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Event-based modeling and simulation for optimizing order picking

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Abstract

Manually-performed order picking is a very common, yet very expensive process in warehouse operation. Multiple pickers work simultaneously in the picking area to respond to customer orders “as soon as possible”. To do so, company policies are devised to meet performance requirements, while guaranteeing minimum interference among pickers. Here we model a person-to-goods manual system by means of an event graph (EG). An EG-based representation covers the event-driven logic of the picking system, as well as the need of providing a highly-detailed description of the system logic. EGs also represent the common ground for integrating complementary analysis techniques, such as discrete-event simulation, digital twins and process mining, which allows to move towards a truly connected supply chain. We then resort to simulation to exploit the benefit of replacing a time-free order behavior with a time-window based organization for order collection. Numerical results are presented to support decision making in a real cooperative that provides wholesale distribution to customers in Central and Sothern Italy.

Keywords: Order picking process; event graphs; simulation; what-if optimization

1. Introduction

Warehouse design and organization has received a great deal of attention because of the role it plays in the supply chain operations by ensuring seamless item storage and distribution. The aim of this manuscript is not to present an exhaustive and detailed analysis of the literature on warehousing research, nor describe how traditional storerooms have changed into more automated and service-based systems that bear greater efficiency and effectiveness. For this matter, the reader may refer to pre-existing literature and, in particular, to some very recent works (Kumar et al. 2021; Glock et al. 2021; Yener and Yazgan 2019). Here we focus on *order picking*.

Commonly defined as the process of retrieving items from their storage locations in response to customer orders, order picking is considered one of the most time-consuming and work-intensive operations in warehouses (Masae et al. 2020). Besides, in most companies it is still performed manually by human operators. So, there are different types of problems that can be addressed when dealing with the order picking process and many of them can benefit from simulation (van Guils et al., 2018). From now on, we will examine what order picking issues have been modeled and solved with simulation-based approaches. The objective of this work is to define where our case study lies within this landscape and how simulation can be used to highlight the (known/unknown) relationships between order picking and the neighboring warehouse operations that feed or are fed by this process.

To begin with, different types of simulation techniques have been used to model the order picking process. These techniques range from using pseudorandom number generators (Kostrzewski 2020), Monte Carlo-based approaches (Al-Araidah et al. 2021; Marcoulaki et al. 2005), discrete-event (Güller and Hegmanns 2014; Andriansyah et al. 2011; Molnár 2005) and object-oriented modelling (Yang 2008).

The simulation of order picking decisions is the main focus of most of the research efforts we have examined. These include picking strategies and policies as stand-alone issues, related to specific key performance indices (Urzúa et al. 2019; Hong 2019; Burinskienė et al. 2018; Urzúa et al. 2018; Elbert and Muller 2017; Bahrami et al. 2017; Wasusri and Theerawongsathon 2016), or in conjunction with other features such as system size (Kauke et al. 2019), number of pickers/carts (Klodawski et al. 2018) and layout (Navarro 2020).

Research on the simulation of the order picking process has also been carried out based on the assessment and restructuring of the warehouse's layout (Kašparová and Dyntar 2021; Altarazi and Ammouri 2018; Ulbrich et al. 2007), storage assignment (Faria and Reis 2015; Yang 2008) or simply by focusing on internal vehicle routing in order to minimize the travel time and/or distance (Shetty et al. 2020; Bharre and Chung 2020; Bučková et al. 2017; Lerher et al. 2016; Zhu et al. 20011; Guo et al. 2011; Zhou et al. 2010).

The simulation of the order picking process - with the goal of estimating its performance - has clearly been driven by hard technological solutions, for example, miniload versus Kiva systems (Bozer and Aldarondo 2018; Güller and Hegmanns 2014; Andriansyah et al. 2011), pick-by-vision versus pick-by-light (Renner and Pfeiffer 2017) and vehicle loop systems (Lu et al. 2001). This entails simulating and comparing manual versus automated solutions (Coelho et al. 2018; Francisco et al. 2016; Andriansyah et al. 2009), a hybrid combination of the two (Winkelhaus et al. 2022) and, in some cases, even accounting for human-machine interaction (Souiden et al. 2021). On the other hand, soft factors have had their share of advantages and many off-the-shelf software environments have been used to design effective order picking systems among which Witness (Kašparová and Dyntar 2021), Gurobi (Shetty et al. 2020), Flexsim (Navarro 2020), ProModel (Merkuryeva et al. 2006) and Arena (Kawczynski and Aguilar-Sommar 2006).

As a final remark, the literature also includes some consolidated guidelines on how to simulate general order picking models and applications (Quinn and Norman 1979; Kelly 1979), as well minimize error picking rates (Goldscheid et al. 2007).

