Volume 16 • Issue 3 • 2024

sciendo

ISMSME
International Society for Manufacturing, Service and Management Engineering

received: 8 February 2024
accepted: 31 July 2024

pages: 98-114

Optimising picking operations in distribution centres: a simulation and algorithm-based approach for travel distance reduction

Caio Jorge Gamarra
Mauro Sampaio
Fábio Lima

ABSTRACT
This study examines the pivotal role of the logistics sector in corporations, particularly those with diverse product portfolios. It focuses on the time-intensive "picking" process, driven by various products and material handling requirements for order fulfilment. The research presents a methodology that combines distribution centre modelling for simulation with an optimisation algorithm to enhance operational efficiency. The goal is to determine an optimal route for product retrieval, minimising employee travel distances, using the simulated annealing algorithm. The results showcase a significant 7 % reduction in employee travel distance during collection. This research is relevant to academia and practical applications as it presents an opportunity to reduce operational costs in distribution centres, enhance the efficiency of picking operations, and improve the competitiveness of companies. Furthermore, it contributes to operations research by addressing a complex problem with significant practical implications using a rather unused method to solve this problem of picking operations. The approach is empirically applied in a prominent Brazilian beverage company. This methodology proves valuable for optimising logistics operations in various industrial contexts, highlighting its practical applicability.

KEY WORDS
logistics, picking, optimisation, simulated annealing, discrete simulation, digital manufacturing, distribution centre, logistics centre

10.2478/emj-2024-0026

Fábio Lima
Centro Universitário FEI,
Av. Humberto de Alencar
Castelo Branco, 3972-B São Bernardo
do Campo - SP, 09850-901, Brazil
ORCID 0000-0002-5500-3191

Corresponding author:
e-mail: flima@fei.edu.br

Caio Jorge Gamarra
Instituto Mauá de Tecnologia,
Sao Caetano do Sul, Praça Mauá 1
São Caetano do Sul - SP, Brazil
ORCID 0009-0000-2117-8033
e-mail: caio.gamarra@maua.br

Mauro Sampaio
Centro Universitário FEI,
Av. Humberto de Alencar
Castelo Branco, 3972-B São Bernardo
do Campo - SP, 09850-901, Brazil
ORCID 0000-0002-1217-6295
e-mail: msampaio@fei.edu.br

Introduction

Optimising picking operations in distribution centres is a highly relevant topic within logistics and operations management, given that the costs associated with this process can account for over half of the total operational costs (de Koster et al., 2007; Richards, 2018). In the broader context of the logistics and supply chain management literature, enhancing the efficiency of picking operations has been a constant concern. In this regard, strategies such as layout reconfiguration, automation technologies, and the

Gamarra, C. J., Sampaio, M., & Lima, F. (2024). Optimising picking operations in distribution centres: a simulation and algorithm-based approach for travel distance reduction. *Engineering Management in Production and Services, 16*(3), 98-114. doi: 10.2478/emj-2024-0026

analysis of item-picking sequences have been subject to investigation. However, as proposed in this study, restructuring the picking list for operators represents a valuable contribution to addressing the persistent challenges related to information updating in distribution systems, an issue often overlooked in academic literature and business practice.

The academic literature encompasses many studies that examine optimising logistics operations (Hsieh & Tsai, 2006; Van Gils et al., 2018). Nevertheless, a conspicuous research gap exists concerning the specific inquiry into the relationship between the picking list generated by the Warehouse Management System (WMS) and the physical layout of warehouses in distribution centres, particularly in the Brazilian context. This lacuna in research assumes pronounced significance in light of the potential consequences, given that a misalignment between these components can lead to superfluous expenditures and operational inefficiencies, a matter of paramount gravity in an industry where costs associated with operator movement and handling may eclipse 50 % of the total expenditure (De Koster et al., 2007; Richards, 2018).

More thorough research and analysis are needed to reduce picking time within distribution centre operations and address various challenges. These encompass operational inefficiency, resource profligacy, delivery delays, impediments to system updates, and a diminished competitive edge within the market. These repercussions translate into heightened costs, compromised operational efficacy, and customer discontent, underscoring the need for a scholarly and systematic approach to investigate and deploy optimisation strategies.

In summary, this study addresses the following research query: To what extent does utilising an optimisation strategy based on simulation and algorithms for finding shorter routes impact the reduction of travel distances for workers in the context of picking operations within distribution centres?

The primary aim of this study is to investigate the extent to which the implementation of an optimisation strategy grounded in simulation and algorithmic route selection influences the reduction of travel distances for workers engaged in picking operations within distribution centres. At this inquiry stage, the "central phenomenon" is broadly characterised as optimising picking routes in distribution centres.

This study will employ data collection, discrete event simulation modelling, and the simulated annealing algorithm to optimise picking operations in distribution centres, assessing the impact of the optimisation strategy on efficiency.

This research is relevant to both academia and practical applications as it presents an opportunity to reduce operational costs in distribution centres, enhance the efficiency of picking operations, and improve the competitiveness of companies. Furthermore, it contributes to operations research by addressing a complex problem with significant practical implications.

The second section of this paper will review relevant literature on the topic under examination. The third section will detail the methodology employed in this research. Results obtained from this methodology will be presented in the fourth section. Conclusions and anticipated contributions of this investigation will be discussed in the fifth and final section of the paper.

1. Literature review

This section delves into the following pivotal academic domains: (1) picking sector in logistics, (2) collection routing policies in warehousing environments, (3) optimisation in "picker-to-part" warehousing environments, (4) meta-heuristic approaches, (5) simulated annealing, and (6) simulation for discrete event modelling.

1.1. Picking sector in logistics

In logistics, warehouses play a central role in facilitating efficient customer service. Many companies have evolved their perception of warehouses from mere storage facilities to integral components contributing to customer satisfaction. Among various warehouse operations, the picking sector is particularly crucial for maintaining operational efficiency and improving customer service. The picking process involves selecting and segregating products into pallets based on customer orders for subsequent shipment. This process, defined as order picking, fulfils customer requests and can encompass a range of clients, including independent customers, organisations, or automated systems.

Kulak, Sahin and Taner (2012) categorise the picking process into two primary methods:

- Picker-to-Part: In this manual process, an operator is responsible for physically collecting items

based on customer orders and navigating the warehouse to locate the specified items.
- Part-to-Picker: This automated process involves delivering items to the operator, eliminating the need for manual item retrieval.

Several factors influence productivity in the manual picking model, including warehouse layout, travel distances, delays during item collection, equipment preparation, information dissemination for subsequent retrievals, and the search for specific items. However, the most critical factor affecting efficiency is the physical movement of the operator during item retrieval. The choice of the operator's route significantly impacts the time and effectiveness of the process (Lu et al., 2016).

Determining the optimal collection route for a specific set of locations involves establishing an efficient sequence for collecting items. This sequence aims to minimise the distance travelled, optimise routes, streamline processes, and ultimately increase the product dispatch rate.

Among the various factors that can increase item collection times, the distance travelled by workers is predominant and can account for over 50 % of the collection time. Since travel time does not add value to the product and generates additional costs, reducing travel time is crucial for minimising operational expenses in picker-to-part systems (Lu et al., 2016). De Koster (2007) underscored the importance of reducing travel distance to decrease picking time and improve operational efficiency in warehouse operations.

The picking sector has received extensive attention from researchers, encompassing strategic and operational aspects. Diefenbach and Glock (2019) categorise warehouse problems into five areas: layout, product allocation, zone allocation, batch picking, and operator collection routes. This study focuses on optimising operator collection routes to reduce the distance travelled by operators.

