Proceedings of the 2012 Winter Simulation Conference
C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, eds.

OPTIMIZING ASSEMBLY LINE SUPPLY BY INTEGRATING WAREHOUSE PICKING AND FORKLIFT ROUTING USING SIMULATION

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ABSTRACT

The significance of system orientation in production and logistics optimization has often been neglected in the past. An isolated view on single activities may result in globally suboptimal performance. We consider a manufacturing process where assembly lines are supplied from a central logistics center. The different steps, such as storage, picking and transport of work-in-process materials to and from the assembly lines, strongly influence each other. For instance, if the picking process batches orders that need to be transported to the same target, a reduction of travel distances can be achieved. The individual problems are coupled and validated via simulation, which leads to more robust and applicable results in practice. We test our approach on a scenario based on real-world data from Rosenbauer, one of the world's largest suppliers of firefighting vehicles. Our results indicate that warehouse optimization can lead to a more efficient transport in an integrated problem formulation.

1 INTRODUCTION

Material handling is an important activity in manufacturing. Raw materials and work-in-process materials are stored and picked in warehouses and transported within production plants or distribution centers. In manufacturing, material handling can make up to 20% - 50% of the total operating expenses as pointed out by Tompkins et al. (2010). In this work we deal with two aspects of material handling in a production plant: warehouse picking and forklift routing.

Our research was motivated by an industrial application where multiple production lines are supplied from various warehouses at the production plant at Rosenbauer. The material is stored in high rack storage areas and picked by employees utilizing forklifts. After the parts have been picked in the warehouse, they are handed over to four smaller forklifts at predefined intermediate storage places. These then transport the picked parts to workstations in the production line. The transport demands of parts from the warehouses to the workstations and between workstations are highly dynamic and transport orders and routes are not yet optimized. Because in our scenario the arrival of the transportation requests depends on the warehouse picking process, it makes sense to consider the problem as an integrated formulation.

Previous work has shown potential for improving pick efficiency at the plant in Leonding via storage assignment optimization (Kofler et al. 2011). In many order picking environments the travel time to retrieve an order has been found to be the largest component of labor, amounting to 50% or more of total order picking time (Tompkins et al. 2010). However, previous studies with Rosenbauer have shown, that not considering the interdependencies with the in-house transport increases uncertainty about how the entire

978-1-4673-4781-5/12/$31.00 ©2012 IEEE

process will be affected by storage optimization. Thus, the integrated view of picking and routing is crucial for the practical realization of the optimized process.

In this work we perform a simulation study to show how the integrated optimization of warehouse picking and forklift routing leads to a more efficient material handling in our industrial scenario. We show, that the efficiency of the forklift routes transporting the goods from the intermediate storage to the workstations is strongly dependent on the upstream picking processes in the warehouse and analyze the dependencies. The warehouse picking and forklift routing optimization models are coupled by means of simulation and are optimized using metaheuristic algorithms which are implemented in HeuristicLab (Wagner 2009) in a simulation optimization approach.

The rest of this paper is organized as following: In the next subsection we will outline related work and point out our main research contributions; in Section 2 we detail the practical scenario that we analyze in our study; in Section 3 we describe our integrated simulation and optimization approach; in Section 4 we present the test scenario and analyze the numerical results and in Section 5 we conclude our findings and give an outlook how the approach could be extended in the future and how it could be implemented at the company partner.

1.1 Related Work

Simulation optimization has received much attention both by researchers and practitioners. Simulation-based optimization integrates optimization techniques into simulation analysis to evaluate which of a number of possible approaches is the best one (Fu 2002). Especially the combination of simulation with metaheuristics has proven to be fruitful for various application domains (Tekin and Sabuncuoglu 2004).

In this context, HeuristicLab has been used as an optimization component in several simulation studies already. Can, Beham, and Heavey (2008) performed a comparative study of genetic algorithms in a simulation-based optimization context for the buffer allocation problem. Beham et al. (2009) optimized solutions to the facility layout problem by coupling HeuristicLab with simulation. Vonolfen et al. (2011) evolved different resupply and routing policies for rich inventory routing scenarios by means of an evolution strategy and a simulation model. Pitzer et al. (2011) applied simulation optimization to production fine-planning. In this work, we apply simulation optimization to an integrated model of warehouse picking and forklift routing. Simulation and optimization techniques have been applied both to warehousing and internal transport in the context of manufacturing.

In the area of warehousing, Petersen and Aase (2004) compared picking, storage and routing strategies in manual order picking systems using simulation. Kofler et al. (2010) applied simulated annealing and local search to gradually perform cleanup (healing) tasks in a warehouse and showed that competitive results could be reached compared to a complete reorganization. They validate the results using a picking simulation model implemented in the simulation software AnyLogic™ 6 to consider stochastic influence factors and aisle blocking times. Ene and Öztürk (2011) optimized both storage location assignment and order picking in the automotive industry using a linear programming approach and a genetic algorithm.

