Proceedings of the 2013 Winter Simulation Conference
R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, eds.

SOLVING LOCATION PROBLEMS WITH SIMULATION MODELLING - A CASE FROM THE CONSTRUCTION INDUSTRY

Fredrik Persson
Daniel Erlandsson
Alexander Larsson
Maria Johansson

Department of Management and Engineering
Linköping University
SE-581 83 Linköping, SWEDEN

ABSTRACT

Location problems are often solved by means of optimization. Simulation is often used to test the feasibility of an optimal solution after that the optimal solution is obtained. The test by simulation is done with more dynamic circumstances, introducing stochastic behavior. This research proposes to solve location problems directly in a simulation model, combining an optimization algorithm within the simulation model, thus providing solutions that are optimized in a stochastic and dynamic environment. The solution becomes more robust than an optimal solution provided by an optimization model. This methodology is tested on a real location problem in the construction industry, where a construction company is searching for the best location for their logistic distribution center. The location problem is modeled in Arena and solved with OptQuest. The suggested location method using simulation modeling solves the problem with nearly the same accuracy as an optimization model.

1 INTRODUCTION

Facility location problems are usually solved by mathematical programming, searching for an optimal location. In many applications, an iterative method is utilized that combine mathematical programming for facility location problems with simulation to test the robustness of the optimal solution. First, an optimal solution is derived with use of mathematical programming, then that solution is tested in a simulation environment. Simulation has the advantage of the possibility to use dynamic scenarios that can be tested with means of stochastic modeling. The dynamic effects that mathematical programming does not take into consideration can be incorporated into the simulation model (e.g. queuing, stochastic lead times, stochastic capacity levels, etc.). If the optimal solution for some reason is not robust enough, which will be apparent in the simulation model, the optimal solution must be recalculated based on some other principle than before or another location needs to be tested in the simulation model. This might create an iterative process with a risk of many loops before an acceptable solution is created. In this paper, the idea is to solve facility location problems directly in a simulation model, incorporating stochastic behavior from the start. This will shorten the total project lead time for a facility location problem by, possibly, some iterations between optimal solution and simulation evaluation. The final solution should still be as useful as before.

The Swedish construction industry is prone by serious problems concerning delivery and storage of material. Large orders for construction materials are placed to suppliers to get a discount. When materials are stored at the construction site, obsolescence and theft occur and unnecessary time is spent searching and relocating missing or misplaced material. These shortages of material and defective material is often not noticed until the time when material is needed, at the time of consumption (Thunberg 2011). In a distribution center (DC), a proper delivery reception can be made, material can be stored efficiently and just in time deliveries can be made to the construction sites. The possibility to consolidate transports increases as well, both to and from the DC, since material for several construction sites has the same delivery location for the supplier and material from several suppliers can be consolidated when transported from the DC. The question is then where this DC should be located.

The research behind this paper is part of an ongoing collaboration between Linkoping University and Peab, one of Sweden's largest construction companies, together with the municipality of Katrineholm, in the network called Brains and Bricks. The purpose of this research is therefore to formulate the optimization problem of facility location in a simulation model. The rest of the paper is organized as follows. First, some theoretical background is given followed by the research methodology. Then the optimization model is presented followed by the simulation model. After that, results, analysis and conclusions are presented, ending in an outlook into future work.

2 OPTIMIZATION AND SIMULATION

Optimization methods can be divided into subgroups depending on the method used for solving or the structure of the problem. Daskin (2008) divide location models into groups of analytical, continuous, network and discrete models. Analytical and continuous models allow for locations continuously in space. Demand are given by some continuous distribution function. Both these types of models are hard to use for real individual cases because of the assumptions that have to be made. In network models, facilities can only be located on a network of nodes and links where the demand is put on the nodes. These are not always trivial to solve under polynomial time. The last group of models are discrete location models, that mainly can be divided into covering-based models and median-based models. Covering-based models aim to cover all (or a fraction of) customers within some time limit with minimal number of facilities and could be used to locate for example health care facilities and telecommunication stations. Median-based models are used typically when distribution are essential. The distances are weighted by demand, causing the locations to end up near big customers to lower distribution costs. The basic p-median model locates p facilities while minimizing the demand weighted distances between the customers and the allocated facility. It does not however consider the differences in costs among potential facilities or what the optimal number of facilities is, like the Un-capacitated Fixed Charge Location Problem. This could further be complemented by for example capacity and single-sourcing constrains. Although the median-based models are NP-hard to solve, there are several algorithms developed making it possible to solve problems with thousands of customers and potential locations (Daskin 2008). All these models are solved in discrete time. Several of them without consideration to variation of parameter values over time or by uncertainty. This could be taken into account by the use of mean or worst case values or by using dynamic, stochastic or robust optimization.

