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SIMULATION FOR PREDICTIVE CONTROL OF A DISTRIBUTION CENTER

Lourdes A. Medina
R. Ufuk Bilsel
Richard A. Wysk
Vittaldas Prabhu
A. Ravi Ravindran

Department of Industrial and Manufacturing Engineering
Pennsylvania State University
University Park, PA 16802, U.S.A.

ABSTRACT

In this paper we present the application of Simulation for Predictive Control (SimPC) as a decision making tool for improvement of non-automated distribution centers (DCs). SimPC is focused on determining the viability of a given truck–dock assignment schedule, including arrival times and dock assignments for inbound and outbound trucks. SimPC also serves to perform iterative procedures of system parameter adjustments while searching for a viable schedule. The proposed model utilizes real-time data from DC's warehouse management system (WMS) to obtain the current state of the DC, which serves as initial conditions for the simulation. The model emulates the decision rules imbedded in WMS, which include assigning tasks to system-guided resources, selecting storage locations for inbound operations and determining retrieval locations for outbound operations. The SimPC model provides insights for the identification of scheduling problems, guidance for operational and tactical solutions, and serves as a tool to verify these solutions.

1 INTRODUCTION

Distribution centers (DCs) represent a fundamental part of many supply chains. DCs serve as warehouses for finished goods, but more importantly represent an essential link between manufacturers and retailers. While warehouses are primarily focused on storing finished goods, DCs have a broader scope of purpose. One such purpose is to continuously fulfill orders throughout the day, in order to minimize the time to get goods to a customer and facilitate the material flow at the DC. This requires complying with a specific schedule for the delivery of goods, which is the main motivation for the development of the Simulation for Predictive Control (SimPC) of a DC.

Planning and control of warehouses and DCs has been widely studied from the perspective of warehouse activities and systems management, and the development of detailed inventory management, storage allocation and resource assignment models (van den Berg and Zijm 1999). Much of the work in the DC control area has focused on inventory control, including the development of forecast approaches (Suesut and Mongkhoin 2004), the use of agent-based approaches (Ito and Abadi 2002) and the study of inventory accuracy (Wayman 1995). From an operational control perspective, much of the research has been dedicated to automated warehouses, as is the case of Amato et al. (2005) who developed control algorithms for the optimization of the automated systems. Similarly, intelligent agent based frameworks have been used as alternative methods to control automated warehouses by modeling automated elements as agents (Kim et al. 2004).

For almost fifty years, automated storage and retrieval systems (ASRS) have been used for efficient storage and management of inventory (Yin and Rau, 2006). However, an ASRS implementation can involve significant startup costs and may not offer the flexibility that a particular facility needs (Hara et al. 2003). For this reason, the research on the use of ASRS has focused on justifying such investment by assuring the efficient utilization and scheduling of these resources. Numerous research efforts in warehouses and distribution centers have examined scheduling policies and complex algorithms for the optimization of automated equipment, including ASRS, conveyors and automated guided vehicles (AGV). Simulation modeling has also played a significant role in these optimization efforts, where the concept of multi-pass simulation has been shown to be effective for the daily scheduling of ASRS activities, and being further improved by incorporating intelligent search techniques like genetic algorithms (Yin and Rau 2006).

Manually operated facilities are still popular due to the difference in investment and flexibility provided by having forklift trucks as the main equipment utilized for material flow. Manual DCs are labor-intensive and most of the work is performed by operators. Even though the warehouse management systems (WMS) assist in the control of inventory, orders and dispatching of resources, there is little visibility into operations. When there are multiple operations occurring simultaneously (i.e., storage/retrieval locations, task assignment policies), the lack of visibility adds variability to the system, making it difficult to guarantee the viability of a schedule with specific requirements. This leads to the utilization of simulation modeling, which has been identified as a powerful approach for the analysis and improvement of such complex systems (Banks, 1998). However, most of the simulation studies performed for non-automated DCs have focused in the traditional use of simulation as an evaluation tool to decide between design alternatives, and not for the pro-active control of the daily operations.

