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Necessity and complexity of order picking routing optimisation based on pallet loading features

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Abstract. Order picking is the most labour-intensive and costly activity of warehouses. The main challenges of its improvement are the synchronisation of warehouse layout, storage assignment policy, routing, zoning, and batching. Furthermore, the competitiveness of the warehouse depends on how it adapts to the unique customer demands and product parameters and the changes. The operators usually have to manage the picking sequence based on best practices taking into consideration the product stacking factors and minimising the lead time. It is usually necessary to support the operators by making effective decisions. Researchers of the pallet loading problem, bin packing problem, and order picking optimisation provide a wide horizon of solutions but their results are rarely synchronised.

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The research defines the order picking routing problem based on Pallet Loading Feature (PLF). It describes measurement and product stacking rule evaluation methods to highlight when the PLF based optimisation is necessary. The paper shows that in order picking problems based on PLF, the number of combinations a brute-force search algorithm has to examine grows exponentially, which highlights the importance of meta-heuristic optimisation. The study describes a Simulated Annealing algorithm for order picking based on PLF.

1 Introduction

Satisfying the customers from a warehouse with the right products at the right place and time with low cost requires a synchronised and optimised warehousing system. The general warehousing goals are to handle and store items in the storage system and prepare the ordered Unit Loads (UL) for transport.

Order picking is the most labour and capital intensive operation when the operators collect the ordered items and build transport units. As Gamberini et al. highlighted, its cost can reach 65% of the total warehouse management expense [14]. The order picking system (OPS) design depends on several elements: products, customer orders, different types of functional areas, different combination of equipment types, and operating policies for each functional area [2, 12, 14].

The layout design, storage location assignment methods, routing methods, order batching, and zoning are the main decision fields during order picking processes (OPP) development [12]. The main influencing factors of order picking time are moving, searching, picking, and preparation. While travelling time gives 50% of the whole picking time, the primary optimisation task is the routing. Its aim is to sequence the items on the order picking list in order to get the shortest order picking route length [12].

“The Storage Location Assignment (SLA) optimisation is responsible for allocating products to storage locations for the purpose of lowering routing distance, travelling time, material handling cost and improving space utilisation.” [10]. It enables us to take into consideration the ordering frequency of items and product parameters.

During order picking, the operators collect and allocate products to Stock Keeping Units (SKU) where positioning is a general problem. SKU can be for example a pallet, box or bin, which is responsible for forming a material handling unit, protecting the products and supporting material handling. The

Container Loading Problem algorithms are responsible for assigning three-dimensional small items to three-dimensional rectangular large objects (i.e., truck, containers, pallet). Its aim is to hold the basic geometric feasibility conditions and reach the defined problem specific objective function [6].

The basic geometric feasibility conditions are: [6]

- the small items are positioned within the container,
- the small items do not overlap.

Bortfeldt et al. collected and structured the main objective functions and problem types of the Container Loading Problem, where Bin Packing is a minimisation problem. Generally it is responsible for assigning strongly heterogeneous items into a minimum number of containers. In the case of warehouses, Bin Packing algorithms are used, for example, when the customer order has to be separated to ULs, because of, for example, a large quantity order or a high number of items [6].

The Pallet Loading Problem (PLP) is a maximisation problem, which is responsible for packing the maximum number of identical rectangular boxes onto a rectangular pallet [1]. In the case of warehouses the PLP answers the question of how to position the items on the pallet. These items can be defined to this pallet by a Bin Packing algorithm.

The various SKU properties of the ordered products and the specified pallet loading requirements of different partners make the Bin Packing and Pallet Loading Problem complex.

While each influencing parameter of order picking has an impact on the others with a different importance, these factors should be synchronised. It highlights the complexity of the warehousing system development. For example, Webster et al. examined the impact of SLA on warehouse throughput in the case of bucked brigade order picking [24]. Many researchers work on the different segments of the OPP, Bin Packing or PLP development. A huge amount of research has been done in the field of routing optimisation in warehouses (e.g., [23, 9]). Many solutions have been defined for harmonising SLA and routing to decrease the routing distances and times (e.g., [19, 8]). However, while the physical product parameters (dimensions, weight, SKU type) and product stacking properties influence the physically possible picking sequence in order to build stable ULs, researchers rarely take into account these aspects during SLA and routing optimisation. Furthermore, many researchers have attained valuable results in the fields of Pallet Loading and Bin Packing Problem (e.g., [18, 17, 3, 21, 11]), but the solutions are rarely harmonised with SLA and routing algorithms. Shiau et al. solved the multi-container loading problem and defined the order picking sequence but they avoided the SLA [22]. Molnar et al. highlighted the importance of a well sequenced order picking list to support well structured and stable ULs to avoid product damages [20]. While Molnar et al. developed routing optimisation by considering product stacking properties, they determined picking sequence of product classes. Their algorithm minimises the difference from the defined sequence and minimises the distance but sometimes a more flexible and more complex sequencing rule definition could be required, which depends not only on the product parameters [20].

While the product stacking property based order picking is not relevant at every warehouse, the first goal of the proposed research is to define a methodology for determining its relevance for a given warehouse. The second research goal is to support the order picking operators in order for them to make more objective decisions to decrease the order picking lead time and to build stable transport units that avoid product damages, when stacking property is an important factor during order picking.

We already partly discussed the research problem, methods and results in papers [4] and [5]. The aim of [5] was to describe the pallet loading rule modelling, product classification, and decision matrix defining methodology. It examined the complexity of a simple order picking routing case with pallet loading, where the products are stored in separated warehouse zones. The examination highlighted, when the products are stored in separated and sequenced pallet loading parameter based zones, the order picking operators visit the zones in logical sequence and collect the items using general routing algorithms within the zone, then non-evolutionary algorithms can handle the problem and support the operator with right picking sequence. While it was a simplified case of the mentioned research, this current paper examines a more detailed methodology and more complex cases.

The aim of this paper is to define and describe the Order Picking Routing Problem based on Pallet Loading Feature (OPRP-PLF). It describes, clarifies, and applies methodologies, measurement- and evaluation techniques for highlighting the relevance of OPRP-PLF at the examined warehouse to support tactical decisions before algorithm development. The paper explains and applies classification and PLF based order picking decision matrix modelling solutions. The previous versions of these solutions were developed by the authors [5]. Besides the detailed problem description and clarified explanation of methodologies, the novelty of this paper is to apply methodologies for more complex and industrially more relevant cases. While examining the complexity of the problem is necessary before optimisation in order to find the right methodology, the paper proves the complexity of PLF based order picking routing optimisation in the case of one and more UL required orders. The complexity evaluation highlights the importance of meta-heuristic optimisation. As a novelty, the paper examines analytic examples for simple order picking tasks and introduces a Simulated Annealing (SA) algorithm for solving complex PLF based order picking sequencing tasks. The aim of the SA algorithm is to introduce one possible algorithm for the problem to support the operators with quick pallet loading feature related order picking routing decisions.