In terms of internal transport in manufacturing, both person guided vehicles such as forklifts and also automated guided vehicles (Vis 2006) have been studied. It was pointed out by Le-Anh (2005) that internal transport problems are often characterized by a high degree of uncertainty, short travel times and high vehicle utilization rates. Thus, simulation optimization techniques are very valuable in that area and the combination of simulation with heuristics has been applied successfully. Pai (2008) modeled an AGV system in the commercial simulation software ARENA and developed collision avoidance algorithms. Le-Anh, de Koster, and Yu (2010) compared different scheduling approaches in both static and dynamic environments and compare a column generation approach with heuristics.

Integrated formulations of warehousing and internal transport have already been considered for container terminals which are characterized by a tight coupling of the individual processes and also a high degree of automation. Bish (2003) consider loading and unloading of containers from and to ships and storing the containers in the terminal yard. The ships are served by multiple quay cranes and the containers are moved by a fleet of vehicles. Lee et al. (2009) present an integrated model of yard truck scheduling and the storage allocation in a container terminal and develop a hybrid insertion heuristic. Cao et al. (2010) formulate a mixed-integer programming model for this problem and solve it using Benders' decomposition. We apply the idea of an integrated view of warehousing and transport to the application domain of production logistics.

One of the main research contributions of this paper is the integrated simulation and optimization of warehouse picking and forklift routing to streamline the assembly line supply. We illustrate our approach on a complex production environment dealing with the construction of firefighting vehicles.

2 SCENARIO

In the investigated scenario, the primary goal is to guarantee an optimal flow of material within Rosenbauer's largest production plant. Most importantly, the individual workstations and assembly lines need to be supplied with parts from the warehouses and semi-finished goods need to be transported between production areas and back into storage. Production plans and their associated bills of materials are available with daily precision in the enterprise resource planning system (ERP). However, these daily production plans are highly dynamic and rush orders or plan changes occur frequently during the day, thus triggering new transport request from storage into production.

At the plant in Leonding most parts are supplied from a central logistics center located on the premises, including a manually operated high-rack warehouse for pallet storage, which can hold more than 10.000 different parts, as well as medium/small part and bulk storage areas. The desired level of service from the logistics center is that all orders should be fulfilled until the end of the work day, independent of their request time. However, a specific delivery time within the day is not guaranteed.

A significant growth in production volume has strained the capacities of the logistics center within the last couple of years. Utilization of storage and material handling equipment as well as the workload of the warehouse staff is very high. Rosenbauer therefore strives to improve the efficiency of their logistics processes. The high-rack warehouse constitutes a particular bottleneck in the order picking sequence. Its 12 two-sided aisles are served by two forklifts simultaneously. However, the aisles are very narrow so the forklifts have to back out in reverse. Moreover, due to safety consideration the two forklifts cannot operate in a single aisle simultaneously. A warehouse assignment strategy called PF/PA slotting has been successfully applied to a simulation model of the Rosenbauer high-rack, placing the parts in such a way that average order picking times were significantly reduced (Kofler et al. 2011). However, the previous model only considered the flow of parts from goods receipt over storage and picking until they were placed in the intermediate storage area for subsequent transport to the production lines.

While warehouse managers are certainly interested in improving the efficiency of logistic sub-processes, such as order picking, it is still more important to ensure that each machine and workstation is supplied with the right product at the right point in time. At Rosenbauer, four forklifts with a capacity of two pallets each are responsible for the transport of parts to and from the warehouse as well as between production areas. Two other forklifts pick the parts in the high-rack warehouse.

In terms of in-house transport we consider 35 workstations that are served from the warehouse in our simulation study. In the production floor, workstations are connected with each other by means of way points. The forklifts can move between the way points on specified paths. The shortest path is calculated using Dijkstra's algorithm. The warehouse is in the south-east of the production plant. The parts are handed over to the internal transport at the interim storage areas after they have been picked in the high-rack warehouse. Plan data for order completion times in the production and the warehouse is available, but only with daily precision. Transport demands therefore emerge dynamically during the day when a pallet is posted to an intermediate storage location in the warehouse or near the workstations for pickup.

3 METHODOLOGY

To create a model of the warehouse picking and forklift routing, we consider the two processes in an integrated simulation and optimization model. An overview of the integrated picking and routing model is given in Figure 1. As a first step, the storage assignment is optimized to allow an efficient picking process. The approach is detailed in Section 3.1. The resulting storage assignment is validated by means of a picking simulation which models the dynamic interactions between the individual pickers such as blocking of aisles. When simulating orders for a specific day, the model returns the exact times when the picked parts are handed over at the intermediate storage. These release times are passed to the transport simulation. The transport simulation model is used to simulate the internal transport of parts between the warehouse and the individual workstations. Due to the dynamic nature of the upstream picking activity, the specific transport requests arrive during the day and are not known in advance.

