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Original scientific paper

SIMULATION OF RE-ARRANGEMENT AND HEALING IN ROBOTIC COMPACT BIN-STORAGE SYSTEM

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Abstract
This paper proposes a simulation-based optimization method for the Robotic Compact Bin-Storage System (RCBSS). Storage Location Assignment Problem (SLAP) and Order Picking Problem (OPP) on the RCBSS are studied. Four different performance criteria are investigated in the re-arrangement and healing approach. These criteria are picking time, loading time, time spent for re-arrangement, and simulation duration. The simulation results show that the re-arrangement and healing approach effectively minimize the total cost and efficiency, and the designed algorithm efficiently solves the model. This study is expected to minimize the turnaround time, ordering delays, station occupancy time, and robot congestion. It also increases system throughput and customer satisfaction. The study results show that the re-arrangement approach provides much more favourable results for the RCBSS.

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Key Words: Robotic Compact Bin-Storage System, Order Picking, Re-arrangement, Simulation

1. INTRODUCTION

Warehouse management is an indispensable part of the circulation of goods in the production society, which also plays an important role in the company's economy. Compact storage systems (CSS) have been developed and improved in recent decades and are widely used. It is crucial for improving efficiency and reducing costs in terms of the appropriate allocation of the warehouse.

The Storage Location Assignment Problem (SLAP) is the problem of placing products in appropriate areas and regions within the warehouse. The placement of products within the warehouse affects the efficiency of warehouse operations. However, the most critical process in terms of cost is picking. The picking process is divided into picker-to-part and part-to-picker, depending on how the products or pickers move. The picker-to-part system delivers a specific product or product to the shipping area via corridors. There are many studies in the literature on how to increase the efficiency of pickers. With recent technological developments, we have seen the movement of products in warehouses. Pickers no longer have to walk around the warehouse looking for products. These systems, called part-to-picker, have become widespread in recent years.

The Order Picking Problem (OPP) is derived from the Traveling Salesman Problem (TSP) and is widely studied in the literature. At the picking station, the order picker picks from the destination shelf, while the robot that lifts the shelf returns to the storage point. Solutions of TSP and SLAP are both NP-hard models [1-3].

In recent years, it has been realized that the aisles used to transport products take up a significant amount of space in warehouses, leading to the development of compact systems in which the aisles are also used as storage areas. Compact storage studies have been handled and investigated over the last ten years. Compact system picking efficiency is higher than traditional picker-to-part systems, and space utilization is high. The CSS is competitive when limited warehouse space because it has no aisles and the best storage capacity.

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Companies are designing more compact warehouses as land costs in residential areas rise. Areas previously used as collector corridors are now used as storage areas when designing compact warehouses [4]. It allows for the utilization of a bigger portion of the warehouse as storage space. When choosing a product in these systems, it can be required first to allocate other products obstructing the exit. Various methods of compact storage systems are designed in the literature, including puzzle-based storage systems, live cube compact storage systems, and compact AS/RS [5].

The issue of stock allocation for the storage and retrieval of CSS has been extensively studied. Here are some examples of representative literature:

Yan et al. [6] described operational interaction between storage locations and stackers in terms of the typical storage kinds in AS/RS. Using simulation trials, they examined numerous elements that could affect the operational effectiveness of stackers and offered the idea of optimizing storage allocation compared to more conventional approaches. Frias et al. [7] aim to improve the efficiency and safety of the food storage process, and an analysis of storage layouts and storage area layouts is carried out. Gajšek et al. [8] examine productive work potential and protect order pickers from work-related musculoskeletal disorders. Laboratory experiments are used to determine recovery times for units with different characteristics and the required posture according to their revised NIOSH lifting equations guidelines. Ding et al. [9] transform the centralized procurement lot problem into a multi-objective optimization problem and use genetic algorithms to solve the multi-objective optimization problem to achieve Pareto optimality. Realize Reach between each buyer and supplier by creating a multi-objective optimization model with cost, quality, and logistics sub-objectives. Pan et al. [10] presented an approximation method and simulation model constructed with eM-plant software to compare the mean journey times for various warehouse allocation techniques inside a picking system. Chen et al. [11] created a discrete event simulation model to evaluate a CSS's effectiveness and energy usage. Both dedicated and shared storage techniques associated with random and zonal stacks were determined for single-SKUs and multi-SKUs, as well as for dedicated and shared storage indicators such as throughput, robot utilization, and energy consumption of the system. Tappia et al. [12] developed novel queueing network models to measure the performance of single and multi-level shuttle-based compact systems. The effectiveness of SBS/RS was assessed by Marchet et al. [13] in terms of lift and shuttle utilization, average turnaround time, waiting time, and overall cost. Lerher et al. [14, 15] presented a method and a parametric simulation model to estimate the throughput performance of SBS/RS. Re-arrangement or healing might be required if the demand for the stored goods changes over time. Re-arrangement of the warehouse might seem like a good idea, but moving just a few products will be less expensive than doing so entirely [16]. Re-arranging some things in the warehouse is a strategic choice because it alters their placement [17]. Christofides and Colloff [18] first studied the re-arrangement strategy in the warehouse.