2 Order Picking Routing Problem based on Pallet Loading Feature (OPRP-PLF)

The proposed research defines the Pallet Loading Feature (PLF) and the Order Picking Routing Problem based on Pallet Loading Feature (OPRP-PLF). PLF is defined as logistics system property, which requires the right picking sequence and pallet loading method to build stable ULs and to avoid product damages. The challenges of OPRP-PLF are to minimise the order picking lead time, build stable transport units and avoid product damages, when industrially relevant but rarely discussed PLF based order picking sequencing is necessary.

The PLF and the OPRP-PLF depends on product properties, order picking list characteristics, and the order picking system, which has several factors:

- Product properties
  - Weight,
  - Shape,
  - Size,
  - Stock Keeping Unit,
  - Stacking properties.
- Order picking list characteristics
  - Ordered items,
  - Ordered quantity,
  - Length of picking list,
  - Number of product types on the list, with different stacking properties,
  - Special customer rules for pallet loading.

- Order picking system
  - Previously picked units and the sequence,
  - Product assignment in the warehouse.

Each product has several parameters, which define their physical stacking property and the required picking sequence (i.e., weight, shape, size). SKUs are not only boxes but bags, cans or any amorphous units, which also have huge impact on stacking property.

The characteristics of orders also influence the OPRP-PLF and the right picking sequence. Its evaluation is essential during warehouse development. The ordered items' property and the ordered quantity influence the stacking properties. For example a high quantity from a small and weakly packaged product can behave together like one simple box and after its picking, the picker might be able to pick further boxes. Some different items with different types of SKU or packaging also can behave stronger together, rather than separately. The length of picking list highlights the necessity of the routing optimisation. A short list usually does not require complex and maybe time consuming optimisation. However, it is necessary to optimise the longer and more complex picking lists, which will save time for the warehouse operation. The number of different product stacking types also influences the requirements of PLF based optimisation. More and more different product types on the same picking list increase the complexity of the order picking sequence, which requires applying optimisation algorithms for OPRP-PLF. The customers usually define the expected pallet loading rules, which usually limit the possible picking sequence. For example the customer sometimes expects "sandwich ULs", which needs to pick a pallet after every picked record to separate items in the same UL. This UL type has an impact on the OPRP-PLF and sometimes changes the stacking properties of items.

The order picking processes themselves have an impact on the OPRP-PLF. During order picking, the previously picked items and its quantity usually influence the possible further picked items and sequence. The picking positions of the products (SLA) have a high impact on picking distances, which influence the necessity of the routing optimisation to reach the shortest lead time and follow the stacking rules.

2.1 OPRP-PLF related decisions

The OPRP-PLF based development is connected to strategical, tactical, and operative decisions. Related to our research the following main challenges and questions arise regarding the different decision levels.

On a strategic level the warehouse management has to determine the long term business strategy, the main services offered, the main industry (Fast-Moving Consumer Goods (FMCG), automotive, pharmaceutical ...), the infrastructure requirements, and development goals.

On a tactical level several decisions should be made regarding policies and algorithms. It is important to define an ordering policy, as it is allowed for the customers to purchase order (minimum quantity, SKU, ordering time window, etc.). The handled product types and those possible SKUs should also be determined. The product properties will be one input to define the relevance of OPRP-PLF, which must be examined on tactical level as an initial step of algorithm development. Warehousing algorithms (storing in, storing out, replenishment, routing) should be developed, which hopefully will support the operational decisions. If the OPRP-PLF is relevant, the warehousing algorithms should take into consideration the OPRP-PLF with the right weighting. The SLA should also be determined on a tactical level and continuous re-engineering is necessary based on seasonal or periods of changing demand.

On the operational level the warehouse management has to make several decisions hopefully supported by algorithms. When the orders arrive at the warehouse and the order picking tasks are defined, it is necessary to determine: does the ordered quantity fit into one UL or how many UL will be necessary? It is a complex and important question of how the ordered items will be separated to ULs. The optimised order picking routing of the rightly defined UL picking lists should result in the shortest order satisfaction lead time and result in stable ULs. The routing optimisation is strongly connected with the SLA and with the PLF. Due to complex OPRP-PLF, in the case of a well designed SLA and routing algorithm, the shortest picking distance might not result in the shortest lead time, because the picker might have to spend time on UL reconstruction during order picking. The necessity of reconstruction can be caused by higher or lower ordered quantity, as it is assumed during SLA, because different amounts of product can behave differently on the UL. In this case a longer distance might result in shorter lead time because of less pallet loading time. On an operational level the routing algorithm should decide, how to reach the shortest lead time. The possible solutions are to collect items in the right PLF based sequence and walk more or pick with shorter routing and spend time on redesigning the contents of the UL when it is necessary. The best choice depends on the SLA, the time requirement of movements, and the length and contents of the picking list. The increasing frequency and time requirement of pallet loading and reconstruction can highlight the decreasing efficiency of SLA and the necessity of its re-engineering. The well-defined Key Performance Indicators (KPIs) can highlight the necessity of tactical decisions or re-engineering.

3 Defining the necessity of optimisation for OPRP-PLF

PLFs are unique characteristics of each warehouse. It is an important factor mainly at distribution warehouses where order picking has a high importance, and the handled products have a huge number of variants. The unique nature of warehousing systems requires that methodology be defined for determining warehouse by warehouse the relevance of OPRP-PLF and the importance of applying optimisation algorithms for it. The proposed research defines the relevance of OPRP-PLF with time measurements of warehousing processes and with the evaluation of the modelled pallet loading sequencing possibilities.

3.1 Defining the relevance of OPRP-PLF with measurement

Measuring the warehousing processes is essential to understand the real nature of the developed warehouse and collect information about the most time consuming movements, relation of causes and effects. The warehousing processes are separable for elementary movements (i.e., travel, administration, pick, search, setup), which can highlight the relevance of PLF at a given warehouse. It is necessary to examine the processes step by step to overlook the sequence, the frequency, the time distribution, and the casual relations of elementary movements. The PLF dependent movements and those that are relevant are different warehouse to warehouse. Some typical steps are the UL reconstruction, travel time, and wrapping [4].

3.1.1 UL Reconstruction

The picker spends time on UL reconstruction when rebuilding the UL structure during order picking. Frequent UL reconstruction movement highlights the importance of PLF and the necessity of SLA re-engineering [4].

3.1.2 Travelling speed

When the PLF is relevant at the measured warehouse and re-engineering of the OPP is necessary, the order picking operators usually move longer distances and have longer routes for similar picking lists and lower the travelling speed during picking to avoid the products from falling down [4].

3.1.3 Wrapping

Wrapping is sometimes necessary to strengthen the picked ULs during the long and complex picking tasks. The wrapped ULs are much more stable, which results in less product damage and higher travel speed during order picking. The frequency and the time requirements of wrapping during OPP are measurable. The necessity of wrapping during picking can highlight the relevance of PLF [4].