The study by Hara et al. (2003) is one of the few studies that addressed the use of online scheduling of forklift trucks in non-automated warehouses with the objective of improving forklift task planning. Other research in non-automated warehouses include the identification of improvements by the evaluation of WMSs (Gale, Oliveros, and Silvan 2002), and the development of conceptual models of the warehouse operations (Zhou, Setavoraphan, and Chen 2005). The literature of non-automated DC management lacks simulation based control models, contrasting with the extensive number of control-related studies in automated DCs. Such differences in the use of simulation-based control models between automated and non-automated DCs may be explained by the differences in DCs properties. In automated warehouses there is little or no randomness and variability in the operations, given that the tasks are performed automatically in a deterministic manner. However, for non-automated warehouses the human factor is present, having multiple operators performing their work differently, which adds human variability. Furthermore, building simulation models for non-automated DCs or warehouses has been recognized as a difficult task, compared to automated DCs (Gale, Oliveros, and Silvan 2002; Takakuwa et al. 2000). Takakuwa et al. (2000) and Zhou, Setavoraphan, and Chen (2005) provide a variety of guidelines for modeling non-automated DCs and warehouses.

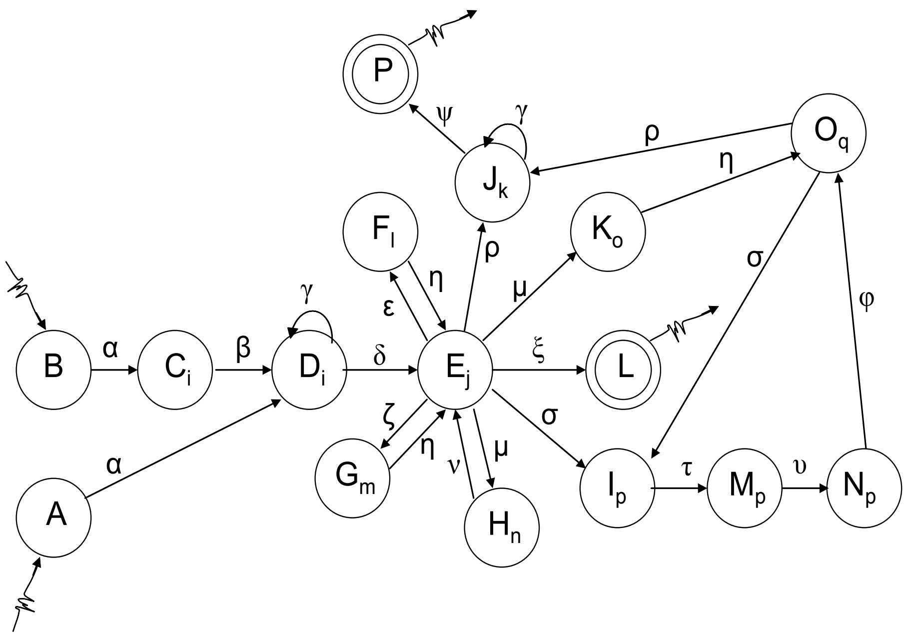
This paper presents a SimPC to be used as a tool to improve decision making in non-automated DCs. The proposed SimPC includes stochastic features for a realistic representation of operations. The model includes real-time data management capabilities to use information directly from the DC's WMS, which adds further control capabilities such as the development of advanced dispatching rules, more comprehensive and customizable performance metrics and tactical and operational parameters adjustments. The SimPC is developed to be readily integrated with the WMS in terms of accurately modeling the decision making logic in the WMS based on the current DC inventory and resource workload. The SimPC is flexible enough to be linked to other decision making tools such as scheduling optimization models.

The paper is organized as follows. Section 2 provides background information of the DC environment being considered. Section 3 describes the SimPC modeling approach with all of its elements, including an example that illustrates the benefits of SimPC in terms of the DC's schedule feasibility. Section 4 concludes the paper and presents future research directions.

2 BACKGROUND

The SimPC approach is developed for a large-scale and highly stochastic, non-automated distribution center. The use of shared resources and a class-based storage policy are just some of the contributions to variability in the operations of the DC. The class-based storage policy provides a general and organized approach for the storage of products, with the objective of grouping products of similar demand levels into the same class (Yin and Rau 2006). However, the space is not fully dedicated, allowing a large range of storage locations for materials in the same classification. In the case of shared resources, forklift trucks are considered as the most relevant ones, given that these work on almost any type of task, including replenishments, storage requests and retrieval tasks, at any point in time. Thus, forklifts are not tied to a specific inbound material to be stored or outbound shipment to be fulfilled. Moreover, other resources (e.g. loading teams, unloading teams, verifier operators) are also shared, but to a lesser extent. That is, these resources are shared with more than one truck, but have to work on these trucks one at a time. From a modeling perspective, inbound and outbound trucks compete for the same set of resources, which has significant implications on the viability of the evaluated truck–dock assignment schedule.