Unlike any of the above contributions to the modeling and simulation of the order picking process, we base our M&S efforts on event graphs which capture the discrete-event paradigm of simulation (Wagner 2021). Event graphs represent the common ground for complementary analysis techniques of queueing-based models, such as event simulation, digital twins and process mining. All of these techniques are deemed necessary by both academic and non-academic stakeholders to better exploit the plethora of data available in today's industry and achieve a truly connected supply chain. The rest of this paper is organized as follows. The problem description and conceptual model describing the current order picking practice in PAC 2000A is proposed in sections 2 and 3, respectively. The simulation model is presented in section 3. Results and discussion of the simulation experiments are provided in section. Conclusions are drawn in the final section.

2. Problem Definition

This section briefly describes the main warehouse operations carried out by PAC 2000 A. PAC 2000 A is a cooperative that provides wholesale distribution to customers in Italy. It retails different types of food products, i.e. frozen food, fresh fruits, vegetables, beverages, baked goods, meat products, and general groceries. Most of PAC's distribution centers share the same general pattern with respect to the flow of goods, as well as the information required for product management. Although our study accounts for overall warehouse organization and management, herein we focus on the interaction among *receiving*, *picking* and *shipping* goods and, as a result, the logistics processes entailed by these warehouse functions.

The *receiving* process is triggered by the work of a purchasing agent or buyer who is responsible for purchasing goods for one or more retail outlets. He/she sends orders to suppliers through PAC's AS/400 system. Once the goods have been ordered, supplier parties each organize their own deliveries. In doing so, a supplier can book a so-called delivery "reservation window" by means of TC1, a collaborative logistics platform used by the community in this grocery network to track and manage unloading time slots. If a supplier decides not to book a delivery, then the related goods can be unloaded at one of PAC's distribution centers only within a fixed time window (e.g. before 9:00 a.m.). Goods reception is physically initiated when the transporter arrives at the warehouse and hands in the required transportation documents. In order to assign an unloading dock to the transportation vehicle, warehouse operators perform internal control procedures on these documents. If successful, goods are unloaded by man-driven electric pallet trucks (with footboards). At this point, the incoming goods are carefully inspected by warehouse operators who also record their arrival in the AS/400 system via a portable terminal. The documents are then signed, stamped and returned to the transporter who can finally leave the warehouse. These goods are now ready to be stocked in the warehouse by means of man-operated forklifts.

The *picking* process is the first step in order fulfilment. In PAC's racking system-based warehouses, order picking is performed manually directly from the shelves and according to a "person-to-goods" principle. This means that order fulfilment is carried out by pickers who go to the products, one by one. The order pickers drive around the warehouse on man-aboard pick vehicles or even forklift trucks - whenever goods are larger and/or heavier. These vehicles travel horizontally through the aisles according to a route-optimized S-shaped path. While doing so, pickers are supported by voice-picking technology via a headset that, on the side, provides verbal instructions to follow and, on the other, collects verbal codes as responses. Specifically, based on the input from the AS/400 system, voice commands indicate the path to follow and the locations of the items on the picking list. The order picker reaches each single destination identified by the tuple <row, slot, location>, confirms his/her position through a corresponding check digit and then picks up the (number of) indicated items. If an item is (partially) out of stock, then replenishment occurs by moving additional units of the missing item from an upper storage slot to the assigned picking place. Picking tasks for these temporarily "unavailable" items are rescheduled by the AS/400 at the end of the process. Upon completion of the picking list, the order picker provides for item packaging and communicates the number and type of supports deployed. This information is stored on the AS/400 system. As a final step, pallets are first transferred and placed on the assigned loading dock in the shipping department and then loaded into the truck. The transportation documentation is handed over to the transporter.

The purpose of the *shipping* process consists in sending out ordered goods to retail outlets (customers) within a fixed time window. The shipping process starts with delivery scheduling activities based on customer orders. These orders are not known in advance: they become available over time. Orders are automatically divided into picking lists by the AS/400 system. Each picking list contains a maximum number of items (e.g. 110 items) and the priority of the list is based on the due delivery date and time. Of course, lists stemming from the same order have the same priority. Each list is assigned to a loading dock based on its priority, the potential combination with other stores bearing similar delivery routes and the availability of the loading docks. This information is stored on the AS/400 system. Following this assignment and after the related order picking process previously described has been completed, the orders are ready to be sent out.