3.2 Modelling the pallet loading possibilities

The OPRP-PLF depends on product properties, order picking list characteristics, and order picking systems. The possible PLF factors' combination and importance are different warehouse to warehouse, which makes the PLF examination and implementation into the order picking algorithms complex. In the previous part of the research [5] a methodology has been defined to model the possible sequencing rules. The resulted PLF based Decision Matrix (PLFDM) allows us to examine the nature and the complexity of proposed problem. It defines the pallet loading possibilities and the order picking sequencing rules. It will be the basis of the loading algorithm during order picking routing optimisation based on PLF. One, two, and three dimensional loading algorithm can control the possible picking sequence based on the PLFDM. In the case of the 1D problem, a full layer of products is picked into one column and only the vertical sequencing is important. The 2D problem handles neighbouring pallet wide columns on the pallet. The 3D problem is the most complex, because it allows to build any columns on the pallet. This paper will apply the PLFDM to the 1D order picking problem. [5]

4 Methodology to define the PLFDM

The warehouses usually do not have enough and appropriate data regarding the handled items (i.e., dimensions, shape, weight) or those that are changing too often to support a complex PLP or Bin Packing algorithm. However, based on known, easily measurable, and rarely changing information it is possible to classify the items and every order line. Furthermore, the warehouse operator's best practices and experiences are essential and valuable inputs to the classification. The defined Pallet Loading Classes (PLC) have PLF based logical connections (i.e., we should not put heavy goods on fragile products), which will be the basis of the PLF based OPP algorithms [5].

This section summarises and clarifies the mentioned classification process step by step based on previous research of the authors [5].

4.1 Classification of the product parameter based classes

The products are grouped based on physical product parameters, which has different stacking properties (Eq. (1)). The usually considered factors of Product Classes (PC) are the SKUs, the packaging solution, and the item property. Equation (2) shows a possible industrial example [4, 5].

$$\mathsf{PC} = \{\mathsf{A}, \mathsf{B}, \mathsf{C}, \mathsf{D}\} \tag{1}$$

$$\mathsf{PC} = \{\mathsf{PlasticBin}, \mathsf{CartonBox}, \mathsf{SmallBox}, \mathsf{Fragile}\} \tag{2}$$

4.2 Classification of the product and order parameter based classes

The defined PCs are specified based on order parameters to define the Product and Order Parameter based Classes (POPC). If it is necessary we separate PCs into further classes. The high quantity of the same item usually has different stacking parameters. For example element B (CartonBox) of the PC set is separated into High Quantity (HQ) and Low Quantity (LQ) elements (Eqs. (3) and (4)). In this case, if the ordered Quantity (Q) is equal to or higher than 4 then the order line is classified as B_{HQ}. Four carton boxes – which are stored in a full layer on the pallet – can be more stable on a UL than only one carton box. If the ordered Quantity (Q) is smaller than 4, then the order line (r) is classified as B_{LQ}. Equations (5) and (6) show an example of the CartonBox class. [4, 5]

$$\mathsf{B}_{\mathsf{HQ}} \in \mathsf{POPC} \mid (\mathsf{r}_{\mathsf{PC}} = \mathsf{B}) \wedge (\mathsf{Q} \geqslant 4) \tag{3}$$

$$\mathsf{B}_{\mathsf{LQ}} \in \mathsf{POPC} \mid (\mathsf{r}_{\mathsf{PC}} = \mathsf{B}) \wedge (\mathsf{Q} < 4) \tag{4}$$

$$\mathsf{CartonBox}_{\mathsf{HQ}} \in \mathsf{POPC} \mid (\mathsf{r}_{\mathsf{PC}} = \mathsf{CartonBox}) \wedge (\mathsf{Q} \geqslant 4) \tag{5}$$

$$\mathsf{CartonBox}_{\mathsf{LQ}} \in \mathsf{POPC} \mid (\mathsf{r}_{\mathsf{PC}} = \mathsf{CartonBox}) \wedge (\mathsf{Q} < 4) \tag{6}$$

4.3 Classification of the special product and order parameter based classes

The Special POPCs (SPOPC) are defined with consideration of previously picked units and their sequence (Eq. (7)). The picked items on the pallet form a physical structure, which influences the choosing of subsequent items. For example, it is possible to pick one layer of small boxes, after one layer of small boxes but the third layer of small boxes would destabilize the UL, so in this case it is forbidden to pick one layer of small boxes after two layers of small boxes (Eq. (8)). [4, 5]

$$S \in SPOPC \mid (POPC_{t-1} = Y) \wedge (POPC_{t-2} = Y) \tag{7}$$

$$\begin{aligned} SmallBoxSmallBox \in SPOPC \mid \\ (POPC_{t-1} = SmallBox) \wedge \\ (POPC_{t-2} = SmallBox) \end{aligned} \tag{8}$$

Where t is the actual picking step, $t-1$ is the previously picked POPC, and $t-2$ is the last but two picked POPC.

4.4 Defining the PLFDM

PLF based Decision Matrix (PLFDM) models the PLF based sequencing logic. The predecessors (rows) are the elements of the Pallet Loading Class (PLC) set, which are the union of POPC and SPOPC sets. The successors (columns) are the elements of the POPC set (Eqs. (9) and (10)). [4, 5]

$$PLC = POPC \cup SPOPC \tag{9}$$

$$PLFDM : PLC \times POPC \mapsto \{0, 1\} \tag{10}$$

$$PLFDM\,(PLC_i, POPC_j) = \begin{cases} 1, & \text{if } POPC_j \textbf{ can} \text{ be picked after } PLC_i \\ 0, & \text{if } POPC_j \textbf{ can't} \text{ be picked after } PLC_i \end{cases} \tag{11}$$

The PLFDM values are 0 or 1, depending on pallet loading possibilities. If it is possible to pick the examined item (one element of POPC) after the already picked units (PLC element), then the PLFDM value is 1 (true). Otherwise picking is forbidden, so the PLFDM value is 0 (false) (Eq. (11)). Table (1) and Table (2) illustrate an example PLFDM. [4, 5]

	$POPC_1$	$POPC_2$	$POPC_3$	$POPC_4$	$POPC_5$
PLC_1	1	1	1	1	1
PLC_2	0	1	1	1	1
PLC_3	0	0	1	1	1
PLC_4	0	0	0	1	1
PLC_5	0	0	0	0	1
PLC_6	0	0	0	0	1

Table 1: Pallet Loading Feature based Decision Matrix (PLFDM).

	PlasticBin	CartonBox_{HQ}	CartonBox_{LQ}	SmallBox	Fragile
PlasticBin	1	1	1	1	1
CartonBox_{HQ}	0	1	1	1	1
CartonBox_{LQ}	0	0	1	1	1
SmallBox	0	0	0	1	1
SmallBoxSmallBox	0	0	0	0	1
Fragile	0	0	0	0	1

Table 2: Pallet Loading Feature based Decision Matrix (PLFDM) example.