The complexity of the DC under analysis is illustrated using a state graph in Figure 1, which represents all the possible states and transitions of the materials in the DC. This diagram demonstrates the importance of state E_j, which is located at the center of the graph and refers to state of a pallet on a forklift truck resource. Particularly, forklift trucks are required for many of the state transitions, being indispensable for the storage operations and any movement related to drive-in racks. For this reason, emphasis is on the Task and Resource Management (TRM) feature within the WMS module (in this case within SAP), which serves as a tool for controlling system guided resources such as forklift trucks and pallet jacks. This feature is part of the latest version of WMS offered by SAP, which was selected as the framework for this study, allowing the definition of specific data required for SimPC. The use of these programs support the realistic development of SimPC by providing information in real-time. A general description of the data to be utilized is discussed in Section 3.



A – Inbound truck load (pallets)	Ip – Pallet in buffer area p
B – Inbound truck load (cases)	Jk – Pallet at outbound dock k
Ci – Cases in bulk dock i	Ko – Pallet at case picking rack o (level 1)
Di – Pallets at inbound dock i	L – Re-work area
Ej – Pallet in forklift j – TRM algorithm	Mp – New pallet in buffer area p
Fl – Complete pallets in drive-in rack l	Np – Wrapped pallet in buffer area p
Gm – Partial pallets in single-deep rack m	Oq – Pallet in pallet jack q
Hn – Pallet at case picking rack n (level 2)	P – Cases in truck load

Figure 1. State graph of DC operations

TRM provides as a set of rules to be followed when assigning tasks to system guided resources. Using TRM as the task selection tool brings additional uncertainty to this work, which is aligned with the motivation of having SimPC aimed for highly stochastic non-automated DC. TRM decision making consists of a multi-objective approach, in which various criteria and sub-criteria are considered for the task assignment of a particular resource at a specific time. Having a dynamic scheduling approach, as is the case of TRM, has been identified as a good policy to be followed since it permits re-scheduling of the tasks as new tasks are added into the system (Hara et al. 2003). This is also supported by Randhawa and Shroff (1995) where the authors state that dynamic scheduling "accounts for the dynamic nature of the system". For the dynamic scheduling of the resources in real-time, it is necessary to have electronic task assignment capabilities, usually executed through the use of onboard messaging screens and handhelds.

In addition to the TRM, different algorithms could be considered for other important decisions needed at any typical DC, which may include deciding on where to store the products when received from an inbound truck or where to take the product from to comply with a shipment requirement. These decisions may be as simple as selecting a random location, or evaluating different elements (e.g. distances, material expiration date, DC balance) for each storage and retrieval location. The structure of SimPC allows for the easy plug and play of different rules, defined as events and coded as sub-routines. For this reason, and the importance of the forklift trucks illustrated previously, attention is only given to the TRM algorithm, since it adds stochastic features that, in real life, could make a difference in the viability of a specific schedule. The different elements of the TRM algorithm are described more in detail at Section 2.1.

2.1 TRM

The TRM algorithm is the mechanism that selects the task to be performed by a resource at a specific time. The TRM algorithm provides a priority value all the tasks and the task with the highest values are the ones that are performed. Task priority is calculated dynamically, based on the current location of the resources and the time elapsed since the task was created. However, before the task sorting can be performed, tasks that are not feasible need to be eliminated from consideration. A specific task may result permanently infeasible if the resource type is not allowed to perform that type of task. This could be the case of forklift trucks versus pallet jacks, in which the former may be dedicated to tasks requiring material movement from different levels (e.g. movements from/to drive-in racks), while pallet jacks can only perform tasks in the floor level (e.g. case picking). Temporal infeasibility may be encountered at specific times, being based on the current state of the system. An example of this may be having hallway capacity constraints, in which zones within the DC may be restricted to allow only a certain amount of resources assigned simultaneously to perform tasks at that particular area.

The criteria and sub-criteria considered in the TRM Algorithm are given in Table 1. The three main criteria to be considered are: Latest starting date (LSD), Route and the Static and Synchronization. The LSD priority calculation requires system and task parameters including task expiration time, task duration and speed of the slowest resource. There are various sub-criteria included under the Route criteria, but only the "distance from source" element adds variability into the system since this value depends on the current resource location and the origin location for the task. The other three sub-criteria under Route are resource dependant elements used to differentiate among the different resource abilities. The Static and Synchronization criterion consist of the static priority and the synchronization priority. Static priority depends on two elements, the activity and the host. Activity refers to the type of task to be performed, in which different priority values could be given to inbound, outbound and replenishment tasks. Host allows giving different task priorities based on the resource that created the task. The synchronization portion is mainly used to increase the priority of tasks that are related or dependent of one another. Finally, the system will calculate the overall priority value based on the priorities given to each criteria and sub-criteria, and the weight given to each of these.