1.2. Collection routing policies in warehousing environments

Collection routing policies represent a critical facet of warehouse operations, with their principal objective being the minimisation of the distance traversed by operators while retrieving customer order items. This strategic pursuit primarily aims to mitigate operator fatigue, curtailing task execution durations and thereby augmenting overall operational efficiency. Masaiek, Glock, and Grosse (2019) underscored the paramount importance of this subject matter. Notably, within the context of order-picking processes, where travel time accounts for more than 50 % of the total dedicated time, the scientific community has directed considerable attention towards the intricate nuances encompassing collection routing policies. Several academic compendia and bibliographic surveys, including seminal works such as

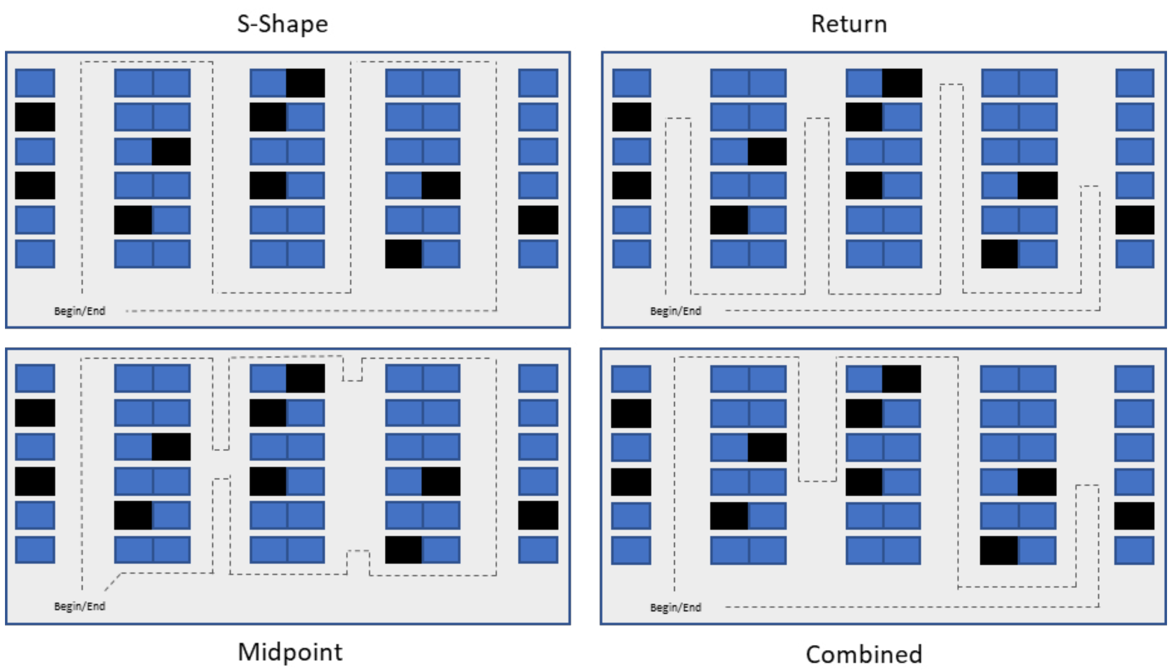

Fig. 1. Illustration of methodological approaches to picking areas

those authored by Grosse, Glock and Neumann (2017) and van Gils et al. (2018), have contributed to the comprehensive exploration of this domain.

Within the ambit of collection routing policies, a taxonomy of methodological approaches has emerged, each distinguished by unique nomenclature and specific operational mechanisms. Some of these methodologies, i.e., s-shape, return, midpoint, and combined, are outlined by Sancakli (2022) and illustrated in Fig. 1.

The methods illustrated in Fig. 1 were described by van Gils et al. (2018). The s-shape method requires the operator to visit every corridor, as long as at least one item needs to be collected while entering the next corridor on the same side they left the previous one. The return method indicates that the operator should always enter and leave the corridor by the same side, as long as the corridor has any product to be picked.

The midpoint method requires the operator to collect at least one item and go halfway through it. If a corridor has items on both sides, the operator should first collect the ones on one side, and later, when completing the route, they should enter the other end of the corridor to collect the items on the other side. Lastly, the combined method indicates that the operator can go through an entire corridor, leave it, go to the next, walk halfway through that corridor and leave it by the same end they entered and so on, mixing the s-shape and midpoint methods.

Heuristics, as mentioned above, are widely applied to solve operator routing problems due to advantages in computational efficiency and easy implementation (Cortés et al., 2017).

1.3. Optimisation in "picker-to-part" warehousing environments

Several facets warrant scholarly inquiry in warehouses utilising the "picker-to-part" operational paradigm. As posited by Li, Huang and Dai (2017), four distinct avenues of investigation emerge: the optimisation of warehouse layout, product allocation within storage positions, batch-picking strategies, and route optimisation for operatives engaged in item retrieval tasks.

The notion of reevaluating the trajectories undertaken by operators during item collection has garnered substantive scholarly attention, frequently drawing analogies with the renowned Traveling Salesman Problem (TSP) (Li, Huang & Dai, 2017). Some scholars categorise this endeavour within multi-aisle warehousing configurations as a specific instance of the Steiner Traveling Salesman Problem (STSP) (Kulak, Sahin & Taner, 2012).

Notably, it is incumbent to acknowledge that determining the picking operator's route represents an NP-Hard (Non-deterministic Polynomial time) computational conundrum. Given this inherent complexity, problem resolution is typically pursued by adopting heuristics or optimisation methodologies (van Gils et al., 2018; Li, Huang & Dai, 2017). Heuristic approaches are conventionally enlisted, aware that they do not guarantee optimality. However, they offer a viable pathway to convergence towards a generally satisfactory solution, provided that the problem has been adequately comprehended and modelled (Diefenbach & Glock, 2019). Notably, applying optimisation methods persists in pursuing an optimal outcome, notwithstanding their computational demands and the intricacies involved.

As expounded by Masae, Glock and Grosse (2019), the extant literature has proposed three distinct categories of algorithms to address this challenge:

- Exact algorithms are characterised by their ability to invariably discern an optimal solution, as the Traveling Salesman Problem exemplifies.
- Heuristic algorithms are problem-specific and tailored to produce reasonably proficient solutions across most instances, exemplified by the "S-shape" and "Midpoint" methodologies.
- Meta-heuristic algorithms transcend problem specificity and furnish high-level guidelines and strategies to offer approximate solutions, exemplified by the bee colony and ant colony algorithms.

1.4. Meta-heuristic approaches

Another avenue for investigating how optimal operator routes are determined lies in deploying meta-heuristic techniques, constituting a set of guiding principles for crafting optimisation algorithms tailored to operator routing challenges (Kulak, Sahin & Taner, 2012). As highlighted by Cortés et al. (2017), prior research has explored the application of meta-heuristic algorithms, including genetic algorithms, ant colony optimisation, and particle swarm optimisation, to address operator routing problems.

Pinedo (2018) augments this discourse by enumerating prevalent meta-heuristic algorithms, encompassing simulated annealing, tabu search, genetic algorithm, ant colony optimisation, beehive, and others. These algorithms are categorised as local search algorithms and further — into improvement and constructive subcategories. Improvement-type algorithms commence their procedural trajectory with a randomly generated solution and iteratively seek enhanced outcomes by manipulating preselected variables at the outset of the process. Notably, local search methodologies do not guarantee optimality but consistently strive to improve the incumbent solution. Determining termination criteria is incumbent upon the programmer and contingent upon the improvement level achieved through iterative cycles.

Ardjmand, Sanei Bajgiran and Youssef (2019) offered insights into the work of Matusiak et al. (2014), wherein simulated annealing was harnessed to investigate batch formation under precedence constraints and operator routing. Their approach encompassed two sub-algorithms: an a-star algorithm for routing solutions and simulated annealing for batch-related challenges. Their findings demonstrated less than 1.2 % errors compared to optimal solutions involving more than three orders.

Furthermore, Ardjmand, Sanei Bajgiran and Youssef (2019) expound upon the research by Chen et al. (2015), who formulated a mixed-integer nonlinear programming model to address batch, sequencing, and operator routing challenges, all geared towards minimising order execution times. Their innovative approach amalgamated the capabilities of genetic algorithms and ant colony optimisation to resolve these intricate logistical issues. Similarly, Cheng et al. (2015) introduced a hybrid methodology comprising particle swarm optimisation and ant colony optimisation to tackle batch-related challenges and operator routing complexities.

However, it is noteworthy that most extant research endeavours and studies confine their scope to predefined warehouse layouts. While such constraints do not necessarily undermine the applicability of the aforementioned meta-heuristic algorithms, they can curtail the universality of their deployment. It is pertinent to underscore that several studies scrutinising picking operations also delve into item allocation intricacies and the architectural configuration of the picking area. In light of these limitations, this present work endeavours to conceptualise a solution framework agnostic to the peculiarities of warehouse layouts.

1.5. Simulated annealing

Simulated annealing, initially introduced by Kirkpatrick et al. (1983) and Cerny (1985), originated from the adaptation of an algorithm developed by Metropolis et al. (1953) for modelling atomic arrangements in solids aimed at achieving the lowest energy state, a process analogous to cooling. Kirkpatrick et al. and Cerny recognised its potential application in optimisation problems, establishing analogies between the physical system and combinatorial optimisation:

Optimisation solutions correspond to physical states.

- The cost of an optimisation solution is analogous to the energy of a physical state.
- The selection of a neighbouring solution in optimisation mimics the perturbation of a physical state.
- The global optimum in optimisation aligns with the ground state in the physical system.
- Local optima in optimisation resemble rapid cooling phenomena in the physical system.

