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# Distribution-service network design: an agent-based approach

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**Abstract**

Decisions to locate facilities within product-service network should satisfy all stakeholders' objective in supply chains. To provide solutions for such strategic decisions, many method and approaches have been applied including operations research, fuzzy decision making, etc. Reviewing the efficient and effective methods, agent-based models (ABM) are proved to provide competitive solutions to distributed problems. In this paper an agent-based model for the facility location problems is presented. Agents are defined as regional warehouses and cities; optimization rules are applied to the behavior of agents in distribution-service network environment. Agents make decision on the location of facilities based on autonomy factors and Optimization rules which are derived from similar optimization problems in facility location. Proposed model is implemented to a case in automobile after sales services network. The efficiency of proposed model is evaluated by defined performance measures under demand uncertainty. It is concluded that embedding optimization behavior into autonomous agents can provide productive solutions for complex decision in uncertain environment.

## 1. INTRODUCTION

In past two decades, the concept of supply chain (SC) has attracted both practitioners and academics as an integrated solution for many of the challenges in competitive market. Supply chain management is introduced as an approach to integrate material and information flows among suppliers, manufacturers, warehouses and customers by organizing and coordinating functions, resources and operations. One of the important fields in supply chains is the design of distribution networks which directly affects customers' satisfaction and corporate profitability. In this regard, managers are mostly challenged through optimizing decision such as location of warehouses, transportation modes, inventory management, etc.

Optimization of facility location as strategic decision with long-term effects has shown considerable role in each firm's performance (Owen and Daskin, 1998). Methods used to optimize such decisions vary from pure optimization methods and mathematical programming to decentralized simulation methods such as simulation-based optimization. The advantage of pure optimization methods is the ability to gain optimum or near optimum solutions for the problem. However, centralized nature of these methods provides some concerns such as reasonable time of computation, ability to consider shifts in variable and lack of interaction with social-technical systems which may affect the provided solution. In contrary, agent-based methods are proved to provide promising solutions for problems with complex, distributed and heterogeneous domains (Wooldridge, 2002; Weiss, 1999). Reviewing comparison of these methods (Davidsson *et al.*,

2007), we conclude that these method can be arranged as complementary of each other.

Agent-based models (ABMs) consist of a set of elements (agents) characterized by some attributes, which interact each other through the definition of appropriate rules in a given environment. ABMs can provide an effective approach to solve problems with the large size of the domain in nature where the structure of the domain changes frequently (Barbati *et al.*, 2012).

A hybrid method would include the advantages of both approaches (ABMs and pure optimization). First way is to apply an optimization technique to the problem, then re-plan the solution by agents. A second way is to embed optimization rules in agents and perform agent-based modeling. The second way arranged as simulation-based optimization method ensures managers that different scenarios under variety of uncertainties are tested and optimum\near optimum solutions are obtained. In such cases, instead of using thousands of equations with time consuming solution processes, simple equations are formulated with fast and competitive solutions.

In this paper, a hybrid model to embed optimization rules in agents' interaction is presented. The novelty of research is to propose a general model which is suitable for any facility location problem with similar scope and assumptions. The bottom-up decentralized structure of the model ensures that individual agents are satisfied regarding to the selected objective function. A variety of objective functions are formulated to increase the capability of model and to support managers with versatile analyses.

In section 2, the literature to apply agent-based models in location problems is reviewed. Proposed model with application in an after-sales network design is presented in section 3. Simulation results for individual objective functions are compared with each other and with pure optimization problem in section 5. Finally, conclusion and suggestions are provided in section 6.

## 2. LITERATURE REVIEW

Application of agent-based modeling in facility location decisions is rarely conducted in reviewed literature, compared to other areas of supply chain management such as production planning, scheduling and capacity planning (Barbati *et al.*, 2012). We categorized the literature based on field of research, type of agents, environment and applications.

Mengual *et al.* (2013) proposed a model to locate mobile stations such as laptops and tablets in an indoor environment using wireless technology. In this model each mobile device are defined as an agent called fuzzy location software agent (FLSA). Agents are embedded in continuous environment which collect the power from distributed access points inside the building. FLSAs communicate with each other and other local agent type called fuzzy location management software agents (FLMSA) as a part of forming an infrastructure management Wi-Fi network of the organization. The aim of the model was to correctly estimate the location of a mobile terminal indoors in a room or adjacent rooms which is applied to a real work station.

