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Spatial Modeling using Agents

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ABSTRACT

Simulation is a decision support technique that is often used to represent systems of interest and to experiment with them. Multi-Agent Simulation (MAS) is increasingly being used for modeling systems that comprise of autonomous and interacting system components. In such systems, the interactions among the underlying system components may be dependent on their spatial characteristics (e.g., dimension and location in three-dimensional space). The work presented in this paper describes an agent-based approach to spatial modeling through the use of a case study in container loading. The contribution of this paper is the demonstration of the feasibility of using MAS for spatial, proximity-based modeling, wherein not only agent behavior but also their physical dimension and their location in the three dimensional space are key considerations.

KEYWORDS

OR/MS, Decision Support, Simulation, Multi-Agent Simulation, Container Loading, Optimization.

INTRODUCTION

A computer simulation uses the power of computers to conduct experiments with models that represent systems of interest (Pidd, 2004). Experimenting with the computer model enables us to know more about the system under scrutiny and to evaluate various strategies for the operation of the system (Shannon, 1998). Simulation techniques like Monte Carlo Simulation, Discrete-Event Simulation and System Dynamics thus enable the decision makers to make better and more informed decisions. Multi-Agent Simulation (MAS) is yet another simulation technique that is increasingly being used in Operations Research and Management Science (OR/MS) to model systems that comprises of autonomous and interacting system components. MAS takes a bottom-up approach to modeling by focusing on writing instructions that specify the behavior of the agents that make-up the real-world system that is being studied (with no instructions to specify the behavior of the simulation), such that the overall system behavior emerges as a result of the actions and interactions of the individual agents (Deadman, 1999). MAS is particularly appealing for modeling scenarios where the consequences on the collective level are not obvious even when the assumptions on the individual level are very simple.

In this research the use of MAS for *spatial, proximity-based modeling is proposed*; this would enable representation of a real or imaginary system that is characterized by the existence of autonomous entities that come in *physical contact* with each other, and the *entity interactions resulting from this physical contact*. For modeling the spatial, proximity-based interactions in MAS, it is imperative that the agents are bestowed with properties with regard to their physical dimensions (e.g., length, breadth and height) and their location in the spatial space (e.g., location of the agents being modeled in a 3-Dimensional space). This paper uses the example of a pile of stacked boxes (entities) that contain perishable items of cargo; in such cases, badly deteriorated items can affect those in their immediate vicinity (e.g. through the spread of mould). More specifically, the example applies to container loading optimization. The author has chosen this example since the field of container loading presents the prospect of using *Container Loading Algorithms (CLAs)* – described in the next sub-section – thus, allowing the author to generate various experimental scenarios to experiment with the feasibility of spatial modeling through use of agents.

Container Loading Algorithms

The efficient loading of cargo into freight containers - and, more generally, the proficient packing of smaller items into larger objects - has been a subject of intensive research in OR/MS for at least thirty years. George and Robinson (1980) were among the first to propose an algorithm for constructing a container loading plan. Their approach was heuristic in nature and based on the idea of building a series of 'walls' of items across the width and height of the container. Since then numerous different approaches have been developed for both the knapsack version of the problem - where the space available is fixed and loading all the cargo may not be possible - and, to a lesser extent, its bin-packing form - where all of the cargo involved must be stowed and a cost-effective way of using a set of containers is sought. In this paper the term CLA is used to describe any approach which is designed to produce container loading plans. The CLAs used in this paper are not presented here owing to

the page restriction (also, it may be outside the scope of the MAS mini-track for which the paper is written). However, these algorithms have been previously published and the reader is referred to Bischoff (2006).

The remainder of this paper is structured as follows. The next section presents an introduction on computer simulation. Following this, a literature review is presented; it discusses existing work on MAS in the context of OR/MS research. Next, the spatial, proximity-based MAS approach is presented, together with implementation, experimentation and presentation of results. The concluding section summarizes the research presented in this paper.

COMPUTER SIMULATION

Computer simulations are generally used because they are cheaper than building (and discarding) real systems; they assist in the identification of problems in the underlying system and allow testing of different scenarios in an attempt to resolve them; allow faster than real-time experimentation; provide a means to depict the behavior of systems under development; involve lower costs compared to experimenting with real systems; facilitate the replication of experiments; and provide a safe environment for studying dangerous situations like combat scenarios, natural disasters and evacuation strategies (Brooks, Robinson and Lewis, 2001; Pidd, 2004).