4.5 Merging the compatible records in the PLFDM

The resulted PLFDM usually contains records, which have exactly the same values. These PLCs have different properties but they behave in the same way during order picking. This is the reason why those records can be merged, which can simplify the PLFDM. For example in Table (3), where PLC_5 and PLC_6 are merged this results in $PLC_{5,6}$. [5]

	$POPC_1$	$POPC_2$	$POPC_3$	$POPC_4$	$POPC_5$
PLC_1	1	1	1	1	1
PLC_2	0	1	1	1	1
PLC_3	0	0	1	1	1
PLC_4	0	0	0	1	1
$PLC_{5,6}$	0	0	0	0	1

Table 3: Merged pallet loading feature based decision matrix (PLFDM)

5 Defining the importance rate of PLF based order picking process development

After defining the PLFDM of a warehouse, it is possible to evaluate the matrix and define the relevance of PLF based order picking routing optimisation. The Pallet Loading Rate (PLR) is defined based on the amount of pallet loading restrictions; otherwise it is based on the amount of the edges in the PLFDM. Basically, when every POPC can be picked after every PLC, the PLFDM contains 1 in every cell, then the PLF is not relevant at the given warehouse and the Pallet Loading Rate (PLR) is 0. When more and more restrictions (0 value) are defined in our PLFDM then the complexity of OPP and the importance of PLF based routing optimisation is growing. The PLR is calculated by Equation (12), where MaxNum_e is equal to the number of true values in the PLFDM when every POPC element can be picked after every PLC element. Num_e equals to the number of true values in the PLFDM when PLF is modelled [4].

$$\mathsf{PLR} = 1 - \frac{\mathsf{Num}_e}{\mathsf{MaxNum}_e} \tag{12}$$

As part of the research the PLR values have been classified based on intervals, which describe the importance of PLF based routing optimisation at the examined warehouse [4].

- PLF is not relevant, when $\mathsf{PLR} = 0$,
- PLF is weakly relevant, when $0 < \mathsf{PLR} \leqslant 0.2$,
- PLF is relevant, when $0.2 < \mathsf{PLR} \leqslant 0.4$,
- PLF is strongly relevant, when $0.4 < \mathsf{PLR}$.

Tables (4)–(7) show examples for each PLR category.

6 Complexity of PLF based routing optimisation

This paper examines the OPRP-PLF to define the complexity of PLF based order picking routing optimisation. Two main cases have been defined for OPRP-PLF, which might have further sub-problems:

- optimising an order with items, which can be picked into 1 UL and order separation is not necessary,
- optimising an order, which will be picked into more than 1 UL and order separation is necessary.

	POPC_1	POPC_2	POPC_3	POPC_4	POPC_5
PLC_1	1	1	1	1	1
PLC_2	1	1	1	1	1
PLC_3	1	1	1	1	1
PLC_4	1	1	1	1	1
PLC_5	1	1	1	1	1

Table 4: PLFDM example, when PLF is not relevant

	POPC_1	POPC_2	POPC_3	POPC_4	POPC_5
PLC_1	1	1	1	1	1
PLC_2	1	1	1	1	1
PLC_3	1	1	1	1	1
PLC_4	0	0	1	1	1
PLC_5	0	0	0	1	1

Table 5: PLFDM example, when PLF is weakly relevant

	POPC_1	POPC_2	POPC_3	POPC_4	POPC_5
PLC_1	1	1	1	1	1
PLC_2	1	1	1	1	1
PLC_3	0	0	1	1	1
PLC_4	0	0	0	1	1
PLC_5	0	0	0	0	1

Table 6: PLFDM example, when PLF is relevant

	POPC_1	POPC_2	POPC_3	POPC_4	POPC_5
PLC_1	0	0	1	1	1
PLC_2	0	0	1	1	1
PLC_3	0	0	0	1	1
PLC_4	0	0	0	0	1
PLC_5	0	0	0	0	0

Table 7: PLFDM example, when PLF is strongly relevant

The paper determines the formula for both cases to calculate the possible number of order picking sequencing variations and it examines the behaviour of those in the case of several order picking lists whose length and contents are different.

The aim of this research is to define the complexity and the nature of the search space, which should be handled by the order picking operator. It is not an objective of the paper to classify the investigated problem into a specific complexity class. Its goal is merely to emphasize the supra-exponential growing of the proposed problem.

6.1 Complexity of order picking of one UL without order separation

First, a simpler case is examined when order picking of one UL should be optimised and order separation is not necessary. In this case the customer purchases an order, which will be picked by an operator to one UL. The important questions are:

- How many different picking sequences of the ordered products are possible?
- Is the operator able to find the right sequence of picking herself/himself or is an algorithm necessary?
- What kind of optimisation algorithm is necessary for this kind of problem depending on its complexity?

Each order picking list can contain every PLC every time. While the rules of PLFDM are true, any sequence of the PLCs is possible. The main parameters, which influence the number of sequencing variations of a picking list, are the number of records (k), the number of PLCs (n) and the occurrence of the PLCs (i) in the order picking list.

The PLC occurrence is necessary because every PLC contains several products, which usually have their own picking positions. The possible variations of the picking positions within a PLC have to be considered. i is defined from the order picking list point of view, to count the occurrence of PLCs, which are on the order picking list (Eq. (13)). When a PLC occurs i times in a picking list then its possible sequencing variations have to be counted due to the different picking positions ($i!$) (Eq. (14)). The sum of occurrence values (i) has to be equal to the number of order picking list records (k) (Eq. (15)). The number of records (k) has to be equal to or higher than the number of PLCs

(n) (Eq. (16)). When $k = n$ then the picking list contains 1 product from each PLC and then the variations of occurrence ($i!$) is not necessary (Eq. (17)).

$$i > 0 \tag{13}$$

$$V = i_1! \cdot i_2! \ldots \cdot i_n! \tag{14}$$

$$k = i_1 + i_2 + \ldots i_n \tag{15}$$

$$k \geq n \tag{16}$$

$$V = i_1 \cdot i_2 \ldots \cdot i_n \tag{17}$$

For example, when the following inputs are given:

- Number of different PLCs on the list equals 3 ($n = 3$), $\mathsf{PLC} = \{A, B, C\}$,
- Number of order picking list records equals 12 ($k = 12$),
- A PLC occurs 5 times, $i_1 = 5$,
- B PLC occurs 4 times, $i_2 = 4$,
- C PLC occurs 3 times, $i_3 = 3$.

The number of variations for the above mentioned example is $5! \cdot 4! \cdot 3! = 17280$.

This example is just one case, each n and k pairs have several combinations depending on the occurrence of PLCs. Equation (18) shows the formula, which defines the number of possible combinations.

$$C_{k;n} = \binom{k-1}{n-1} \tag{18}$$

One possible combination is when the occurrence values are balanced ($i_1 \approxeq i_2 \approxeq \ldots \approxeq i_n$) and this reaches the minimum number of variations. In the case of the mentioned example the minimum number of variations equals 13824 when:

- $n = 3$,
- $k = 12$,
- A PLC occurs 4 times,
- B PLC occurs 4 times,
- C PLC occurs 4 times.

Another possible combination is when one of the occurrence values is maximum and the others equal 1, and this reaches the maximum number of variations (Eq. (19)).

$$(k - (n-1))! \cdot (1!)^{n-1} = (k - n + 1)! \tag{19}$$

In the case of the mentioned example the maximum number of variations equals 3628800, when:

- $n = 3$,
- $k = 12$,
- A PLC occurs 10 times,
- B PLC occurs 1 times,
- C PLC occurs 1 times.