Maka *et al.* (2011) presented an agent-based model for warehouse logistics systems and proved the efficiency of the proposed model compared to standard central management system. Agents were defined as central warehouses and a central warehousing agent was used to control the interactions and warehousing operations in a system. Bruno *et al.* (2010) introduced and agent-based framework suitable for use with GIS-based data. Different objective functions could be embedded to deal with various facility location problems with easily modeling and solution process compared to similar mathematical programming approaches. Agents were defined as demand points and facilities and were implemented on some samples.

Schumacher *et al.* (2008) presented a multi agent system where the agent environment may have the role of governing infrastructure that supervises agents by setting laws and regulation. The presented model indicates that how traffic jams and accordion phenomena can be handled by proper local regulations on speed limits of each roadway segment. Chao *et al.* (2008) proposed a multi agent system (MAS) to simulate multiple linear and non-linear relationships and factors including culture, policy, history and systems between the people, facilities, and government as agents. The core idea is that simulation modeling is appropriate method to deal with non-linear complex system problems.

Moarref and Sayyaadi (2008) suggested distributed algorithms to solve continuous n-median problems which are applied in facility location problems. In the case study, they endorsed that the main advantage of multi agent system is the robustness to failure of single robots.

The agent-based model proposed by Mele *et al.* (2007) retrofits a supply chain by optimized facility location decisions. In this model, the performance of each set of supply chain configurations was assessed through a multi agent model coupled with a Genetic Algorithm. This is to optimize the operational variables associated with each design candidate. Sirikijpanichkul *et al.* (2007) presented an agent-base model which is combined with traditional optimization techniques. The proposed approach located the new facilities by negotiation of agents and test of different scenarios and objectives to select the best location.

To sum up, reviewed studies indicates the need for further research to provide agent-based models coupled with optimization techniques. In this paper, we proposed an agent-based model to deal with facility location decisions. Embedding optimization within agents is conducted by definition of some objective functions. These objective functions stem from similar location optimization and mathematical programing techniques. After simulation of different scenarios and conducting sensitivity analysis, the best set of facilities location is proposed. In next section details of the model is presented.

## 3. PROPOSED MODEL

### 3.1. Problem definition in case study

Logistics and service networks play an important role in corporation's profitability and customers' satisfaction. The

aim of establishing such networks is to respond to customers' demand at minimum time with the best quality. In industries with high customer requirements such as car manufacturing, design of optimal logistics network is vital; we select the case in this industry. The reasons inspired network managers to revise the current network includes product diversity, distribution cost, number of daily spare part orders and competition among suppliers. One idea was to study the feasibility of establishing regional warehouses to supply the partitioned demand of customers; therefore, instead of supply demand from one central warehouse, some regional warehouses needs to be located. The question is how many regional warehouses and where to locate them.

### 3.2. Model description

Based on the defined problem, structure of the logistics network is illustrated in figure 1. In this figure, levels and interaction between the elements of logistics network is depicted. The difficulty is the daily demand of customers that requires a dynamic model to supply those demand. The model should define the borders among customers in each region to optimize the objective functions.
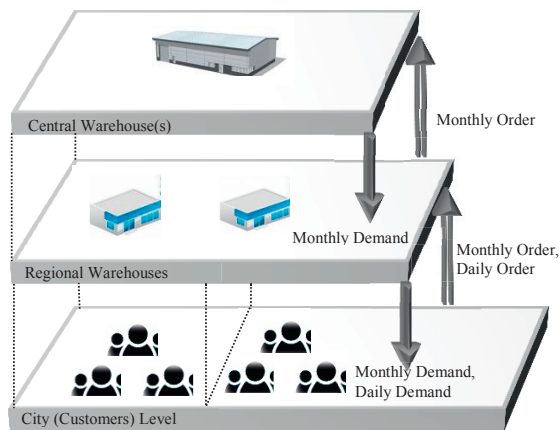


Fig. 1. Structure and interactions of targeted distribution network

The proposed model includes two main phases: agent-based simulation and performance measurement. In the first phase, agents are defined as regional warehouse (RWs) in interaction with city agents (accumulated customers' demand). Detail steps of proposed is shown in Table 1. Optimization rules are embedded in steps 4 to 7 where new agents are selected based on each objective function and new location is nominated due to interaction between two agents.