3. Conceptual Model

As well put by Lee Schruben (Schruben 1983), a formalized description of a system structure may be used as a preliminary step in top-down simulation model development. Bearing this in mind, the first step of our approach is based on the representation of the events that drive the logic and dynamics of the warehouse processes of interest. This event-driven solution, commonly known as event graph (EG), appears to be the most suitable for building the conceptual model: emphasis is placed directly on system events and the dual state-time relationship of the system events, while entities appear only implicitly as event attributes (cit.op.). Besides, when properly organized, they can be successfully used to build reusable simulators (Schruben 1995).

An example of an EG element is illustrated in Figure 1 according to which *t* time units after the occurrence of event *i*, event *j* is scheduled to occur, provided that condition *c* holds at the time event *i* occurs. Parameter value *p* is passed as argument to event *j*.

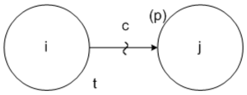

Figure 1. Illustration of an EG element

Technically speaking, the function of events is two-fold: they change the values of the variables used to describe the state of system, as well as trigger the occurrence of future events. The changes that occur in the system state at each event time are represented by the vertices (nodes) in the graph, while the relationships between the events are represented by directed edges (arcs) between event vertices. Relationships are used to specify conditions and parameters that require coding inside the simulation procedures; in particular, they account for the change of entity attributes and update cumulative statistics and counters.

Figure 2. EG model for managing order picking of warehoused goods.

This stated, let us begin graph construction by introducing some terminology and notation to simplify exposition:

- NL: number of lists to be processed;
- NRL: number of references (items) un a list;
- NC: number of picking cars;
- NF: number of forklifts;
- NFO: number of forklift operators;
- NR: number of replenishments to be performed for the picking list being processed;
- (r,s,l): tuple that identifies the row, slot and location of a reference to be picked;
- p(r,s,l): 0 if position where a picking car stops to perform reference picking of (r,s,l) is free, 1 otherwise;
- s(r,s,l): number of items of reference in picking position (r,s,l);
- st(r,s,l): number of items of reference in stocking position (r,s,l);
- l(r,s,l): number of items of reference in picking position (r,s,l) required by the picking list under process;
- s: type of support(s);
- ts: time to retrieve support(s);
- ttp: time to travel to picking position of reference;
- tp: time to perform reference picking;
- ttr: travel time to picking position of reference requiring replenishment;
- tr: time to perform replenishment;
- adj: 0 if next reference is in the same row and within 4 slots, 1 otherwise.

The EG of the company's order picking process has been conceived according to the picking operator's view: these operators initial picking operations upon assignment of order lists and, thus, their activities drive the system events. The representation is given in Figure 2. In particular, it focuses on the picking process in conjunction with stock replenishment; together they ensure that, as required by retail practice in order fulfilment, the right goods are in the best place and in the best quantity.

A detailed picture of the information given in the above EG representation is portrayed in Table 1. For every event (vertex) listed in the table, a brief description is provided, followed by the state change(s) triggered by the event (in curly brackets) and the related enabling conditions or activities (on directed edges).

