Operational Simulation-Based Decision Support in Intralogistics Using Short-Term Forecasts

Marcel Müller(✉), Tobias Reggelin(✉), and Stephan Schmidt(✉)

Otto von Guericke University Magdeburg, Universitätsplatz 2, 39106 Magdeburg, Germany
{marcell.mueller, tobias.reggelin, stephan.schmidt}@ovgu.de

Abstract. Simulation models are still often only part for decision support in the planning area. For short-term decisions at the operational level, there have been good fundamentals since the 1990s, but still relatively few implementations, especially in the logistics sector. Our approach is to use real-time data to provide short-term forecasts, by using a simulation model that provides required information. Due to current hardware and a well-chosen degree of abstraction of the model, real-time decision support ("real-time" means in this context: fast enough to support the decision) is possible. This paper presents a concept of a procedure model for the realization of such operational simulation-based decision support, applied to the picking area of an industrial laundry. The operational use of the simulation model is part of the project "Laundry Order Consolidation System (LOCSys)", which aims to improve the picking & storing processes in the clean area of an industrial laundry through automation.

Keywords: Real-time simulation · Real-time decision making · Virtual commissioning · Industrial laundry

1 Introduction

Today's decision-makers have to analyse rapidly complex problems in the intralogistics to make the right decision. There are not many tools to support this process but usually many data is available. A concept to use this data, in an easy way to optimize the own decision based on forecasts, would deliver a great benefit for the decision-makers.

In planning of processes in intralogistics, the use of material flow simulation models is quite common. The benefit of such simulation models does not necessarily end in the planning process. Modern simulation approaches and the current rapid hardware enable simulation runs in an extremely short time, fast enough to deliver decision support for operational decisions. According to Rogers and Gordon [9] "real-time" decision support implies a reaction time of the support tool that is smaller than the time until the decision has to be made.

Many simulation software already offer numerous integrated optimization tools: Beside classical optimization algorithms, this can also be artificial neural networks and

I. Kabashkin et al. (Eds.): RelStat 2018, LNNS 68, pp. 345–352, 2019.
https://doi.org/10.1007/978-3-030-12450-2_33

genetic algorithms for an artificial intelligence approach. Furthermore, many programs offer also a wide range of interfaces to connect the model with databases or a programmable logic controller (PLC).

For our approach, we develop a simulation model, which provides valid short-term forecasts by using real-time data to validate different picking order sequences. The optimization tools can directly use these data for changing various control parameters to optimize the target parameters or alternatively an extern algorithm uses the simulation results to create new (optimized) control parameters. Renewed simulation runs enable the validation of this optimization. The decision-maker can use the highly accurate results for the decision in his specific situation. The idea of real-time simulation is not new and appeared beside the idea of real-time decision making to control manufacturing systems [7, 9]. Since the 90s researchers already applicate real-time simulation for example to "assign due dates on logistics-manufacturing networks" [10] or in combination with artificial neural networks to control flows in sewerage networks in real-time [6]. Despite the progress in this area, research continues to focus on other use cases and new concepts nowadays.

We applicate our approach initially in the area of industrial laundries. These companies are under a high cost pressure. Although the turnover of the laundry industry as a whole is increasing, market concentration is taking place in Germany. With increasing costs due to rising minimum wages, some laundries are trying to tap new potential with innovative solutions. For example, the use of simulation models helped to find optimization potentials and to improve the processes [1]. Real-time simulation models go one-step further and provide meaningful results in a timely and therefore more useful way. However, there are not many applications of real-time simulation for industrial laundries. At least one approach describes the use of a real-time algorithm that optimizes the sequence in order to save resources with a predictive control [8]. A specific simulation-based approach is missing in this context.

As part of the current project "LOCSys—Laundry Order Consolidation System", a group of researchers and small- and medium-sized enterprises develop an automatic picking solution for industrial laundries. In addition to the classic simulation model for the planning of this solution, the picking solution communicates also to an operational simulation model, which is used during operation to map an emulation and to make short-term forecasts. This paper presents the conceptual model for this real-time connection of the simulation model.

2 Laundry Logistics

2.1 Closed-Loop Supply Chain

Industrial laundries are, in contrast to the classical manufacturing industry, characterized by a material cycle, which is the basis for the business model. There are many similar terms to describe laundry cycles because the topic of sustainability has a strong influence describing cycles in the economy. We use a closed-loop supply chain to describe the laundry cycle in the best way. Figure 1 shows a schematic representation of the laundry cycle. The circular structure consists of the relationship between customer and industrial laundry. The figure also shows clearly that the circuit is not completely closed. Purchases of laundry items or worn out laundry items vary the amount of items in the circulation.