Simulated annealing operates as a "refinement heuristic" algorithm, initiating with an arbitrary solution and aiming to improve it through variable manipulation and local search. Importantly, it does not guarantee optimality. Its primary objective is to find a nearby solution superior to the current one. Each iteration explores potential solutions in the vicinity, accepting or rejecting them based on intrinsic criteria. This iterative process is designed to escape local optima and converge toward global optima (Pinedo, 2018).

Grounded in statistical mechanics, simulated annealing commences with a random solution. During each iteration, it explores neighbouring solutions. If a neighbouring solution is superior in the objective function, it becomes the new current solution; otherwise, its acceptance depends on the probability of accepting "worse results". The temperature parameter determines this probability. As simulated annealing progresses, the temperature gradually decreases, reducing the acceptance of "worse results". Cooling strategies can vary, with two common approaches being fixed-rate cooling and percentage-based cooling until a low temperature is reached. It is worth noting that simulated annealing is highly sensitive to this temperature parameter, necessitating careful tuning to ensure effective convergence (Ardjmand, Sanei Bajgiran, & Youssef, 2019).

Simulated annealing is employed as an optimisation tool to locate global optima within extensive search spaces by simulating the cooling process until a stable state is reached (Fayyaz et al., 2018). Fig. 2 illustrates the expected behaviour when employing

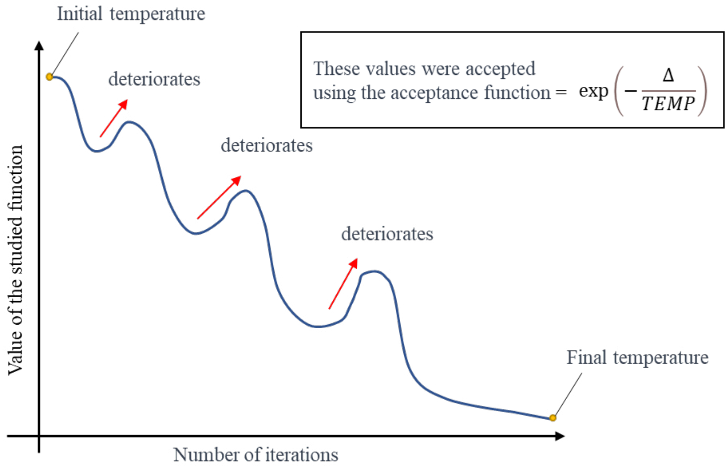

Fig. 2. Expected behaviour when accepting deteriorations

this algorithm. The method initiates with a high temperature to facilitate the escape from local minima and accepts "worse results". As the temperature decreases, the acceptance of "worse results" diminishes, allowing the algorithm to avoid getting trapped in local minima given sufficient iterations or time (Fayyaz et al., 2018).

The likelihood of accepting deteriorating solutions is determined by the acceptance function ($g\ (\delta, T)$), typically represented as exp(−δ/T), where δ represents the difference between solutions, and T is the temperature parameter. When $\delta = f(j) - f(i)$ is less than zero, solution j is accepted as the new current solution. Conversely, it is only accepted if the acceptance function exceeds a random value ($g\ (\delta, T) > random\ (0{,}1)$).

Simulated annealing begins with a relatively high temperature to prevent premature convergence to local minima. The temperature is gradually reduced, and multiple attempts are made to improve solutions near the current solution for each temperature value. The algorithm terminates when a predefined stopping criterion is met, which can be related to the final temperature value. However, depending on the cooling rate, it may take considerable time and computational resources to reach this point. It is also common to set an iteration limit for each temperature. Once this limit is reached, the algorithm accepts the current function value, regardless of whether it has completed the desired processing and cooling of the function (Sibalija, 2018). A flowchart showing its processes is depicted in Fig. 3.

1.6. Simulation for discrete event modelling

Simulation for discrete event modelling is a widely employed technique for modelling systems that evolve in discrete time instants, contingent upon the occurrence of specific events. This approach enables the analysis of "what if" scenarios, facilitating the evaluation of how alterations in one or more parameters influence the behaviour of a given system. To this end, the simulation modeller must possess proficient modelling, analysis, and decision-making skills to derive meaningful results. It is worth emphasising that simulation is a tool for conducting tests in operational scenarios but does not guarantee optimal outcomes. Nevertheless, when applied judiciously, it can yield substantial results.

Therefore, while discrete event simulation aims to represent real systems as closely as possible, it provides the modeller with the ability to better understand the studied system, making it possible to identify excess capacity, constraints, bottlenecks, and uneven utilisation, which can be provided with a solution after testing on different scenarios (Forbus & Berleant, 2022).

According to Pegden, Shannon and Sadowsky (1990), simulation can be used to test hypotheses to confirm how and why certain events occur. Consequently, it allows for the measurement of the performance of a real system concerning different operational situations (Law, 2007). Thus, computational simulation can prevent misguided decisions that may jeopardise a company's operation or result

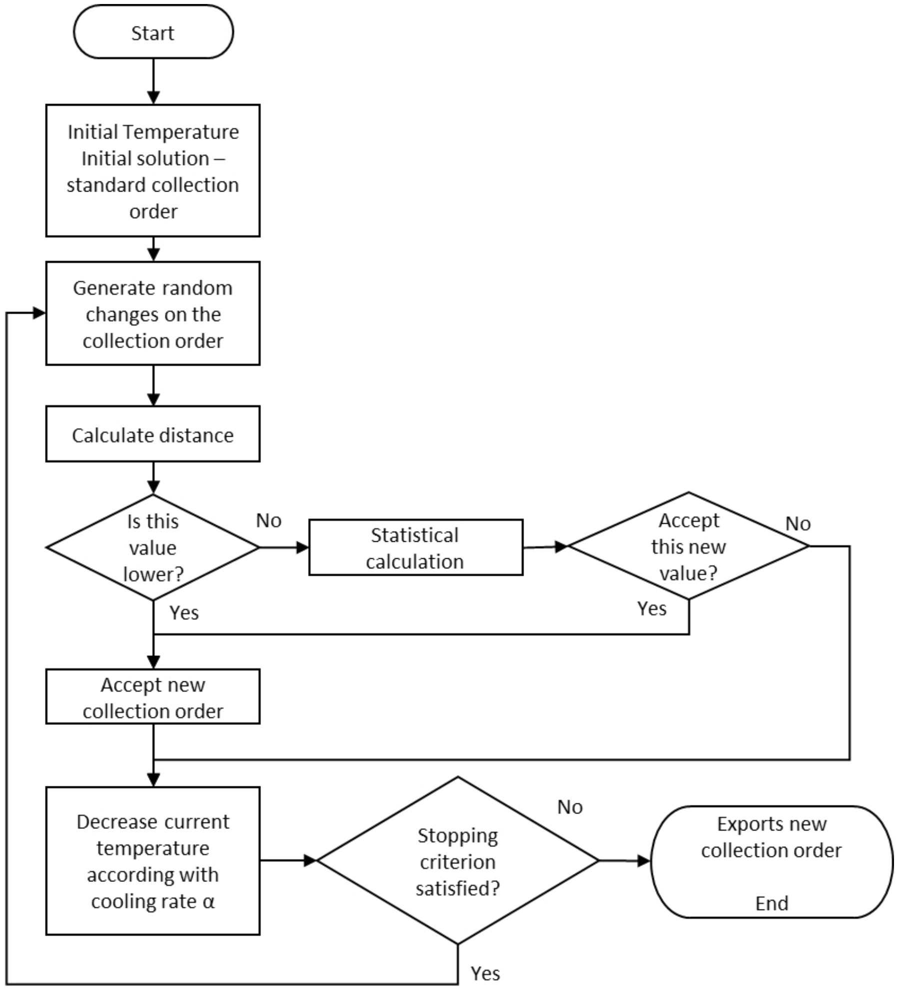

Fig. 3. Flowchart of simulated annealing

in inappropriate investments (Krajewski & Ritzman, 2001).

According to Law & Kelton (2000), simulation offers the following benefits:

- Development of adaptable models reflecting reality, testing various scenarios and operational possibilities of a system without resource commitment.
- Ability to simulate complex systems (possessing stochastic elements) inadequately described by deterministic mathematical models.
- Evaluation of the distribution of available resources, allocating them appropriately to the process and ensuring high production levels.
- Better control over experimental conditions compared to practical implementation in the real system.
- Analysis of long periods of time of an option within a reduced simulation time.
- Identification of existing bottlenecks in the system and studies related to process optimisation.

