Adaptive Simulation Techniques for Modeling Material Flow Systems

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Abstract—This paper summarizes and analyses simulation techniques for material flow systems. The analysis deals with primary the applicability of various simulation methods for the purpose of adaptive simulation models.

I. INTRODUCTION

Material flow systems build key part of production facilities. A properly functioning, optimized material flow system is a necessary component of a flexible, automated manufacturing system. But material flow systems are not restricted to production. Warehousing, logistic chains of transported goods, intermodal terminals and many other cases belong also to the material flow systems. Modeling of material flow processes poses a great challenge for scientists, because of the complexity of the processes and the changing of the system’s behavior over time. There are however several publications solving this type of problem, using various methods. Detailed description and classification of the used models includes section II.

Modeling may serve different purposes. Next list (from [1] collects various strategic and operational issues form the logistics):
- Supply Chain structure (SCS)
- Process redesign (BPR)
- Supplier selection (SS)
- Facilities/ Capacity planning (FCP)
- Supply chain integration (SCI)
- Information sharing (ISH)
- Bullwhip effect (BE)
- Reverse logistics (RL)
- Replenishment control policies (RCP)
- Supply chain optimization (SCO)
- Cost reduction (CR)
- System performance (SP)
- Inventory planning/management (IPM)
- Planning & forecasting demand (PFD)
- Production planning & scheduling (PP-SCH)
- Distribution & transportation planning (DTP)
- Dispatching Rules (DR)

Certainly the goal of a simulation and the so the necessary KPI’s determine the applicable simulation model as well.

One of the greatest problems of applying simulation models is the time-variant feature of the modeled processes. Even if the simulation starts with exact parameters from the real modeled system, and the model is accurate, if some features of the material flow system change, the modeling error increases over time. This feature is a main disadvantage using simulation techniques, as pointed put by Nyhuis et al. [2].

An example of the above phenomenon is presented in Figs. 1 and 2. Typical KPI’s of logistic systems are for example stock amount at a certain location or utilization of materials handling machines. If the simulation is used for operational purposes modeling error can be decreased if it is possible to update the simulation in regular time intervals with actual data. Such an increase of the accuracy has of two fundamental sources:
- First there should be appropriate devices and interfaces in the logistic system in order to supply the necessary information.
- Secondly, the simulation itself must be capable to obtain and process these data in order to adapt itself.

This paper surveys available simulation models for logistics, classify them, and draws a conclusion which ones are most applicable for adaptive modeling purposes.

II. CLASSIFICATION OF USED MODELS

Models can be classified using various aspects. One aspect is the goal of the simulation modeling as quoted in section I. A second distinguishing feature of the applied techniques is the depth of the model. There are two ways:
some problem’s research enables modeling only a part of the system, others not. In the first case more attention is drawn to the details of the system part, but interaction with the other system parts is neglected. If the whole system’s modeling is needed, too much details causes sometimes unfeasible amount of programming work.

From theoretical aspect most important classifying feature is the model’s type. There are three basic methods applied in logistic processes’ simulation:

- system dynamics models,
- discrete event simulation models,
- agent-based models.

System dynamics (SD) and discrete event simulation (DES) models have many common features. SD modeling (see an example in Fig. 3) is mainly a network oriented approach, where the word ‘dynamics’ refers to change over time. SD models are composed of three main objects: stocks, flows and delays [3], which interact with each other over time to form a unified structure.

SD models try to give an overview of the entities flows in the system, and the relations they may use. Stocks of entities at certain nodes of the structure are also easy to recognize. Therefore these models are very suitable for problems associated with continuous processes with feedback. The clear appearance of SD models enables good understanding of the processes based solely on visual examination. Taking a look at Figure 3, it is easy to recognize which factors influence for example the number of new fish per year. As behavior of the elements are simplified, SD models’ typical application is at strategic level, mainly for long term processes. In logistics such areas are the planning & forecasting demand, and analysis of future supply chain structures.

Discrete event simulation (DES) modeling is a similar approach to the SD models. DES models have also nodal elements and connections but the elements are the far important components. Each elements may possess complex functionality, however these are executed mostly passively. That means the element (see the different icons in Figure 4.) typically wait for incoming objects, which trigger various functions which can not only effect that object but other part of the model as well.

The example in Fig. 4 represents a two-channel healthcare facility, where the personnel’s utilization and typical queue length can be determined.

This way DES models are very appropriate for analysis of complex operating systems, without losing detailed information. DES models also support stochastic behavior then SD models do.