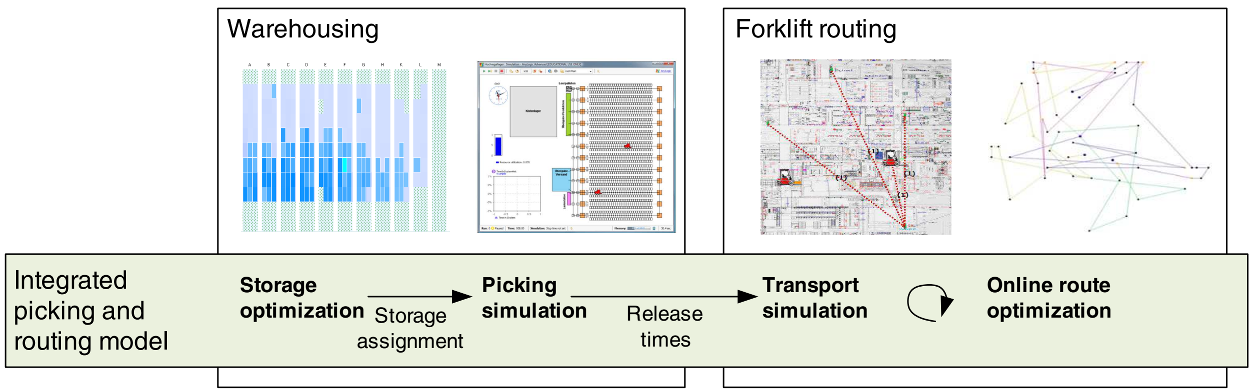

Figure 1: Methodology.

New transport requests arrive whenever picked parts are handed over from the warehouse to be transported to the workstations. These arrival times are determined by the picking simulation. Whenever new requests arrive, the route plans for the forklifts are updated accordingly by an online optimization algorithm which is detailed in Section 3.2. This integrated problem formulation allows us to analyze the dependencies of the picking and the routing processes and to globally optimize the scenario. The individual models for slotting/picking and routing are detailed in the following.

The value of simulation in this study is twofold. Firstly, simulation serves as an important component to apply in a scenario technique. Using a simulation environment as a placeholder for a real system allows us to consider and test a large number of cases. It would not be possible to test them all in a real production environment. Secondly, simulation models are used to verify optimization results (candidate solutions). An evaluation would not be possible in a closed formulation because dynamic interactions between several variables have to be considered. In this work we deal with deterministic simulation models because it would increase the complexity significantly if we included stochastic influence factors. However, in the model description we indicate where stochastic variables could be introduced in the models. In the following we will detail our simulation and optimization models for warehousing and routing.

3.1 Warehousing

The goal of slotting or storage location assignment optimization is to determine the *best* place to store each part in a warehouse; for instance in such a way that the picking effort is reduced. To consider the specific constraints of the warehouse, a simulation model is used to evaluate solutions provided by the optimization process.

3.1.1 Storage Optimization

The optimization model used for storage optimization (slotting) is the storage location assignment problem (SLAP). It was first formulated by Hausman, Schwarz, and Graves (1976). The objective is to slot products in a warehouse in such a way that the cost of picking orders is minimized. Constraints of the specific warehouse layout have to be considered such as storage space and interactions between the pickers.

In this paper we will use Pick Frequency / Part Affinity (PF/PA) slotting which combines slotting by turnover and affinity. Slotting by turnover based metrics ensures that fast-moving parts should be located in easily accessible pick areas. Slotting by affinity means that parts that are frequently ordered together should be positioned close to each other in the warehouse.

The mathematical formulation of PF/PA was introduced by Kofler et al. (2010). The PF/PA measures are defined as following:

$$PF = \sum_{i=0}^{n} \frac{orderRatio(p_i)}{|L(p_i)|} \cdot \sum_{s \in L(p_i)} dist(s, intStorage)$$

$$PA = \sum_{i=0}^{n} \sum_{j=0}^{n} \frac{affinity(p_i, p_j)}{|L(p_i)| \cdot |L(p_j)|} \cdot \sum_{s_k \in L(p_i)} \sum_{s_l \in L(p_j)} dist(s_k, s_l)$$

The $orderRatio$ is the relative number of orders in which product p_i occurs. The $affinity$ function specifies the relative number of orders in which products p_i and p_j occur together. The distance between storage location s_k and s_l is given by the $dist$ function. $L(p_i)$ indicates the set of all location where the packing units of product p_i stored at location s_k is greater than 0. The $intStorage$ variable represents the interim storage area where the picked orders are transported to and handed over to the forklifts which transport them to the workstations.