Mostly, re-arrangement is performed when there is downtime or overtime [17]. Due to the high labour cost in traditional manual warehouses and despite the reduction in picking time, little work was found in the literature on this topic. Companies did not favour it as it increased picking costs. However, with the widespread use of technology in today's warehouses and the need to design more compact storage systems, the re-arrangement process's importance has increased, accompanied by a reduction in re-arrangement costs. In the past, the re-arrangement process in a warehouse required a picker to move the products to be transferred using forklift-like equipment [17]. However, nowadays, the products in a warehouse are moved with unmanned equipment such as cranes, lifts, or robots, so the cost of re-arrangement decreases. Since there are no aisles in compact warehouse systems, re-arrangement has become a greater necessity as one product has to be moved to pick up another.

According to the literature on this subject, a warehouse's design as a compact storage system significantly impacts the warehouse's lead time. A wide range of compact storage system types has been investigated in the literature by simulation [19]. The simulation analysis is used in our study to see the effects of re-arrangement on the RCBSS. Therefore, this study stands out among others in the literature.

This work presents a dynamic strategy to solve SLAP and OPP problems in compact storage systems using a re-arrangement or healing approach. Re-arrangement or healing approaches are tested in proposed simulations on different sample sets. This simulation compares the re-arrangement or healing approach to CSS. A series of examples demonstrate the design and assignment of storage. Performance comparison of different approaches is observed in real problems. This approach is tested according to various performance criteria.

2. SYSTEM DESCRIPTION

In this section, we first describe the RCBSS, then define the problem definition briefly after giving the main notation about both the system and the problem. Lastly, the assumptions of the study are explained.

2.1 The robotic compact bin-storage system

As seen in Fig. 1, robotic compact bin-storage systems (RCBSS) are warehouses with autonomous robots, bins, ports, and an information management system. Products are kept in bins carried by robots in these systems. Since the places where the robots move are also used for storage, and there are no specific aisles for their mobility, RCBSS are regarded as compact storage systems [20].

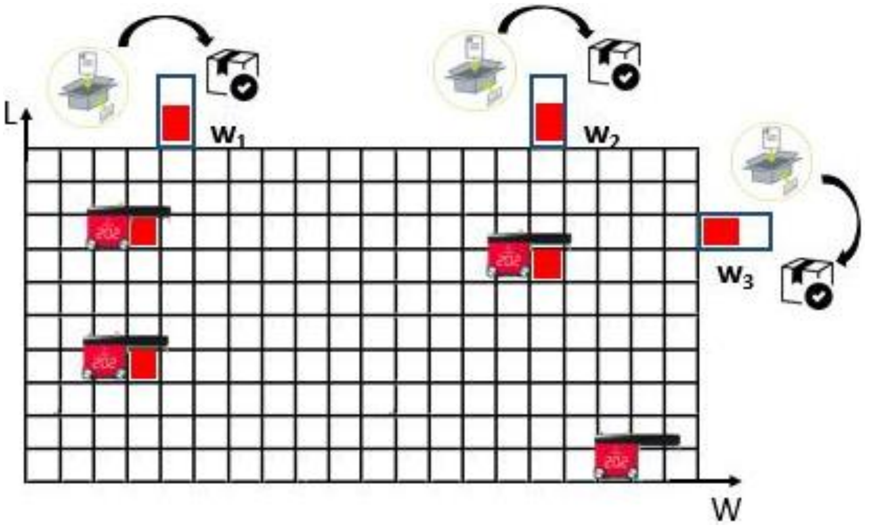

Figure 1: The robotic compact bin-storage system.