Computer simulation can be applied in a wide range of application domains for a variety of purposes. In manufacturing, computer simulation can be used to increase productivity by achieving a better operating balance among resources (Zimmers and Brinker, 1978). Simulation can be used for assessing the performance of asset and liability portfolios in the finance and insurance sectors (Herzog and Lord, 2003). In the military it can be applied to support training, analysis, acquisition, mission rehearsal and for testing and evaluation (Page and Smith, 1998). In healthcare, simulation can be used to model the highly uncertain nature of illness (e.g., bird flu epidemics) and to represent the complexity of subsystem interactions (e.g., interaction of blood supply chains with hospitals) (Lowery, 1998). It can be used for the study of human-centered systems through integration of human performance models with system performance models (Laughery, 1998). It can be applied to Business Process Re-engineering as simulation can model the interaction between the various business process elements and can provide quantitative estimates of the impact that a process redesign is likely to have on key performance measures (Bhaskar, Lee, Levas, Pétrakian, Tsai and Tulskieet, 1994).

There are several simulation techniques that can be used in the context of OR/MS. Among them, the three widely used simulation techniques are – DES, MCS and SD. DES is a simulation technique that emerged in the UK in the late 1950s. In a DES the behavior of a model, and hence the system state, changes at an instant of time (Brooks et al., 2001). DES is widely used to model queuing systems. MCS is a statistical technique, with roots in World War II, which uses a sequence of random numbers to generate values from a known probability distribution associated with a source of uncertainty (Rubinstein, 1981). It is formed by a class of computational algorithms that rely on repeated random sampling to compute a result. This method is usually employed when it is impossible or infeasible to compute an exact result using fixed values or deterministic algorithms. SD comes from industrial engineering in the 1950s. It is a modeling approach which focuses on the analysis of the behavior of complex systems over time. It involves internal feedback loops and time delays that affect the behavior of the entire system. SD adopts a holistic systems perspective and uses stocks, flows and feedback loops to study complex systems (Serman, 2001). These elements differentiate it from other simulation techniques and help in the understanding of how even apparently simple systems display inexplicable nonlinearity. The central concept is that change to one part of a system will impact all other parts of an interrelated system. MAS is the most recent of the other OR/MS simulation methods and has been used since the mid-1990s to solve a variety of financial, business and technology problems.

APPLICATION OF MULTI-AGENT SIMULATION IN OR/MS: A LITERATURE REVIEW

MAS has several application areas. In healthcare, MAS has been used for modeling the spread of pathogens that are transmitted by direct contact (Hotchkiss, Strike, Simonson, Broccard and Crooke, 2005); Stainsby, Taboada and Luque (2009) have used agents to model hospital emergency departments; Sibbel and Urban (2001) have integrated agent-based approaches to classical simulation systems to enable better hospital management. In financial trading, MAS has been used to model New Electricity Trading Arrangements (NETA) in the UK (Bunn and Oliveira, 2001); application of this technique has been demonstrated in the financial market for price formation using realistic trade mechanism (Raberto, Cincottia, Focardib and Marchesic, 2001). Multi-Agent-Based Social Simulation (ABSS) is the application of MAS in the social sciences context. Its use has been reported in the study of social dilemmas by Gotts, Polhill and Law (2003); Downing, Moss and Pahl-Wostl (2001) report on the use of a prototype agent-based *Integrated Assessment Model* for understanding climate policy; ABSS have also been used for modeling of social interactions and influence (Marsella, Pynadath and Read, 2004). Luo, Zhou, Cai, Low, Tian, Wang, Xiao and Chen (2008) and Moulin, Chaker, Perron, Pelletier, Hogan and Gbei (2003) have used MAS for crowd management. Further application of this technique has been reported in supply chain management

(Kaihara, 2003), in freight transportation (Davidsson, Henesey, Ramstedt, Törnquist and Wernstedt, 2005), in the military (Cioppa, Lucas and Sanchez, 2004), for emergency evacuations (Pan, Han, Dauber and Law, 2007), in the management of the environment (Hare and Deadman, 2004), and in cell biology (Pogson, Smallwood, Qwarnstrom and Holcombe, 2006), among other.