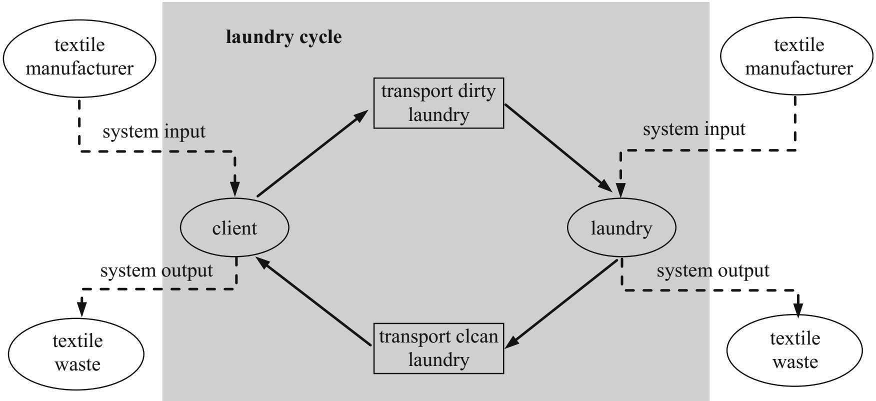

Fig. 1. Schematic representation of the laundry cycle.

The focus of our application is on industrial laundries, as there is no influence on the customer. The consideration of transport logistics between customer and laundry is an interesting field, but the conventional and new approaches for typical transport logistics problems are applicable here.

2.2 Processes in Industrial Laundries and RFID

The difficult handling of the laundry items decisively influences the logistical processes of industrial laundries. Although large areas, in particular in the washing process, have already been automated, the workers are still processing many operations manually, especially between some process steps and above all in the picking area. Therefore, there are current efforts to automate the picking area. This automation solution is based on real-time data in order to react in an optimal way to every current situation. An important prerequisite for this is the use of radio-frequency identification (RFID). Industrial laundries are increasingly using this technology, for example to obtain information about the loss of laundry in the laundry cycle. The use of this technology makes it possible to process data, with the help of further data from the merchandise management system, in order to make a real-time decision.

Since the considered system is the industrial laundry, it would make sense to collect data using RFID in the incoming goods department to identify the incoming laundry items and to have as much time as possible to make a decision. Figure 2 shows the processes in an industrial laundry and puts the simulation model in a context. There will not only be an identification point in the goods receipt, but also in the picking area. However, the latter will probably just make fast calculations and smaller variant comparisons to make a real-time decision.

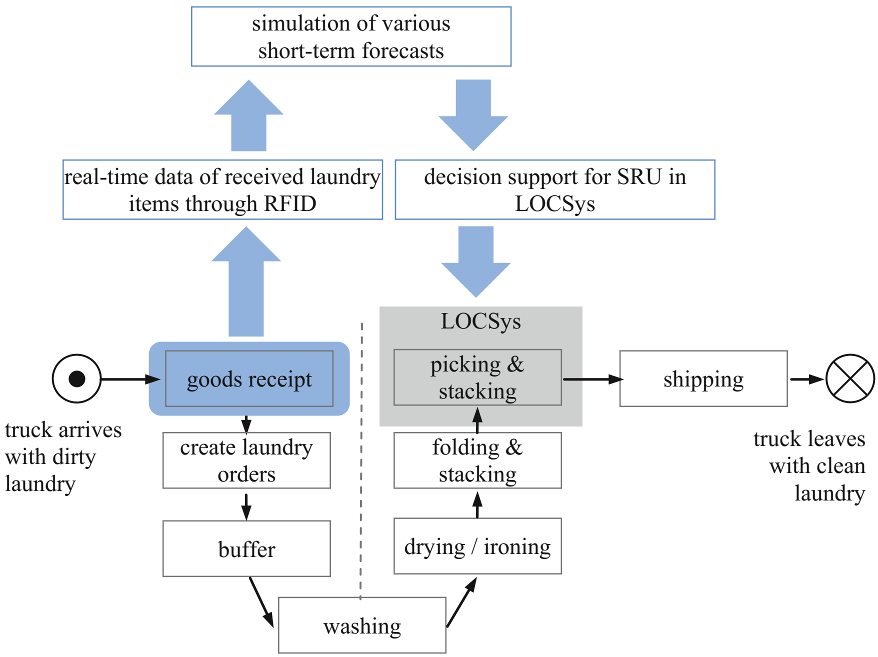

Fig. 2. Typical processes in an industrial laundry and early concept of the core processes for operational decision support of LOCSys.

The picking solution "LOCSys" consists currently of one rack row and a mounted on rails storage and retrieval unit.