Table 1. Steps of Agent-Based simulation phase (steps 1 to 3 in Fig. 2)

| No. | Steps |
|---|---|
| 1 | Define agents (RWs and Cities), |
| 2 | Assign attributes to the agents based on real data, |
| 3 | Assign one RW agent to each City agents, |
| 4 | Find two RW agents based on objective functions, |
| 5 | Interaction of selected RWs to locate new cumulative RW agent, |
| 6 | Delete both of RW agents, |
| 7 | Map new RW agent in model and assign related attributes, |
| 8 | Redo from step 4 to fulfil desired objective function, and |
| 9 | Report results for Second Phase. |

The result of interaction in step 5 is to select which RW agent will inherit the cumulative attributes of those agents and which RW agent will be deleted. Assumptions in the modeling are as follows:

- Customers' demand is accumulated in cities as the attribute of city agents,
- Location and interaction of agents are based on information obtained from GIS maps,
- Distance is approximated by Euclidean and standard norm methods,
- Daily and monthly demand of cities are estimated based on 5 years data of customers covered by RWs,
- Statistical distribution functions of demand are applied in the second phase to evaluate scenarios with stochastic demand, and
- All cities should be supplied by regional warehouses.

The proposed agent-based model is coded in Anylogic 6.8 educational software. By means of a step-wised fashion in a GIS environment, the objective functions, parameters and scenarios are embedded in the model. In the second phase of proposed model, some performance measurement indexes in terms of time, cost and efficiency are defined and applied to test the performance of proposed embedded objective functions. Performance measurement indexes (PMIs) are listed in Table 2.

Table 2. Performance Measurement Indexes defined to evaluate scenarios,

| Code | Steps |
|---|---|
| PMI1 | Total transportation cost of monthly demand, |
| PMI2 | Total transportation cost of urgent demand, |
| PMI3 | Total Transportation cost, |
| PMI4 | Total establishment cost, |
| PMI5 | Total cost, |
| PMI6 | Min time of supplying urgent demand, |
| PMI7 | Average time of supplying urgent demand, and |
| PMI8 | Max time of supplying urgent demand. |

In order to model the process of facility location by application of agents in the software, a list of parameters and variables should be defined. These elements are used to model the attributes of agents and specification of interactions during simulation as shown in Table 3.

Table 3. Elements of agent-based model,

| Elements | Type | Application |
|---|---|---|
| Latitude | Parameter | Locating cities and RWs in GIS map |
| Longitude | Parameter | Locating cities and RWs in GIS map |
| Demand | Parameter | Cumulative demand of covered customers |
| Min Distance RW | Variable | Search of nearest RW agent in each state |
| Volume | Variable | Cumulative demand of covered cities |
| Distance type | Parameter | Definition of distance calculation method |
| Objective function code | Parameter | Selection of RWs locating method |
| No. of facilities(RWs) | Variable | Selection of desired No. of facility to locate |
| Capacity and cost rates | Parameter | Definition of rates to performance measurement |

The mechanism of interaction between agents and between agents and environment is introduced in step-wised procedure in Fig. 2. The presented sequence of interaction is main feature in agent-based simulation. For more descriptions, pseudo codes of two main interactions between agents are listed in Table 4-5.

Table 4. Pseudo code for agent's interactions in "Propose RW agents to find new location" in Fig. 2.

| No. | Steps |
|---|---|
| | For all remained *RW* agents to be located, |
| 1 | Find *RW(i)* and *RW(j)* fit with selected objective function, |
| 2 | Calculate minimum distance between *RW(i)* and *RW(j)* based in selected distance type, |
| 3 | Check the constraints on distance, volume, etc. for accumulated *RW* ( *RW(k)*), |
| 4 | Propose *RW(i)* and *RW(j)* to "find location for new *RW* agent" |

Table 5. Pseudo code for agent's interactions in "Find new location for new *RW* agents" in Fig. 2.

| No. | Steps |
|---|---|
| | For proposed *RWs* agents (*RW(i)* and *RW(j)*), |
| 1 | Decide on applying Autonomy level of agents to be included to the model, |
| 2 | Calculate attributes of new *RW* ( *RW(k)*) based on optimization and autonomy level (shown in Table 3), |
| 3 | Propose *RW(k)* as new regional warehouse to "locate final *RW* agent" |

By applying each objective function, simulation-based optimization is conducted in this study. A detail of the defined objective functions and specifications is described in Table 6. These objective functions are used as interaction rules between RW agents as shown in pseudo codes and step-wised model (Fig. 2).