During the complexity examination the maximum formula is going to be used (Eq. (19)) because the order picking routing optimisation algorithm has to be able to handle in this case as well, which results in the highest number of variations and causes the highest complexity.

The $(k - n + 1)!$ formula (Eq. (19)) takes into consideration the PLF rules in the case of standard triangular and symmetrical PLFDM and it has some important facts:

- Many industrial cases are reducible to standard triangular and symmetrical PLFDM. However, some special industrial cases can result in neither symmetrical nor standard triangular PLFDM, which might modify the real number of variations.
- When the inverse PLFDM is examined, the number of possible variations will be the same. It highlights that the proposed formula is not applicable in PLF based order picking routing optimisation without the PLFDM.
- The proposed formula assumes that each product has only 1 picking position. However, sometimes more than 1 picking position of a product is also possible.

The aim of this formula (Eq. (19)) is to highlight the importance and complexity of PLF based order picking routing optimisation. In this case the specific cases and the inverse solutions are negligible. It could be said that when PLFs are implemented into the order picking routing optimisation, the algorithm should be able to handle a unique (non-symmetrical and non-standard triangular) PLFDM with the exact picking rules.

Generally, the necessary data (n, k, i_1, i_2,... i_n) regarding the order picking list will be available during PLF based order picking routing optimisation to see each possible variation. The algorithm will optimise the picking sequence of several order picking lists whose parameters will be different depending on the customer orders.

The $(k-n+1)!$ formula (Eq. (19)) is compared to the e^k formula to examine the complexity of the OPRP-PLF. Equation (20) can prove the exponential growth of variations, where n is an optional constant and k goes to infinity.

$$\lim_{k\to\infty} \frac{e^k}{(k-n+1)!} = \lim_{k\to\infty} \frac{e \cdot e \cdot e \cdot \ldots \cdot e}{(k-n+1)\cdot(k-n)\cdot(k-n-1)\cdot\ldots\cdot 3\cdot 2\cdot 1\cdot\ldots\cdot 1} = 0 \tag{20}$$

Equation (20) goes to 0 because each $\frac{e}{(k-n+1)}, \frac{e}{(k-n)}, \frac{e}{(k-n-1)} \ldots$ quotient goes to 0 and the further quotients $\left(\frac{e}{2}, \frac{e}{1} \ldots\right)$ are constants. This result means that the number of variations ($(k-n+1)!$) has a stronger growth than the e^k has. It proves that the proposed formula has at least exponential growth. It could be said that a heuristics optimisation method would be necessary for PLF based routing optimisation.

Each warehouse handles shorter and longer picking lists. Table (8) represents an example when $n = 3$ and k is between 1 and 15. In this case when $k = 12$ and $n = 3$, which is definitely possible in real life, the possible sequencing variations equal 3628800. It could be said that it is impossible for the order picking operator to be able to define a nearly optimal sequence by herself/himself without any support. Naturally, there are possible cases when k and n are smaller but in this case complex heuristic optimisation might not be relevant (i.e., in Table (8), when $n = 3$ and $k = 6$ there are 24 possible variations). It is necessary to examine the nature of picking lists on a tactical level and determine whether the order picking lists require complex PLF based optimisation or not. When there is a possibility for several complex order picking lists then implementation of PLF based heuristic routing optimisation is necessary. However, the Warehouse Management System should be able to decide on an operational level which list will be sequenced by complex and maybe time consuming algorithms and which will be handled by simple algorithms or by the order picking operator herself/himself.

k	MaxVar	e^k
1	0	2.72
2	0	7.39
3	1	20.09
4	2	54.60
5	6	148.41
6	24	403.43
7	120	1 096.63
8	720	2 980.96
9	5 040	8 103.08
10	40 320	22 026.47
11	362 880	59 874.14
12	3 628 800	162 754.79
13	39 916 800	442 413.39
14	479 001 600	1 202 604.28
15	6 227 020 800	3 269 017.37

Table 8: Number of order picking sequencing variations, when $n = 3$ and k is growing.

6.2 Complexity of order picking when order is separated to several ULs

This section examines the case when the purchased order should be separated to ULs because the ordered amount of products is higher than 1 UL's capacity. The defined ULs have the same parameters and behave in the same way as the previously discussed picking lists. The important questions are:

- How many different variations are possible for separating an order and sequencing the picking items of each UL?
- Is the operator able to find the right separation of an order and picking sequence of each UL herself/himself or is an algorithm necessary?
- What kind of optimisation algorithm is necessary for these kinds of problems depending on its complexity?

The main parameters, which influence the number of separating and sequencing variations of an order, are the number of records (Order:K, UL:k), the number of PLCs (Order:N, UL:n) and the occurrence of the PLCs (Order:I, UL:i).

It is assumed that the number of possible ULs could be equal to or lower than the number of ordered records (K) (Eq. (21)). The sum of each UL's length (k_1, $k_2 \ldots k_{UL_{num}}$) equals K(Eq. (22)). The order picking sequencing variations of each possible UL are counted by the previously defined formula, $V = i_1! \cdot i_2! \ldots \cdot i_n!$ (Eq. (14)). Based on the combination with repetition formula, Eq. (23) defines the possible order separation combinations, where $UL_{num} = K$, because of Eq. (21).

$$UL_{num} \leqslant K \tag{21}$$

$$K = k_1 + k_2 + \ldots + k_{UL_{num}} \tag{22}$$

$$\binom{UL_{num} + K - 1}{UL_{num} - 1} = \binom{2 \cdot K - 1}{K} \tag{23}$$

Equation (24) sums up the possible separating combinations and sequencing variations of each UL.

$$\begin{aligned} \sum_{k_1,k_2,\ldots,k_K=0}^{k_1+k_2+\ldots+k_K=K} \binom{K}{k_1} \cdot V_{k_1} + \binom{K-k_1}{k_2} \cdot V_{k_2} + \ldots + \\ \binom{K-k_1-k_2-\ldots-k_{K-3}-k_{K-2}}{k_{K-1}} \cdot V_{k_{K-1}} + \\ \binom{K-k_1-k_2-\ldots-k_{K-2}-k_{K-1}}{k_K} \cdot V_{k_K} \end{aligned} \tag{24}$$

The model counts using the maximum number of variations of each UL, when $i >= 0$, thus $V_{k_j} = k_j!$. Differently from Eq. (13), $i = 0$ is allowed because in this case the order picking lists are combined during examination, thus the exact occurrence of each n is unknown. It is a specific case, which results in the highest number of variations, although during optimisation the exact occurrence of each n might be known. In this case the proposed formula can be simplified as Eq. (25) shows. Some further simplifications result in Eq. (26), which defines the possible variations for separating an order and sequencing the picking items of each UL.

