As a tendency, the difference becomes the more significant, the higher the actual amount. Independently, the difference becomes more significant, the higher the standard deviation around the initial estimation (visible from comparing N(25,1), ..., N(25,15)). This is better visible in beat 11040 from N(25,1), ..., N(25,15) as each measurement is the mean of five instances taken for that configuration.

The second observation is based on performing randomized variation of predicted waste amounts. For an originally estimated total amount of 25 tons, random variations of waste amounts per street were taken from a Gauss distribution for a series of varying standard deviation values. For beats with ID 11040 and 11034, the difference based on N(25,15) is bigger than 3 resp. 2 kilometers.

Table 1. Extra distance travelled to landfill by the trucks in following beats for different waste amounts per day (in meters)

<table>
<thead>
<tr>
<th>Beat ID (# of streets, # of sub-beats)</th>
<th>11040 (235,48)</th>
<th>11034 (236,42)</th>
<th>11048 (173,74)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Waste (Tons)</td>
<td>UCAR</td>
<td>CAR</td>
<td>UCAR</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>10575.12</td>
<td>10308.04</td>
<td>11376.5</td>
</tr>
<tr>
<td>15</td>
<td>11325.34</td>
<td>10661.76</td>
<td>11705.64</td>
</tr>
<tr>
<td>18</td>
<td>11558.32</td>
<td>10575.12</td>
<td>11862.18</td>
</tr>
<tr>
<td>22</td>
<td>24550.34</td>
<td>23131.88</td>
<td>24757.82</td>
</tr>
<tr>
<td>25</td>
<td>22839.28</td>
<td>22756.76</td>
<td>24746.30</td>
</tr>
<tr>
<td>N(25, 1)</td>
<td>22860.06</td>
<td>21968.05</td>
<td>24746.30</td>
</tr>
<tr>
<td>N(25, 2)</td>
<td>22433.35</td>
<td>22323.06</td>
<td>24801.12</td>
</tr>
<tr>
<td>N(25, 5)</td>
<td>22738.66</td>
<td>22517.26</td>
<td>24205.54</td>
</tr>
<tr>
<td>N(25, 10)</td>
<td>23029.77</td>
<td>22715.83</td>
<td>23932.02</td>
</tr>
<tr>
<td>N(25, 15)</td>
<td>25794.67</td>
<td>22925.54</td>
<td>24022.86</td>
</tr>
</tbody>
</table>

7. Discussion of applicability

While proven to be initially useful for the application context, the capabilities of the DSS can be utilized for related decision problems. One of them is redesign of beats. Another one is the optimization of fleet size and fleet configuration.

The amount of waste is an important factor in designing beats. Some beats may have waste amount lower or higher than their truck capacity. So, we may need to adjust the boundaries of such beats to make them bigger or smaller. The results of arc vehicle routing can effectively determine how the boundaries should be adjusted to optimize route length while we are trying to utilize trucks full capacity. The amount of waste in a beat should be close or relevant to the capacity of its assigned truck. This is useful for deciding which type of truck is most appropriate in which beat.

Waste amount prediction plays a very important role in beat designs. The more accurate the waste amount prediction, the more efficient the beat design. In addition, some other parameters should be considered in designing beats like street type, population density, and different types of available trucks. For instance, big trucks cannot be assigned to a densely populated beat having narrow streets.
So far, the usage of the prototype was limited to black cart services. However, with data now also available for other types of services, the proposed methodology can be applied to them as well.

8. Summary and future research

We have presented DSS solution for capacitated arc routing which is based on predictive patterns for the amount of waste over the period of a year. The proposed solution serves as a proof-of-concept. Further empirical investigations are needed to evaluate the usefulness of the DSS prototype. As any DSS, the solutions are not prescriptive. Instead, they are intended to serve as a recommendation for the decision-maker.

The current modeling is limited to the capacity of trucks. At this point, timing factors are excluded. However, there often are situations when the driver runs out of time in a day before we run out of capacity. In such cases the bottleneck is not the capacity of the truck but the time allotted to service a set of streets. For that purpose, it may be worth-while to look at the right sizing of fleet based on weight, time and capacity of truck.

Another limitation is that the current routing is not taking care of left and U turns. Existing results from [15] need to be customized to the specifics of the arc routing problem in our context. Minimizing risk is considered in terms of reducing the number of U-turns. Taking U-turns is very difficult and depending on how busy that intersection is, taking a U-turn is very risky as well. On top of that, garbage trucks are very large in size and moreover, they collect garbage from one of the end of the streets which leads to even more difficulty in taking a U-turn. So the aim is to not only minimize the length of the route but also to reduce the riskiness of the overall route. This has been started to be approached as a trade-off decision problem.

Finally, the integration between prediction and actual routing needs to be intensified. Continuous performance analytics would allow making better predictions, which implies better routing and assignment of trucks to beats.

9. Acknowledgement

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