3 Problem Description and Real-Time Decision Making

In our application, we face the complex challenge of combining a typical scheduling issue with a space allocation and stacking problem. Due to this, a decision making based on real-time data is essential, because several questions must be answered based on this data:

- Which is the next laundry stack to transport (storage, relocate or retrieve)?
- Where should the laundry stack be stored or relocated?
- Should it put the laundry stack on another laundry stack?

Inaccurate data would quickly lead to incorrect or non-optimal answers to these questions. The incoming material flow in industrial laundries is very variable in its quantity and composition. A simple use of historical data to estimate the overall state of the system supposedly known is thus not possible.

The optimization of sequence of different picking orders using certain limited resources is a typical scheduling problem. Scheduling problems are not new [2] and neither are the real-time approaches to solve them: with the emergence and spread of computers and networks in production and logistics, researchers were already looking for real-time solutions to optimize these problems with these new technologies in the 1990s [7, 9]. According to Rogers and Gorden there are three different approaches for solving scheduling problems: the chosen simulation-based one, "O.R. tools" and "A.I. concepts" [9]. Many approaches in the literature focus on applications in manufacturing systems and less on typical logistics solution as a warehouse.

Our simulation-based approach is also called "Simulation-based Real-time Decision-Making (SRDM)" [3] or "On-Line" simulation [4, 9, 12]. Looking less at the decision-making component and focusing more on testing the real system, our approach can also be described as a virtual commissioning [11], which leads also to typical results of an emulation [5]. The intended picking algorithm in our project could be considered as an A.I.-approach but will not be discussed further in this paper as it is still in development and not yet completely clear. We can already state at this point that the combination of the two approaches (simulation and A.I.) should be able to overcome the three-part problem.

4 Concept

4.1 Simulation Model, Picking Algorithm and PLC

To optimize order picking and warehousing, an efficient data exchange between simulation model, picking algorithm, PLC and the real logistics solution is required. Figure 3 shows the conceptual data exchange model at a high aggregation level. The central point of exchange are various data tables, which can be located on a normal computer with network connection in the enterprise. The merchandise management system or the corresponding part of an ERP software provides data about the current state of the overall system at regular intervals (e.g. every hour/day). This allows the system to know exactly which and approximately where a laundry item is currently located in the industrial laundry. Customer orders that result in picking orders can either be transmitted via the ERP system, separately in another software or directly by the customer. The actual real-time data comes from the real automated picking solution. This can be primarily the position of the SRU, as well as data on the instantaneous speed of the SRU and possibly faults that occur. With this data, the picking algorithm can specify the (approximately) optimized sequence of the picking orders. For this purpose, the algorithm uses not only its normal decision patterns but also the simulation model, as long as the real system allows sufficient simulation runs in time. The algorithm can conclude this period of time from the open picking orders and the current items of laundry in the picking area.

The simulation model needs the real-time data from the data tables for initialization in order to establish the current state of the real system. Already completed transport orders have been noted in the data tables and give conclusions about the current occupancy of the warehouse, despite the lack of sensor technology at this point. The current position of the SRU is also transferred after a processed transport order and is thus at least partially given in real time, if the SRU has no current transport order.

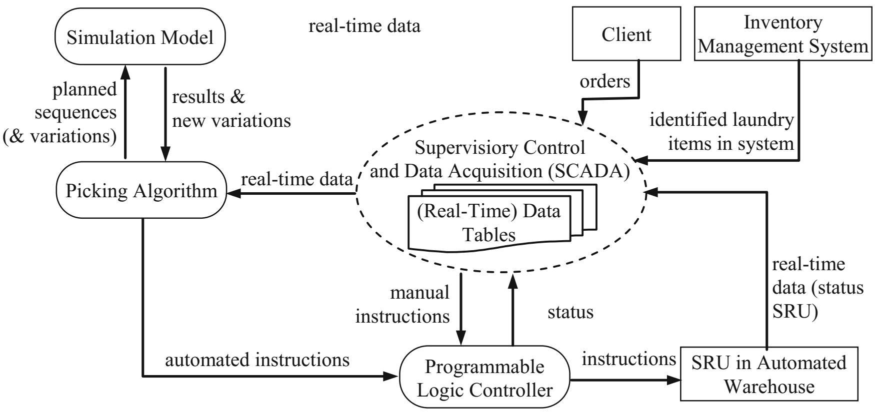

Fig. 3. Conceptual data exchange model between simulation, algorithm, PLC and real system.

After simulation, the picking algorithm receives the results. This can also result in possible new variations of the sequence that the algorithm did not sent before. The picking algorithm then forwards the sequence of the picking orders to the PLC as separate transport requests. The PLC then translates the transport requests into corresponding control commands. However, manual control commands can also be issued via the user interface of the SCADA and allow the change of automated created sequence or to create new transport orders.