$$\begin{aligned} \sum_{k_1,k_2,\ldots,k_K=0}^{k_1+k_2+\ldots+k_K=K} \frac{K!}{(K-k_1)!} + \frac{(K-k_1)!}{(K-k_1-k_2)!} + \ldots + \\ \frac{(K-k_1-k_2\ldots k_{K-2})!}{(K-k_1-k_2\ldots k_{K-1})!} + \frac{(K-k_1-k_2\ldots k_{K-1})!}{(K-k_1-k_2\ldots k_K)!} \end{aligned} \tag{25}$$

$$\sum_{k_1,k_2,\ldots,k_K=0}^{k_1+k_2+\ldots+k_K=K} \frac{K!}{(K-k_1)!} + \frac{(K-k_1)!}{(K-k_1-k_2)!} + \cdots + \frac{(k_{K-1}+k_K)!}{k_K!} + \frac{k_K!}{0!} \tag{26}$$

Equation (20) proves, that sequencing 1 UL is at least an exponential problem and requires heuristic optimisation. When an algorithm separates orders to ULs and sequences each UL it will be at least an exponential problem as well, which requires heuristic optimisation. It could be said that supporting the order picking operator with a separating and sequencing algorithm is even more important in this case because this problem is even more complex.

7 PLF based order picking optimisation

Depending on the length and complexity of one UL's picking list, there are 3 different levels for handling the possible picking sequence.

- When the picking lists are short (k is low, like 2-6 records) and/or the lists are simple (contain a low number of POPC, n is low) then the order picking operator is usually able to define the optimal sequence for picking, which results in the shortest picking lead time.
- When the lists are longer but still not longer than about 10 records, an enumeration based algorithm can find the best sequence using a computer. In the case of a 10 records long list the number of possible solutions are $10! = 3628800$ (when reconstruction is allowed), which can be handled by a computer without an intelligent algorithm.
- When the lists are longer than about 10 records ($k > 10$), a quick algorithm is necessary. The growing number of records results in an exponentially growing complexity, which is unmanageable within a short time window by the operators or simple heuristics. Meta-heuristic based solutions usually can be an appropriate solution to get a nearly optimal picking sequence quickly.

The following subsections introduce analytic examples for simple cases and a Simulated Annealing (SA) algorithm for more complex picking lists. The examples and the SA algorithm are defined for a 1D loading during the order picking.

The aim of this paper is to describe one possible algorithm for the complex cases to introduce the nature of the problem. While several further methodologies are possible (e.g. genetic algorithms, branch and bound methods, multi-restart hill climbers), it is not an objective of this paper to find the best methodology. We leave it for future research. Further aim is to confirm, that supporting the order picking operators with OPRP-PLF algorithms is essential to get a nearly optimal picking sequence quickly. The reasons why the SA algorithm is applied, are its potential application in an evolutionary based search, its possibility to avoid local optimum, and the good experiences about its effectiveness and simplicity.

First of all, the next subsection discusses the objective function, which evaluates the order picking sequencing solutions.

7.1 Evaluation of order picking sequence - objective function

The proposed research evaluates the possible order picking sequencing solutions based on time requirements. Counting the lead time of each picking task begins when the picking operator starts the list and picks up an empty pallet at the start-end position. The lead time measurement is finished when the picking operator has transported the ready UL to the start-end point. During order picking the picker visits each picking position on her/his list, picks the ordered items and reconstructs the UL structure, if it is necessary. The objective function (T) summarises the picking time, the UL reconstruction time, the travelling time and other time requirements (Eq. (27)). The aim of the OPRP-PLF is to minimise the order picking lead time of stable unit loads (Eq. (29)).

$$\mathsf{T} = \mathsf{T_P} + \mathsf{T_R} + \mathsf{T_T} + \mathsf{T_O} \tag{27}$$

$$\min\left(\mathsf{T_P} + \mathsf{T_R} + \mathsf{T_T} + \mathsf{T_O}\right) \tag{28}$$

$$\min\left(\mathsf{T}\right) \tag{29}$$

The picking time ($\mathsf{T_P}$) depends on several parameters, which are usually unique for each warehouse, for example ordered quantity, weight, shape and SKU of the ordered product. In the later described test examples a constant is going to be used for the picking time (10 sec/ordered record) for simplification (Eq. (30)).

$$\mathsf{T_P} = \sum_{i=1}^{k} \mathsf{t_{P_i}} \tag{30}$$

The reconstruction time ($\mathsf{T_R}$) depends also on several unique factors. During the order picking the picker collects the items based on the defined sequence, when he/she reaches a record that can't be picked after the already picked items, the picker has to unload items from the UL until the actual picking record can be picked. When the actual picked items are allocated to the UL the unloaded items should be loaded back onto the UL in the right sequence. In this case it is assumed that the picker unloads the items separately in order to load everything back in the right sequence to avoid the Tower of Hanoi problem. Equation (31) shows our formula for reconstruction time, where r_p is the number of problematic records where reconstruction will be necessary, and r_r is the number of records with stronger POPC after the problematic record, and this shows the number of unpicked records. In the later described test examples a constant is going to be used for reconstruction time (t_R equals 7.5 sec/ordered record) for simplification.

$$T_R = \sum_{i=0}^{r_p} r_{r_i} \cdot 2 \cdot t_{R_i} \tag{31}$$

Equation (32) defines the travelling time based on the picker's moving speed ($v = 1,6m/s$) and the distances between positions (S). S_{r_{i-1},r_i} is the travelling distance from the position of the previous record to the position of the actual record. S_{r_0} and S_{SE} define the start-end point where the picking starts and ends.

$$T_T = \frac{S_{r_k,SE}}{v} + \sum_{i=1}^{k} \frac{S_{r_{i-1},r_i}}{v} \tag{32}$$

Further time parameters (like for example extra administration, correction, and searching) are definable with the other time T_O parameter. In the later described test examples T_O equals 0 seconds.

The overall task is to minimise T (Eq. (29)) subject to k (number of records on the order picking list), r_p, r_r, and the distances between positions S.

7.2 Analytic solution for simple cases

When the picking lists are short (k is low, like 2-6 records) and/or the list is simple (contains low number of POPC – n is low) then the order picking operator is usually able to define the optimal sequence for picking, which results in the shortest picking lead time. This subsection describes some simple picking lists and their calculated objective functions. The lead times are calculated using the previously described formulas based on a simple distance matrix (Table (9)), where the values are defined in meters. The possible UL building rules are described in Table (10). Obviously in the explained cases the warehouse operator defines the right sequence without any calculation, based merely on experience and best practices.

	Pos 1	Pos 2	Pos 3	Start-End
Pos 1	0	50	20	100
Pos 2	50	0	30	80
Pos 3	20	30	0	10
Start-End	100	80	10	0

Table 9: Distance matrix for the simple cases.

	A	B	C
A	1	1	1
B	0	1	1
C	0	0	1

Table 10: PLFDM for the simple cases.

The first simple case has 2 records ($k = 2$) and contains 2 POPCs ($n = 2$). Table (11) shows a possible picking sequence when UL reconstruction is necessary based on the PLFDM because the record number 1 (POPC property is "B") is picked before the record number 2 (POPC property is "A"). Table (12) describes a better picking sequence when reconstruction is not necessary and the travel time is equal to the previously discussed solution.

