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The minimum p-envy location problem with requirement on minimum survival rate

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ABSTRACT

In location problems for the public sector such as emergency medical service (EMS) systems, the issue of equity is an important factor for facility design. Several measures have been proposed to minimize inequity of a system. This paper considers an extension to the minimum *p*-envy location model by evaluating the objective of the model based on a survival function instead of on a distance function since survival probability is directly related to patient outcomes with a constraint on minimum survival rate. The model was tested on a real world data set from the EMS system at Hanover County, VA, and also compared to other location models. The results indicate that, not only does the enhanced *p*-envy model reduce inequity but we also find that more lives can be saved by using the survival function objective. A sensitivity analysis on different quality of service measures (survival probability and traveled distance) and different choices of priority assigned to serving facility is discussed.

1. Introduction

Emergency medical service (EMS) is a public service that involves life-or-death situations which often require immediate medical assistance. The EMS system is designed to be able to respond to a 911 emergency call to provide urgent medical treatment and/or transport. The system is activated by an emergency call, and then the EMS center dispatches the appropriate medical units to the call. Most EMS systems' performance is measured by the percentage of calls responded to (covered) within some fixed time standard, known as the response time threshold (RTT). Ideally, a system should be able to respond to a call within the RTT. However, it may not be possible to deliver care within the RTT for all customers; people who live in remote areas usually have to wait longer. For example, Fitch (2005) notes that 90% of calls in urban areas should be responded to within a 9 min RTT while 90% of calls in rural areas should be responded to within 15 min. Moreover, when considering coverage, there is no practical difference between a call responded to within 1 min and 8 min and 59 s. This is not reflective of patient outcomes; for example, patients who have cardiac arrest need help within 6 min otherwise; brain damage is likely to occur (Mayer, 1980).

Since EMS systems provide important life-saving services, they are expected to serve the public fairly. A patient's chance of receiving timely service is directly affected by the locations and availability of service facilities. Many performance measures in facility location models have been introduced to equalize the chance of access to service between customers. Typically, the objective of these models is to minimize inequity of the system in terms of distance, or to minimize the variation of the distances between demand locations and facilities that serve them. The standard statistical dispersion measures that are used as inequity measures for equitably locating facilities include range (see e.g. Brill, Liebman, & ReVelle, 1976; Erkut & Neuman, 1992), variance (see e.g. Berman, 1990; Maimon, 1986; Kincaid & Maimon, 1989), mean absolute deviation (see e.g. Berman & Kaplan, 1990; Mulligan, 1991), and sum of absolute differences (see e.g. Keeney, 1980; Lopez-de-los-Mozos & Mesa, 2001, 2003). Moreover, the Gini coefficient, which is commonly used to measure inequity of income, has been widely used in the field of equitable facility location design (Drezner, Drezner, & Guyse, 2009; Erkut, 1993; Maimon, 1988). For a review of measures for equity in facility location, see Marsh and Schilling (1994).

In this paper, we apply the concept of envy as one way to capture inequity of the system. The minimum envy model was first introduced in location problems by Espejo, Marin, Puerto, and Rodriguez-Chia (2009). Envy is a measure that considers the differences in service quality between all possible pairs of customers.

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Since people feel no dissatisfaction when they are better off than others, only negative effects are considered in the minimum envy model. Unlike other measures, the envy measure takes into account all individual effects compared with each other which results in overall satisfaction to the whole system. To say that one customer is better than another customer, we need to define a standard way to quantify the dissatisfaction of each individual which can be done in several ways. Most location models included in Espejo et al.'s (2009) work considers customers' dissatisfaction based on the distance from the customers' locations to their closest facilities, assuming that all customers are only serviced by their closest facilities. This representation is appropriate for some public services, such as post office locations or school locations where the customer travels to the facility, but not necessarily for EMS systems. In an EMS system, the ambulance stationed at the closest facility is not always available to serve the customers, and in that case the ambulance stationed at the next closest facility might instead be dispatched.

To take this into account Chanta, Mayorga, Kurz, and McLay (2011) developed the minimum p-envy model which defines dissatisfaction of customer in zone i as a function of distance from zone i to all p serving facility locations weighted by priority of the serving stations. In this paper, we propose an enhancement to the p-envy model presented in Chanta et al. (2011) which focuses more directly on patient outcomes. We redefine envy as differences of customers' satisfaction between zones (as opposed to dissatisfaction), and we consider satisfaction as measured by the survival probability of each demand zone (as opposed to distance from a station), which more accurately reflects patient outcomes. The differences of calculating envy based on dissatisfaction or satisfaction is presented along with a study of assignment of priority weights to the p serving stations. Moreover, the performance of the model is evaluated in regards of patients' outcomes.