A stochastic model solution contains several outcomes along with the probability of each of them coming true. It can be used if distributions can be found for the parameters of the system. Both the parameter distributions and the outcomes can be discrete or continuous and this affects what method to use for solving the problem (Xu 2008). As in deterministic optimization, the solution method is chosen based on the structure of the problem. Common approaches are to divide the problem into smaller solvable pieces, solve interesting deterministic scenarios or draw parameter values to solve several deterministic problems by sampling where sample solutions converge to the optimal solution. Upper and lower bounds could also be found. In dynamic programming a problem is turned into several sequential sub problems, related to each other so that they cannot be solved independently. It is not a simple task to accomplish the relationship between the sub problems. When succeeded, a problem with m decision variables has turned into m sub problems with only one variable in each. In each stage (sub problem) the state of the decision variable is established (Ventura 2008). In a stochastic dynamic model, the result of every sub problem depend on the decision taken before, and can be described by a known probability. This is an advantage against common stochastic optimization where all values are drawn before solving the problem. In dynamic programming, the increasing number of states causes the biggest problem (Ventura 2008). In stochastic dynamic simulation, each sub-problem to be solved represents a discrete instance in time. This means that only systems with discrete time intervals can be modeled and solved by the method. One possible application are economical models where the only events present take place at the turn of each quarter of a year.

Simulation can solve both dynamic and stochastic problems. Simulation could for example be used to evaluate the results presented by mathematical programming. The advantage is then that the solution is tested in a dynamic environment, possibly at a higher level of detail with variability in parameter values and executed for a period of time. For further information on simulation see Law (2007) or Kelton, Sadowski, and Sturrock (2007) Combining optimization with simulation more intimately, the possibility to optimize given variability in parameters arises, making the dynamics of the systems matter already when it comes to finding a solution. The area of simulation optimization methods could be divided into groups of ordinal optimization models, statistical selection models, gradient based search models, random search models, heuristics and meta models (Fu, Glover, and April 2005).

In simulation based optimization the simulation model is often a discrete-event continuous-time model. This means that time is treated as a continuous variable. In discrete-event discrete-time models, such as in stochastic dynamic optimization, time is locked at certain intervals or values (end of month, end of year, etc.). Zeigler, Praehofer, and Kim (2000) points out that a discrete-event continuous-time model is nothing but a discrete-event discrete-time model with a very small discretized time interval. However, discrete-time models have the drawback that they are unsuited for logistic applications and more suited for simulation computer systems (Zeigler, Praehofer, and Kim 2000). To use a discrete-event discrete-time model to depict a logistic system would mean that a lot of information is lost. Delayed transports tend to not pinpoint the discrete time intervals for example. To use stochastic dynamic optimization in real logistics applications would imply that you either get many sub-problems to solve (as many as the smallest discretized time interval) or a solution that lack crucial information due to the truncating behavior of the discrete time instances. This is the main motivation for why simulation based optimization is chosen for this type of location problems, and not stochastic dynamic optimization.

3 METHODOLOGY

This research is based on a case study where a location problem is solved by means of simulation modelling. The case study was carried out at construction sites located in a region in the middle of Sweden. The sites were all part of a pilot project where a DC concept was tested for the first time. This pilot study incorporated testing the concept at a transaction level and no thought was put on location issues at that time. However, the case study provided all data used in the simulation model. The case is described in more detail in the next section.