Next, extant literature that report on the use of MAS for container management in general and container loading in particular is presented. Henesey (2006) have investigated the use of agent-based technologies to improve performance of container terminals. The use of MAS architecture to solve the automatic container allocation problem in a port container terminal is described in Rebollo, Julian, Carrascosa and Botti (2000). The use of agents to simulate and optimize cargo handling storage space in a maritime port is reported in Kefi, Ghedira, Korbaa and Yim (2009). MAS has been used to model the management of stakeholder relations in container terminals through use of agents that simulate different stakeholder behavior (Henesey, Notteboom and Davidsson, 2003). Henesey, Davidsson and Persson (2006) report on the use of the *SimPort* MAS tool to evaluate eight transshipment policies. Bin, Wen-Feng and Yu et al. (2009) have used MAS, together with knowledge discovery, to model a container terminal logistics system through use of 14 kinds of agents. The project *Container World* has modeled both the business and the operational aspects of the container business in the UK through use of multi-agent methodology (Sinha-Ray, Carter, Field, Marshall, Polak, Schumacher, Song, Woods and Zhang, 2003).

Although there are several MAS studies in the general area of port management, container terminal management and container business management (some of these studies have been referred to in the preceding paragraph), to the best of the authors' knowledge, there is no previous work on the use of MAS in the specific area of container loading. Thus, it is arguable that the authors are among the first to report on the use of MAS in the context of optimization of container loading space. Furthermore, the authors propose a proximity based MAS modeling methodology, wherein both the agent behavior and the physical dimensions of the agents are key considerations.

SPATIAL, PROXIMITY-BASED MODELLING USING MULTI-AGENT SIMULATION

MAS provides us the building blocks (the agents) for incorporating the proposed spatial, proximity-based modeling methodology. In a conventional MAS model the agent interactions are usually defined by the modeler using package-specific functionalities. For example, AnyLogic™ defines four pre-defined agent layouts in continuous space (random, ring, arranged and spring mass layouts) and two layouts in discrete space (random and arranged layouts) (XJ Technologies, 2011). However, the pre-defined agent arrangements and the inter-agent relationships are inappropriate for the MAS application, since they do not consider the physical dimensions of the agents; nor are the inter-agent relationships defined based on the physical proximity of these agents to each other. Thus, the approach presented in this paper requires that the agents be endowed with physical properties (length, breadth and height) and be identified in the spatial space (through location coordinates). This will enable us to define inter-agent relationships based on physical proximity with the other agents. An example will make this obvious. Figure 1 (left) shows a randomly-selected agent in question (red box), and at least eight other agents surrounding this "red" agent. In this case the proximity relationships are identified based on the x, x', y, y', z and z' coordinates of each agent, and these in-turn generate the dynamic inter-agent relationships.

Implementation

The objective of this study is to explore a novel application of MAS for spatial, proximity-based modeling; this is achieved through a case study on container loading optimization. More specifically, an investigation is undertaken with regard to the trade-off between container utilization and the cross-contamination among boxes containing perishable goods through use of proximity-based MAS modeling. The solution is implemented using the simulation package AnyLogic™. Additionally CLAs have been used to generate the following, (a) dimensional properties (length, breadth and height) for every agent, (b) the location of every agent in the spatial space, and (c) generation of a freshness index (a randomly generated value between 5 and 30) that is assigned to different *Box Types*. For example, if there are 5 boxes of a particular Box Type (i.e., these five boxes have similar dimensions), each of these boxes will have the same freshness index. This index is used to denote the number of simulated days for which the contents of the box will remain mould free. As the simulation progresses in time, at the end of every simulated day, the freshness value associated with each box is decreased by one (if freshness > 0).

When the freshness level of a particular box reaches zero, it is said to be mould affected. The color of the box is changed to green so as to enable easier identification (Figure 1 – right). No sooner does a box become mould affected, it starts to cross-contaminate other boxes that physically surround it. This cross-contamination is reflected in the model by the proximity-based interactions sent by the agent (representing the mould affected box) to all the surrounding agents. Thus, in Figure 1 (left), if the red box/agent were to become mould affected, it would immediately send messages to all the eight boxes/agents surrounding it. The message is a signal to the other agents (each of whom has their own copy of freshness index) that they

have now been contaminated. Upon receiving this message, each agent immediately decreases the existing value of its freshness index by 1 (if freshness index > 0). This is in addition to the drop of 1 unit of freshness that is applicable to every agent (if freshness > 0) at the end of each simulated day. The logic of the model, as described above, is repeated till the end of the simulation time. After the successful execution of the MAS, several pieces of data are collected, including, the number of mould affected boxes, maximum freshness value associated with an item of cargo, average cargo freshness, histogram associated with freshness data. This completes one simulation run. Several such iterations, each with a different container loading plan, are performed so as to enable the stakeholder to decide on a trade-off between the loading efficiency and the percentage of mould affected boxes. Experiments and results are described next.