Table 1. Details of EG model for managing order picking of warehoused items

Event (vertex)	Description	State Changes {in brakets}	Enabling Conditions/Activities (on directed edges)
PalletRackingStorage	Operator receives picking list via the voice-picking set	-	At least one list requires processing ($NL>0$); at least one picking car is availale ($NC>0$)
StartPickingOperations	Operator starts picking operations	The number of lists to be processed is decreased by one ($NL=NL-1$); The number of available picking cars is decreased by one ($NC=NC-1$)	-
SupportRetrieval	Operator retrieves supports	-	The id of the type of support (s) to be retrieved is passed as a parameter
StartTravelToPicking	Operator starts travel to picking position	-	Time to retrieve support (ts) elapses; The id of the picking location is passed as a parameter (r,s,l); At least one reference on the list is left for picking ($NRL>0$) and the picking position of the current reference is not adjacent to the last position of the preious reference ($adj=0$)
EndTravelToPicking	Operator ends travel to picking position	Picking position of relerence (r,s,l) is set to non available ($p(r,s,l)=1$)	At least one reference on the list is left for picking ($NRL>0$) and the picking position of the current reference is adjacent to the last position of the preious reference ($adj=1$)
StartReferencePicking	Operator starts reference picking	The number of references in picking position (r,s,l) is decreased by the number ordered in the list under process ($s(r,s,l)=s(r,s,l)-l(r,s,l)$); The number of references in the list left for picking is decreased by one ($NRL=NRL-1$)	The number of references in picking position (r,s,l) is greater than or equal to the number ordered in the list under process ($s(r,s,l)>l(r,s,l)$)
StartPartialPicking	Operator starts partial reference picking because of reference unavailability	The number of references ordered in the list under process is dereased by the number of references in picking position (r,s,l) ($l(r,s,l)=l(r,s,l)-s(r,s,l)$); The number of references in picking position (r,s,l) is set equal to zero ($l(r,s,l)=0$)	The number of references in picking position (r,s,l) is smaller than the number ordered in the list under process ($0<(r,s,l)<l(r,s,l)$) and the rest is covered in the stocking position ($st(r,s,l)\geq l(r,s,l)-s(r,s,l)$)
RetrievalReplenishmets	Operator retrieves replenished references	-	No references on the list are left for picking ($NRL=0$) and there are replenished references to be retrieved ($NR>0$)
EndReferencePicking	Operator ends reference picking	slot(r,s,l)=0 Picking position of relerence (r,s,l) is set free ($p(r,s,l)=0$)	
EndPickingOperations	Operator ends picking operations	The number of available picking cars is increased by one ($NC=NC+1$)	No references on the list are left for picking ($NRL=0$) and there are no replenished references to be retrieved ($NR=0$)
CallReplenishment	System calls reference replenishment	The number of references requiring replenishment is increased by one ($NR=NR+1$)	Sr=0
StartTravelToReplenish	Forklifter starts travel to replenish picking position	The number of available forklifts is decreased by one ($NF=NF-1$); The number of available forklift operators is decreased by one ($NFO=NFO-1$)	At least one list forklift ($NF>0$) is availale and at least one forklift operator is availale ($NFO>0$)
EndTravelToReplenish	Forklifter ends travel to replenish picking position	Picking position of relerence (r,s,l) is set to non available ($p(r,s,l)=1$)	The id of the position ((r,s,l)) to be replenished is passed as a parameter Time to travel to position to be replenished (ttr) elapses;
StartReplenishment	Forklifter starts replenishishment	The stocking position of the reference decreases ($st(r,s,l)\downarrow$) and the picking position of the reference increases ($s(r,s,l)\uparrow$)	-
EndReplenishment	Forklifter ends replenishishment	Picking position of relerence (r,s,l) is set free ($p(r,s,l)=0$) The number of available forklifts is increased by one ($NF=NF+1$); The number of available forklift operators is increased by one ($NFO=NFO+1$)	Time to perform replenishment (tr) elapses;

4. Simulation Model

Starting from the related EG representation, the (discrete-event) simulation model of the order picking process is able to disclose scenarios that can provide a measure of the potential impact of the decisions that affect or, in turn, are affected by the process. Based on the planning level at which they occur, these decisions can cover strategic, tactical and operational problems in the warehouse organization and/or operation. Here, we focus our attention on order picking and operational decisions. As a matter of fact, we refer to a decision that belongs to a category that is adjusted more frequently in correspondence to the current external and internal conditions and can have impacts for no longer than a year or even a day. In this sense, the operational scenario of interest that can heavily affect the order picking process if implemented is how PAC currently collects customer orders.

For the time being and with respect to orders, the service contract of a customer specifies a time limit on the delivery day(s), but not on the specific hour of the day. As a result, a single delivery springs from a (verbally) agreed schedule between PAC and its customers as to when the goods will be delivered. Currently, PAC applies three different delivery policies:

- AxA: same-day delivery service;
- AxB: 24-hour delivery service;
- AxC 48-hour delivery service.

Order collection, however, does not occur within a specific time-window of the morning and/or afternoon. Orders come in rather dynamically and one or more orders from the same retailer may be placed at any time during the hour of the day and batched eventually before being processed.

As opposed to the above hour-free order placement policy, the company would like to test an alternative policy according to which any order is deemed accepted if placed within one of two possible time windows: one in the morning (e.g. before 9:00 a.m.) for a same-day delivery service AxA, one in the afternoon (e.g. 1:00 p.m.) for a 24-hour delivery service AXB, either of the two for a 48-hour delivery service AxC. So, the objective of comparing these two operational policies via simulation would consist in evaluating the effect on warehouse performance of both alternative policies, especially in terms of, for instance, system and operator throughput, operator/vehicle utilization and, of course, congestion-related phenomena.

The corresponding EG-based simulation model has been designed and is currently under development from scratch in Visual Basic. Given that the order picking process has also been implemented, verified and validated under Arena version 15.00.00004 (Copyright© 2016 Rockwell Automation Technologies, Inc.) in a companion paper by other authors (Alfano et al.) involved in the same research project, here we resort to the above Arena model to preliminarily test the previously described operational scenario. In the Arena representation, the order picking process has been conceived according to the following four sub-models, i.e. *i*) order creation per retailer, *ii*) list (of item) generation per retailer, *iii*) item picking, and *iv*) management of truck docks, as shown below in Figure 3.