The simulation model was built in Arena and OptQuest was used to get an optimal solution of the location problem. The DC location is optimized with respect to different objectives, such as minimizing transportation cost or time, minimizing warehouse cost or time, and minimizing variance in cost and time for delivery to each construction site. The simulation model was built according to common simulation methodology, *cf.* Persson (2003) and does not differ from the methodologies described in *e.g.* Law (2007). The first step (*i*) is the project planning or problem formulation where the outline of the study is determined. The next step (*ii*) is the conceptual modeling. The conceptual model describes the system under investigation. The conceptual model is validated as the next step (*iii*). The computer-based model is created as step (*iv*). This model must be verified (*v*) and validated (*vi*). Model verification aims at estimating if the simulation model is a valid representation of the conceptual model while model validation aims at estimating if the model is a valid representation of the system. The experimentation step (*vii*) consists of experimental runs with the simulation model. The results of these runs are then analyzed (*viii*) and the result of that analysis is the base for the recommended decision or implementation (*ix*). To this approach is also attached the use of OptQuest in the experimentation step.

In this research, the location problem will be approached in two different ways; pure optimization and an optimization combined with a simulation model. Results are then compared and conclusions are drawn regarding the feasibility of the method.

4 CASE DESCRIPTION

The data for the case study comes from two different sources. First, in 2009, a pilot study of a DC concept in the construction company was undertaken to test the ideas of materials handling in a large scale. Materials was delivered to a terminal (DC), where it was stored, marked and shipped in a just-in-time fashion to the construction site. Second, in 2012, a second pilot study incorporated in total three different construction sites with a DC located at a strategic position in-between the three sites. The idea with the DC is to function as a docking facility where minor adjustments can be carried out in a controlled environment. The facility can also be used to coordinate the logistics flow from supplier to construction site in order to make the correct material arrive at the site at the right time. This may create a more flexible supply chain and reduce the construction project down time due to lack of material.

From August 2009 until October 2010, the construction company together with a logistics company, carried out the first pilot project aiming to evaluate the effects of a DC. In that project, materials that usually created problems at a construction site (i.e. kitchens, doors, windows and general fittings) was transported via a DC, unlike the conventional transport solution directly between supplier and construction site (Thunberg 2011).

From January 2012 until May 2012, the second pilot study incorporated three construction sites and a DC. The same types of materials was handled at the DC (i.e. kitchens, doors, windows and general fittings). All other material was transported directly to the site.

The results on logistics operations were positive in both pilot studies. The sites showed shorter handling times, less damaged goods, and more precise deliveries. The next step before a region wide implementation would be to calculate the location of the DC for the whole region. In total, 16 different locations for the DC facility where feasible due to regional conditions. The DC must be able to store material, have the right conditions for infrastructure, and suitable conditions for warehouse operations. In figure 1, the 16 possible DC locations together with the two suppliers and the 114 construction sites are depicted in a coordination system.

5 THE SOLUTION: OPTIMIZATION

The location problem can be solved with help of conventional optimization methods with different objective functions. In this research, two optimization models with different main objectives is constructed. A number of suggested DC locations are given as input to the models, and the models return the optimal location for the DC, depending on the objective. The models are presented in the following two sections.

5.1 Minimize Total Transport Time

The first model minimizes the total transport time (from supplier to DC and from DC to construction site); see main objective function (1). The input needed for the transport time model are distances between each supplier and DC, distance between each DC and construction site and at last the average speed of trucks that transport the requested material.

$$\min \sum_{i=1}^{n} \left(\sum_{j=1}^{m} \frac{d_{site_{i,j}}}{v_{avg}} x_{i,j} + \sum_{k=1}^{l} \frac{d_{sup_{i,k}}}{v_{avg}} y_i \right) \tag{1}$$