Robotic compact bin storage systems offer a variety of advantages. Compact storage facilities have no aisles, increasing efficiency by 40 % to 60 %. During operations like installation and expansion, product shipping might continue. By using robotic picking and storage, product loss is reduced. The work will be profitable for the company.

When constructing the robotic compact bin storage system, analysis approaches must determine some characteristics. The physical layout of the warehouse, the locations for deliveries and shipments, the number of robots, and the robots' movement.

2.2 Problem description

The issue of positioning goods in the proper regions and locations of a warehouse is referred to as the SLAP. In essence, warehouses have two categories of product addresses: fixed (dedicated) and shared addresses. Whether a product can be found in the warehouse or not, a shelf or cell is assigned to it in warehouses with fixed product addresses. This warehouse can be planned using mathematical models to minimize travel distances between products. Products A and B are kept in separate cells in warehouses where they share an address for a set period. In most RCBSS, various parts of the warehouse are utilized at various times to store various products. Assigning storage areas while considering the full variety of products is not a solution. This study examines the dynamic placement and shared storage of products in RCBSS throughout several periods. Such as picking time and loading time are computed.

2.3 Main notations

In RCBSS, the time required to transport a storage unit from a cell to the input/output (I/O) area and defined as T_p must be determined. The RCBSS robots, which have a rectangular prism-like shape, are placed in the top layer and can move in two directions. Part of the time it takes the robot to reach a cell is due to this horizontal movement. However, if the desired cell is in one of the lower layers, some time is needed to move the containment units to other cells. The time it takes a robot at the I/O point to reach a cell, retrieve a storage unit back to the I/O point, and return it to its initial location, i.e., the components of the T_{jkl} parameters should be thoroughly analysed. The symbols that mathematically represent the dynamics of RCBSS are listed in Table I with their descriptions.

Table I: RCBSS notations.

Notation	Description	Notation	Description
T_{jkl}	Time for the robot to move from a bin to its dwell point	h_b	Height of a bin
$T_{pick/retriev}$	Time for the robot to pick from its dwell point to the retrieval position	w_b	Width of a bin
$T_{horizontal}$	Time for the robot to move a bin on horizontal	l_b	Length of a bin
$T_{vertical}$	Time for the robot to move a bin on vertical	H	Height of the system
p_{hi}	The sequence of product i in the x-axis	W	Width of the system
p_{wi}	The sequence of product i in the y-axis	L	Length of the system
p_{li}	The sequence of product i in the z-axis	C	The capacity of the system
t_{lu}	Time for the lift to pick from its dwell point to the retrieval position	V_l	Speed of the lift
T_o	Time for the order to be picked completely	V_R	Speed of the robot
T_p	Time for the bin to be picked completely	n_R	Number of robots
$T_{d,R}$	Time for the robot to move from its idle point to its dwell point	P_p^{idle}	The probability that the robot is idle, $p = 1, 2, \ldots, n_R$
T_R	Time for the robot to dig a bin from its dwell point	n_w	Number of workstations
T_{R,w_i}	Time for the robot to move from its dwell point to the workstation	N_{hst}	The sequence of the top product in the x-axis
T_p^{rem}	Time for the man to pick up in workstation	N_{wst}	The sequence of the top product in the y-axis
W_{w_i}	Workstation idle time	N_{lst}	The sequence of the top product in the z-axis
W_R	The order waiting time in the queue	a_j	Required storage space for product j
D_i	Demand rate of product i by the number of bins per unit time		

System capacity:

$$C = HWL \tag{1}$$

Number of storage units kept in a column, width, and length:

$$N_{hst} = H/h_b \tag{2}$$

$$N_{wst} = W/w_b \tag{3}$$

$$N_{lst} = L/l_b \tag{4}$$

Time required for the robots to remove a storage unit from the lower layers:

$$T_R = \frac{(N_{hst} - p_{hi})h_b}{v_l} + t_{lu} \tag{5}$$

Time required for the robot to move from the idle point to the product pick-up point:

$$T_{d,R} = \frac{(N_{wst} - p_{wi})w_b}{v_R} + \frac{(N_{lst} - p_{li})l_b}{v_R} \tag{6}$$

The time it takes the robot to allocate the product from the pick-up point to its relevant workstation:

$$T_{R,w_i} = \frac{(\frac{N_{wst}}{2} - p_{wi})w_b}{v_R} + \frac{(N_{lst} - p_{li})l_b}{v_R} \tag{7}$$