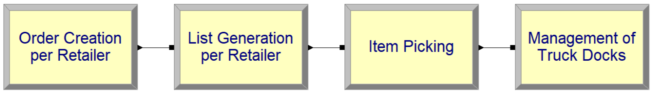

Figure 3. The order picking process sub-models in Arena.

Based on the company data collected in this year's month of May, both the distribution function of the number of orders per day and the probability of the daily customer orders arriving during hours from 1 to 24 have been derived and are reported in Table 2, along with the distribution function that best represents the inter-arrival times of orders per hour of the day.

Table 2. Distribution functions for "as is" order arrival pattern.

Feature		Distribution Function/Probability
Number of daily orders		130 + 1.03e+03 * BETA(0.797, 1.69)
P(daily orders arrive during hour *i*)		Inter-arrival pattern during hour *i*
i ∈[1-5, 23, 24]	P(i) = 0	-
i = 6	P(i) = 0.004	EXPO(767)
i = 7	P(i) = 0.016	2.16e+03 * BETA(0.236, 1.37)
i = 8	P(i) = 0.110	WEIB(3.99, 0.211)
i = 9	P(i) = 0.053	EXPO(126)
i = 10	P(i) = 0.142	EXPO(48.6)
i = 11	P(i) = 0.104	WEIB(1.31, 0.198)
i = 12	P(i) = 0.046	1.32e+03 * BETA(0.303, 2.45)
i = 13	P(i) = 0.074	WEIB(1.05, 0.196)
i = 14	P(i) = 0.023	2.32e+03 * BETA(0.44, 3.51)
i = 15	P(i) = 0.037	3.22e+03 * BETA(0.18, 3.3)
i = 16	P(i) = 0.104	WEIB(0.11, 0.198)
i = 17	P(i) = 0.024	1.89e+03 * BETA(0.314, 2.17)
i = 18	P(i) = 0.082	WEIB(0.273, 0.19)
i = 19	P(i) = 0.065	1.8e+03 * BETA(0.344, 5.17)
i = 20	P(i) = 0.036	1.72e+03 * BETA(0.298, 3.12)
i = 21	P(i) = 0.007	WEIB(3.76, 0.163)
i = 22	P(i) = 0.073	WEIB(0.0124, 0.247)

Alternatively, the same data has been reorganized to meet the requirements of the new procedure according to which orders should arrive within one of two possible time windows. Practically speaking, this means that, instead of considering 24 time slots, the probabilities of the daily customer orders arriving during a specific hour of the day have now been clustered into two groups, i.e. [0-12] and [13-24], as one may observe in Table 3.

This stated, in the new policy senior management is pushing retailers belonging to the first group to deliver their orders by 9:00 a.m. and those in the second group to do so before 1:00 p.m.

Table 3. Distribution functions for "to be" order arrival pattern.

Feature	Distribution Function/Probability
Number of daily orders	130 + 1.03e+03 * BETA(0.797, 1.69)
P(daily customer orders arrive during hour *i*)	
i ∈[0-12]	P(i) = 0.475
i ∈[13-24]	P(i) = 0.525

As for the rest of the input data, additional details may be found Tables 4 through 6 in (Alfano et al.) with respect to: items included in each order; percentage of items located in each aisle of the warehouse; number of units to be picked for each item; volume of each item; type of supports (i.e. pallet and/or roll); distribution functions for picking related tasks (i.e. picking service time, support(s) retrieval time, notification time of support info, and placing time on truck dock); working schedule of order pickers.

5. Results and Discussion

The numerical results of the what-if optimization - in terms of point estimates - are reported in Tables 4 and 5, depending on whether the company uses a packing approach per number of items or per volume of items. Of course, the change in the order collection procedure does not affect some of the performance measures related to major company resources, such as the number of lists or number of trucks used to fulfil retailer orders, since the number of daily orders is practically the same.

In the sample scenario under analysis, improvements can be achieved in both terms of completion time of operations (i.e. makespan) and utilization factor of the personnel performing picking operations (i.e. pickers). As one may observe, the time windows policy outperforms the hour-free policy. As a matter of fact, in the former case operations are completed before 6:00 p.m., whereas in the latter case this is not accomplished. Not only does the hour-free collection policy finish after, it also cannot be completed within the current workday. The resulting backlog will require additional hours (the next day) and, thus, additional personnel in order to be carried out.

Table 4. What-if optimization for packing by number of items.

Performance	Hour-free	Time windows
makespan	5:27 (next day)	17:35
n° of lists	438	438
n° of trucks	41	41
picker utilization	0.67	0.89

On the other hand, picker utilization has increased by at least 30% in both cases. This is due to the fact that order picking operations are more concentrated over a smaller period of time.