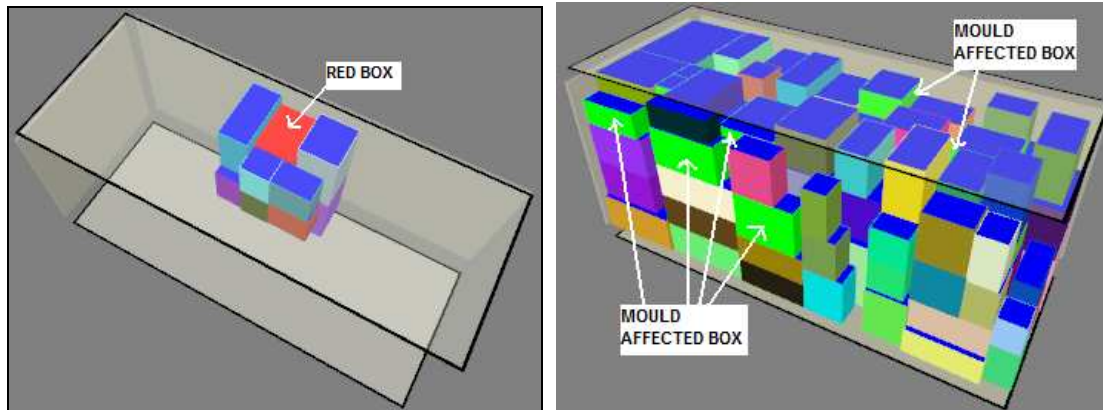


Figure 1: Detection of proximity among agents (left); Mould affected boxes during simulation (right)

Experimentation and Results

For the experimentation the CLAs that were originally proposed by Bischoff (2006) were used. The CLAs model individual “boxes” that belong to different “box types”. The predominant factor that distinguishes the various box types are the boxes’ physical dimensions, i.e., length, breadth and height. Given a weakly heterogeneous mix of box types as the input, the CLAs produces hundreds of alternative container loading plans, each having a corresponding container utilization rate. Given a specific heterogeneous mix of box types (subsequently referred to as “Box Type Mix”, or *BTM* for short), using the benchmark algorithms allowed us to determine the most efficient loading pattern by comparing the container utilization rates associated with the various loading patterns that are output by the algorithm.

For the cross-contamination scenarios being experimented, a total of four BTMs were used - namely, **BTM20**, **BTM40**, **BTM70** and **BTM100** - each of which represents a specific *Box Type Mix* with 20, 40, 70 and 100 box types respectively. The CLAs were used to generate 100 container loading plans for each of the four BTMs. The container utilization rates were then ranked for the aforementioned loading plans, and three specific loading plans for every BTM were selected. These were as follows (where, $x=20,40,70,100$): (a) loading plan with the lowest container utilization (**BTM x *min***); (b) loading plan with utilization percentile rank of 50 (**BTM x *mid***); and (c) loading plan with the highest container utilization (**BTM x *max***). Each BTM is a unique experiment group; each group comprises of three separate loading plans that are simulated by the (**BTM x *min***, **BTM x *mid*** or **BTM x *max***). These individual simulations will henceforth be identified by the BTM number and a corresponding loading plan. For example, **BTM40*max*** will refer to the simulation using the container loading plan with the highest container utilization (*max*) and which is specific to the experiment group **BTM40**.

Figure 2 illustrates, for each of the three multi-agent simulations pertaining to the four BTM experiments, the number and the corresponding percentage of boxes affected with mould. Although the results for all the BTMs are presented in the same figure, comparison cannot be made across BTMs since the freshness index of the items of cargo (generated using random numbers that are assigned to box types) changes from one experiment type to the next. The graph shows the existence of trade-offs between container loading efficiency and % of boxes affected with mould. For example, in relation to **BTM70** experiments, the loading plans selected for simulation had utilization efficiency of 72.10% [Total boxes selected = 96] (**BTM70*min***), 81.68% [101 selected] (**BTM70*mid***) and 86.70% [110 selected] (**BTM70*max***) respectively; the corresponding %s of mould affected boxes being output by through MAS were 55.21%, 61.39% and 54.55% (refer to the secondary vertical axis shown in Figure 2). Thus, changes in container utilization rates (brought about by a change in loading plan) does have an effect on the % of items that are affected by mould. Let us consider the trade-off point for the **BTM70** experiments. The stakeholder, having seen the results of three iterations, may decide to use the loading plan that provides 86.70% utilization

efficiency (BTM70max) – and not BTM70min which provides 72.10% efficiency and also has a slightly higher % of boxes affected with mould (55.21%, as against 54.55% in the case of BTM70max). The results for the BTM experiments show the absence of either positive or negative correlation between container utilization percentage and the % of boxes affected with mould. For example, in the case of BTM40, the % of mould affected boxes would roughly be the same for BTM40min (68.42%), BTM40mid (68.07%) and BTM40max (69.23%) loading plans.