Overall, TRM provides a practical approach to the DC management as it considers many different aspects of the operation, when compared to the predominant focus of minimizing travel time. The use of additional criteria such as meeting specific deadlines seems to be more promising from a practical stand point (van den Berg 1999).

Table 1. TRM Criteria and Sub-criteria

MAIN CRITERIA	SUB-CRITERIA	SUB-SUB-CRITERIA
LSD		
Route	Distance from source	
	Resource -handling unit	
	Resource -working area	
	Resource type - level	
Static & Synchro	Static	
	Synchro	Activity
		Host

3 PREDICTIVE CONTROL SIMULATION MODELING APPROACH

The SimPC approach incorporates significant real-time data input. Figure 2 shows an IDEF representation of the major processes within each element. Section 3.1 describes the sequential method in which this simulation model operates, being consistent with discrete-event simulation characteristics. The inputs into SimPC are a major part of this approach, since these correspond to the necessary information to run the simulation model and provide meaningful results. The truck–dock assignment schedule is an essential part of this data input, providing information about inbound and outbound trucks. For inbound trucks, the schedule provides the time in which the truck will be at a dock to start the unloading operations, while for outbound this has to be divided in two different elements. The first element corresponds to the time the load accumulation tasks should be started, which involves the creation of tasks into WMS for the picking of the material from the racks and temporary storing them at a dock cage or buffer area. The second time element refers to the start of dock operations, which consist of loading the material into the truck. Dock operations can only be performed when the truck is at the dock.

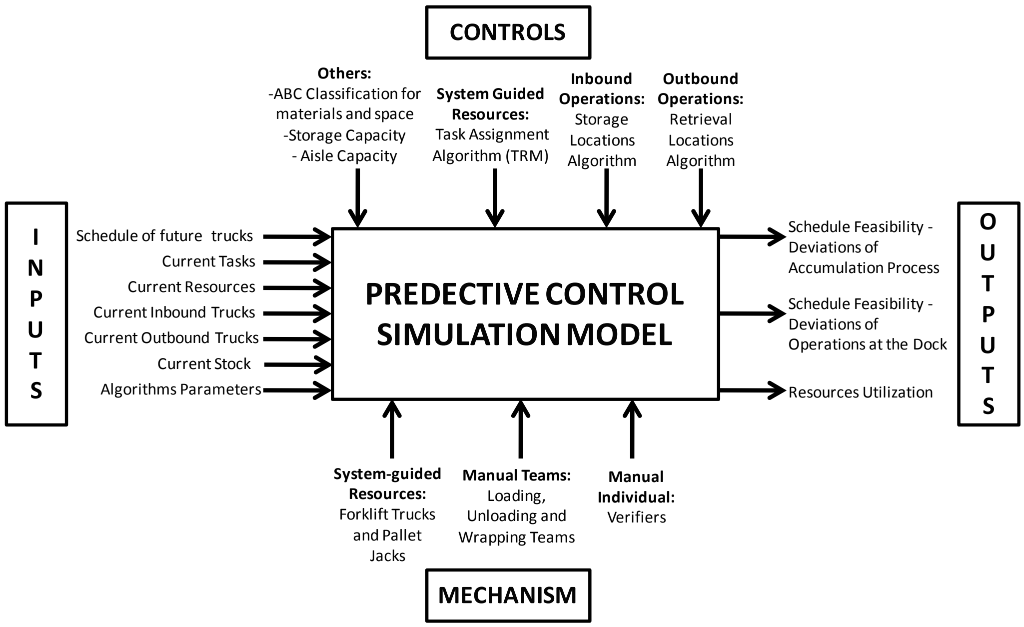


Figure 2. An IDEF representation for SimPC

Within the scope of this work, it is assumed that this truck–dock assignment schedule is given, typically from an optimization model using time estimates, or a rule-based methodology. However, the schedule generated for either one of these optional methods will not be able to capture the dynamics of a large-scale and highly stochastic non-automated DC. This fact sustains the contribution of SimPC, since simulation modeling allows characterizing the different processes independently to the extent of individual resource variability, providing in this way a higher resolution of the DC operations. Further, by having all the processes defined together as part of a simulation model permits emulating the DC operations and the actual prediction of what is expected to happen in the future. This way, a specific schedule can be simulated, being able to measure its viability with a focus on operational deviations. The analysis is to be performed based on resources and operational parameters initially defined for the DC, requiring the incorporation of real-time data gathering.