Table 5. What-if optimization for packing by volume of items.

Performance	Hour-free	Time windows
Makespan	5:32 (next day)	17:35
n° of lists	381	381
n° of trucks	36	36
picker utilization	0.64	0.88

Overall, the above numerical results encourage the senior management of the company and, in particular, the Logistics Director (one of the authors of this paper), to introduce a novel order collection practice based on suitably-defined daily time windows. Whatever be the packing policy adopted (i.e. by volume or number of items), our results show that a time window-based organization allows to achieve appreciable savings on both time completion of operations and picker utilization level. Hence, the soon-to-come consequential managerial action of our effort will be that of proposing to retailers, in compliance with their needs and expectations, the above process innovation in PAC's order management.

6. Conclusions

When tackling the organization of manually-performed order picking in large-scale retail distribution, the effectiveness of an event graph-based (EG) representation is currently being assessed with respect to model development in cooperation with senior management. The simulation model derived from the EG has been preliminarily implemented in Rockwell Arena, also for both verification and validation purposes. Scenario analysis has already allowed to compare alternative order collecting policies with/without time-windows. According to company figures in the month of May 2022, the time-windows based policy outperforms the current hour-free practice. This stimulates even more our ongoing effort poured into the design and implementation of the EG-based simulation model, as well as a more sophisticated analysis of both simulation input data and output results in the framework under development.

As for the direction of future work, interesting possibilities lie in both short and medium-term projects. In the former case, we wish to extend the current order picking scenario to better adapt to the wider concept of order commitment. In the latter, the event graph and, thus, the corresponding simulation model, will most likely represent the core component of a digital twin built around the order picking process. Rather than resorting to probabilities and distribution functions, system dynamics will be guided by events as they occur in real-time allowing the decision-making process to benefit of the prediction capabilities of the simulation model.

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References

Al-Araidah, O., Okudan-Kremer, G., Gunay, E.E. and Chu, C.-Y. (2021). A Monte Carlo simulation to estimate fatigue allowance for female order pickers in high traffic manual picking systems. *International Journal of Production Research*, 59(15): 4711-4722.

Alfano, S., Brettone A.S., Groccia M.C., Sia, R., and Vita, A.F. (to appear). Optimizing the order picking process via simulation: a case study. In *21st International Conference on Modelling and Applied Simulation*, MAS 2022, Rome, IT, September 19-21.

Altarazi, S.A. and Ammouri, M.M. (2018). Concurrent manual-order-picking warehouse design: A simulation-based design of experiments approach. *International Journal of Production Research*, 56(23):7103-7121.

Andriansyah, R., De Koning, W.W.H., Jordan, R.M.E., Etman, L.F.P. and Rooda, J.E. (2011). A process algebra based simulation model of a miniload-workstation order picking system". *Computers in Industry*, 62(3):292-300.

Andriansyah, R. Etman, P, and Rooda, J. (2009). Simulation model of a single-server order picking workstation using aggregate process times. In *1st International Conference on Advances in System Simulation*, SIMUL 2009, September 20-25, Porto, PT, art. no. 5283980, 23-31.

Bahrami, B., Aghezzaf, E.-H., and Limere, V. (2017). Using simulation to analyze picker blocking in manual order picking systems". *Procedia Manufacturing*, 11 1798-1808.

Bharre, S. and Chung, S.H. (2020). Routing optimization for warehouse order picking via simulation. In *Proceedings of the 2016 Industrial and Systems Engineering Research Conference*, ISERC 2016, Anaheim, CA, USA, May 21-24, 2210-2215.

Bozer, Y.A. and Aldarondo, F.J. (2018). A simulation-based comparison of two goods-to-person order picking systems in an online retail setting. *International Journal of Production Research*, 56(11):3838-3858.

Bučková, M., Krajčovič, M. and Edl, M (2017). Computer simulation and optimization of transport distances of order picking processes. In *Procedia Engineering*, 192:69-74.

Burinskienė, A, Davidavičienė, V., Raudeliūnienė, J., and Meidutė-Kavaliauskienė, I. (2018). Simulation and order picking in a very-narrow-aisle warehouse. *Economic Research-Ekonomska Istrazivanja*, 31(1):1574-1589.

Coelho, F., Relvas, S., and Barbosa-Póvoa, A.P. (2018). Simulation of an order picking system in a manufacturing supermarket using collaborative robots. In *Proceedings - European Council for Modelling and Simulation*, ECMS 2018, Wilhelmshaven, DE, May 22-25, 83-88.