The PF/PA score calculated by $\alpha \cdot PF + \beta \cdot PA$ can be configured with two parameters α and β that determine how strongly the turnover (PF) and affinity (PA) should influence the overall assignment evaluation. A detailed description of the approach plus hints how to determine appropriate settings of α and β can be found in Kofler et al. (2011).

The PF/PA score can be coupled with a variety of algorithms for optimization. In this paper we use simulated annealing (SA), a metaheuristic that was modeled after the annealing process in metallurgy. One of the advantages of simulated annealing is that it offers a strategy to escape from local optima by employing a temperature parameter to guide the search. The algorithm has been first proposed by Kirkpatrick, Gelatt Jr, and Vecchi (1983). The algorithm was implemented in HeuristicLab.

In this particular scenario, SA generates moves that swap the content of two pallets in the high-rack warehouse or move a pallet to an empty location, while considering capacity constraints. Contrary to greedy search techniques, which only accept moves that improve the fitness of a solution, SA accepts moves that decrease the fitness with a certain probability. As the algorithm proceeds, a step-wise reduction of the temperature according to a predefined cooling scheme reduces the likelihood that bad moves get accepted. The simulated annealing algorithm runs were all configured in the following way: Exponential annealing scheme, start temperature 100, end temperature 1E-06, 1.5 million iterations. Details about the convergence and runtime behavior of the SA algorithm for this problem have been examined by Kofler et al. (2011).

3.1.2 Picking Simulation

We use a simulation model for picking to evaluate dynamic influence factors between the pickers that could not be analyzed in a closed formulation given an optimized storage assignment. In this case we consider the blocking of isles when multiple pickers want to enter it to retrieve items. The picking simulation retrieves the optimized storage assignment and simulates the effects on the picking process. The model has been implemented in the commercial software AnyLogic^{TM}. It is a discrete and deterministic model. In future work it could be extended to consider stochastic influence factors such as stochastic picking or travel times. During the simulation run, statistics for scenario evaluation are collected such as makespan, distance traveled and blocking time.

The model consists of a resource pool of six workers that perform the picking process. There are two forklifts which are operated by one worker each. The model includes the layout of the warehouse including the high rack storage area, its aisles and the paths that lead to and from the handover locations. The high rack has two different picking zones, the bottom two rows in each aisle are served by four human workers. The other picking zone is only served by the two forklifts and covers all rows above the second. Due to the heterogeneity in the type of pickers several problems arise. Foremost is the problem that a forklift cannot move past a human picker in an aisle due to safety considerations. In the simulation model it is taken account of that a forklift is blocked when it would have to access a location that is behind a location currently picked by a human worker. Additionally the forklifts may block themselves if both would have to access the same aisle. The blocking state results in idle times which are counted and summed. Human pickers on the other hand do not block each other.

The current strategy for the workers to move in the warehouse is to start in the first aisle from left to right, and then continue to the next aisles in ascending order always entering on the left and continuing on the right. The human pickers however can pass the aisles on both ends and will choose the shortest path also visiting the aisles in ascending order. The workers are moving from location to location and spending a certain time at each location picking. The times are based on real world observations and increase with the number of items to be picked. After the order is completed the pickers move to the interim storage areas where they leave their pallets and start over with a new order. If both parts of the order are completed the order is marked as being finished and ready to be transported. The ready times of the individual orders are collected which serve as an input for the forklift routing model.

3.2 Forklift Routing

Forklift routing is concerned with finding optimized routes for performing the required transport requests between the warehouse and the production lines efficiently. The transport requests arrive dynamically during a day and the release time is determined by the warehouse picking process. We use a simulation environment to model a day of operations and the dynamic arrival of requests. The simulation environment is coupled with an embedded online optimization component that optimizes the routes whenever a new request appears. Both the simulation and optimization component for the routing have been implemented in HeuristicLab. The coupling between the simulation and optimization component is flexible, which means that the optimization component can be exchanged and different algorithms can be used for route optimization.

3.2.1 Transport Simulation

To model the dynamic problem of transporting the picked orders to the workstations a simulation model is used. It serves as a replacement for the real system, where orders are revealed dynamically during the day. We use a discrete and deterministic model for simulating the transport operations between the warehouse and the workstations. It models the transportation problem environment and specifies constraints such as the underlying transportation network. Within the simulation environment, transport requests are triggered dynamically during a simulated day by the upstream warehouse picking process. During a simulation run, different performance figures are collected such as driven distance or resource utilization. In future work, a stochastic model could be considered which could include factors such as vehicle breakdowns or stochastic travel and service times.