As listed in Figure 2, most of the data input consists of information providing the current state of the system, such that the schedule can be evaluated at the most realistic conditions. This information is obtained at the moment the simulation run is initiated. Some of these data elements include: current tasks for system guided resources, available resources and their state; information about the different inbound and outbound trucks, the current stock, and various operational parameters, among others. The actual complexity is in terms of the scalability of this information, including ranges like: a thousand simultaneous tasks, nine hundred materials and fifteen thousand possible storage/retrieval locations.

Operational parameters can also be adjusted to a certain extent to render a given schedule viable. From a modeling and experimentation perspective, the SimPC developed in this paper proposes an iterative process in the search for the arrangement of resources and parameters that will guarantee the schedule viability. Many of these parameters are part of control elements, which mainly consists of major algorithms utilized for decision making, as is the case of the TRM algorithm previously discussed. Here, specific criteria weights and priority values could be altered as part of the iterative process. In addition, there are other control features, which extend to having a class based (A, B, and C) classification for the materials and storage locations, including capacity constraints in terms of the storage space and incorporating a dynamic capacity named aisle capacity to specify a maximum number of resources allowed simultaneously in specific areas. However, these last ones are fixed policies, not to be changed for the schedule viability objective. Other set of parameters being considered are in terms of the mechanisms (Figure 2), which refer to the specific resources necessary to perform the different tasks. Moreover, this decision making procedure is better described in terms of tactical and operational decisions, concepts defined and explained as part of the schedule example included in Section 3.2.

In terms of the outputs, traditional performance measures could be included, however in this diagram (Figure 2) only the ones relevant to this work are included. These mainly correspond to a measure of deviations from the original truck–dock assignment schedule given as input data, and the schedule achieved by the simulation model. Also, measures regarding the utilization of resources can contribute to these efforts.

3.1 The Model

The simulation model consists of a Visual Basic (VB) software program which maintains information for discrete event simulation. The preference for VB, instead of a simulation package assures a fast simulation run of the model, which is required to perform scheduling evaluation in a daily basis. Furthermore, the use of VB facilitated the incorporation of rule-based algorithms as the TRM previously discussed. Still, the design structure of the software, illustrated in Figure 3, is not dissimilar to that of SIMAN or Arena.

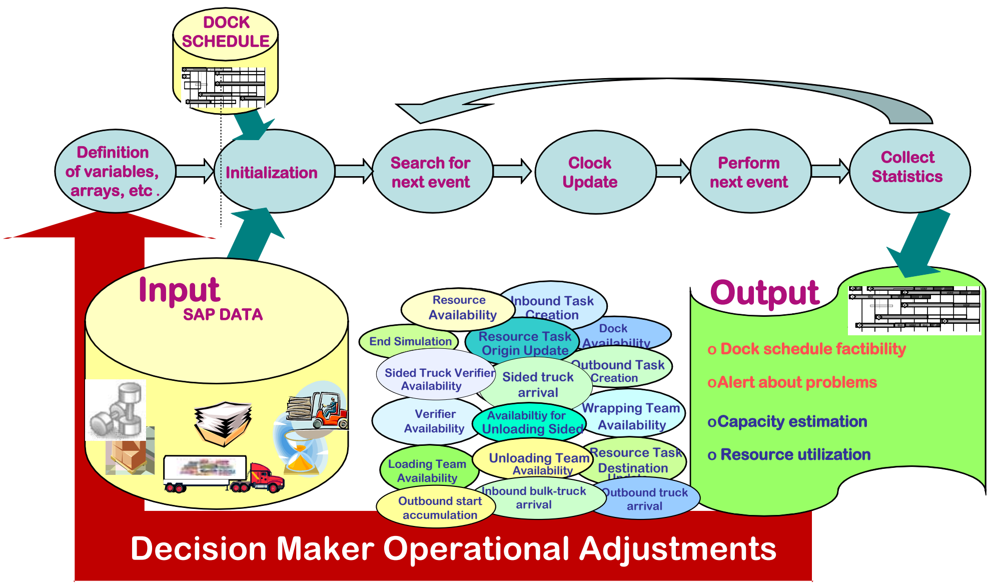


Figure 3. Simulation structure

Describing Figure 3 from left to right, the variables and data arrays are defined first, as they will be used as data input to save system parameters and simulation control logic. The second step is the initialization procedure, which includes the inclusion of the truck–dock assignment schedule required to provide with specific times in which the different operations are expected to be initiated. The other portion of the data input in the initialization procedure refers to the data from WMS. Most of this corresponds to the information illustrating the current state of the system, which needs to be updated at the start of every simulation run. Information that is mainly used a part of the decision making logic may be updated with less frequency.