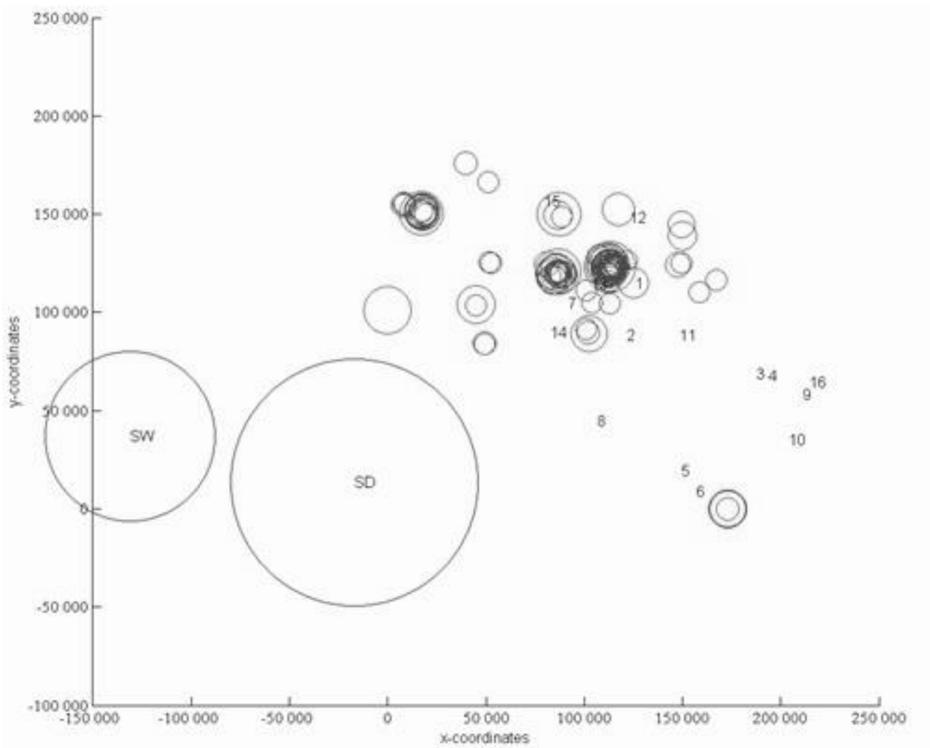

Figure 1: Numbers (1-16) denotes possible DC locations. Circles denotes construction sites, the size of the circle corresponds to the size of the construction site. Several circles at the same coordinates either indicate two construction sites nearby or the same construction site with several orders (due to input data limitations). Big circles denote suppliers (i.e. SD: Supplier of Doors and SW: Supplier of Windows).

The model is subject to the following constraints;

- All construction sites must be covered by a DC, equation (2).
- Only one DC is allowed to open, equation (3).
- A construction site cannot be covered by a DC if the DC has not been opened, equation (4).

$$\sum_{i=1}^{n} x_{i,j} = 1, \forall j \tag{2}$$

$$\sum_{i=1}^{n} y_i \leq 1 \tag{3}$$

$$x_{i,j} - y_i \leq 0, \forall \{i, j\} \tag{4}$$

Explanation of the notation used above;

- n = number of DC locations.
- m = number of construction sites.
- l = number of different materials (doors, windows, etc.).
- v_{avg} = average speed of truck transport.
- x_{ij} = decision variable (if construction site j is covered by DC i then x_{ij} is equal to 1, otherwise 0).
- d = distance (km) between DC and suppliers (d_{sup}) / construction sites (d_{site}).
- y_i = binary variable; y_i is equal to 1 if the DC is placed in location i, otherwise 0.

This model should be seen as a time static model as it only contains one transport per link in the network. In reality there are several shipments on each link between suppliers/DC and between DC/construction sites. The number of shipments depends on the quantities ordered to the construction sites (among others). The model described above (minimize total transport time) is hard to compare with the simulation/optimization described in section 6. This is because the optimization model does not consider partial deliveries from supplier to DC or from DC to site as is the case with the simulation model.

