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IFAO-SIMO: A SPATIAL-SIMULATION BASED FACILITY NETWORK OPTIMIZATION FRAMEWORK

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ABSTRACT

This paper describes an innovative framework, iFAO-Simo, which integrates optimization, simulation and GIS (geographic information system) techniques to handle complex spatial facility network optimization problems ever challenged from retailing, banking and logistics nowadays. At the top level of iFAO-Simo, an optimization engine serves to generate and test candidate solutions iteratively by use of optimization algorithms such as Tabu Search and Genetic Algorithms. For each scenario given by the candidate solutions, a discrete event simulation engine is triggered to simulate customer and facility behaviors based on a GIS platform to characterize and visualize the spatial, dynamic and indeterministic environments. As the result, the target measures can be easily calculated to evaluate the solution and feedback to the optimization engine. This paper studies a real case of banking branch network optimization problem, and the results show that iFAO-Simo provides a useful way to handle complex spatial optimization problems.

1 INTRODUCTION

Nowadays, the emergence of spatial optimization problems are increasing in many industries. For example, banking branches serve as the most important channel to deliver financial products or services. To win in the competitive and turbulent marketplace, both the target customers and competitors around each potential branch location should be studied carefully. Recently, spatial optimization methodologies are highly encouraged to support the strategic branch investment decisions on new marketplace entrance or current branch fleet optimization (opening, moving, cutting, upgrading or degrading branches). The requirements of such kind of spatial facility network optimization also arises in other industries, e.g., retail store transformation (site location, store capacity, merchandise mix, etc).

An intuitive way to handle the above problems is to leverage traditional optimization algorithms. For example, Guerra and Lewis (2002) defined a mathematical model and used a linear programming solver to obtain the optimal site characteristics. Since most optimization techniques, e.g., simulated annealing (Kirkpatrick, Gelatt, and Vecchi 1983), Tabu search (Glover 1990) and Genetic Algorithms (Goldberg 1989), follow the idea of searching candidate solutions by iteration according to certain solution quality index such as the concept of 'fitness' in Genetic Algorithms, how to evaluate a candidate solution from spatial and non-spatial information becomes the key issue for problem solving. Unfortunately, there are still few reports on that till now.

A possible way for it is to borrow the ideas of simulation-based optimization techniques applied in complex non-spatial optimization problems, i.e., simulations are employed to carry out "what if" analysis for each candidate solution. For spatial simulation, different from traditional simulation in business and social science, geographical information and spatial characteristics should be incorporated. Such kind of spatial simulation methods have gradually attracted more attentions in the last several years. Wiley and Keyser (1998) used discrete event simulation by incorporating GIS to support transportation incident management decisions. Born (2005) used WebGPSS to drive a simulation to solve innovative business strategy problems. Biles, Sasso, and Bilbrey (2004) described the integration of GIS with simulation modeling of traffic flow on inland waterways. Gonçalves, Rodrigues, and Correia (2004) proposed a conceptual framework to integrate GIS and multi-agent system perspectives in the context of modeling and simulation (M&S) of complex dynamic systems. Box (1999) discussed the integration of GIS and agent-based simulation.

Therefore, combining traditional optimization techniques with spatial simulation will provide an attractive way to handle spatial optimization problems. Based on this idea, iFAO-Simo, a spatial-simulation based framework is proposed in this paper. As an important component of iFAO (IBM Facility Network Analysis and Optimization Engine), an ocean data statistics analysis engine from IBM China Research Laboratory, iFAO-Simo integrates optimization, simulation and GIS techniques coherently to support the challenging spatial decision making process of facility network optimization in banking, retailing etc.

The rest of this paper is organized as follows. In Section 2, the framework of iFAO-Simo is described in details including the optimization engine, discrete event simulation package and GIS based behavior models. A real case of banking branch reconfiguration problem solving (i.e., to optimize a whole branch city network for profitability, efficiency and cost effectiveness by way of opening, moving, cutting, upgrading or degrading branches) is then studied to demonstrate the benefits of iFAO-Simo framework in Section 3. Finally, the conclusions and remarks are presented.