The order completion time of a storage unit when the robot and workstation are available:

$$T_p = T_R + T_{d,R} + T_{R,w_i} + 2\ t_{lu} + T_p^{rem} \tag{8}$$

$$T_p = \frac{(N_{hst} - p_{hi})h_b}{v_l} + \frac{(N_{wst} - p_{wi})w_b}{v_R} + \frac{(N_{lst} - p_{li})l_b}{v_R} + \frac{(\frac{N_{wst}}{2} - p_{wi})w_b}{v_R} + \frac{(N_{lst} - p_{li})l_b}{v_R} + 2\ t_{lu} + T_p^{rem} \tag{9}$$

The order completion time of a storage unit when the robot and workstation are not available:

$$T_p = W_R + T_R + T_{d,R} + T_{R,w_i} + W_{w_i} + 2\ t_{lu} + T_p^{rem} \tag{10}$$

Order completion time:

$$T_o = \{T_p \quad n_R \quad a_j \quad P_p^{idle} \quad P_w^{idle}\} \tag{11}$$

Product frequency value (F_i); Caron et al. [21] proposed the above frequency calculation method in their study. At the same time, we define *x*, the ratio of the area required for a product to the total area, and the skewness value of the ABC demand curve.

$$F(x) = \frac{(1+s)x}{s+x}\ , F(x) \geq, x \leq 1\ and\ s + x \neq 0 \tag{12}$$

Picking frequency is obtained through the calculation of the frequency of the products collected in the order:

$$F_{pick} = \frac{Collection\ amount\ of\ product\ A}{Total\ amount\ of\ products\ to\ collect} \tag{13}$$

Loading frequency; is used in the storage allocation of products arriving at the warehouse in suitable locations; this parameter is related to the economic order quantities of the products.

$$F_{Load} = \frac{Amount\ of\ product\ A\ to\ load}{Total\ amount\ of\ products\ to\ Load\ x\ A_{EOQ}} \tag{14}$$

In detail, Chan and Chan [22], the use of parameters can be explored in depth. These parameters are the cube-per-order index (*COI*), the density-turnover index, the order rates or frequencies, the amount of turnover, the travel time or distance of the picker and the number of trips, and the patterns of order data. The *COI* parameter, defined by Heskett [23], was later widely used in the literature.

It was decided to use the following parameters according to the nature of the problem by examining the storage unit transport time, product frequency value, and volume parameters.

2.4 Assumptions

1. The time the storage unit spends at the workstation (T_p^{rem}) is considered constant.
2. Lift (V_l) and Robot speed (V_R) are considered constant.
3. The time taken to load/unload a storage unit from the lift (t_{lu}) is considered constant and equal.
4. The time required for an order (T_o) is the sum of the picking times of the storage units containing the products (T_p).

3. METHODS

3.1 Warehouse re-arrangement or healing

Re-arrangement and healing are different ways of reorganizing the warehouse. This study defines the healing approach as organizing 50 % of the warehouse. The re-arrangement problem was first defined as a traditional rectangular warehouse by Christofides and Colloff [18]. It was discovered that the labour required in the picking process accounted for a sizeable amount of the costs when the components that make up the picking costs in traditional warehouses were examined. Since picking is done automatically in the current generation of warehouses rather than by people, we think moving some products would be more cost-effective when the system is not in use. The decision was made to move the critical products rather than re-arrange the warehouse as a whole. An issue with route optimization is the movement of storage units without regard to the I/O point of the warehouse [17].

In a traditional warehouse, re-arrangement is planned in downtime or must be done over time. Therefore, re-arrangement in traditional manual warehouses can incur high labour costs. For this reason, this strategy was abandoned in the literature half a century ago. However, with the widespread use of technology in today's warehouses and the need to design more compact storage systems, the re-arrangement process has increased, accompanied by a reduction in re-arrangement costs. In the past, the re-arrangement process in the warehouse required a picker to move the products relocated with forklift-like equipment. However, as the products in a warehouse are moved with unmanned equipment such as cranes, lifts, or robots, re-arrangement costs have decreased. Since there are no corridors in compact warehouse systems, re-arrangement has become necessary as one product has to be moved to pick up another [16].

3.2 Simulation

Simulation is an operational model of an existing or proposed system and provides decision support by testing different scenarios or process changes. This can be coupled with virtual reality technologies to create a more immersive experience.