5.2 Minimize Total Transport Work

A second model minimizes the total transport work (from supplier to DC and from DC to construction site); see the main objective function (5).

$$\min \sum_{i=1}^{n} \left(\sum_{j=1}^{m} d_{site_{i,j}} x_{i,j} w_{DCsite_j} + \sum_{k=1}^{l} d_{sup_{i,k}} y_i w_{supDC_k} \right) \tag{5}$$

The input data needed for the transport work model are distances between each supplier and DC, distance between each DC and construction site and the weight of the material transported at each link. The weight depends on type of material. The constraints, equations (6), (7) and (8) equal the constraints in the total transport time model, equations (2), (3) and (4).

$$\sum_{i=1}^{n} x_{i,j} = 1, \forall j \tag{6}$$

$$\sum_{i=1}^{n} y_i \leq 1 \tag{7}$$

$$x_{i,j} - y_i \leq 0, \forall \{i,j\} \tag{8}$$

The notation used above is similar to the total transport time model. Only the average speed parameter is replaced by a weight parameter;

- *w* = metric tonne per construction site or DC, subscript DC to Site (*DCsite*) or Supplier to DC (*supDC*).

6 SOLVING THE PROBLEM: SIMULATION

A simulation model built in Arena was also used to solve the problem for three different objective functions. At first, a conceptual model of the system is created. The conceptual model consists of four parts; supplier, transport (supplier – DC), DC and transport (DC – construction site).

The system that is modelled is a supply chain from suppliers to a distribution centre and further on to a specific set of construction sites. The distribution centre, for which the location is unknown, will collect, temporarily store and ship construction materials to on-going construction projects in the region.

The construction sites (e.g. managers or similar) places order for construction material containing quantity, shape (or other attributes to define site specific material), and delivery date.

The model does not handle any activities at the supplier besides order handling. This means that the order is received and released for transport to DC. The structure of the data (from the pilot projects) is fitted to one truck load and this is implemented in the model as the partial deliveries. Ordered material (doors and windows) are then transported from supplier to the DC. This activity is associated with transport time, variation in transport time, cost of transport and transport work. At the DC, materials are unloaded, stored and then finally shipped to the construction site when the material is needed. The aim is to load all material (regardless of supplier) that a specific construction site needs during one day in one specific truck load. DCs are associated with running costs (e.g. personnel, forklifts, etc.), unloading time, loading time, duration of storage and warehouse costs. Ordered material (doors and windows) are transported from DC to the construction site. This activity is also associated with transport time, variation in transport time, cost of transport and transport work. At the construction site, materials are unloaded and this activity is associated with time for unloading.

6.1 Specification of the Simulation Model

The simulation model is modelled as three different sub-models. By storing data specific to a supplier, DC or a construction site in arrays it is possible to create a relatively small model in terms of number of elements. The first sub-model represents the suppliers and the model reads order data from a data file and sends the order further trough the next sub-model based on the information it reads in the data file. The transport activity between the sub-model is individual for each order and because the orders are structured as one full truckload, no co-loading with other orders are performed. In the second sub-model, which represent the distribution centre that is active (the DC that is tested in that simulation run), the model get orders from the first sub-model and register its arrival. After the registration the order is stored and will wait for a request from a construction site before the order proceeds in the system. The storage records the required space at the distribution centre. The DC sub-model, is modelled so that many different locations are possible by simply changing a setting in the sub-model, thus providing for easy shifting of different locations.

The last sub-model represents the different construction sites. This sub-model generates demands from the same file as the suppliers (the first sub-model) but is delayed by the lead time for the product it demands. This procedure is possible because of how the input data is structured. When the demand is created it will search for the order matching the demands at the distribution centre. If there is demand created that does not find what it demands, the demand will be waiting until the order arrives at the distribution centre. When the order is received at the construction site the orders transport work and transport time will be recorded and the systems total transport work and transport time will be updated.