Thus, simulation serves as a powerful means to support decision-making, enabling potentially good solutions to real system problems. However, to obtain applicable results that reliably represent the reality of a system, it is necessary to apply well-defined modelling and simulation techniques.

In parallel with the work conducted by Ardjmand, Sanei Bajgiran and Youssef (2019), this study also seeks the utilisation of tools that enable the efficient evaluation of operator routes within a specific layout, leveraging simulation models to obtain critical parameters aimed at optimising picking routes.

As elucidated by Dijkstra and Roodbergen (2017), two primary methods exist for assessing the distance travelled in collection routes. The first entails the creation of a simulation model, while the second involves the development of formulas grounded in the statistical properties of adopted route models. The authors employed both methods to assess the allocation of storage locations in a warehouse to minimise the distance travelled and found substantial agreement between the results obtained through the simulation model and the developed mathematical methods.

In a context akin to the present study, Quader and Castillo-Villar (2018) underscored the significance of decision management as a pivotal factor in the pursuit of efficiency enhancement and cost reduction in warehouse operations. These researchers proposed a simulation model that tests different route and SKU allocation heuristics to maximise operator utilisation or reduce order cycle times. This model allowed for evaluating how the system would dynamically perform in a picking zone with multiple aisles.

2. Research methods

This study proposes integrating a discrete event simulation model with applying the optimisation algorithm known as simulated annealing. The outlined approach necessitates acquiring and using information about the picking area within a Distribution Center. This entails constructing the simulation model based on the collected data, virtually generating data that may be challenging to obtain physically and applying the simulated annealing algorithm (Fig. 4) to determine the optimised collection route to maximise operational efficiency.

The concluding phase of the methodology addresses the validation of the distance covered by operators while following the optimised route, comparing it with the route suggested by the optimisation algorithm. This validation is conducted once again through the discrete event simulation model.

2.1. Simulation model

The model employed for this study has been crafted using Siemens' Plant Simulation software. The primary aim of this model is to represent the warehouse system and its operational dynamics. However, it is noteworthy that the discrete event aspect, which introduces stochastic elements through statistical distributions, has been deliberately excluded. The model serves two principal functions.

The initial function pertains to creating a "from-to" table, elucidating the distances between all positions within the warehouse (Fig. 5). It is imperative to underline the critical significance of this dataset for the subsequent execution of the route optimisation algorithm. In the authentic operational milieu, acquiring these values is a formidable undertaking, primarily due to the time-intensive nature of data procurement and the inherent impracticality of allocating human resources to undertake this task within a sector of the enterprise characterised by nearly continuous operations throughout the day.

The efficacious execution of this task requires utilising the physical layout of the company premises, complete with scales, corridors, and actual spatial configurations, which is indispensable as a foundation for constructing a model. This model is predi-

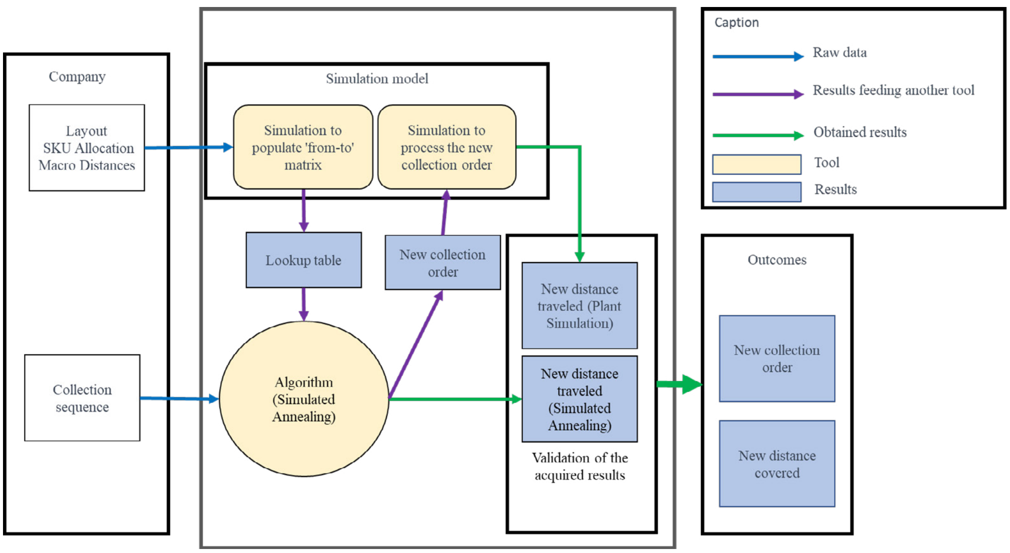

Fig. 4. Flow of the proposed methodology

cated on this empirical data and incorporates the locations of collection points corresponding to each pallet position. Once the model has been judiciously fashioned, an operative command may be executed, instructing an operator to traverse from a designated place A to all other positions, meticulously recording the inter-position distances within a "from-to" table. This meticulously compiled dataset is earmarked for prospective utilisation by the route optimisation algorithm. Fig. 6 furnishes a brief yet illuminating exemplar elucidating the procedural intricacies entailed. It visually encapsulates the operator's movements during data acquisition, with recorded data being meticulously chronicled within a spreadsheet.

Fig. 7 embodies a segment of the meticulously populated spreadsheet engendered through the agency of the simulation model. Herein, the first column is dedicated to enumerating the terminology of all positions, while the initial row designates the terminus to which the operator's peregrination must be directed.

This repository may be seamlessly integrated into the route optimisation algorithm after consummating the function mentioned earlier and comprehensively filling the "from-to" table with distance data. This symbiotic amalgamation facilitates the retrieval of pertinent data necessary for the second function of the simulation model (Fig. 8). In this subsequent phase, supplementary elements are introduced into the model's operational purview in addition to the data employed so far. These include, among other things, the allocation of products within respective positions and the imposition of a novel order for collection, as proffered by the route optimisation algorithm. These augmentations empower the model to scrutinise and appraise the aggregate distance traversed by operators while effecting the fulfilment of all orders within the ambit of the study period. This invaluable metric substantiates the basis for a comparative analysis of both methodologies, thereby affording insight into the efficacy of the respective tools.