2 iFAO-Simo FRAMEWORK

As shown in Figure 1, the framework of iFAO-Simo mainly consists of (1) an optimization engine to drive a top-leveled optimization, (2) a DES (discrete event simulation) engine to drive individual-based simulation processes and (3) individual behavior models with data from GIS platform. The optimization engine generates candidate solutions iteratively and the DES engine simulates the potential objectives of each solution with the support from GIS based behavior models. The optimal solution can eventually be visualized through GIS platform.

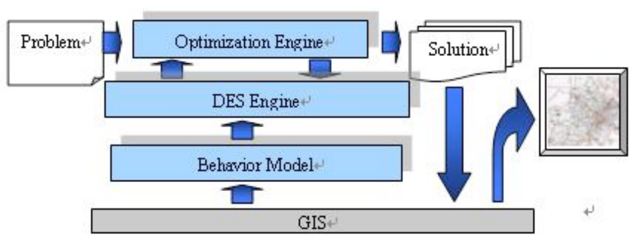


Figure 1: iFAO-Simo framework.

2.1 Optimization Engine

Before running iFAO-Simo framework, we should model scenarios into optimization problems. Due to the complexity of real facility network optimization problems, we build various searching modules in the engine, each of which encapsulates a heuristic searching algorithm. Currently, iFAO-Simo offers searching modules of simulated annealing, tabu search and genetic algorithms (see in Figure 2), and then the appropriate one will be chosen according to real needs.

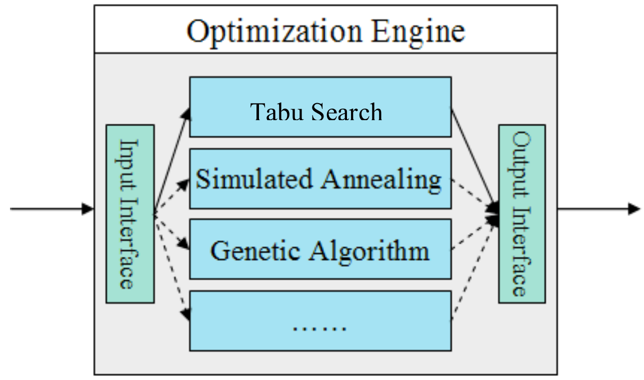


Figure 2: Optimization engine.

All the heuristic algorithms share the same idea of an iteration of generating candidate solution(s) -> evaluating solution(s) -> generating new solution(s). In site location scenarios, the basic problem is to select good locations for multiple types of facilities. Thus each candidate solution will take the form of a vector to indicate the location of each facility, i.e.,

$$S_i = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}.$$

Then S_i is encoded in suitable forms according to the selected heuristic algorithms. In traditional applications of heuristics, the evaluation is based on a certain kind of fitness functions (as the fitness function in Genetic Algorithm). However, in many real complex cases, it is usually too hard to get a reasonable fitness function. Then it motivates us to adopt discrete event simulation mechanisms in iFAO-Simo as follows.

2.2 Discrete Event Simulation (DES) Engine

Discrete event simulation is carried out in terms of the specification of general discrete event simulation (Law and Kelton 2000). For each candidate solution generated by the optimization engine, the simulation engine starts a DES, which runs for certain periods and generates result data. Then based on predefined criteria, the candidate solution can be evaluated by these data.

The DES engine is composed of a standard discrete event simulation logic, a dynamic event list and a statistical module (see in Figure 3). The dynamic event list maintains events to happen in the future and the simulation logic triggers these events at appropriate time. During the simulation, events can be added or removed from the event list dynamically. The statistical module collects data during the simulation, and generates output of the target evaluation results.