The simulation model uses the following data:

- Average velocity for transportation
- Handling time for loading and unloading a truck at the distribution centre
- An order plan containing:
    - Time when the order is create [start time]
    - Lead time for different products
    - What type of product the order contains
    - Which site that demands the order
    - The quantity in the order
    - Planed delivery [start time + lead time]
    - Weight of a single product
    - Size of a single product
    - The economic value of a single product
- Coordinates of distribution centres, suppliers and construction site which will generate:
    - Distance between suppliers and each distribution centre
    - Distance from each distribution centre to each construction site

6.2 Finding the Best Location using OptQuest

By representing the choice of which distribution centre that is active in the simulation with an assigned value (the distribution centre number) to a variable, the optimization tool OptQuest can find a good location for distribution centre. OptQuest is based on a tabu-search heuristic that does not guarantee that the solution it finds is the optimal solution. For rather small problems, as the case in this paper, the optimal solution will be found because the heuristic will try all 16 feasible solutions to the location problem.

The record-modules in the model make it possible to create three different objective functions in OptQuest; minimize the total transport work for the system, minimize the total transport time for the system and minimize the total holding cost for the system. The location problem will be solved with all three objectives separately.

OptQuest presents the best solutions after a problem is solved. In the case study, all (16) solutions is presented and the best solutions are saved. A deeper analysis is then preformed for the best solutions, to identify variance in the value of the solution. For each simulation results are given regarding the total required space in the distribution centre and how many of the orders that are delayed when they arrived at construction site.

6.3 Validation and Verification

The most efficient way to avoid errors, both logical and input data related, is to use a structure developing process. Sargent (2007) describes four different types of validation, and most of them require involvement of the customer or user of the model to discuss the outputs reliability.

A frequently used validation method is to incorporate the validation in the development of the simulation model (Sargent 2007). In this project has a validation test been performed when a new part of the model was developed. For instance, when the transport work recording process was implemented in the model the result was compared with a calculation of the input data and the test had matching results. More information and understanding of how the situation is in the construction industries leads to more knowledge of the system and a better possibility for the developer of model to validate the model in the development process.

7 RESULTS

7.1 Result of the Optimization Models

When minimizing the total transport time, the optimization model chooses DC 1 as the optimal solution. The value of the objective function is 76 hours.

When minimizing the total transport work, the optimization model chooses DC 14 as the optimal solution. The value of the objective function is 837 726 metric tonne * km.

7.2 Result of the Simulation Model

From the simulation model, several outputs are given as results in order to have different measurements to determine the best location for a DC. The results are presented in the following sections and is presented with a graph containing all possible DC locations for each objective function. The simulation model is run for one year and in ten replications, using different random number seeds. No warm-up time was used since all activities are based on orders and both site and DC are empty from time to time.

In figure 2 the result of minimizing the total transport time for the system is presented. All possible locations are shown and the four best locations are marked with white bars.

In table 1, the result of seven selected DCs are reported, the four best and the three worst. An interesting observation is that the best DCs, with respect to transport time, is placed (geographically) close to each other. These DCs also lies close to the big cluster of construction sites, see also figure 1. The big difference between the optimization model and the simulation (76 hours against 3 583 hours) depends on the structure of the model. In the optimization model, each route is only operated once for each construction site and material, while in the simulation model each route is operated each time a shipment is made.

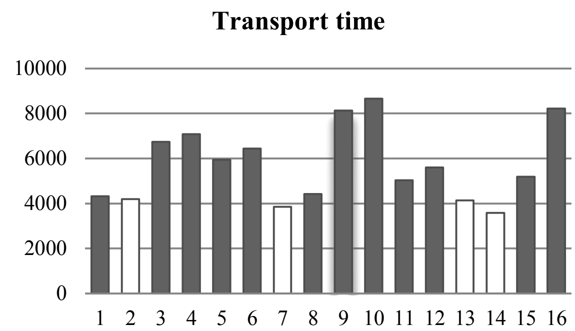

Figure 2. All solutions when minimizing transport time with the best solutions in white.

Table 1. Minimizing Transport Time

DC	Transport time (h)	Min (h)	Max (h)
2	4 191	4 167	4 215
7	3 849	3 826	3 865
9	8 126	8 095	8 156
10	8 653	8 624	8 706
13	4 136	4 111	4 154
14	3 583	3 556	3 602
16	8 218	8 183	8 253

In figure 3 are the result when minimizing the total transport work for the system. All possible locations are shown and the four best locations are marked with white bars.