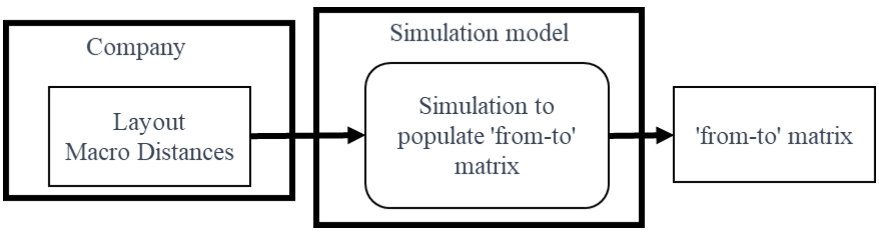

Fig. 5. Representation of the first function of the simulation model

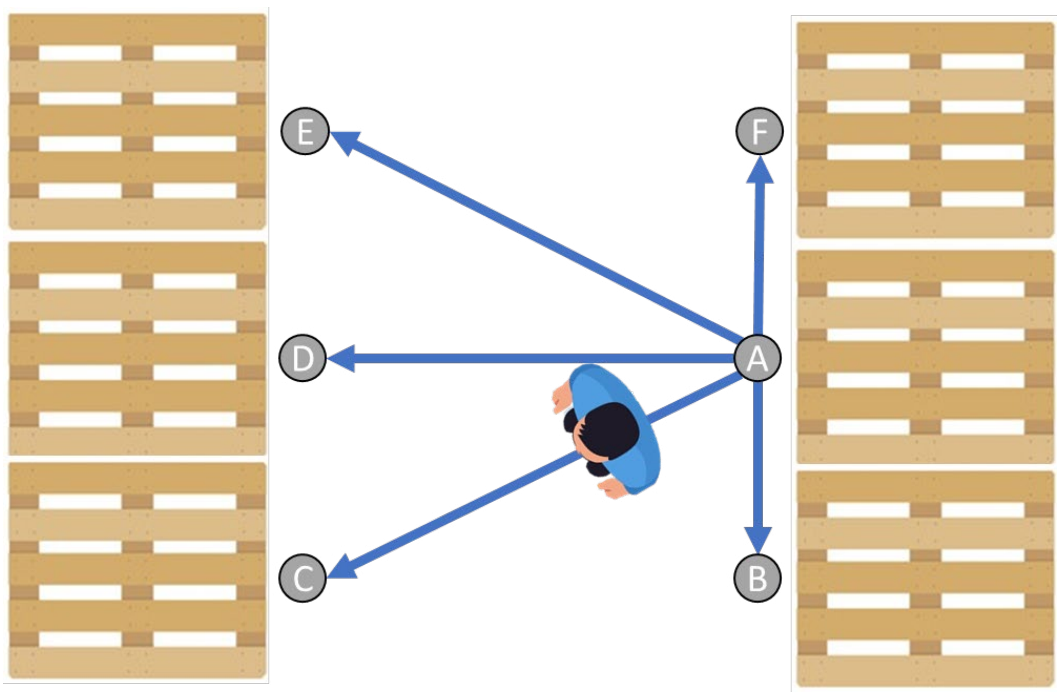

Fig. 6. Example of distance collection

	string 1	string 2	string 3	string 4	string 5
1		.CDD.Norte.OA001	.CDD.Norte.OA002	.CDD.Norte.OA003	.CDD.Norte.OA004
2	OA001	0	1.060546875	2.12109375	3.181640625
3	OA002	1.060546875	0	1.060546875	2.12109375
4	OA003	2.12109375	1.060546875	0	1.060546875
5	OA004	3.181640625	2.12109375	1.060546875	0
6	OA005	4.2421875	3.181640625	2.12109375	1.060546875
7	OA006	5.302734375	4.2421875	3.181640625	2.12109375
8	OA007	6.4638671875	5.4033203125	4.3427734375	3.2822265625
9	OA009	4.04271457628784	5.08155279817584	6.1278328864355	7.17830148960638
10	OA010	1.81452171434648	2.5190680972737	3.41298087508767	4.38185944284487
11	OA011	1.57759100310795	1.81452171434648	2.51906809725915	3.41298087508767

Fig. 7. Example of "from-to" table

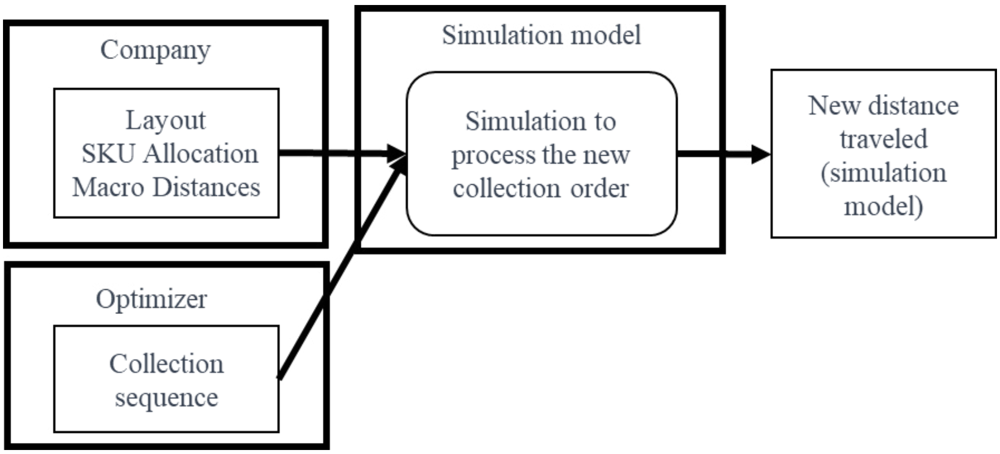

Fig. 8. Representation of the second function of the simulation model

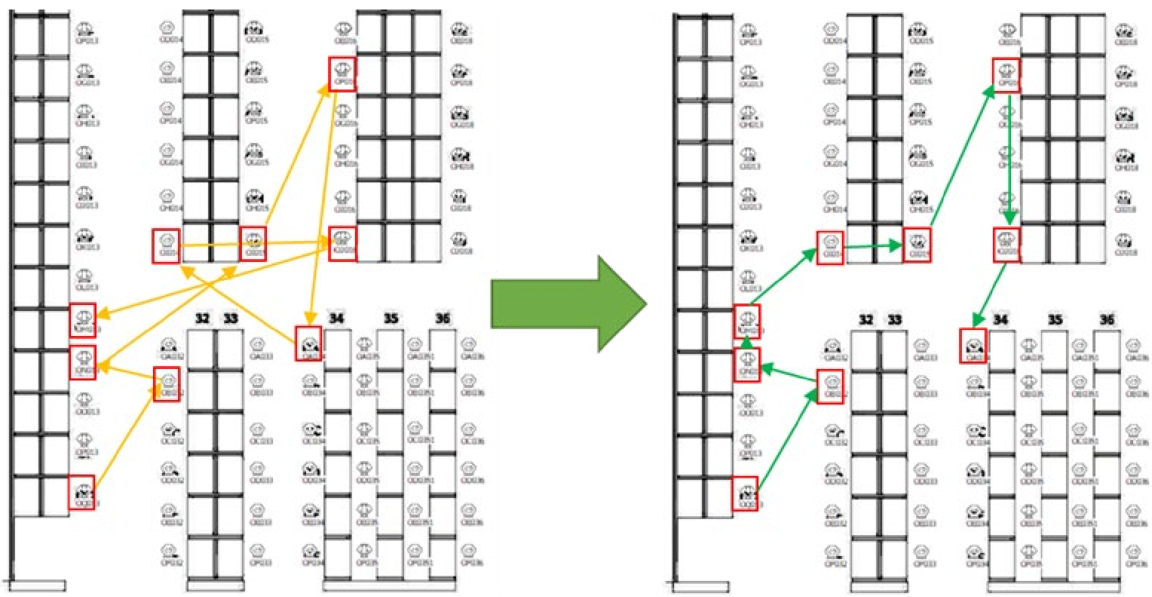

Fig. 9. Example of a reorganised collection route

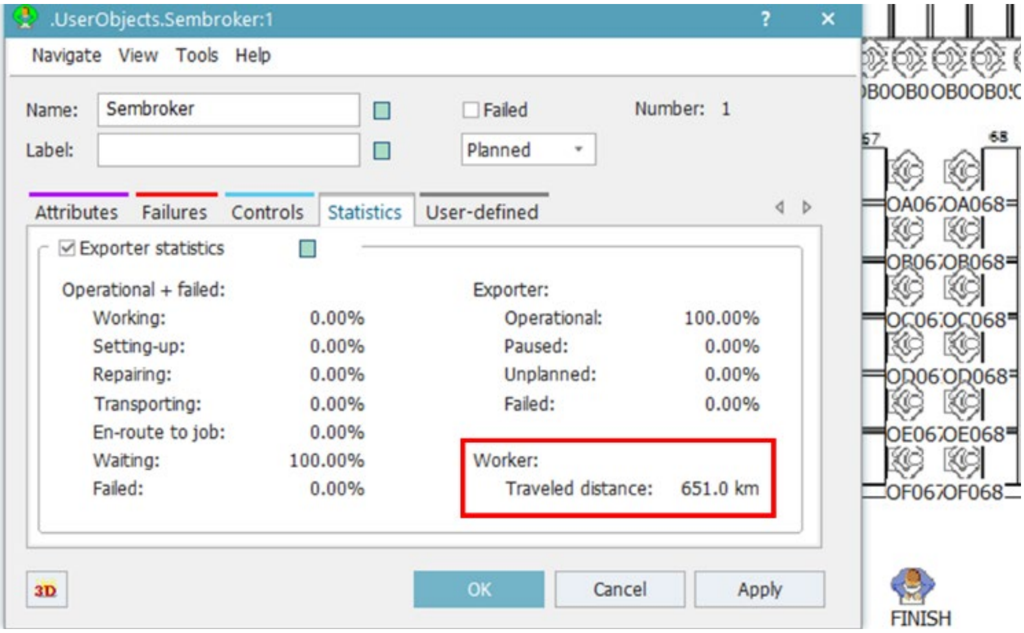

Fig. 10. Presentation of results

During this phase, the operative uses the newly prescribed collection route for gathering items. Notably, in certain instances, these routes may need to be more efficient, thereby accentuating the total distance covered by operators. However, such inefficiencies are rectified by applying the chosen optimisation methodology, simulated annealing (Fig. 9).

For both functions delineated above, the simulation model accords due consideration to the real-world dimensions of the warehouse.

Upon traversing all collection routes, the simulation model is primed to proffer a comprehensive exposition of the total distance covered (Fig. 10). Two distinct rounds of analysis are executed to facilitate a rigorous comparative evaluation. The initial round adheres to the original sequence of operations, whereas the subsequent round adopts the reordered sequence. The intent is to discern and evaluate operator dispositions to ascertain whether the new item collection sequence for orders exhibits superior efficiency.