Subsequently, the simulation operates as a discrete-event simulation: it searches for the next event to be performed from a pool of the seventeen possible events shown in the center of Figure 3. After selecting this event, the clock is updated to the time that the event should be performed, which allows doing various events in the same clock time. The process continues by executing the logic of that specific event and collecting the necessary statistics. An example of an event is the "Resource Availability" which happens when system-guided resources (forklift trucks or pallet jacks) become available. This event's logic mainly consists of performing the task selection by following the rules of the TRM algorithm.

Messages from the simulation include: a check of the truck–dock assignment schedule viability as well as providing some alerts about any problems that were encountered (i.e. not enough material for replenishment). Statistics used in traditional simulation modeling, such as those related to capacity estimation and resource utilization, may also be collected over the simulation run. The simulation will continue the search/perform routine for an event until the "end simulation" event in selected. The end simulation event terminates the simulation and provides summary statistics. The simulation may be re-run after making operational adjustments (e.g., number of resources, priority changes in the TRM algorithm) in order to comply with the input schedule.

The actual simulation program consists of eighty VB sub-routines, in which the use of variable arrays is one of the major elements. The use of databases would have facilitated managing the vast amount of data to be used; however, these would require a large number of queries of information continuously required by the simulation, increasing the simulation time. An increase in simulation time would limit the use of this tool for real-time decision making and for daily evaluation of the system.

In terms of the characterization of the DC operations, it was necessary to describe the variability of resources though probabilistic distributions. This was not limited to manual resources (referring to loading teams, unloading teams and wrapping team), being also a necessary measure for system guided resources. For example, in the case of forklift drivers, WMS productivity historical data for random operators through different periods of the month and year was utilized for these purposes. This information was used for the development of an allowance probabilistic distribution, obtained through the comparison of the simulation results with the real operations. This way, the human factor has been incorporated for forklift trucks, in which these allowances consider the difference in operators' capabilities.

3.2 Scheduling Example

Assuring a viable schedule has been the main motivation for developing the SimPC Approach. Figure 4 illustrates the case of obtaining a non-viable truck-dock assignment schedule from SimPC. The diagram includes two schedules for the next twelve hours from the current clock time. The schedule at the top of Figure 4 represents the plan being used as input data for SimPC, while the schedule at the bottom is the result after emulation the decision making at the DC with SimPC. In this example, time identified as fourteen represents the current clock time in which the evaluation is performed where data is gathered from WMS to obtain the current state of the DC. Each row represents the schedule of a dock, while each column delineates a different time of the day. Within each row of the schedule, the tasks required for inbound and outbound trucks are divided in two major classifications: storage/accumulation (for inbound/outbound) tasks and operations at the dock. Simulation results provides a more detailed schedule indentifying the dock operations as idle, in the verification process or in charge of the loading/unloading team (LT/UT).