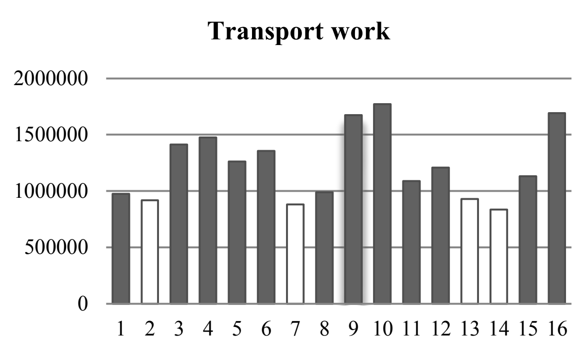

Figure 3. All solutions when minimizing transport work with the best solutions in white.

The four best DC locations with respect to total transport work is the same as the four best DC locations with respect to total transport time. In Table 2, the objective function values for the seven selected DCs are presented. Worth noting is that the same weight was transported the same distance in all replications, giving no variance at all in the results. The best DC (location 14) has approximately the same objective function value in the simulation model as well as in the optimization model (837 726 against 836 125).

In figure 3, the result when minimize the total holding cost for the system are presented. All possible locations are shown and the four best locations are marked with white bars. The difference between different DC locations is very small and can almost be neglected. In Table 3, the result for seven selected DCs is presented.

Table 2. Minimizing Transport Work

DC	Transport work
2	917 856
7	880 612
9	1 672 857
10	1 771 851
13	930 223
14	836 125
16	1 690 238

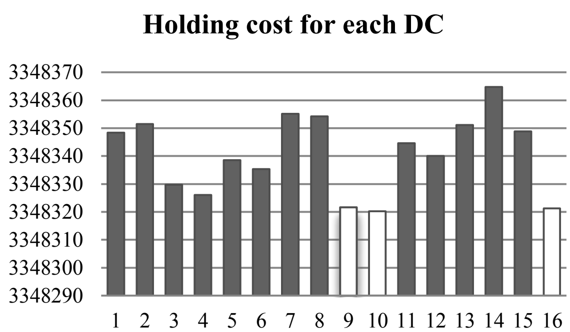

Figure 3. All solutions when minimizing holding cost with the best solutions in white.

Table 3. Minimizing Holding Cost

DC	Holding cost	Min	Max
2	3 348 351	3 348 318	3 348 412
7	3 348 355	3 348 323	3 348 400
9	3 348 321	3 348 275	3 348 405
10	3 348 320	3 348 272	3 348 402
13	3 348 351	3 348 319	3 348 411
14	3 348 364	3 348 329	3 348 405
16	3 348 321	3 348 273	3 348 404

8 ANALYSIS

Table 4 summarizes the results from the two optimization models and the three simulation models. From the table, it is clear that the optimized transport time solution differs much from the others. This is due to the fact that the optimization model does not consider partial deliveries from supplier to DC or from DC to site in the same way as the simulation model does. The comparison between optimal and simulated solution in the case of transport time is therefore unfeasible. This is a shortcoming for the proposed methodology.

Looking at the transport work, both the optimal solution and the simulated solution find the same DC (number 14) and the value of the transport work differs with less than 0.2 %. Both methods arrive in this case to the same conclusion.

Table 4: Results in comparison

	Optimal		Simulation		
DC	Tranport time	Transport work	Tranport time	Transport work	Holding cost
1	**76**		4 281	985 133	3 348 349
2			4 191	917 856	3 348 351
7			3 849	880 612	3 348 355
9			8 126	1 672 857	3 348 321
10			8 653	1 771 851	**3 348 320**
13			4 136	930 223	3 348 351
14		**837 726**	**3 583**	**836 125**	3 348 364
16			8 218	1 690 238	3 348 321

For holding cost, no optimal solution were derived and the comparison is also here unfeasible. All materials are more or less only bound to pass the DC (i.e. not to be stored for a long time) and the distances in time is relatively short from DC to construction site (i.e. same day delivery). This implies that the holding cost is almost the same at all DCs. The results from the simulation model also state this fact that the location of a DC does not have an impact of the holding cost. However, the holding cost only depends on the amount of material (or value of the material) and the time it is stored at DC. But in reality, this cost depends on where the DC is located. Building cost, cost for labours and hire of land (among others) may differ depending on location. It also depends on if the DC is owned by the construction company itself or if there is a third party logistics company that handles the DC.