**1. Before simulation:**

*set simulation preferences:*
- *Distance type,*
- *Objective function,*

**2. Start-up code of simulation**
- *Locating initial set of customers (cities)*
- *Calculation of minimum distance between cities,*

**3. Simulation**

| | **On before step** | **On step** | **On after step** |
|---|---|---|---|
| **Environment** | - *Update simulation screen,*<br>- *Check the conditions to stop simulation,* | | *Clean-up Simulation Screen*<br>*Locate Final RW agents* |

| | **On before step** | **On step** |
|---|---|---|
| **Agents** | *Locate Remained List of RW agents*<br>*Propose RW agents to find new location (based on objective functions)* | *Find location for new RW agents* |

**4. Destroy code of simulation**
- *Sorting Regional Warehouses,*
- *Calculate distance of Optimized Solutions,*
- *Calculate Performance Measurement Indexes,*

Fig. 2. Step-wised model including sequence and interaction of functions based on AnyLogic software,

Table 6. Objective functions applied in proposed agent-based model,

| Code | Objective Function | Method of Search New Location | S/M | Distance | Capacity | # of RWs | Efficiency |
|---|---|---|---|---|---|---|---|
| OB1 | Min. Distance | Based on nearest distance among all RWs | S | ✓ | | | |
| OB2 | Min. Distance < 300 | If distance between two RWs is less than 300 Km | S | ✓ | | | |
| OB3 | Max. Capacity < 600 | If cumulative capacity of two RWs is less than 600 units | S | | ✓ | | |
| OB4 | Max. Capacity< 600 and Min. Distance <300 | If first, cumulative capacity is less than 600 units; then, distance between two RWs is less than 300 Km | M | ✓ | ✓ | | |
| OB5 | Min. Distance <300 and Max. Capacity< 600 | If first, distance between two RWs is less than 300 Km; then, cumulative capacity is less than 600 units | M | ✓ | ✓ | | |
| OB6 | Max. Distance location | Finds the longest distance to central warehouse then searches min. distance less than 300 Km | S | ✓ | | | |
| OB7 | Max. Distance location (Far first focus) | Finds the longest distance to central warehouse then searches min. distance less than 300 Km if new location is less than 600 Km far from all covering customers | M | ✓ | | | ✓ |
| OB8 | Max. Coverage | Based on nearest distance among all RWs to cover all customers by predefined No. of RWs | M | ✓ | | ✓ | |

The "Included Objective (s)" header spans the Distance, Capacity, # of RWs, and Efficiency columns.

## 4. DISCUSSION

The data collected based on 5 years logistics operations in studied network is used to run the simulation. The results based on objective functions and PMIs are indicated in Table 7. Managers may decide to select best strategy based on individual or multiple PMIs. For example, OB3 proved to provide minimum total cost and minimum average supply time among others.

The GIS based map used within the model provided visionary of results and accurate calculations for the location of RW agents. Fig. 3 illustrates the results of model on GIS map by selection of OB3 as objective function.
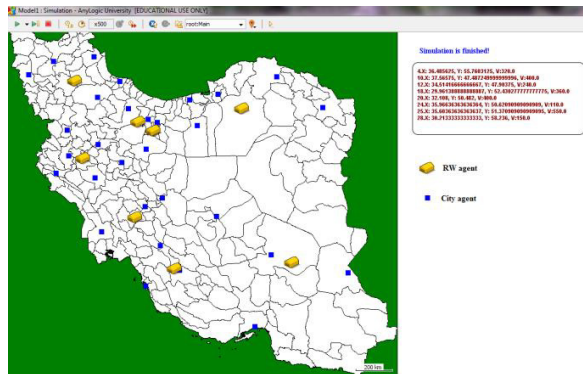


Fig.3.Application of GIS map to locate results of the best scenario of agent-based model in Table 8,

One of the most important features of service networks is variability and unpredictability of demand. We modeled this variation as demand uncertainty. Hence, based on the analyzed data, distribution function of demand in each city was selected. These distribution functions were set in the model to generate customers 'demand in cities in each period.

Analysis of results in Table 7 shows that minimum transportation cost occurs where the only constraint is on demand covering capacity. It indicates that waving constraints on distance and authorizing agents to decide would improve the results. This claim is proved by following PMI2 to PMI5 which minimum costs are observed in OB3.

In terms of time, PMI6 indicates that OB6 provides a rapid response to the demand of customer. However, following PMI7 proves that average time of supplying urgent demand is not efficient with OB6. PMI8 shows that in all scenarios there is at least one city agent which is more than 300 km from RW agents; it causes the maximum supplying time to be 24 hours. It's concluded that OB3, OB4 and OB5 have shown best average time of supplying urgent demand.

Before decision on the optimum location of regional warehouses, sensitivity analysis, validation and comparison analysis are conducted. In this regard, pure optimization model by using mixed integer linear programming (MILP) model is used and the PMIs are compared for the current state, optimum state (based on MILP) and agent-based model. Top scenarios in proposed model with minimum difference from MILP (pure optimum model) are listed in Table 8.