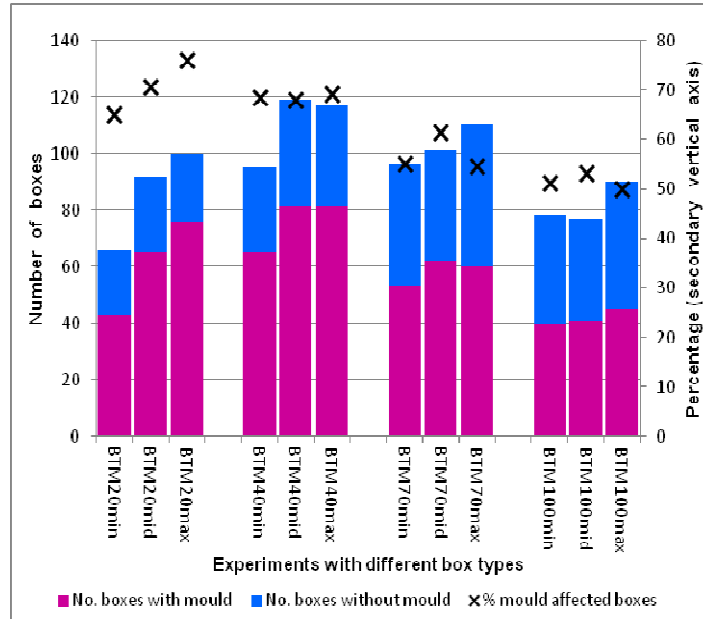


Figure 2: % mould affected boxes, grouped by BTM (left)

BIN RANGE	BTM20min	BTM20mid	BTM20max
0.00-3.00	65.15%	70.65%	76.00%
3.01-6.00	0.00%	0.00%	0.00%
6.01-9.00	0.00%	4.35%	1.00%
9.01-12.00	0.00%	0.00%	0.00%
12.01-15.00	1.52%	2.17%	6.00%
15.01-18.00	7.58%	6.52%	5.00%
18.01-21.00	10.61%	10.87%	8.00%
21.01-24.00	10.61%	3.26%	2.00%
24.01-27.00	1.52%	2.17%	2.00%
27.01-30.00	3.03%	0.00%	0.00%
Total Boxes	100.00%	100.00%	100.00%

Table 1: Data showing freshness percentages corresponding to the BTM20 simulation experiments

Table 1 above presents freshness values (divided into well-defined bin ranges) for the BTM20 experiments that were performed. It shows that for all the three loading plans that were simulated, between 65 to 76% of items had already developed mould or would be mould affected in the next three days (note the freshness/bin range: 0.00-3.00). It further shows that if BTM20min loading plan is selected, then approximately 33.33% of items will remain relatively fresh (bin/freshness range: 15.00 to 30.00) by the end of the simulation – and this value is at least 50% more when compared to the corresponding freshness values of the alternate loading plans. Here again there may be an opportunity for a trade-off!

CONCLUSION

Simulation is a decision support technique which enables the stakeholders to experiment with systems of interest. Simulation techniques such as Monte Carlo Simulation, Discrete-Event Simulation and System Dynamics are widely used in Operations Research/Management Science (OR/MS) with the objective of better operations management. Multi-Agent Simulation (MAS) is arguably the most recent of these simulation techniques; it models the overall behavior of a system through use of autonomous system components that communicate with each other through use of messages. In this paper the need for spatial, proximity-based inter-agent interaction has been highlighted; it has been argued that modeling proximity through MAS enables us to simulate scenarios such as the spread of communicable diseases, cross-contamination, the spread of fire, or indeed, simulating the spread of mould among perishable items of cargo. A novel application of MAS in container loading optimization has been presented in this paper. The application of this approach will enable the stakeholders to analyze the trade-offs between container loading efficiency and other cargo-related considerations which has direct bearing on the physical placement of cargo in containers (e.g., stability and fragility of cargo, propagation of mould). It should be emphasized that the approach does not in itself seek to define the most appropriate trade-off between the factors involved. This decision is left to the user. In summary, the contribution of this paper is the demonstration of the feasibility of using MAS for spatial, proximity-based modeling and its application in container loading.

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