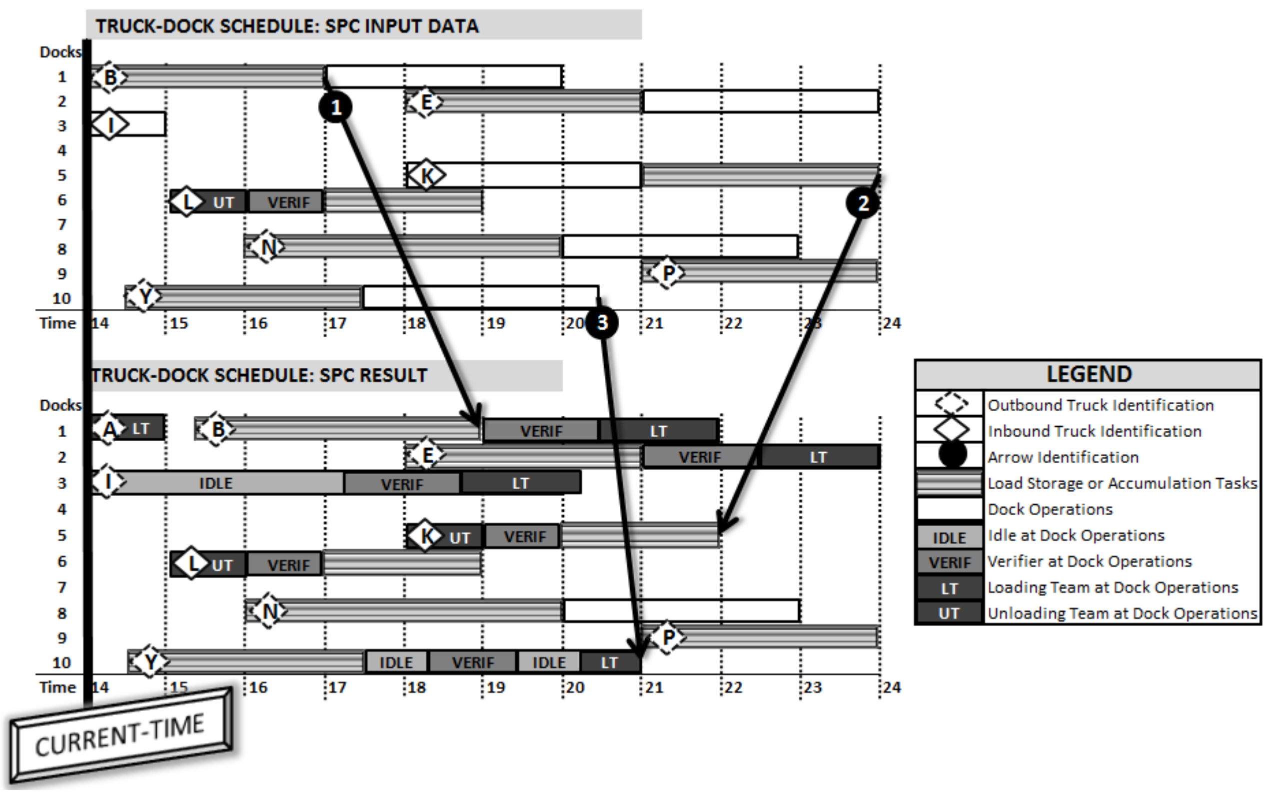


Figure 4. Truck-dock schedule comparison

Arrows indicate different scenarios of the operations for this example, which include possible delays or work performed in advance. For instance, arrow numbered one illustrates two reasons for delay, an extension in the accumulation tasks for outbound truck B and a delay in a previous truck (A) assigned to the same dock. The second arrow presents the opposite case, in which work is done in advance for inbound truck K, having reduced the overall operations for this truck by two time units. Arrow numbered three demonstrates the benefit of measuring specific tasks in the dock operations. Here it is evident that the reason for delay are two idle times, having the first one prior to the verification process and the second one before initiating the truck loading. This means that the resources following the idle time were not available at the needed times to make this portion of the schedule viable. Further, these details provide insights to identify the reason for a non-viable schedule, which as illustrated may include having system congestion as an effect of large delays in the accumulation tasks. These delays could also be a result of having problem at the dock operations, in which the reasons of delay may be identified by analyzing the allocation of specific idle times.

After identifying the reasons for delays, the problem shifts to determining the decisions needed to achieve the intended schedule. SimPC is aimed to contribute at the tactical and operational level of the decision making process. While tactical decisions may be concerned with aspects as the dimensions of the resources and the layout arrangement requiring some investment, the operational decision are limited to assignment and control of the available resources (Rouwenhorst et al. 2000). Operational decision should be considered first to ensure fulfillment of day to day tasks at the DC. In terms of the typical DC delineated in Section 2, this would include modifying resource assignments and altering the TRM Algorithm parameters. In terms of the TRM Algorithm, the number of alternatives to evaluate is combinatorial, for which certain guidelines should be developed. Operational decision will only be useful for the improvement of the accumulation procedures through modification of the TRM Algorithm since in the presence of a fixed schedule dock operations can only be improved by increasing the number of resources. Moving to the upper level of the decision making process, both the accumulation process and the operations at docks can be improved by performing tactical decision in which variations in the number of resources is allowed with certain cost implications.