Elbert, R. and Muller, J.P. (2017). The impact of item weight on travel times in picker-to-parts order picking: An agent-based simulation approach. In *Proceedings - Winter Simulation Conference*, Las Vegas, NV, USA, December 3-6, 3162-3173.

Faria, F. and Reis, V. (2015). An original simulation model to improve the order picking performance: Case study of an automated warehouse. *Lecture Notes in Computer Science* (including subseries *Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*), 9335, 689-703.

Francisco, R.P., Campos, D.P., Frazzon, E.N., and Machado, R.L. (2016). On the application of modelling and simulation to compare human- and automation-based order-picking systems. In *IFAC-PapersOnLine*, 49(12):1062-1067.

Glock, C.H., Grosse, E.H., Neumann, W.P., and Feldman, A. (2021). Assistive devices for manual materials handling in warehouses: A systematic literature review. *International Journal of Production Research*, 59(11):3446-3469.

Goldscheid, C., Deuse, J., Schlüter, N., and Crostack, H.-A. (2007). Optimization of order picking quality by simulation of test strategies. *ZWF Zeitschrift fuer Wirtschaftlichen Fabrikbetrieb*, 102(6):351-354.

Güller, M. and Hegmanns, T. (2014). Simulation-based performance analysis of a miniload multishuttle order picking System. In *Procedia CIRP*, 17 475-480.

Guo, J., Zhou, L., and Zhu, J. (2011). Stochastic model and simulation research for random-storage S-type manual order picking. In *Key Engineering Materials*, 467 92-97.

Hong, S. (2019). A performance evaluation of bucket simulation approaches. *Computers and Industrial Engineering*, 135:120-131.

Kašparová, P. and Dyntar, J. (2021). Effective designing of order picking systems using dynamic simulation. *Acta Informatica Pragensia*, 10(1):108-120.

Kauke, D, Rett, A., and Fottner, J. (2019). Draft planning of order picking systems by simulation – impact of various planning problems on the performance development of different order picking systems. *Logistics Journal*.

Kawczynski, L. and Aguilar-Sommar, R. (2006). Comprehensive design of an order picking line by simulation. In *IFAC Proceedings Volumes*, 39(3):365-370.

Kelly, D.L. (1979). Application of simulations to order-picking planning and design. In *Fall Industrial Engineering Conference*, *American Institute of Industrial Engineers*, Houston, TX, USA, November 13-16, 135-140.

Klodawski, M., Jachimowski, R., Jacyna-Golda, I., and Izdebski, M. (2018). Simulation analysis of order picking efficiency with congestion situations. *International Journal of Simulation Modelling*, 17(3):431-443.

Kostrzewski, M. (2020). Sensitivity analysis of selected parameters in the order picking process simulation model, with randomly generated orders. *Entropy*, 22(4), art. no. 423.

Kostrzewski, M., Gnap, J., Varjan, P., and Likos, M. (2020). Application of simulation methods for study on availability of one-aisle machine order picking process. *Communications - Scientific Letters of the University of Zilina*, 22(2):107-114.

Kumar, S., Narkhede, B.E., and Jain, K. (2021). Revisiting the warehouse research through an evolutionary lens: A review from 1990 to 2019. *International Journal of Production Research*, 59(11):3470-3492

Lerher, T., Strmčnik, V., Potrč, I., Šraml, M., Jerman, B., and Zrnić, N. (2016). Simulation-based performance analysis of order picking systems. In *13th International Conference on Industrial Logistics*, ICIL 2016, September 28 - October 1, Zakopane, PL, 144-155.

Lu, M., Kise, H. Karuno, Y., and Tanabe, M. (2001). Simulation for permutational circulative vehicle routing system: Application to order picking in an AS/RS. *Transactions of the Japan Society of Mechanical Engineers, Part C*, 67(661):3040-3046.

Marcoulaki, E.C., Broulias, G.P., and Chondrocoukis, G.P. (2005). Optimizing warehouse arrangement using order picking data and Monte Carlo simulation. *Journal of Interdisciplinary Mathematics*, 8(2):253-263.

Masae, M., Glock, C.H. and Grosse, E.H. (2020). Order picker routing in warehouses: A systematic literature review. *International Journal of Production Economics*, 224 art. no. 107564

Merkuryeva, G., MacHado, B.C., and Burinskiene, A. (2006). Warehouse simulation environments for analysing order picking processes. In *International Mediterranean Modelling Multiconference*, I3M, Barcelona, ES, October, 4-6, 475-480.

Molnár, B. (2005). Multi-criteria scheduling of order picking processes with simulation optimization. *Periodica Polytechnica Transportation Engineering*, 33(1-2):59-68.

