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A fuzzy queuing location model with a genetic algorithm for congested systems

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Abstract

This article presents a fuzzy location–allocation model for congested systems. In service networks, such as health and emergency services, public safety, fire fighting and so on, the location of servers and allocation of demand nodes to them have a strong impact on the congestion at each server and as such, on the quality of service. The previous efforts in this area have concentrated on enhancing the reliability and quality of service with a probabilistic orientation. In this paper we utilize fuzzy theory to develop a queuing maximal covering location–allocation model which we call the fuzzy queuing maximal covering location–allocation model. We consider fuzzified queuing parameters as well as fuzzified constraints to develop a new mathematical model which we convert to a single objective integer programming model. Our model considers one type of service call, one type of server and includes one constraint on the quality of service in the form of a service time or a queue length constraint. A genetic algorithm is developed to solve and test the model using up to 50-node networks. We also propose extensions to our model.

Keywords: Location; Fuzzy sets; Queuing; Congested systems

1. Introduction and literature review

In designing the service networks such as medical centers, fire fighting facilities, police stations, and so on, location of service facilities and allocation of service calls to servers, drastically affect the congestion of demand.

As of now, numerous models have been developed to provide the highest level of service and hence, achieve the lowest level of congestion possible. For a short review of discrete location models, among the different classifications of discrete location–allocation models we adopt the one which is proposed by Current et al. [1]. Current et al. introduced eight basic facility location models which are set covering, maximal covering, p-center, p-dispersion, p-median, fixed charge, hub, and maxisum. Each of these models attempts to optimize a specific objective function by locating the new facilities within a network. All these models can be developed with multi-objective function, or with dynamic assumption, and with stochastic structure.

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Since our model belongs to the class of maximal covering model, a short review of related models in deterministic and stochastic version is in order. The location set covering problem (LSCP) that is a version of set covering problem, was developed by Toregas et al. [2] in 1971. This model was an attempt to locate the least number of servers to cover all the demand nodes with at least one server within the time or distance standard. This model's main drawback was its unrealistic assumption of unlimited budget that leads to the full coverage of all nodes. This led to emergence of the Maximal Covering Location Problem (MCLP) by Church and ReVelle [3] in 1974. This model sought to maximize the population of calls which have a server within the time or distance standard while imposing a limit on the number of servers. As such, not all nodes receive coverage. This model did not consider the idea of server congestion and assumed that free servers were available at the time of any call. Besides, parameters and structure of constraints were assumed to be deterministic.

The idea of server congestion was first considered by Larson [4,5]. He developed models in which the steady state busy fraction of servers was calculated and used to solve the location problem. In spite of using the queuing theory notions in location models, such models lacked a probabilistic structure until 1983 when Daskin [6] presented a probabilistic version of MCLP which he called Maximal Expected Covering Location Problem (MEXCLP). This model attempts to maximize the expected population coverage. Later, Berman et al. developed some models using queuing theory for congested networks [7–9].

A good review of such models is found in [10]. In 1989, ReVelle and Hogan [11] presented their probabilistic MCLP model which they called the Maximal Availability Location Problem (MALP). This model attempts to locate a specified number of servers such that the population coverage is maximized provided that each service call has one server within the time or distance standard with probability α.

Then Marianov et al. proposed several models in which the number of requests for service was not constant in time, but instead, a stochastic process [12–14]. Utilizing queuing theory in the estimation of the busy fraction proposed by Marianov and ReVelle [14], they called their model the Queuing Maximal Availability Location Problem (QMALP). This model assumes that the travel time between any two nodes is probabilistic and the server's busy fraction is no longer constant. Two years later, Marianov and Serra [13], presented their queuing maximal covering location–allocation model (QMCLAM). Aside from two changes, this was the same model as MCLP. The changes are: (a) allocation of demand nodes to servers is considered within a distance or time standard, and (b) for location–allocation, they take advantage of the queuing theory in such a way that no call for service has to wait longer than a specified time with probability α.

As for application of fuzzy theory toward location models, all efforts except one can be categorized in the class of the qualitative models. The only quantitative fuzzy model was developed by Canos et al. in 1999 [15]. They treated the classical p-median problem as a fuzzy model and came up with an exact method of solution.

2. Motivation of applying fuzzy theory and the basic definitions

In this section we intend to discuss the motivation for resorting to the fuzzy theory in a location–allocation model and present some basic definitions from fuzzy theory.

Most of our traditional tools for formal modeling, reasoning, and computing are crisp, deterministic, and precise in character. Precision assumes that the parameters of a model represent exactly either our perception of the phenomenon modeled or the features of the real system that has been modeled. In the exact words of one of the leading researchers in the area of fuzzy theory [16, p. 3], "for factual models or modeling languages, two major complications arise:

1. Real situations are very often not crisp and deterministic, and they cannot be described precisely.
2. The complete description of a real system often would require far more detailed data than a human being could ever recognize simultaneously, process, and understand.

So real situations are very often uncertain or vague in a number of ways. Due to lack of information, the future state of the system might not be known completely". There are different approaches for modeling under uncertainty, such as probability theory and fuzzy theory.