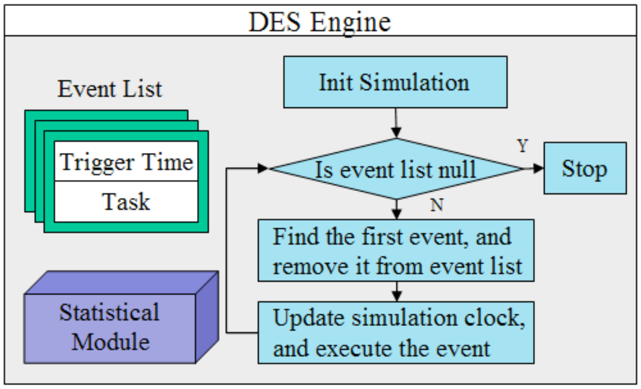


Figure 3: DES engine.

2.3 Behavior Model

Behavior model is the basis of simulation. In facility network optimization scenarios, there are at least two kinds of the behavior models, *i.e.*, customer behavior model and facility behavior model.

2.3.1 Customer Behavior Model

Customer behavior model describes how customers behave when they are doing business with the facility network. According to customer behavior theory in marketing science (Hawkins, Best, and Coney 1997), customer shows rich behavior patterns, and the term "customer behavior" also covers many aspects, such as habit, preference, selecting, tolerance, etc. In this paper we only consider three major aspects, including demand generation, facility selection and facility visiting, that will affet facility network configuration.

Demand Generation: The customers are distributed in certain regions of the map. They are staying in different geographical layers (such as residential buildings, office buildings, supermarkets, etc.), and demands are generated everyday from these customers. For simplicity, we identify a series of demand sources in the map to reflect the major habitant locations. In each day, each demand source will continuously generate a stream of customers with certain demand quantity.

Facility Selection: Each customer has a sight range (in Figure 4, the concept of sight range represents the region inside which the customer will do his business with the facilities). The customer will search all the facilities inside his range and identify all the available ones. And among these available facilities, the customer will choose one to do business.

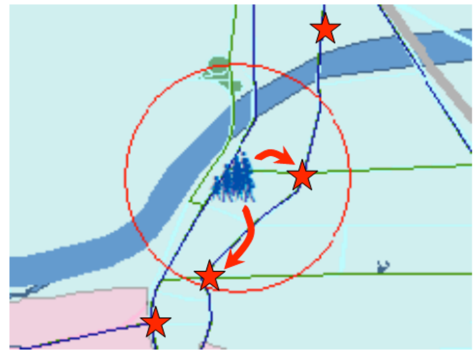


Figure 4: Customer sight range.

Facility Visiting: Once a customer enters the selected facility, he observes the situation inside the facility (e.g., queue length), and decides whether or not to join into current queue and wait for the service, or to switch to other available facilities nearby, or goes back home directly without doing any business.

2.3.2 Facility Behavior Model

Facility behavior model describes how each facility operates when serving its customers. Similar to the customer behavior model, we select 2 major aspects, including business time and capacity.

Business Time: Each facility has its business time, during which the customers receive financial services. For example, some facility opens between 9:00 am and 18:00 pm every day while the self-service devices (e.g., ATM) are available in the 7×24 manners.

Capacity: Each facility serves its customer queue under some rules (such as FIFO, or first serve customers that have higher priorities). For each customer, the facility needs some time to finish the service. Each facility has its service capacity that can be denoted by the maximal queue length. When a facility's customer queue length reaches the capacity, this facility becomes unavailable.

With different assumptions on the above aspects, we can build appropriate models according to the problem scenarios to be handled.

2.4 GIS Platform

GIS platform offers spatial information of the objects in the whole region such as streets, rivers, buildings, etc. All the data in the GIS platform are organized into geographic layers, which can be queried for more comprehensive analysis.