The route plan calculated by the route optimization is assigned to the vehicles. The actual transports are simulated in discrete time steps. In each time step, the vehicles move according to their assigned routes and service the transport requests. Dispatching the forklift drivers in practice could work using mobile devices that show the currently assigned routes. In the simulation model, the communication between the simulation and the algorithm is realized using an event mechanism. There are three different types of events: a vehicle has moved, a new transport request has arrived and a transport request has been serviced. Whenever an event happens, the optimization component is notified which adapts the current routes. The updated route plan is then sent back to the simulation component and executed by the forklifts.

3.2.2 Route Optimization

As an optimization model, the dynamic pickup and delivery problem with time windows (PDPTW) is used. The model formulation we use is adapted from Savelsbergh (1995) and Berbeglia, Cordeau, and Laporte (2010). The underlying transportation network is represented as an undirected graph $G = (V,A)$ with a vertex set $V = \{0\} \cup P \cup D$. The set P contains all pickup points $i^+ \in P$ and the set D contains all delivery points $i^- \in D$. The vertex 0 denotes the depot. The problem consists of static requests which are known in advance and immediate requests which appear during the operation. A request R is characterized by a demand d_R, a source vertex i^+ and a destination vertex i^-. For each vertex $i \in V$ a time window is given which is characterized by an opening time to_i and a closing time tc_i. The service has to occur inside this time frame. The requests are served by a homogeneous fleet of vehicles with a given capacity C. The goal is to minimize the total route length given the capacity and time window constraints. The route length can be obtained by summing the length of the arcs $A = (i, j) : i, j \in V, i \neq j$ that are used in the route plan.

Among other techniques, metaheuristics have been applied successfully to dynamic variants of the PDP. A grouping-based genetic algorithm is applied to a set of benchmark instances by Pankratz (2005). Genetic algorithms have been first proposed by Goldberg (1989); for theoretical considerations about genetic algorithms applied to combinatorial optimization problems and system identification the reader is referred to Affenzeller et al. (2009). Gendreau and Potvin (1998) apply a tabu-search heuristic based on a neighborhood of ejection chains. The concept of ejection chains is further examined in Gendreau et al. (2006). Apart from metaheuristics, insertion heuristics are popular in the context of dynamic vehicle routing.

In this work we apply an online genetic algorithm, similar to one applied to dynamic PDPTW instances by Pankratz (2005) but it has been adapted to our specific scenario. The applied genetic algorithm uses mutation and crossover operators proposed by Potvin and Bengio (1996); i.e., the one-level exchange mutator, two-level exchange mutator, route-based crossover and sequence-based crossover. They are implemented using a route-based encoding. An overview over different encodings for VRPs is given by Vonolfen et al. (2012). In terms of algorithm parameters, a population size of 50 is used with a proportional selection and a mutation probability of 5%.

Whenever the simulation state changes, each individual of the population is carefully updated according to the new situation to preserve information during the planning process. New orders are inserted into each individual at the best possible insertion position. The execution time of the algorithm has been set to 50 generations in each time step. These parameters have been retrieved empirically by testing different configurations.

4 TEST CASE AND RESULTS

We validate our simulation and optimization model by performing experiments on a test-case which is based on real-world data provided by Rosenbauer. The data will be published on our website: http://dev.heuristiclab.com/AdditionalMaterial. Our test-case is based on a one-day production snapshot retrieved from Rosenbauer's ERP system. The day of operation is simulated in concrete time steps (in minutes) and the planning horizon stretches until the end of the second shift.

We acquired the orders from the production plan and extracted the associated parts that have to be picked. All in all, 487 parts need to be retrieved from the high-rack warehouse, which are then placed in 89 pallets and transported from the intermediate storage area in the warehouse to the workstations. The size of the orders varies significantly; about half consist of only a single pick line, conversely 10% are very large orders with 20 to 50 pick lines. The order sizes are dependent on the target production area. Generally speaking, vehicle assembly lines request larger amounts of parts, therefore servicing these areas is more work-intensive. From the perspective of the forklift operators, transport requests from the warehouse into production appear dynamically during the simulated day. The test case also contains 89 transport requests from the workstations back to the warehouse. Since the backhaul transports depend on the manufacturing process, which is not included in our model, we assume a uniform distribution of backhaul transports appearing during the day. This sums up to a total of 178 dynamic transport requests that are considered in our test case.

In addition, we retrieved historical pick data from the warehouse over a time period of half a year to calculate order profiles for the PF/PA warehouse assignment algorithm. The order profiles store the number of picks for each part as well as their pair-wise correlation with other parts in the observed time period. Five random warehouse assignments (R1-R5) were generated as a reference. In addition, the PF/PA algorithm was executed with 5 different settings:

PF Only the pick frequency is used in the optimization, thus frequently picked parts are assigned to more favorable locations in the warehouse.