2.2. Route study algorithm

The algorithm employed for route optimisation in this study has been founded upon the simulated annealing methodology, which was deliberately chosen due to its inherent capability to converge towards favourable outcomes efficiently. This method was selected for its agility, which renders it suitable for deployment in the routine operations of enterprises characterised by the picking process, and for its relatively straightforward implementation. Notably, alternative optimisation algorithms, including particle swarm and ant colony, were subjected to experimentation. However, the results could have been more attainable in one instance. At the same time, the feasibility of configuring the algorithm with the data and variables available for this study proved elusive.

The algorithm's initialisation phase encompasses the specification of control parameters pertinent to the simulated annealing method. These parameters contain the initial temperature, the final temperature, and the cooling rate. After parameter delineation, the algorithm necessitates inputting initial data elements. These comprise the extant collection sequence, the "from-to" distance matrix, and supplementary attributes germane to products associated with multiple pallet positions. Once these inputs are ascertained, the algorithm calculates the cumulative distance incurred by the initially proposed solution.

The subsequent phase embarks upon the operationalisation of the simulated annealing algorithm, a process contingent upon the current temperature surpassing the predefined final temperature threshold, serving as the algorithm's termination criterion. During this phase, permutations are systematically executed, substituting one item for another within the extant collection sequence. The objective is to evaluate prospective reductions in the total distance traversed by the assisting operators. Distance metrics are recalculated after each permutation, employing

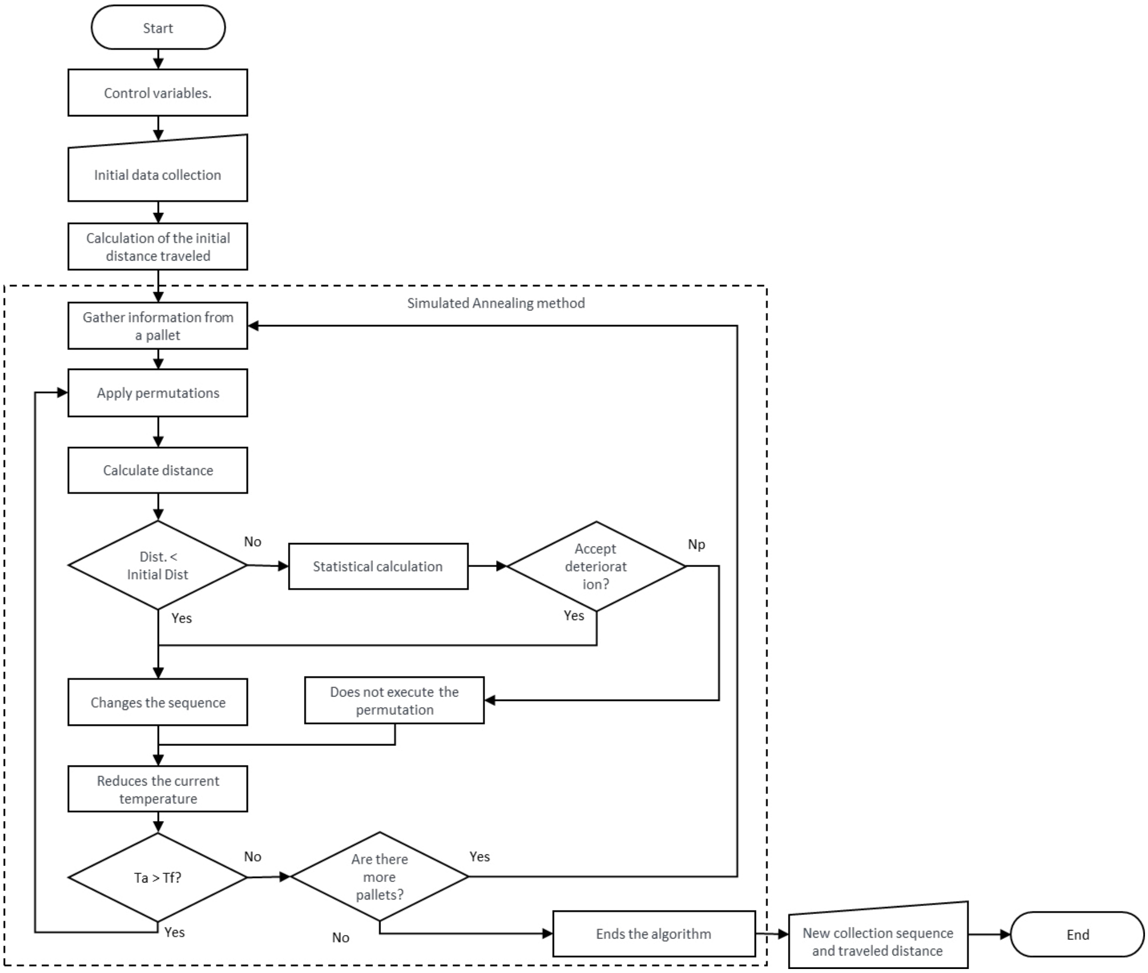

Fig. 11. Flowchart of the proposed algorithm's operation

the nearest neighbour rule as the heuristic measure. An alternative to the most immediate neighbour rule could have entailed deploying an exact method, the Traveling Salesman Problem algorithm. Other options include the heuristics (s-shape, return, mid-point, combined, and others), although they might not converge to an optimal result while needing little computational power to provide a solution. Furthermore, other meta-heuristics, such as tabu-search, genetic algorithm, and beehive, can be used to calculate and find a solution for this problem. This work used simulated annealing due to the difficulty of acquiring data from the actual picking zone, solving this by the "from-to" matrix acquired by the simulation model.

Nevertheless, this avenue should have been pursued, given the anticipated escalation in computational complexity. Consequently, computational expenses and processing timeframes could escalate to levels that preclude the practical application of this algorithm. This consideration is accentuated by selecting a compiled programming language, which tends to extend computational times. Importantly, it should be underscored that permutations are confined solely to items in the same pallet. This deliberate constraint safeguards against inadvertent allocations of products to orders for which they were not requisitioned.

Post-permutation distance calculations engender an assessment of disparities between the newly derived distance and the original benchmark. In cases where the recalculated space proves to be shorter than the original, the algorithm affects a substitution of the extant collection sequence with the revised variant. Embracing the core principles of simulated annealing, a statistical procedure presides over the determination of the acceptance or rejection of ostensibly suboptimal outcomes. This statistical regimen operates with the purpose of forestalling entrapment within local minima and facilitating the exploration of superior solutions. Consequently, even when the recalibrated distance exceeds the original metric, a consultation invokes a function adjudicating whether the revised value warrants acceptance as a valid response. This process promotes the formulation of a novel collection sequence.

After each iterative cycle, the algorithm orchestrates a systematic temperature reduction per the predefined cooling rate established at the inception of the algorithmic process. This modus operandi precipitates alterations within the item collection sequence encapsulated within the pertinent order. These permutations continue unabated until the temperature descends to a point below the stipulated final temperature or until the universe of potential swaps within the confines of the order or pallet becomes wholly exhausted. At this juncture, an evaluation is conducted to ascertain the existence of any residual unanalysed pallets. The procedural cycle iterates until no further pallets remain available for permutation. The outcome of this algorithmic endeavour furnishes a novel sequence for item collection, along with a precise calculation of the requisite distance for the execution of this collection itinerary.

Fig. 11 illustrates a comprehensive flowchart encapsulating the sequential operations executed by the proposed algorithm, meticulously aligning with the procedural description.

2.3. Integration of models

The fusion of the simulation model and the route optimisation algorithm through applying the simulated annealing methodology constitutes a crucial aspect of this research. This section outlines the procedural framework that governs this integration.

As depicted in Fig. 4, data flow within the proposed framework is structured as follows: the dataset provided by the organisation, encompassing the facility layout, inter-corridor distances, SKU allocation, and the existing collection sequence, serves as the external input for the route optimisation algorithm. The collection sequence forms the core of this algorithm, guiding simulated annealing-based reconfiguration. The remaining dataset elements are used in the simulation model. This model has a dual purpose. First, it constructs a "from-to" matrix, providing essential data for the route optimisation algorithm, which would be challenging to collect physically.

The route optimisation algorithm begins after receiving the necessary dataset (the "from-to" matrix, SKU positions, and collection order). It generates a new collection order and calculates the distance covered under this new sequence. The simulation model is then used to validate the results. The new collection order is inputted into the model to extract the distance covered. This allows for a comparison to assess whether the new collection sequence reduces the overall distance travelled by operators.