Navarro, M.M. (2020). Simulation of a manual order picking system in a convenience store chain distribution center. In *Proceedings of the LACCEI international Multi-conference for Engineering, Education and Technology*, July 27-31, art. no. 629:759-767.

Quinn, E.B. and Norman, T.A. (1979). Application of simulations to order-picking planning and design. In *Fall Industrial Engineering Conference*, *American Institute of Industrial Engineers*, Houston, TX, USA, November 13-16, 126-134.

Renner, P. and Pfeiffer, T. (2017). Augmented reality assistance in the central field-of-view outperforms peripheral displays for order picking: Results from a virtual reality simulation study. In *Adjunct Proceedings of the 2017 IEEE International Symposium on Mixed and Augmented Reality*, ISMAR-Adjunct 2017, Nantes, FR, October 9-13, art. no. 8088476, 176-181.

Schruben, L.W. (1983). Simulation modeling with event graphs. *Communications of the ACM*, 26(11):957-963.

Schruben, L.W. (1995). Building reusable simulators using hierarchical event graphs. In *Winter Simulation Conference Proceedings, 1995*, Arlington, VA, USA, December 03-06, 472-475.

Shetty, N., Sah, B., and Chung, S.H. (2020). Route optimization for warehouse order picking operations via vehicle routing and simulation. *SN Applied Sciences*, 2(2), art. no. 311.

Souiden, S., Cerqueus, A., Delorme, X., and Rascle, J.-L. (2021). Simulation model for a semi-automated retail order picking system under uncertainty. In *IFIP Advances in Information and Communication Technology*, IFIPAICT, 629 759-767.

Ulbrich, A., Galka, S., and Günthner, W.A. (2007). Simulation of multi-Level order-picking systems within rough planning for decision making. In *21st European Conference on Modelling and Simulation: Simulations in United Europe*, ECMS 2007, Prague, CZ, June 4 - 6, 542-547.

Ulbrich, A., Galka, S., and Günthner, W.A. (2009). Simulation as decision support for the planning of order-picking-systems. In *Summer Computer Simulation Conference 2009*, SCSC 2009, Part of the 2009 ISMc, Istanbul, TR, June 13-16, 41(3):322-

327.

Ulbrich, A., Galka, S., and Günthner, W.A. (2010). Secure planning of order picking systems with the aid of simulation. In *Proceedings of the Annual Hawaii International Conference on System Sciences*, Koloa, Kauai, HI, USA, art. no. 5428648.

Urzúa, M., Mendoza, A. and González, A.O. (2019). Evaluating the impact of order picking strategies on the order fulfilment time: A simulation study. *Acta Logistica*, 6(4):103-114.

Urzúa, M., Mendoza, A. and González, A.O. (2018). Improving order fulfillment time: A simulation study to evaluate picking strategies. In *IISE Annual Conference and Expo*, Orlando, FL, USA, May 19-22, 1139-1144.

Wasusri, T. and Theerawongsathon, P. (2016). An application of discrete event simulation on order picking strategies: A case study of footwear warehouses. In *Proceedings - 30th European Conference on Modelling and Simulation*, ECMS 2016, Regensburg, DE, May 31 - June 3, 121-127.

Winkelhaus, S., Zhang, Grosse, E.H., and Glock, C.H. (2022). Hybrid order picking: A simulation model of a joint manual and autonomous order picking system. *Computers and Industrial Engineering*, 167 art. no. 107981.

van Gils T., Ramaekers, K., Caris, A., and de Koster, R. (2018). Designing efficient order picking systems by combining planning problems: state-of-the-art classification and review. *European Journal of Operational Research* 267:1–15.

Wagner, G. (2021). Business process modeling and simulation with DPMN: Processing activities. In *Proceedings - Winter Simulation Conference*, Phoenix, AZ, USA, December 13-15, 1-15.

Yang, M.-F. (2008). Using simulation to object-oriented order picking system. *Information Technology Journal* 7(1):224-227.

Yener, F. and Yazgan, H.R. (2019). Optimal warehouse design: Literature review and case study application. *Computers and Industrial Engineering*, 129:1-13.

Zhou, L., Zhu, J., and Guo, J. (2010). Stochastic model and simulation research for random-storage return-type manual order picking. In *2010 International Conference on Logistics Engineering and Intelligent Transportation Systems*, LEITS2010 - Proceedings, Wuhan, CN, November 26-28, art. no. 5664970 308-311.

Zhu, J., Guo, J., and Zhou, L. (2011). Research on stochastic model and simulation for sorted-storage S-type manual order picking. In *Key Engineering Materials* 467-469:98-103.