PA Only part affinity is considered, which clusters parts together that occur in the same orders. However, their pick frequency is not considered.

C1 Combined setting where PF and PA are weighted equally.

C2 Combined setting where PF and PA are weighted 100:1.

C3 Combined setting where PF and PA are weighted 200:1.

The 10 generated warehouse assignment were then fed into a simulation model of the Rosenbauer high-rack warehouse to simulate the picking process for the one-day snapshot. The routing within each picking order was optimized in the simulator. However, we also wanted to investigate how different order sequences would affect both the warehouse picking process as well as subsequent transport. For this preliminary study, we did not integrate a third schedule optimization, but instead chose two exemplary schedules:

Clustered In this schedule, orders are grouped by their target manufacturing area. For instance, all orders that need to be transported to a welding machine are scheduled in sequence, followed by all paint shop orders etc. The advantage of this approach is that the forklifts are more likely to find two pallets with the same destination on the intermediate storage location at a particular point in time. On the other hand, this can lead to congestion, because both forklifts in the warehouse might need to enter the same aisles.

Balanced Conversely, in the second schedule picking orders were shuffled to increase the probability that the warehouse forklifts will operate in different areas of the warehouse.

For each combination of pick schedule and warehouse assignment the warehouse simulation model would simulate release times for the individual orders. Additional simulation outputs are the makespan, that is the total duration until the last picking order is finished, the blocking time and the total distance traveled by the warehouse forklifts.

The order picking results are then used as input for the embedded online transport optimization approach. Transport requests are only revealed to the optimization once a pallet has been posted to an intermediate storage area. The optimization couples simulation and optimization to dynamically calculate the best routing for the forklifts supplying production. As key indicators the transport simulation logs the total makespan, that is the time until the last order is at its target destination, the distance covered by the transport forklifts and the average number of pallets waiting for pickup. The results are summarized in Table 1.

Regarding the warehouse results, it should be noted that slotting by pick frequency (PF) or part affinity (PA) only produced inadequate results, although they reduce the total picker travel times considerably. However, the high blocking times in the PF and PA test runs show that both of these approaches lead to

Table 1: Results of the test runs. The best achieved results are marked bold.

		Warehouse			Routing		
Picking	**Storage**	Makespan (minutes)	Distance (km)	Blocking (minutes)	Makespan (minutes)	Distance (km)	Queue (pallets)
Clustered	R1	490	17.85	90	506	35.27	10.00
	R2	534	16.58	241	557	36.58	14.42
	R3	395	18.81	**19**	473	**33.19**	12.06
	R4	386	17.95	66	473	34.51	13.30
	R5	467	17.14	125	483	34.98	12.74
	PF	708	11.60	325	731	34.95	7.41
	PA	597	11.93	509	626	38.55	7.43
	C1	433	12.20	236	**472**	34.41	16.89
	C2	378	11.93	179	473	35.36	14.97
	C3	453	**11.49**	230	476	34.98	10.08
Balanced	R1	419	17.85	240	501	38.02	8.15
	R2	658	16.58	377	714	47.52	**3.50**
	R3	**348**	18.81	46	479	36.39	11.66
	R4	351	17.95	52	474	36.59	10.65
	R5	429	17.14	143	494	38.65	8.99
	PF	502	11.60	233	570	41.20	6.87
	PA	502	11.93	244	560	39.97	6.21
	C1	367	12.20	50.5	474	35.89	10.19
	C2	398	11.93	162	494	38.73	9.96
	C3	419	**11.49**	198	490	37.77	8.54

congestion. Indeed, congestion issues are a known problem for both turn-over based slotting strategies (such as PF, the cube-per-order-index etc.) as well as affinity based slotting strategies (PA, order oriented slotting, etc.). Even random slotting (R1-R5) performs better than PF or PA only slotting in all test runs but one. Although not very sophisticated, random slotting is still frequently used in practice. The advantages of random slotting are ease of implementation and a more balanced picker traffic. On the other hand random slotting can lead to longer picker travel distances as shown in the table: The pickers in the random slotting instances had to travel more than 17km to retrieve all parts, while PF, PA and PF/PA slotting yielded travel distances below 13km. Finally, combined PF/PA slotting (C1-C3) performs better than random assignments, seemingly striking a balance between distance optimization and congestion avoidance, which both influence the primary optimization target of the makespan.

Regarding the picking strategies, the results suggest that a PF/PA slotted warehouse should not be coupled with pick schedules that group picking orders by target area. This makes sense because PF/PA slotting attempts to position parts that are frequently ordered together in closely located storage areas; cluster picking therefore increases the likelihood of congestions.