The second simple case has 3 records ($k = 3$) and contains 3 POPCs ($n = 3$). Table (13) and Table (14) evaluate 2 possible picking sequences when reconstruction is necessary and when it is not required, respectively. The results show that the second solution's lead time is lower when reconstruction is not necessary. It is highlighted that in this case the picker has to travel a longer route to avoid reconstruction and reach a lower lead time. It could be said that the picker has to take into consideration the PLF and not to minimise the route length. When the number of records is higher and/or the picking list is more complex the picking operator won't be able to make the right decision without any IT support, which defines the nearly optimal sequence.

Record ID	Position	POPC	T_P	r_{r_i}	T_R	S_{r_{i-1},r_i}	T_T	Lead Time
1	Position 2	B	00:10	0	00:00	80	00:50	
2	Position 1	A	00:10	1	00:15	50	00:31	
	Start-End					100	01:02	
Sum			00:20		00:15	230	02:23	**02:58**

Table 11: Simple case 1 ($k = 2$ and $n = 2$) **with** reconstruction.

Record ID	Position	POPC	T_P	r_{r_i}	T_R	S_{r_{i-1},r_i}	T_T	Lead Time
2	Position 1	A	00:10	0	00:00	100	01:02	
1	Position 2	B	00:10	0	00:00	50	00:31	
	Start-End					80	00:50	
Sum			00:20		00:00	230	02:23	**02:43**

Table 12: Simple case 1 ($k = 2$ and $n = 2$) **without** reconstruction.

7.3 Simulated annealing algorithm for PLF based order picking optimisation

This paper applies a simple optimisation algorithm for OPRP-PLF to find nearly optimal picking sequences in an effective way by using an enumeration based algorithm. The basis of the applied Simulated Annealing (SA) algorithm is defined by Kirkpatrick et al. for Travelling Salesman Problems (TSP) [16]. This research generalised the method for a population based Simulated Annealing algorithm. Each individual defines a possible picking sequence of the order picking list as part of a population. Each individual was developed independently based on SA methodology.

The initial population has N_{ind} individuals, which contains 1 previously sequenced individual (eugenic individual) and $N_{ind} - 1$ randomly defined permutations of order picking list records. The eugenic individual is sequenced by POPC properties to define a reliable starting solution, and its role is to verify that our SA algorithm can provide a better solution than simple sequencing.

Each individual is evolved for N_{iter} iterations without any information exchange between the individuals. The individuals do not consider the PLFDM, the PLF aspects are considered in the objective function. In iteration $Iter$ every individual is perturbed randomly. The number of perturbed records (Num_{PR}) are randomly defined between 2 and Max_{PR}, where Max_{PR} is defined by Eq. (33) with rounding, where k is the number of picking records. If Max_{PR} is lower than Min_{PR} ($Min_{PR} = 4$) then $Max_{PR} = Min_{PR}$. The randomly selected Num_{PR} records are perturbed and the other records are fixed

Record ID	Position	POPC	T_P	r_{r_i}	T_R	S_{r_{i-1},r_i}	T_T	Lead Time
3	Position 3	B	00:10	0	00:00	10	00:06	
1	Position 2	C	00:10	1	00:15	30	00:19	
2	Position 1	A	00:10	2	00:30	50	00:31	
	Start-End					100	01:02	
Sum			00:30		00:45	190	01:58	**03:13**

Table 13: Simple case 2 ($k = 3$ and $n = 3$) **with** reconstruction.

Record ID	Position	POPC	T_P	r_{r_i}	T_R	S_{r_{i-1},r_i}	T_T	Lead Time
2	Position 1	A	00:10	0	00:00	100	01:02	
3	Position 3	B	00:10	0	00:00	20	00:13	
1	Position 2	C	00:10	0	00:00	30	00:19	
	Start-End					80	00:50	
Sum			00:30		00:00	230	02:24	**02:54**

Table 14: Simple case 2 ($k = 3$ and $n = 3$) **without** reconstruction.

on the list. Equation (33) is used iteration by iteration to decrease the impact of the perturbation.

$$\mathsf{Max}_{PR} = \left(1 - \left(\frac{\mathrm{Iter}}{N_{\mathrm{iter}}}\right)\right) \cdot k \tag{33}$$

The perturbed individual is kept if it gives a better solution than the unperturbed (origin) individual or if Eq. (34) holds, where $r \in [0, 1]$ is a uniform random number and τ is a positive scaling factor. The eugenic individual is overwritten only when the lead time of the perturbed individual is lower than that of the unperturbed individual. Algorithm (1) summarises the individual overwriting procedure.

$$r < e^{((-\mathrm{Iter}\cdot\tau)/N_{\mathrm{iter}})} \tag{34}$$

The SA algorithms are tested with one complex picking list, which is picked in a warehouse where 480 items are randomly allocated on 480 picking positions. The test picking list contains 20 records ($k = 20$) and 6 POPCs ($n = 6$). Table (15) shows the parameters of the SA algorithm.

Because of the stochastic nature of the SA algorithm, this paper tested the algorithm on 10 different random generator seed values. Table (16) shows the objective function results of the 10 runs in ascending order by $\mathsf{NotEugenicLeadTime}(T)$. It highlights, that $\mathsf{NotEugenicLeadTime}$ individuals generally

if *Individual* = *Eugenic individual* **then**
| Overwriting the original individual
else
| **if** $\mathsf{T}_{\mathsf{unperturbed}} < \mathsf{T}_{\mathsf{perturbed}}$ *or Eq. (34) holds* **then**
| | Overwriting the original individual
| **end**
end

Algorithm 1: Individual overwriting procedure

reached lower lead time T. The deviation highlights the stochastic nature of the algorithm, but every result is acceptable.

Figure (1) shows iteration by iteration the best eugenic and not eugenic individuals of the SA algorithm (Seed=1: SA+1) for PLF based routing optimisation. Axes X visualise the iterations and axes Y visualise the objective function values (T). The red (initially lower) points show the decreasing lead time of 1 eugenic individual. The green (initially upper) triangles show the changing of the not eugenic individuals' lead time. The decreasing number of accepted weaker solutions shows the nature of the SA algorithm. It could be said that the best not eugenic individuals exceeded the eugenic individual. The graph proves, that the eugenic individual was never overwritten by a weaker individual. Furthermore, the not eugenic individual was overwritten by a weaker individual with a decreasing probability.

Table (17) shows the top 10 individuals after SA optimisation. The best solutions needed some reconstructions for the defined picking task in the case of the given SLA. It proves the importance of PLF based order picking optimisation to reach a lower picking lead time. The SA algorithm found significantly better solutions than the eugenic individual ("I1"). The results highlighted that the SA algorithm is able to define a reliable solution for the PLF based routing problem.