In iFAO-Simo, the GIS platform acts as the data provider and result visualizer. The spatial parameters of the behavior model are determined through the related layers of the GIS data. And the optimization results can be more intuitively presented into the map through GIS viewer.

3 CASE STUDY

In this section, an example of banking branch network optimization will be given to demonstrate the practicability of iFAO-Simo on complex spatial decision problems.

In this real case, one of the Chinese biggest banks plans to extend its business to a new city by opening a series of new branches. In order to maximize the performance of this new branch network, the bank needs to study carefully on how to locate the branches in the city with suitable branch types. Generally, these new branches can be located intuitively based on previous experiences. However, the branch locations together with type can be more accurately optimized from iFAO-Simo framework automatically.

3.1 Experimental Setup

From the habitant layer of the city's GIS data, we identify a series of major demand sources that are distributed in different areas. Based on a more detailed survey of the customers in these demand sources, statistical methods are applied to calculate the parameters of demand generation, customer demand quantity and customer's sight range.

It's assumed that each customer will search branches inside his sight range and choose one according to his preferences. When a customer goes into a facility, he joins into the queue and wait for service until his business is completed.

According to the branch development strategy, three standard types of branches (I main-branch, II sub-branch and III minor-branch) are considered here with different business content and service capacity (see in Figure 5a). For each branch, the business time is between 9:00 am and 18:00 pm every day. The branch handles the customer queue under the FIFO rule. The service time for a customer and each branch's capacity are obtained through the survey from the customers and bank managers.

To evaluate the results, two major metrics, i.e., total profit and average customer waiting time, are selected and indicate the performance of the whole branch network. With this optimization framework, these metrics will be output as the results.

We define two facility selection mechanisms to identify customer behaviors as follows:

1. Nearest Policy - customer chooses the nearest branch in his sight range (which implies that the distance is a key factor when customer chooses branches)
2. Random Policy - customer randomly chooses a branch in his sight range (which implies that customer does not care about the distance of the branches)

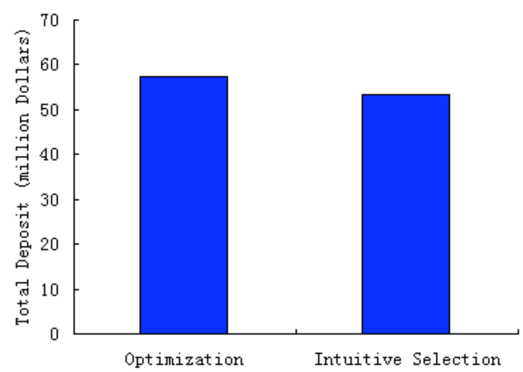
Under each selection mechanism, we compare the optimization results of intuitively selection and iFAO-Simo.

When using iFAO-Simo framework, tabu search module is employed with the max length of movement set as 1500 and tabu list length as 500.

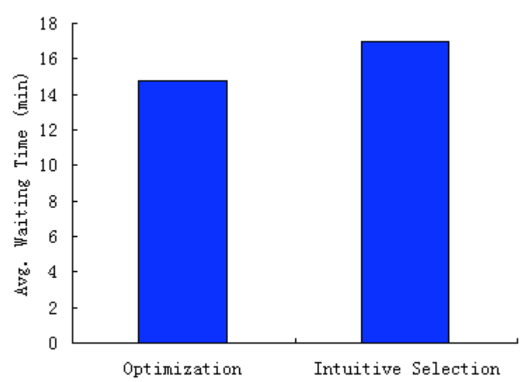
For each candidate solution, the DES engine run 10,000 periods (which means 10,000 days in the simulation) to collect statistical data for solution evaluation.

BR: Type I; BR: Type II; BR: Type III

(a) Optimal branch locations and types.



(b) Predicted deposit through simulation.



(c) Predicted waiting time through simulation.

Figure 5: Simulation results under nearest policy.