Based on the warehouse assignment and picking results alone, we would probably conclude that a PF/PA slotting approach with balanced picking would be a good choice for this scenario. Random slotting sometimes attained similar makespan results, but the additional benefit of reduced travel distances (and thus reduced wear and tear on the warehouse forklifts) weighs in its favor. However, when the transport to and from the warehouse is also considered, the situation changes. The forklift transport benefits from clustered picking so much that it can absorb a small delay in the release times and produce a better total result. This shows, that for the entire, integrated scenario minimizing the makespan of the warehouse picking process is not enough to ensure that the subsequent transport can exploit its full potential. In addition, the integrated optimization also gives an indication of intermediate storage requirements via the average queue length. If the available floor space in a warehouse is limited, some strategies that require larger intermediate storage areas might not be feasible as well. It can also be a relevant factor to decide which PF/PA variant to take.

5 CONCLUSION

In this paper we coupled warehouse assignment, picking and transport of work-in-process materials to and from the assembly lines into an integrated problem formulation. We tested our approach on a scenario based on real-world data. Our results indicate that warehouse optimization can lead to a more efficient transport if the picked orders are provided in a sequence that also considers the downstream transport requirements. The main contribution of the paper was the development of the integrated model and a preliminary assessment of interrelations between capacity requirements, storage and pick strategy, travel distances, blocking times and the transport order makespan. Since the initial results seem promising, we plan to extend our approach in the following ways:

First of all, the blocking times in some of the results are outrageously high. The reason for that is because the picking sequencing is currently realized in a very basic fashion in the warehouse simulation model. After the warehouse forklift has delivered a pallet to the intermediate storage area it will proceed to the next order and pick the individual order lines according to a distance optimized route. If the aisle it wishes to enter is already occupied it will wait indefinitely, doing nothing until the second forklift leaves the aisle. A human operator would probably proceed to pick the other other lines or switch to an other order in the mean time.

Secondly, we have only conducted a scenario-based analysis of potential savings. To fully understand the effects and interrelations between the various factors, the experiments would need to be conducted again in a much more rigorous fashion, with replications for the simulation and optimization runs to account for stochastic effects. A sensitivity analysis for the various parameters would also be highly advisable.

In addition, although the model is integrated the optimization runs are currently only conducted in sequence, by forwarding intermediate results from warehouse assignment to picking to routing. An integrated optimization approach could automatically address issues such as load balancing and global evaluation as well as guide the search towards solutions that are feasible for all sub-scenarios.

Finally, we currently treat the manufacturing process as a black box and can only react to changes in transport demands or volumes. If the given target due dates are impossible to fulfill with the available logistics capacities, the optimization can only report a failure. However, by integrating production fine-planning optimization as forth sub-problem, the circle would be closed and the optimization could, for instance, suggest a slightly altered production plan that would lead to a feasible overall solution.

ACKNOWLEDGMENTS

Part of the work described in this article was done within the Regio 13 program sponsored by the European Regional Development Fund and by Upper Austrian public funds. Part of the work was carried out within the Josef Ressel Centre for Heuristic Optimization and supported by the Austrian Research Promotion Agency (FFG).

REFERENCES

Affenzeller, M., S. Winkler, S. Wagner, and A. Beham. 2009, April. *Genetic Algorithms and Genetic Programming: Modern Concepts and Practical Applications (Numerical Insights)*. 1 ed. Chapman & Hall.

Beham, A., M. Kofler, S. Wagner, and M. Affenzeller. 2009, December. "Coupling simulation with HeuristicLab to solve facility layout problems". In *Proceedings of the 2009 Winter Simulation Conference*, edited by M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 2205 –2217. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Berbeglia, G., J. Cordeau, and G. Laporte. 2010. "Dynamic pickup and delivery problems". *European Journal of Operational Research* 202 (1): 8–15.

Bish, E. 2003. "A multiple-crane-constrained scheduling problem in a container terminal". *European Journal of Operational Research* 144 (1): 83–107.

Can, B., A. Beham, and C. Heavey. 2008, December. “A comparative study of genetic algorithm components in simulation-based optimisation”. In *Proceedings of the 2008 Winter Simulation Conference*, edited by S. J. Mason, R. R. Hill, L. Moench, O. Rose, T. Jefferson, and J. W. Fowler, 1829–1837. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Cao, J., D. Lee, J. Chen, and Q. Shi. 2010. “The integrated yard truck and yard crane scheduling problem: Benders decomposition-based methods”. *Transportation Research Part E: Logistics and Transportation Review* 46 (3): 344–353.

Ene, S., and N. Öztürk. 2011. “Storage location assignment and order picking optimization in the automotive industry”. *The International Journal of Advanced Manufacturing Technology*:1–11.

Fu, M. C. 2002, July. “Feature Article: Optimization for simulation: Theory vs. Practice”. *INFORMS J. on Computing* 14 (3): 192–215.