Reviewing the results in Table 8, we observed that despite the optimum cost solution provided by MILP, in terms of time, solution provided by OB3 serves customers at least 14% more efficient than MILP. Managers would decide on best option through 5.5% more investment to serve customers 14% faster or vice versa. A weighting mechanism to balance cost and time would help to more accurate solution in future studies..

A comparison of PMIs between current state of service network and provided solution, e.g., OB3 indicates that the hybrid model could save up to 76% cost of system while supplying customer 12 hours faster (63% more efficient). We believe that such great predicted improvement may convince

Table 7. Evaluated PMIs for different scenarios,

| OB Code | PMI1 | PMI2 | PMI3 | PMI4 | PMI5 | PMI6 | PMI7 | PMI8 |
|---------|------|------|------|------|------|------|------|------|
| OB3 | 5327567866 | 3735681809 | 9063249675 | 4000000000 | 13063249675 | 4.14 | 7.02 | 24.00 |
| OB4 | 7009197396 | 4675519552 | 11684716949 | 8000000000 | 19684716949 | 4.07 | 7.02 | 24.00 |
| OB5 | 6884218116 | 4306062842 | 11190280959 | 8000000000 | 19190280959 | 4.07 | 7.02 | 24.00 |
| OB6 | 7006696007 | 3697969350 | 10704665358 | 3000000000 | 13704665358 | 4.02 | 12.26 | 24.00 |
| OB7 | 7370500365 | 4298627073 | 11669127438 | 3000000000 | 14669127438 | 4.83 | 11.01 | 24.00 |
| OB8 | 8522840801 | 4922331282 | 13445172084 | 4440000000 | 17885172084 | 4.58 | 11.57 | 24.00 |

Table 8. Comparison of PMIs among proposed scenarios, current state, and pure optimal state,

| OB Code | PMI1 | PMI2 | PMI3 | PMI4 | PMI5 | PMI6 | PMI7 | Difference from MILP |
|---------|------|------|------|------|------|------|------|----------------------|
| OB3 | 5327567866 | 3735681809 | 9063249675 | 4000000000 | 13063249675 | 4.14 | 7.02 | 5.5% |
| OB6 | 6426487124 | 3852822063 | 10279309188 | 3000000000 | 13279309188 | 4.06 | 9.57 | 7.2% |
| OB7 | 6038561465 | 3789263255 | 9827824720 | 4000000000 | 13827824720 | 4.67 | 8.56 | 11.7% |
| OB8 | 6290851584 | 3883382639 | 10174234223 | 3750000000 | 13924234223 | 4.3 | 9.13 | 12.4% |
| Current State | 13632981595 | 5626327540 | 19259309136 | 2530000000 | 21789309136 | 4.58 | 19.2 | 76.0% |
| Optimum (MILP) | 6056266804 | 3327041754 | 9383308558 | 3000000000 | 12383308558 | 5.14 | 8.24 | 0% |

managers to invest on establishing the regional warehouses according to proposed model.

## 5. CONCLUSION

In this paper, an agent-based model to optimize facility location decision within logistics and service network is presented. Reviewed literature indicated that agent-based models are applied in limited number of facility location studies. Facility location problems are known as NP-hard problem which need complicated methods to find solutions. Novelty of proposed model is summarized as GIS-based solution, versatile objective framework and optimality assessment.

The proposed mode is implemented to optimize facility location decisions in after-sales services network of a car manufacturing corporation. Making use of real data such as 5 years logistics data and GIS-based maps made the measurements and solutions realistic. Moreover, simulation of the model with versatile objective functions provides versatility to the model; therefore, decision makers are enabled with a set of solutions to decide on desired one.

Contribution of this paper is to propose a hybrid agent-based model equipped with optimization behavior of agents to locate facilities within service network. Fortunately, the results of proposed model proved that the model is competitive with other models in terms of cost, time or combination of them. Surprisingly, although simple optimization behavior is embedded within agents' interaction, competitive outcomes are obtained. However, the framework of agent-based models is dynamic and flexible to the environment they are surrounded which is the advantages of ABMs compared to pure optimization methods.

For the future research, improving optimization behavior of agents by revising or adding more objective functions is recommended. Also, the solution space can be divided to some zones and modular location optimization be applied. Including more agent types such as customers or suppliers would enrich the solutions provided for facility location problems where many stakeholders are available.

The proposed model is general and applicable to any case with similar objective and assumptions. We believe that the extension of provided model would move forward the optimality and satisfaction of current solutions in facility location problem.

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