Parameter	Value
$\mathsf{N}_{\mathsf{ind}}$	50
$\mathsf{N}_{\mathsf{iter}}$	1200
τ	10

Table 15: Parameters of the SA algorithm

Scenario	EugenicLeadTime	NotEugenicLeadTime
SA+1	0:12:46	0:12:15
SA+2	0:12:38	0:12:17
SA+3	0:13:34	0:12:17
SA+4	0:12:57	0:12:26
SA+5	0:12:24	0:12:57
SA+6	0:13:17	0:12:17
SA+7	0:12:34	0:12:31
SA+8	0:12:34	0:12:45
SA+9	0:12:28	0:12:28
SA+10	0:12:31	0:12:24
Min	0:12:24	0:12:15
AVG	0:12:46	0:12:28
Deviation	0:00:23	0:00:14

Table 16: SA results of the 10 seeds

8 Conclusion

Several warehouses handle products that require the right picking sequence and stacking method to build stable Unit Loads and to avoid product damages during order picking. The proposed research defined the Pallet Loading Features (PLF), the Order Picking Routing Problem based on Pallet Loading Feature (OPRP-PLF), and those influencing factors.

The warehouse management has to make several tactical and operative decisions to operate cost and time effective PLF, as it will influence the order picking processes to perform proper ULs. While PLF is not relevant at every warehouse, the examination of its importance is essential on tactical level. If PLF is relevant, the operating algorithms should take into consideration the PLFs with the right weighting.

Several operational decisions have an impact on order performance lead time and costs, whose minimisation is a general goal. The main PLF relevant decisions are: how to separate the customer orders to UL order picking lists? How many UL and which UL picking list contents will result in the lowest order picking lead time? If the actual SLA won't let us follow the pallet loading rules and collect the ordered items with the shortest route distance, the picking operator or the routing algorithm should decide whether to collect items in the right stacking sequence and move a longer distance or to pick with a

Ind. ID	T	T_P	T_R	T_T
I43	0:12:15	0:03:20	0:00:45	0:08:10
I1	0:12:46	0:03:20	0:00:15	0:09:11
I14	0:12:47	0:03:20	0:01:30	0:07:57
I6	0:12:58	0:03:20	0:01:00	0:08:38
I31	0:13:08	0:03:20	0:01:15	0:08:33
I3	0:13:12	0:03:20	0:01:00	0:08:52
I16	0:13:23	0:03:20	0:00:45	0:09:18
I33	0:13:24	0:03:20	0:01:45	0:08:19
I32	0:13:26	0:03:20	0:02:00	0:08:06
I25	0:13:26	0:03:20	0:00:15	0:09:51

Table 17: Top 10 individuals of SA+1

shorter routing and spend more time redesigning the contents of the UL during picking. The decision should result in the shortest lead time.

This paper described the methodology for defining the importance of PLF on a tactical level. It introduced how the measurement of warehousing processes can highlight OPRP-PLF. It described the methodology for modelling and evaluating pallet loading rules. The defined PLFDM is the basis of PLF based order picking optimisation, which defines a possible picking sequence to avoid product damages and increase the OPP effectiveness.

Two main cases of customer order fulfilment were explained. The first is when the customer order can be picked into 1 UL and order separation is not necessary. The second is when the customer order should be picked into more than 1 UL and order separation is necessary. The examined cases have some alternative sub-cases, which is necessary to examine in further research. This paper determined a formula for both cases to calculate the possible number of order picking sequencing variations and examined its behaviour in the case of several order picking lists whose length and contents are different. The results proved, where PLF is relevant, the possible sequencing combinations of order picking lists that have an exponential growth. This fact proves the necessity of the heuristic optimisation method for OPRP-PLF, for example Foldesi et al. defined for the road transport travelling salesman problem or Theyset al. and Chen et al. defined for warehouse routing problem [13, 23, 9]. The order picking routing optimisation algorithm has to support the operational decisions, like customer order separation for ULs and the longer distance versus more UL reconstruction time trade-off.

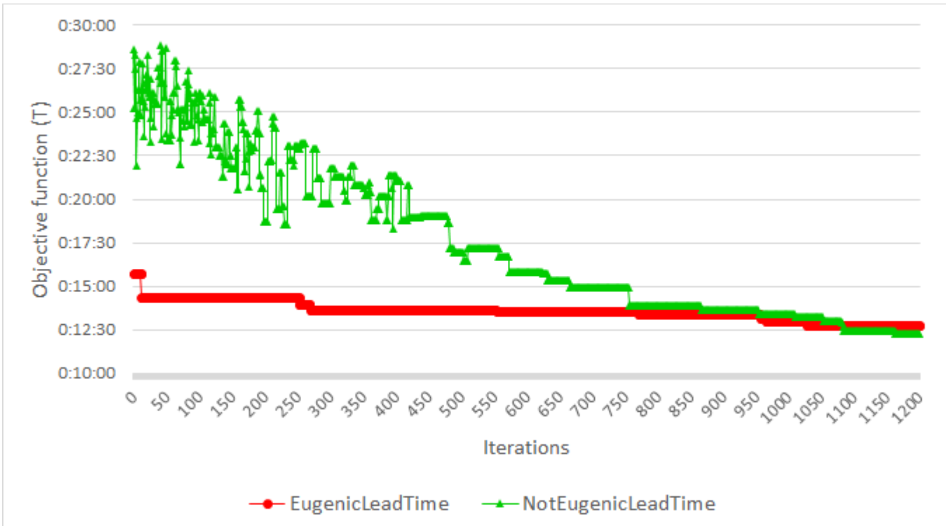

Figure 1: Iterations of the SA algorithm

The paper described some analytic examples for simple cases to introduce operational decisions, which can be made by operators themselves. A Simulated Annealing (SA) algorithm was defined for optimising complex and long picking lists. It resulted in better solutions than a simply sequenced and deterministic optimised eugenic individual. However, as a further research, more effective and quicker algorithms should be developed.

The routing optimisation is usually running on given Storage Location Assignment, whose optimisation and harmonisation with routing are essential. As part of the proposed research SLA algorithms will be developed which take into consideration PLFs and be harmonised with the nature of the orders. The generated SLA alternatives will be evaluated with the developed PLFDM based routing algorithms. The nature of customer demands and the product lines are usually changing, which requires continuous re-engineering of OPP. When the items are dedicated to a position and the SLA is not optimised dynamically, the picking distances will possibly be growing and the routing optimisation will be more important. The increasing order picking lead time usually highlights the necessity of SLA re-engineering. A well-defined Performance Measurement system is the basis of OPP optimisation. It helps realise the changed nature of orders and it highlights the necessity of OPP re-engineering.

The outputs of distribution warehouses are transportation ULs, which are homogeneous or inhomogeneous order picked ULs. These ULs' structure, strength, transportation requirements, and behaviour during transport have a huge impact on supply chain management, influence its effectiveness, and have impact on the possible risks during transportation. The risk management, which is an examined field by many researchers, like [7, 15] also has to take into consideration the PLF to examine the possibilities of product damages during transport.

Understanding the nature of OPP is the first step in harmonising the warehousing processes. The realised warehouse dependent factors have to be implemented into OPP algorithms with the right weighting. The OPP development should be continuous based on well-defined Performance Measurement indicators to harmonise the warehousing system with the changing environment.

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