The SD and DES models have one more difference: time representation. SD simulators use finely-sliced time steps, which means the program engine processes the whole model, and updates states of the contained entities.

DES models apply however an event list, which is updated by the model itself and by external events. This way unnecessary computing is avoided, without reducing accuracy. This solution however causes changing speed in the animation which results less realistic visualization.

Agent-based simulation (ABS) of logistic processes is quite a new but promising technique. In this context agents are software modules which sense and interact with the other part of the logistic model and with other agents. One should here remark that real logistic processes have agents too: forklift operators, logistic decision makers, etc. [5]. It seems obvious that using appropriate software agents the real world’s and the models behavior will be similar. This area must not be confused with agent-based optimization techniques which are widely used in logistics. In ABS systems the model is composed of ‘agents’ which follow their own goals while interacting with other agents (proactive behavior). This modeling looks similar to the DES, but ABS model elements (agents) are active which means the operation doesn’t depend on the presence of the entities flowing in the model.

As many to be modeled cases don’t correspond clearly to either techniques many have tried to implement hydrid models. There is however no real hydrid software platform, so there are two ways for it’s implementation. One way is to implement for example SD models in DES software environment, which is a rather feigned solution. The second way is to use two different software platforms executed in multitasking mode which interact with each other.

Logistic simulation modeling depth can be different. Every modeled system is a part of a greater system and almost every system can be divided into further to subsystems. For example modeling logistic flows in a production facility is a modeled then it seems to be a holistic approach. However the facility is connected to suppliers and buyers, so the model is only a subsystem of the logistic chain. Further it can be divided into subsystems such as warehouse and parts’ supply of production lines.

The above principle can be well explained using the following two case-studies from the scientific literature.
Figure 5. A typical layout of an automated port container terminal.

Figure 5 presents a container terminal simulation, from [6]. This simulation’s neighborhood are the incoming and outgoing transport means carrying certain containers. From the other hand this terminal is a part of a greater intermodal transportation system.

In the modeled terminal following container flows are implemented. The containers are stored in the terminal in so called blocks at the Marshalling yard. This area applies AYCs (automated yard cranes) for deploying and retrieving the unit loads. Transfer points for the AYCs are located in front of each block. Containers are transported to blocks using automated guided vehicles (AGVs). Vessels are loaded and unloaded using quay cranes (QCs) at the apron.

The objective of this research was to schedule all subsystem (QC, AGV and AYC). For optimization and simulation numerical methods have been applied, which were programmed for this specific case. Container terminals are so complex materials handling systems that even it’s subsystems’ modeling poses a hard task. Boysen and Fliedner [7] presented solution for a rail/road terminal’s optimization problem.

A transshipment yard consists of a given number of parallel railway tracks, a storage area to intermediately stock containers and additional truck lanes. Multiple gantry cranes with a cantilever on both sides, which span over tracks, storage area and truck lanes, transfer containers between trucks and railcars. In this system yard partitioning problem for gantry cranes is an important issue. This problem includes scheduling of service slots of trains, and the decision on the containers’ positions on trains. Finally container moves are assigned to the cranes. The optimization was supported by a special developed numerical simulation which contains empirical data.

Both of the above examples applied numerical simulation models. Many researchers choose this way, because they apply such optimizing methods which require conventional programming environment, and simulation is also written in this environment in order to avoid interfacing with commercial logistic simulation software.

Salido et al. [8] applied numerical methods as well. In this case the authors optimize two important areas in container terminals: the berth allocation and the container stacking problem. The berth allocation problem describes the arrangement and scheduling of the vessels along the berth. There is a given set of coming vessels to a berth under certain constraints such as priorities, length and depth of vessels, number of containers, etc. When a vessel berths, export containers to be loaded should be on top of the stacks in the container-yard. Therefore, the container stacking problem consists on rearranging the containers so that the yard crane does not need to do rehandling work at the time of loading.

These two problems are related, which means that an optimal berth allocation plan may generate a large amount of relocations for export containers, meanwhile a suboptimal berth allocation plan could generate a small amount of relocations [8].
General purpose simulation software (mainly DES) are getting more and more popular for the material flow system’s modeling purposes. Parola and Sciomachen presented simulation based analysis of intermodal container flows [9].

For the research the authors used “Witness” simulation environment. This general type simulation environment supports system’s modeling which consists of parallel processed modules. Implemented modules are presented in Figure 8. Thanks to the modular buildup, the model can be easily adapted for different terminal structures. Simulation parameters are set into the model from interviews.