Gendreau, M., F. Guertin, J.-Y. Potvin, and R. Seguin. 2006. “Neighborhood search heuristics for a dynamic vehicle dispatching problem with pick-ups and deliveries”. *Transportation Research Part C: Emerging Technologies* 14 (3): 157 – 174. ”.

Gendreau, M., and J.-Y. Potvin. 1998. “Dynamic vehicle routing and dispatching”. In *Fleet Management and Logistics*, edited by G. L. T.G. Crainic. Kluwer, Boston.

Goldberg, D. 1989. *Genetic algorithms in search, optimization, and machine learning*. Addison-wesley.

Hausman, W., L. Schwarz, and S. Graves. 1976. “Optimal storage assignment in automatic warehousing systems”. *Management Science*:629–638.

Kirkpatrick, S., C. Gelatt Jr, and M. Vecchi. 1983. “Optimization by simulated annealing”. *science* 220 (4598): 671–680.

Kofler, M., A. Beham, S. Wagner, M. Affenzeller, and W. Achleitner. 2011, aug.. “Re-warehousing vs. healing: Strategies for warehouse storage location assignment”. In *Logistics and Industrial Informatics (LINDI), 2011 3rd IEEE International Symposium on*, edited by J. Tick, 77 –82.

Kofler, M., A. Beham, S. Wagner, M. Affenzeller, and C. Reitinger. 2010. “Rassigning storage locations in a warehouse to optimize the order picking process”. In *Proceedings of the 22th European Modeling and Simulation Symposium EMSS 2010*, edited by F. Longo, 77–82. Fez, Morocco.

Le-Anh, T. 2005, April. *Intelligent Control of Vehicle-Based Internal Transport Systems*. Ph. D. thesis, Erasmus University Rotterdam, Rotterdam, The Netherlands.

Le-Anh, T., R. B. de Koster, and Y. Yu. 2010. “Performance evaluation of dynamic scheduling approaches in vehicle-based internal transport systems”. *International Journal of Production Research* 48 (24): 7219–7242.

Lee, D., J. Cao, Q. Shi, and J. Chen. 2009. “A heuristic algorithm for yard truck scheduling and storage allocation problems”. *Transportation Research Part E: Logistics and Transportation Review* 45 (5): 810–820.

Pai, A. 2008. *Development of deterministic collision-avoidance algorithms for routing automated guided vehicles*. Ph. D. thesis, Rochester Institute of Technology.

Pankratz, G. 2005. “Dynamic vehicle routing by means of a genetic algorithm”. *International Journal of Physical Distribution & Logistics Management* 35 (5): 362–383.

Petersen, C., and G. Aase. 2004. “A comparison of picking, storage, and routing policies in manual order picking”. *International Journal of Production Economics* 92 (1): 11–19.

Pitzer, E., A. Beham, M. Affenzeller, H. Heiss, and M. Vorderwinkler. 2011, aug.. “Production fine planning using a solution archive of priority rules”. In *Logistics and Industrial Informatics (LINDI), 2011 3rd IEEE International Symposium on*, edited by J. Tick, 111 –116.

Potvin, J.-Y., and S. Bengio. 1996. “The vehicle routing problem with time windows -. Part II: Genetic Search”. *INFORMS Journal on Computing* 8:165–172.

Savelsbergh, M. W. P. 1995. “The General Pickup and Delivery Problem”. *Transportation Science* 29 (1): 17–29.

Tekin, E., and I. Sabuncuoglu. 2004. "Simulation optimization: A comprehensive review on theory and applications". *IIE Transactions* 36 (11): 1067–1081.

Tompkins, J., J. White, Y. Bozer, and J. Tanchoco. 2010. *Facilities planning*. 4th ed. New York: Wiley.

Vis, I. F. 2006. "Survey of research in the design and control of automated guided vehicle systems". *European Journal of Operational Research* 170 (3): 677 – 709. ".

Vonolfen, S., M. Affenzeller, A. Beham, E. Lengauer, and S. Wagner. 2011. "Simulation-based evolution of resupply and routing policies in rich vendor-managed inventory scenarios". *Central European Journal of Operations Research*:1–22. 10.1007/s10100-011-0232-5.

Vonolfen, S., A. Beham, M. Affenzeller, S. Wagner, and A. Mayr. 2012. "Combination and Comparison of Different Genetic Encodings for the Vehicle Routing Problem". In *Computer Aided Systems Theory - EUROCAST 2011*, edited by R. Moreno-Diaz, F. Pichler, and A. Quesada-Arencibia, Volume 6927 of *Lecture Notes in Computer Science*, 327–334. Springer Berlin / Heidelberg.

Wagner, S. 2009. *Heuristic Optimization Software Systems - Modeling of Heuristic Optimization Algorithms in the HeuristicLab Software Environment*. Ph. D. thesis, Johannes Kepler University, Linz, Austria.

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