3. Research results

This section presents and discusses the results obtained through the methodology proposed in the previous chapter, which combines a simulation model and the simulated annealing algorithm. The simulation models were developed using Siemens's Plant Simulation software. The programming language used for the algorithm was Python. The choice of Python was based on prior familiarity with the language. The programming was implemented in Python version 3.8.4, adding the NumPy 1.19.0 library. Other libraries used were native to Python and did not require external additions; they were imported using standard Python commands. For instance, the "math" library contains complex mathematical functions, and the "threading" library allows for multithreading, a parallel computing technique that enhances the efficiency of tasks within the program.

3.1. Experimental design

Adopting a three-step approach necessitates consideration of distinct variables within each step, some of which may warrant more extensive analyses than others.

The experiment does not necessitate repetitive iterations in the initial step, involving the simulation model for data collection to construct the "from-to" matrix. This is attributed to the absence of factors capable of introducing variability. The model's function is straightforward, involving a systematic traversal of all positions without stochastic components to populate the requisite table for the subsequent phase.

Subsequently, applying the simulated annealing algorithm for route analysis introduces certain variables that can potentially enhance accuracy, albeit at the cost of heightened computational complexity and, concomitantly, increased computational time. In this experiment, the sole variable under scrutiny pertains to the cooling rate. Remarkably, the initial and final temperatures ($Ti = 1$ and $Tf = 0$) were main-

Tab. 1. Summary of simulated annealing results

Cooling Rate (C.R.)	Initial distance (km)	Reorganised distance (km)	Difference (km)	Difference (%)	Execution Time (h)
0.5	706.26	652.61	53.65	7.60%	0.7
0.9	706.26	649.13	57.13	8.09%	5.4
0.99	706.26	648.01	58.25	8.25%	46

Tab. 2. Results after execution in the simulation model

Cooling Rate (C.R.)	Initial distance (km)	Optimised distance (km)	Difference (km)	Difference (%)
0.5	705.68	655.05	50.63	7.17%
0.9	705.68	651.88	53.8	7.62%
0.99	705.68	651.01	54.67	7.75%

Tab. 3. Comparison between scenarios

Scenario	S.A. Distance (km)	Simulation Distance (km)	Difference (km)	Difference (%)
Initial	706.26	705.68	0.58	0.08%
C.R. = 0.5	652.61	655.05	2.44	0.37%
C.R. = 0.9	649.13	651.88	2.75	0.42%
C.R. = 0.99	648.01	651.01	3.00	0.46%

tained as constants throughout all executions. Three discrete cooling rates, empirically determined as 0.5, 0.9, and 0.99, were examined to ascertain the trade-off between computational runtime and the extent of achieved optimisation.

The inaugural algorithm run was executed with a cooling rate set at 0.5 to assess the feasibility of expedited convergence toward a solution. Given that this initial run successfully proposed a comprehensive reorganisation of all orders spanning a month of operational data within slightly over 48 minutes, it became evident that elevating the cooling rate was a plausible course of action. Subsequent experimentation with a cooling rate of 0.9 produced superior results but incurred a computational time expenditure of approximately five and a half hours. The culminating investigation entailed the application of a cooling rate of 0.99, the primary objective being to determine the degree of optimisation attainable, irrespective of computational time. This ultimate test endured for approx. 46 hours, yielding a further reduction of 0.2 % in the absolute distance traversed by workers in contrast to the preceding experiment.

The conclusive phase encompasses simulation activities to substantiate the outcomes derived from the newly prescribed collection order. In alignment with the previous steps, wherein variations were notably absent within the model designed for constructing the "from-to" matrix, the simulation results retained uniformity when comparing outcomes across the three separate testing iterations.

Initially, this methodology was applied to one of the units of a large beverage company, which provided data on pallet assembly, monthly orders, macro-layout distances, and product allocations. Table 1 summarises the results obtained from the route optimisation algorithm, showing the distance covered during the analysed period (one month), the difference between the initial and reorganised distances, and the execution time for different cooling rates.

For this studied warehouse, the simulated annealing algorithm resulted in a reduction of over 7.5 % in the total distance travelled by the operators. These values are now compared to the simulation model. Table 2 presents the results obtained after this execution, which indicate that using the sequence proposed with the lowest cooling rate would allow for a possible reduction of 7.17 % of the original distance, representing over 50 km of reduced distance travelled in a month.

Comparing the results obtained by both methods, it can be concluded that the application of the simulated annealing algorithm results in a reduction of the distance travelled. This reduction was validated by applying the suggested sequence in a simulation model, as there was no scenario with a difference greater than 0.5 %. The comparison between the results is shown in Table 3.

With low error rates when comparing the algorithm and the simulation model, along with results indicating a reduction in the total distance travelled, the simulated annealing algorithm is a viable option for application in this problem.

4. Analysis of the results

Three aspects warrant a discussion concerning the obtained results: execution time, the derived value and its significance, and the distinctiveness of individual warehouses.

4.1. Execution time

Significant variance in execution times occurred when modifying the cooling rate. The tool executed processes expeditiously for the lowest value (0.5), rendering results within an hour and employing a value of 0.9, which increased execution duration substantially, reaching around 5.5 hours. This remains acceptable given the algorithm's stochastic nature and tolerance for outcomes that marginally degrade performance. In contrast, the highest value (0.99) resulted in exponential runtime expansion, surpassing 45 hours. This extended duration resulted in a more significant number of iterations; however, it could have yielded more substantially improved results, with only a 0.2 % reduction in the total distance travelled.

In the context of the company's daily operations, using a cooling rate of 0.99 becomes unviable within the study's scope, encompassing a 30-day analysis. This is primarily due to the prolonged execution time of the employed methods. Conversely, the other two values demonstrate commendable performance while adhering to reasonable timeframes. This study analysed orders over a 26-day interval; nonetheless, optimal implementation of this methodology would entail daily algorithm runs to reconfigure routes designated by the WMS. This would ensure more efficient item collection operations daily. In such a scenario, execution times would remain within manageable limits compared to the prolonged durations of the present analysis.

Notably, these analyses were conducted using a computer with a seventh-generation Intel Core i7 processor and 16 gigabytes of RAM operating on the Windows 10 platform. Different computer configurations may yield divergent execution durations.

4.2. Findings

Considering the potential to reduce travel distance, thus reducing operating time, the method enables either reducing the number of operators, when technically possible, or increasing the capacity of the warehouse to provide and deliver orders and products.

In this case, the study revised about 15.3 thousand orders in a month timeframe. Considering the decrement of approx. 7 % of the distance, it would be possible to accommodate a demand of approx. 16.4 thousand orders.

Another crucial point to analyse is the issue of the area allocated for the picking sector. In this study, the picking sector had dimensions of 30 meters by 30 meters and the picking operation allocated nearly 250 pallet positions within the area.

In the examined warehouse, the picking department operates with 11 assistants, each responsible for approx. 9 % of the total distance travelled. The results may appear modest; nevertheless, they do not necessitate infrastructure investments and contribute to operational efficiency. This can ensure that the operation does not experience delays, colloquially referred to as "capote". Such delays occur when the process extends beyond the allocated timeframe, resulting in delayed departures of delivery vehicles. By implementing the proposed changes, all trucks can be loaded and ready to commence their routes in the morning. Furthermore, the reduction in the total distance travelled and a few other minor enhancements could reduce one operator, resulting in cost savings over a year.

Given that this company operates more than 100 distribution centres with picking operations, the impact of this tool's implementation across the network of warehouses could yield significant gains and substantial cost reductions, ultimately minimising wastage.

4.3. Warehouse-specific characteristics

Each distribution centre assumes responsibility for servicing a distinct region, subject to various factors like seasonality, localised marketing initiatives, negotiations with retail networks and partners, and several other variables. Consequently, each unit operates with varying average quantities of SKUs on the assembled pallets delivered to customers. In the case of the studied warehouse, this average is relatively low, as illustrated in Fig. 12, with an average of 7.21 different products on each pallet. This limitation reduces the potential for route exchanges and, subsequently, the reduction in distance. For instance, a pallet with only two different SKUs has only two route options: one "from A to B" and the other "from B to A". The larger the quantity of SKUs, the more

864442	**4**	**6**
P01_A_01_1/35	1	1
P01_M_01_1/35	1	1
P02_A_02_1/35	1	1
P02_M_02_1/35	1	3
864443	**38**	**295**
P02_A_02_1/42	4	42
P02_M_02_1/42	12	125
P03_A_03_1/42	15	63
P03_M_03_1/42	6	61
Z_Non_PALLETIZED_ITEM	1	4
864444	**56**	**377**
P01_A_01_1/42	12	85
P01_M_01_1/42	16	45
P02_A_02_1/42	4	9
P02_M_02_1/42	21	213
P03_A_03_1/42	1	12
P03_M_03_1/42	1	12
Z_Non_PALLETIZED_ITEM	1	1
864445	**28**	**185**
P01_A_01_1/42	1	20
P01_M_01_1/42	15	111
P02_A_02_1/42	3	3
P02_M_02_1/42	6	26
P03_A_03_1/42	1	12
P03_M_03_1/42	1	12
Z_Non_PALLETIZED_ITEM	1	1

Fig. 12. Dynamic orders

opportunities there are for algorithm-driven permutations, increasing the likelihood of finding shorter routes and significantly reducing the total distance.