4.2 Data Tables

Table 1 gives an overview of the planned entities for the central exchange of data. In addition to the mentioned attributes, there are relationships between the entities that

Table 1. Overview of the data tables.

Entity	Primary key	Further attributes
SRU	ID	Maximum speed; acceleration
Laundry item	ID	Length, width, height, location object, type of laundry, weight, position in stack
Laundry stack	ID	Location object, x-position, y-height
Shelf level	ID	Length
Transport order	ID/order number	Type of transport (store, relocate, retrieve), creation time stamp, completion time stamp, target object, target x-position
Picking order	ID	Date of delivery, creation time stamp, completion time stamp
Client	Client number	Name

involve further data fields.

A central component of data exchange will be the table with transport requests. Already assigned transport orders must be remembered in order to be taken into account when assigning new transport orders. This is always the case when a new item of laundry arrives via the conveyor belt to the picking area. In addition, the timestamps enable a statistical evaluation of the assigned transport requests. Table 2 shows some example data fields from the transport order table. The records of the transport orders have beside the shown columns also data fields for "stack height", "target stack", "transport mode" and might get more in the future. In this example transport order 9 and 10 are finished yet and transport order 11 would be taken next by a storage and retrieval unit.

Table 2. Example of typical transport orders and some of their attributes.

Transport order number	Creation date	Completion date	Transported stack	Shelf layer	x-position
9	5:24.6667	5:53.3417	stack:3	layer:1	6.556
10	5:25.4333	6:20.4126	stack:4	layer:3	5.514
11	5:51.8333		stack:11	layer:2	0.539

5 Conclusion and Outlook

The project is currently still in the planning phase and the approaches to real-time decision support by means of simulation-based forecasts are to be implemented next year. It has already become apparent that a database as a middleware is required for smooth communication between the simulation model, the picking algorithm and the PLC. The coordination of the data fields and transfer protocols is an important prerequisite.

The paper has given a brief overview of the most important aspects and their state of the art. In addition, it also presented a first data exchange model, which shows how the future interaction should work.

Acknowledgements. As part of the "Zentrales Innovationsprogramm Mittelstand" (ZIM; central innovation program), the Federal Ministry for Economic Affairs and Energy of Germany launched a research and development project to find an innovative solution for automating the picking area in industrial laundries. The project is called "LOCSys—Laundry Order Consolidation System". Part of LOCSys is the use of an operational simulation model to provide short-term forecasts and support the decision-making of the automated picking system.

We are very thankful for the financial support of the ministry, which allows us to research for new picking solutions in the laundry industry.

References

1. Brandau, A., Weigert, D., Tojulew, J.: Applications of simulation to improve operations. In: Simulation in Production and Logistics, Germany, pp. 289–298 (2015)
2. Conway, R.W., Maxwell, W.L., Miller, L.W.: Theory of Scheduling. Addison-Wesley Publishing Company, Reading (1967)
3. Dalal, M., Groel, B., Prieditis, A.: Real-time decision making using simulation. In: Proceedings of the 2003 Winter Simulation Conference, USA (2003)
4. Davis, W.J.: On-line simulation: need and evolving research requirements. In: Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice. Wiley (1998)
5. Hofmann, W., Langer, S., Lang, S., Reggelin, T.: Integrating virtual commissioning based on high level emulation into logistics education. Procedia Eng. **178**, 24–32 (2016)
6. Hunter, A., Hare, G., Brown, K.: Genetic design of real-time neural network controllers Neural Comput. Appl. **6**(1), 12–18 (1997)
7. McConell, P.G., Medeiros, D.: Real-time simulation for decision support in continuous flow manufacturing systems. In: Proceedings of the 1992 Winter Simulation Conference, USA (1992)
8. Peitz, S., Gräler, M., Henke, C., Hessel-von Molo, M., Dellnitz, M., Trächtler, A.: Multiobjective model predictive control of an industrial laundry. In: 3rd International Conference on System-Integrated Intelligence: New Challenges for Product and Production Engineering, Germany (2016)
9. Rogers, P., Gordon, R.J.: Simulation for real-time decision making in manufacturing systems. In: Proceedings of the 1993 Winter Simulation Conference, USA (1993)
10. Ruiz-Torres, A.J., Nakatani, K.: Application of real-time simulation to assign due dates on logistic-manufacturing networks. In: Proceedings of the 30th Conference on Winter Simulation, USA (1998)
11. VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (GMA): Virtual commissioning model types and glossary. In: VDI/VDE 3693, Beuth Verlag GmbH, Germany (2016)
12. Wu, S.-Y.D., Wysk, R.A.: An application of discrete-event simulation to on-line control and scheduling in flexible manufacturing. Int. J. Prod. Res. **27**(9), 1603–1623 (1989)