The traditional way to measure performance of an EMS system is by considering the coverage or the number of calls that can be responded to within a standard time. That is, a call is considered as "covered" if a vehicle located at a facility is able to reach the call location within the RTT, otherwise it is considered as "uncovered." This measure is called 0–1 coverage, which is commonly used in many facility location models. The 0–1 coverage is simple and easy to interpret, but it cannot distinguish systems with response times faster than the RTT; that is, for a 9 min RTT, reaching a call in 4 or 9 min yields the same coverage. Moreover, the 0–1 coverage considers a call responded to within the RTT as a 100% covered call while it considers a call responded 1 s later as a 0% covered call which is not reflective of patient outcomes. Several ways have been proposed to improve how to calculate the coverage such as using a step function or a gradual function (see e.g. Berman, Krass, & Drezner, 2003; Church & Roberts, 1983; Pirkul & Schilling, 1991), for review see Eiselt and Marianov (2009). Another way to relax the 0–1 coverage objective is to integrate a survival function into the model. Erkut, Ingolfsson, and Erdogan (2008) first introduced using survival functions to evaluate the performance of the covering facility location models especially for EMS systems. McLay and Mayorga (2010) also proposed a way to evaluate performance of the EMS system based on survival probability with respect to a piece-wise function of distance. Since response time directly affect the patients' survival rate; it makes more sense to evaluate the performance of the system based on the overall survival probability instead of standard response time. In our model, survival probability is incorporated into the objective as customers' satisfaction. The performance of our model is evaluated against other well know location models in terms of the expected number of lives saved.

The rest of the paper is organized as follows. In Sections 2 and 3 we discuss two important model inputs. In Section 2 we briefly describe how we estimate survival probability of a demand zone using existing models from the literature; followed by the details of calculating the probability of a vehicle being busy using the hypercube model in Section 3. The notation and formulation of the minimum p-envy location model are presented in Section 4. Section 5 provides an illustrative example. Section 6 shows the performance of the p-envy location model in comparison to other location models. Section 7 discusses the sensitivity of the p-envy location model when using different quality of service measures (survival probability and traveled distance) and different choices of priority assigned to serving facilities. Finally, Section 8 provides a conclusion.

2. Estimating survival function

Typically, emergency medical 911 calls are classified by their degree of urgency into three types; priority 1, 2, and 3. Priority 1 calls involve life-threatening emergencies such as cardiac arrest, priority 2 calls may involve life-threatening emergencies, and priority 3 calls are believed to be non-life-threatening. This study focuses on priority 1 call for which patient's survival is highly correlated with EMS response time. In particular, the survival probability of a patient who has cardiac arrest depends on the response time. The survival probability decays linearly to zero from the time of collapse if there is no assistance. However, survival probability may remain stable when paramedics arrive and provide medication and intubation or when patients arrive at a hospital (Erkut et al., 2008). Early EMS response time leads to early sequence of therapy which yields higher chance of survival. Other factors that might affect survival probability of patient are type of trauma, age, sex, etc. Several studies focus on how to estimate the survival probability of patients who have cardiac arrest based on influential variables including response time. For a review see Erkut et al. (2008).

In this study, we selected the survival function estimated by Valenzuela, Roe, Cretin, Spaite, and Larsen (1997). The authors found that age, initiation of CPR by bystanders, interval time from collapse to CPR, interval time from collapse to defibrillation, bystanders CPR/collapse to CPR interval interaction, and collapse to CPR/collapse to defibrillation interval interactions were significantly associated with survival, they also provided a simplified version of the predictive model in which only collapse to CPR and collapse to defibrillation intervals were used as variables; this model performed comparably to the initially more complex model. The simplified model for estimating the survival function is shown as follows:

$$s(t_{CPR}, t_{Defib}) = (1 + e^{-0.260+0.106t_{CRP}+0.139t_{Defib}})^{-1} \quad (1)$$

where s denotes the patient survival probability, t_{CPR} is the interval time from collapse to CPR and t_{Defib} is the interval time from collapse to defibrillation.

For our purposes, let t_{Res} denote the response time or the travel time of an EMS vehicle from a station to an incident. Assume that it takes 1 min after collapse to make a call for EMS dispatching, and CPR is performed immediately upon EMS arrival as well as defibrillation which is used by a paramedic or EMT resulting in $t_{CPR} = t_{Defib} = 1 + t_{Res}$ (these assumptions are similar to those made in McLay and Mayorga (2010)). Then, the model in Eq. (1) can be rewritten as follows:

$$s(t_{Res}) = (1 + e^{-0.015+0.245t_{Res}})^{-1} \quad (2)$$

Fig. 1 shows the relationship between response time and probability of survival from Eq. (2).