3.2 Simulation Results

The simulation results under Nearest Policy are shown in Figure 5. Totally 13 branches including 2 main-branches, 3 sub-branches and 8 minor-branches have been searched in the study area via iFAO-Simo (Figure 5a). Both the deposit and average waiting time are calculated through DES engine. From Figure 5b, Figure 5c and Table 1, it can be seen that the optimal branch network generated by iFAO-Simo, with more deposits and shorter customer waiting time, is better than intuitively selection. The results demonstrate that the spatial optimization framework is more effective to handle such problems as in this scenario.

Table 1: Comparison of the results of optimization and intuitive selection under nearest policy.

	Optimization	Intuitive Selection
Deposit ($)	57277889.44	53208667.37
Waiting Time(min)	14.77	16.98

The other scenario under Random Policy is also studied and the results are shown in Figure 6. Different with the optimal branch network found in Figure 5, 23 branches are suggested with 1 main-branches, 1 sub-branches and 21 minor-branches (Figure 6a) to serve the random customers. It might imply that, when customers select the branches without distance consideration, banks should put efforts to open more small branches to satisfy their demands. As in Figure 6b, Figure 6c and Table 2, both results are almost the same (although result of optimization is still a little better than the intuitive selection). This implies that the performance of the framework depends on the scenario of the problem. When applying this framework into real cases, we may combine the results of optimization and intuitive selection to get better solutions.

Table 2: Comparison of the results of optimization and intuitive selection under random policy.

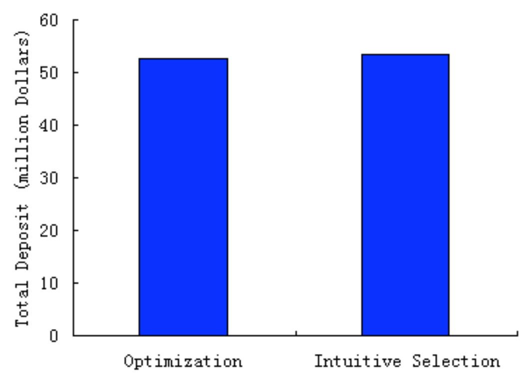
	Optimization	Intuitive Selection
Deposit ($)	52698672.01	53208667.37
Waiting Time(min)	17.08	17.16

4 CONCLUSIONS

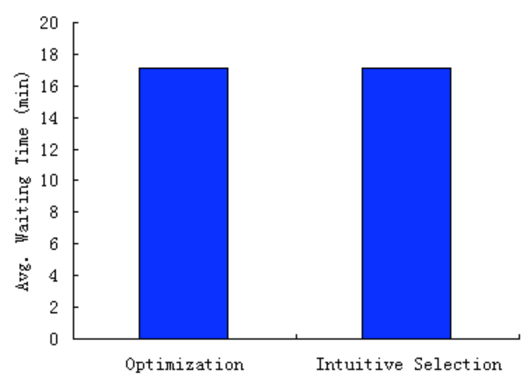
The results of the case study demonstrate that iFAO-Simo framework provides a useful way to handle complex spatial optimization problems. This framework adopts spatial simulation in evaluating candidate solutions generated by optimization techniques, and thus can go beyond the limitation of traditional optimization in handling complex spatial problems. Furthermore, the results can be presented by the GIS platform directly and intuitively.

BR : Type I; BR : Type II; BR : Type III

(a) Optimal branch locations and types.



(b) Predicted deposit through simulation.



(c) Predicted waiting time through simulation.

Figure 6: Simulation results under random policy.

However, besides this preliminary work on iFAO-Simo framework, there are many possible directions of extension. The behavior model in the study case is fairly simple and only captures quite limited aspects of customer behavior. In future research, more elaborate behavior model will be explored. Secondly, in this framework, the optimization algorithm will start a simulation run for performance evaluation of each candidate solution and might result in time-consuming process for problem solving. New mechanisms will be investigated further to improve the framework's performance.

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