4 CONCLUSIONS AND FUTURE WORK

This paper presents a new approach for managing non-automated DCs with the aim of providing a tool that accounts for the variability of such systems. There exists extensive research on the control and use of simulation for automated DCs; however, research on the development of simulation-based decision making tools for non-automated DCs is limited. We introduced the concept of Simulation for Predictive Control (SimPC) as a decision making tool to evaluate the truck–dock assignment schedule viability, while facilitating the identification of the tactical and operational changes required to achieve the intended schedule. Moreover, the large potential SimPC has in identifying solutions in the search for a viable schedule was demonstrated through an example, while the specifics of the model characteristics were also described. Further, this work illustrates the significance of forklift trucks being potentially the main element for material state transitions in non-automated DCs. As part of the future work we would like to analyze in detail the controllable variables affecting the truck–dock assignment schedule, to utilize the SimPC as a learning tool as well. This would permit the development of a rule-based algorithm to decide on the system modifications needed to eliminate some schedule variations.

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AUTHORS BIOGRAPHIES

LOURDES A. MEDINA is currently pursuing her PhD degree in Industrial Engineering at The Pennsylvania State University. She graduated Summa Cum Laude from her BS (2006) in Industrial Engineering from The University of Puerto Rico at Mayaguez, obtaining the highest recognitions in the graduation commencements (Luis Stefani Rafucci Award, College of Engineering Award and Frederick M. Taylor Award). Her areas of interest include simulation modeling and product design. Lourdes is member of various professional organizations, including CIAPR, Alpha Pi Mu and Tau Beta Pi. Her email is <lam458@psu.edu>.

R. UFUK BILSEL holds BS and MS degrees in Industrial Engineering from Galatasaray University and a MEng degree in Industrial and Manufacturing Engineering from Penn State. He is currently pursuing his PhD degree in Industrial Engineering and Operations Research at Penn State. His areas of interest include supply chain optimization and multicriteria decision making in supply chain management, healthcare and finance. His email address is < rub150@psu.edu>.

RICHARD A. WYSK is the William E. Leonhard Chair in Engineering and Professor of Industrial Engineering at The Pennsylvania State University. He received his B.S.(1972) and M.S.(1973) in Industrial Engineering and Operations Research from the University of Massachusetts and Ph.D.(1977) in Industrial Engineering from Purdue University. He has also served on the faculties of Virginia Polytechnic Institute and State University and Texas A&M University where he held the Royce Wisenbaker Chair in Innovation. Dr. Wysk's research and teaching interests are in the general area of Computer Integrated Manufacturing (CIM), product development and manufacturing. Dr. Wysk has coauthored six books including *Computer-Aided Manufacturing*, with T.C. Chang and H.P. Wang -- the 1991 IIE Book of the Year and the 1991 SME Eugene Merchant Book of the Year. He has also published more than 150 technical papers in the open-literature in journals including the *Transactions of ASME*, the *Transactions of IEEE* and the *IIE Transactions*. Dr. Wysk is an IIE Fellow, a Fellow of SME, a member of Sigma Xi, and a member of Alpha Pi Mu and Tau Beta Pi. He is the founder of a small business focused on the development of bactericidal coatings on medical devices (He also received the Army Bronze Star, and two Army Commendation Medals for his service in Vietnam. He has held engineering positions with General Electric and Caterpillar Tractor Company. His email address is <rwysk@psu.edu>.

VITTALDAS PRABHU received his PhD in Mechanical Engineering from the University of Wisconsin-Madison, USA. He is currently a Professor in Industrial and Manufacturing Engineering at Penn State University, USA. His research interests include engineering of distributed control systems consisting of discrete-events, physical processes, and service processes. He teaches courses in controls, manufacturing, information, and service systems. His email address is <prabhu@engr.psu.edu>.

R. RAVI RAVINDRAN is a Professor and the past Department Head of Industrial and Manufacturing Engineering at the Pennsylvania State University. Formerly, he was a Faculty Member in the School of Industrial Engineering at Purdue University for 13 years and at the University of Oklahoma for 15 years. He holds a BS in Electrical Engineering with honors from India. His graduate degrees are from the University of California, Berkeley where he received an MS and a PhD in Industrial Engineering and Operations Research. His area of specialization is operations research with research interests in multiple criteria decision making, financial engineering, health planning and supply chain optimization. He has published two major text books (*Operations Research: Principles and Practice* and *Engineering Optimization: Methods and Applications*) and over 100 journal articles in operations research. He has edited a new Handbook on Operations Research and Management Science that was published in 2008. His email address is <aravi@psu.edu>.