Pallet assembly may involve more than 20 products in other distribution centres. In such cases, it is speculated that the benefits of employing the proposed methodology would yield even more significant results.

Conclusions

The methodology applied in this investigation has ascertained the feasibility of employing the simulated annealing algorithm within this context, reducing travel distance for operators. This inquiry was conducted at a distribution centre affiliated with a prominent beverage corporation in Brazil. A simulation model was adopted to obtain pertinent data about the spatial arrangement and the distances between each item's collection point to facilitate the algorithm's functionality. Furthermore, this model was deployed to authenticate that the alterations and computations enacted by simulated annealing led to a curtailment in the operators' traversal distance.

The examined warehouse manifests a scarcity of distinct SKUs per pallet, and the algorithm managed to effectuate a decrease of no less than 7.6 % in the traversed distance. In a warehouse characterised by a more heterogeneous assortment of orders and a larger volume of items, the benefits of this methodology could be more pronounced due to the augmented prospects for permutations in route sequences for each pallet.

The adoption of simulated annealing was substantiated by the diminishment in travel distances and the expeditious execution of computations within a relatively abbreviated time frame. A series of tests were administered to gauge the influence of the "cooling rate" parameter on distance reduction and execution duration. A modest value rendered results in under an hour, whereas a higher value necessitated more than five hours despite yielding considerably ameliorated outcomes. In a final test, the highest feasible value extended roughly 45 hours to converge towards a solution, delivering a mere 0.2 % enhancement compared to the antecedent scenario.

An additional salient consideration concerning the selected approach revolves around the impact of programming language choice on computational times. An expedited convergence could be attained by utilising a compiled language as opposed to an interpreted one, which was employed in this investigation.

The quantity of orders and assembled pallets can be considered a limitation of this study. Given the constraints of the current programming language, if it surpasses the quantity of orders presented in this study, it may take longer to converge. Another crucial point is acquiring real layout information from the picking area. If this process is inaccurately executed, it may compromise the accuracy of the findings.

In summary, the methodology advanced in this inquiry generates reductions in operator travel distances and exhibits versatility in its applicability across various distribution centres. This is contingent upon the availability of requisite data and input parameters.

Literature

Ardjmand, E., Sanei Bajgiran, O., & Youssef, E. (2019). Using list-based simulated annealing and genetic algorithm for order batching and picker routing in put wall-based picking systems. *Applied Soft Computing Journal*, *75*, 106-119.

Černý, V. (1985). Thermodynamical approach to the traveling salesperson problem: An efficient simulation algorithm. *Journal of Optimization Theory and Applications*, *45*(1), 41-51.

Chen, T. L., Cheng, C. Y., Chen, Y. Y., & Chan, L. K. (2015). An efficient hybrid algorithm for integrated order batching, sequencing, and routing problems. *International Journal of Production Economics*, *159*, 158-167.

Cheng, C. Y., Chen, Y. Y., Chen, T. L., & Yoo, J. J. W. (2015). Using a hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem. *International Journal of Production Economics*, *170*, 805-814.

Cortés, P., Gómez-Montoya, R. A., Muñuzuri, J., & Correa-Espinal, A. (2017). A tabu search approach to solving the picking routing problem for large- and medium-size distribution centers considering the availability of inventory and K heterogeneous material handling equipment. *Applied Soft Computing Journal*, *53*, 61-73.

De Koster, R., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, *182*(2), 481-501.

Diefenbach, H., & Glock, C. H. (2019). Ergonomic and economic optimization of layout and item assignment of a U-shaped order picking zone. *Computers and Industrial Engineering*, *138*, 106094.

Dijkstra, A. S., & Roodbergen, K. J. (2017). Exact route-length formulas and a storage location assignment heuristic for picker-to-parts warehouses. *Transportation Research Part E: Logistics and Transportation Review*, *102*, 38-59.

Fayyaz, Z., Mohammadian, N., Salimi, F., Fatima, A., Tabar, M. R. R., & Avanaki, M. R. N. (2018). Simulated annealing optimization in wavefront shaping controlled transmission. *Applied Optics*, *57*(21), 6233-6239.

Forbus, J. J., & Berleant, D. (2022). Discrete-Event Simulation in Healthcare Settings: A Review. *Modelling*, *3*, 417-433.

Grosse, E. H., Glock, C. H., & Neumann, W. P. (2017). Human factors in order picking: A content analysis of the literature. *International Journal of Production Research*, *55*(5), 1260-1276.

Hsieh, L. F., & Tsai, L. (2006). The optimum design of a warehouse system on order picking efficiency. *The International Journal of Advanced Manufacturing Technology*, *28*, 626-637.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, *220*(4598), 671-680.

Krajewski, L. J., & Ritzman, L. P. (2001). *Operations Management: strategy and analysis* (6th ed.). New Jersey: Prentice Hall.

Kulak, O., Sahin, Y., & Taner, M. E. (2012). Joint order batching and picker routing in single and multiple-cross-aisle warehouses using cluster-based tabu search algorithms. *Flexible Services and Manufacturing Journal*, *24*(1), 52-80.

Law, A. M. (2007). *Simulation Modeling and Analysis* (4th ed.). McGraw-Hill.

Law, A. M., & Kelton, W. D. (2000). *Simulation Modelling & Analysis* (3rd ed.). New York: McGraw-Hill Books.

Li, J., Huang, R., & Dai, J. B. (2017). Joint optimization of order batching and picker routing in the online retailer's warehouse in China. *International Journal of Production Research*, *55*(2), 447-461.

Lu, W., McFarlane, D., Giannikas, V., & Zhang, Q. (2016). An algorithm for dynamic order picking in warehouse operations. *European Journal of Operational Research*, *248*(1), 107-122.

Masae, M. (2020). *Developing efficient order picker routing policies in manual picker-to-parts order picking systems*. Darmstadt, Germany: Darmstadt Technical University.

Masaiek, M., Glock, C. H., & Grosse, E. H. (2019). Order picker routing in warehouses: A systematic literature review. *International Journal of Production Economics*, *224*, 107564.

Matusiak, M., de Koster, R., Kroon, L., & Saarinen, J. (2014). A fast-simulated annealing method for batching precedence-constrained customer orders in a warehouse. *European Journal of Operational Research*, *236*(3), 968-977.

McLean, C., & Leong, S. (2001). The expanding role of simulation in future manufacturing. *Proceedings of the 2001 Winter Simulation Conference*, 1478-1486.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. *The Journal of Chemical Physics*, *21*(6), 1087-1092.

Pegden, C. D., Shannon, R. E., & Sadowsky, R. (1990). *Introduction to simulation using SIMAN*. McGraw-Hill.

Pinedo, M. L. (2018). *Scheduling: Theory, algorithms, and systems* (5th ed.). Springer Cham.

Quader, S., & Castillo-Villar, K. K. (2018). Design of an enhanced multi-aisle order-picking system considering storage assignments and routing heuristics. *Robotics and Computer-Integrated Manufacturing*, *50*, 13-29.

Richards, G. (2018). *Warehouse Management: A Complete Guide to Improving Efficiency and Minimizing Costs in the Modern Warehouse* (3rd ed.). Kogan Page.

Sancakli, E., Dumlupınar, I., Akçın, A. O., Çınar, E., Geylani, I., & Düzgit, Z. (2022). Design of a routing algorithm for efficient order picking in a non-traditional rectangular warehouse layout. In N. M. Durakbasa & M. G. Gençyılmaz (Eds.), *Digitizing Production Systems* (pp. 73-83). Springer.

Shannon, R. E. (1998). Introduction to the art and science of simulation. *Winter Simulation Conference Proceedings*, 7-14.

Sibalija, T. V. (2018). Application of simulated annealing in process optimization: A review. In *Simulated Annealing: Introduction, Applications and Theory* (pp. 1–48). Nova Science Publishers.

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