9 CONCLUSIONS

It is possible to solve facility location problems with a simulation model and for the same objectives it is possible to match the results with solutions from conventional optimization models, as shown in the case of transport work as objective function. For the other unfeasible comparisons more work still needs to be done in order to better match the two types of models.

The advantages of representing the location problem in a simulation model, besides the indication of the stability of the solution, is the possibility to use more time depending variables in the model, that might have large effect on the objective. But to be able to model this behaviour it is necessary to have very detailed input data to the model.

Another aspect of the simulation model is the level of detail. The construction site can often continue to work even if some material has not arrived. In order to model the delayed construction project time (to find out monetary values of a construction delay) a model of the construction site itself would be interesting to look further at.

Future work in this research will focus on expanding the simulation model's scope to incorporate more types of transports (road and rail) and more construction sites and suppliers to be able to find a system both financially and environmentally better.

ACKNOWLEDGMENTS

The funding for this work comes from Brains & Bricks – that is a research collaboration between Linköping University, the municipality of Katrineholm and the construction company Peab, see also www.liu.se/forskning/b2.

REFERENCES

Daskin, M. S. 2008. "What you should know about location modeling". Naval Research Logistics 55:283–294.
Fu, M. C., F. W. Glover, and J. April. 2005. "Simulation optimization: a review, new developments, and applications". In Proceedings of the 2005 Winter Simulation Conference.
Kelton, W. D., Sadowski, R. P., and Sturrock, D. T. 2007. Simulation with Arena. McGraw-Hill.
Law, A. M. 2007. Simulation Modeling & Analysis. 4th ed. McGraw-Hill.
Persson, J. F. 2003. Discrete event simulation of supply chains; modeling, validation, and analysis. Ph.D. dissertation, Linköping Institute of Technology, Linköping, Sweden.
Sargent, R. G. 2007. "Verification and valdiation of simulation models". In Proceedings of the 2007 Winter Simulation Conference, pp. 124-137.
Thunberg, M. 2011. "Performance Measurements for Improving Construction Logistics - A Case Study". In PLANs Forsknings- och tillämpningskonferens 2011 - Logistik i praktisk tillämpning, edited by Persson, F. & Rudberg. M., 125–140. PLAN.
Ventura, J. A. 2008. "Dynamic programming". In Operations Research and Management Science Handbook. Taylor & Francis Group.
Xu, S. H. 2008. "Stochastic Processes". In Operations Research and Management Science Handbook. Taylor & Francis Group.
Zeigler, B. P., H. Praehofer, and T. G. Kim. 2000. Theory of Modeling and Simulation. 2nd ed. Academic Press.

AUTHOR BIOGRAPHIES

FREDRIK PERSSON is an Associate Professor in Production Economics at the Department of Management and Engineering at Linkoping University, Sweden. His research interest includes modeling and simulation of manufacturing system and supply chains in industry, especially the construction industry. Of special interest are simulation methodology and other modeling approaches applied to supply chains, such as the SCOR model. He is currently head of the quantitative logistics group in Brains and Bricks a research consortium focusing on construction industry related topics. His email address is fredrik.persson@liu.se.

DANIEL ERLANDSSON is an undergraduate student in the Master program Communications- and Transport Systems at Linköping University. In the Master program it is possible to focus on logistics and simulation.

ALEXANDER LARSSON is an undergraduate student in the Master program Communications- and Transport Systems at Linköping University. In the Master program it is possible to focus on logistics and simulation.

MARIA JOHANSSON is a Lecturer at the Department of Science and Technology at Linkoping University, Sweden. Her main interests are modeling and simulation with the focus of logistics. Earlier she had the responsibility for the development of simulation and optimization models at Posten in Sweden. Her email address is maria.a.johansson@liu.se.