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### III. INFORMATION SOURCES FOR SIMULATION MODELS

Section II. presented several examples and aspects of materials systems’ simulation. However each simulation model’s functioning depends heavily on the presented data. Conventional ways are application of various data collection methods, as written in [10]:

- visual observation by on-site human workforce (own workers of the company from the production/logistics or independent observers),
- application of Auto-ID equipment (barcode or RFID reader),
- posterior analysis of recorded films by human workforce,
- analysis of production related documents, statistics,
- data mining from ERP systems

Considering the above methods one can conclude that each has it’s advantageous application field. For example using an RFID reader for data collection is advantageous, if an exact cross section of the material flow must be recorded, and the unit loads are already equipped with the appropriate ID label/tag. Generally one can say that the applied systems’ cost increases with the number of the necessary equipment, human work and the complexity of the processing software, tailored to the current material flow system. There are some novel methods, for example application of camera-based data collection system [11].

Using this method one or more cameras are placed at certain positions of the material flow system which are capable of collecting information from the system, mainly by logging the passing unit loads. An example of the system’s application is presented in Fig. 9. By applying cameras before and after a material handling subsystem throughput time and the current number of unit loads in the subsystem can be logged.

There are further possibilities to obtain information from the material flow system. Sky-Trax [12] is an innovative system for localising forklifts in the warehouses, providing spatial information. The system requires two-dimensional barcodes positioned in the roof, an upside positioned reading device and Wireless communication for transmitting data to the centre. Currently the system is used for surveying the forklift fleet, but it’s application for extracting data for the material flow is also thinkable.

### IV. APPLICABLE COMPONENTS FOR ADAPTIVE SIMULATIONS

As written at the end of section I adaptive simulation requires appropriate software and hardware components. However such a system as a whole is not yet known, therefore structure and usable components must be defined as well.

Figure 11 presents a conceptual drawing of the functional elements to be implemented for changing a simulation to be adaptive to it’s environment. It is surprising how many other modules are needed besides the simulation itself to achieve the desired functionality.

The ‘Simulation’ module can be implemented using any of the software means from the examples of section II. There is only one restriction: the simulation must be executable and modifiable from outside by other applications.

Models based on general purpose simulation software are preferred to numerical simulations, because later modifications can be implemented easier this way.

The type of the model can be either SD or DES, or even agent-based, if the real system applies agents as well. Agent-type behavior of the modeled system makes modeling very complicated. In this case the real material flow system adapts it’s behaviors over time (through it’s agents), so the model doesn’t only have to adapt itself to long term changes of the modeled system, but it must be so intelligent that it should be “find out” how the agents in
the real system will behave. This is essential to achieve accurate modeling.

Adaptive simulations must be supplied regularly with data from the modeled system. This can be automatic data acquisition from the company’s logistic control system, transmitted Auto-ID data or object-tracking data.

Regular update doesn’t mean the simulation should process all the information from the modeled system. Therefore a middleware software has also to be implemented, which reduces the amount of information to the simulation.

Simulations are mostly used for optimizing purposes. Therefore the ‘Optimization’ module must be connected to the simulation.

‘Adaptation’ module is used to modify the simulation. It’s reach depends very much on the available functionality of the simulation software. In some cases only change of parameters is executable, other software platforms enable changing and creating relations inside the simulation model.

‘Optimization’ and ‘Adaptation’ modules must be run separately over time.

The heart of the proposed structure is the ‘Supervising AI’ module. It’s main responsibilities are as follows:

- scheduling ‘Optimization’ and ‘Adaptation’ modules;
- controlling the middleware depending on the model’s behavior;
- controlling input and output data for the simulation;
- and generate feedback data for the system supervising personnel through a Human Machine Interface;
- getting direct ‘hints’ from human operators about improvement of it’s functionality.

This last two functionalities are perhaps more complicated than controlling the information flow from the modeled system. Here this artificial intelligence module must generate feedback to the human supervisor, which modifications have been carried out in the model during the adaptation purposes. Depending on the implemented intelligence some remarks for the supervising personnel of the real system would be useful as well. The planned module should enable direct influence from operators as well.

V. CONCLUSIONS AND FURTHER RESEARCH

In this paper framework for the implementation of adaptive simulations has been examined from various aspects. During this usable software and hardware components are surveyed. Next phase of the research deals with more accurate definition of the presented modules. Parallel implementation of a test system is also planned.

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