The simulation-based optimization method is applied annually for random examples in two scenarios. These scenarios are re-arrangement and healing. A part of the re-arrangement is named healing in warehouses. A simulation-based methodology is used to determine the optimal re-arrangement process for a warehouse layout, considering various performance criteria.

The data in this study is for Business to Business (B2B) online retail for one year, covering 38 different countries and providing services to more than 5000 customers. The raw data is analysed, and the confounding factors are systematically removed.

The first objective of this research is to develop a simulation framework for modelling, analysing, and testing warehouses. The framework will provide a tool to evaluate and compare the performance metrics of alternative re-arrangement strategies. The conceptual framework consists of a central simulation modelling component that accepts input data based on the system under consideration and allows experiments with a set of decision variables shown in Fig. 2. This framework aims to create a generalized technique company can use during the warehouse design process to determine and identify the optimal re-arrangement level.

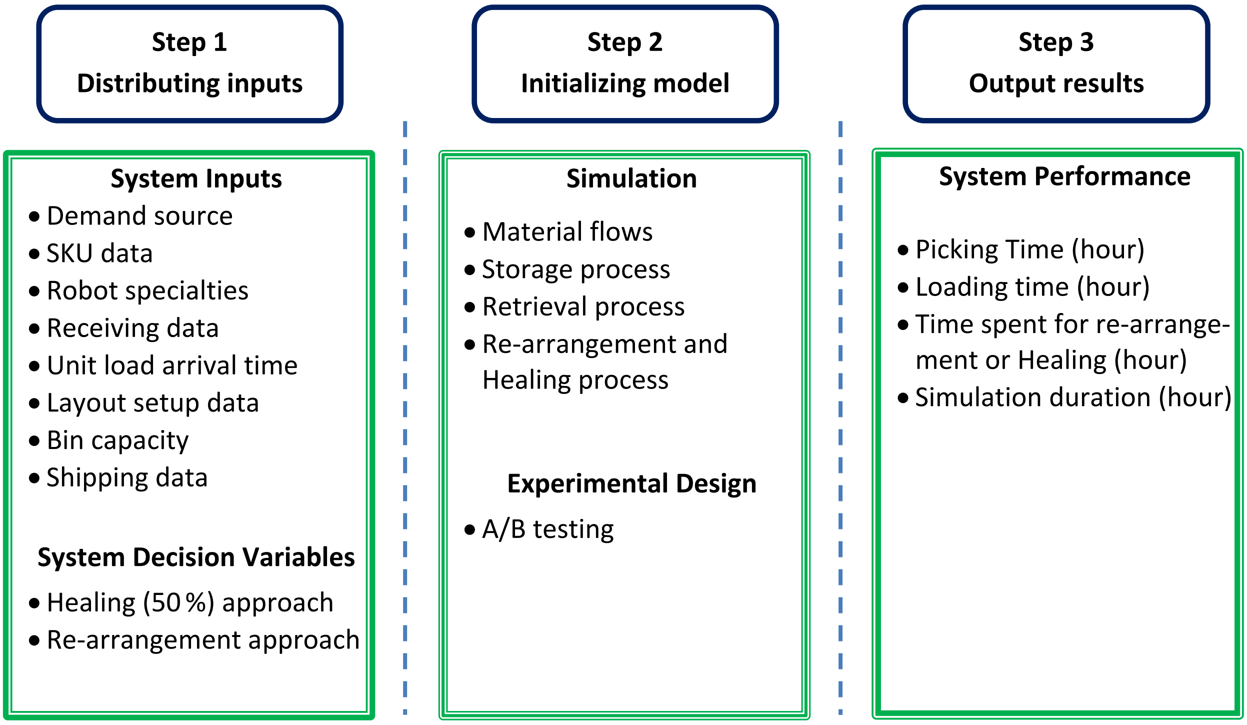

Figure 2. Warehouse simulation model.

This section introduces and explains the framework for warehouse simulation and analysis. The framework aims to develop a data-driven model and generalized simulation techniques that can be used to analyse re-arrangement levels for different system inputs and decision variables.

4. COMPUTATIONAL RESULTS

We analyse the re-arrangement process with the help of a simulation concerning various criteria for increasing warehouse efficiency. These criteria are picking time, the time required for re-arrangement, loading time, and simulation duration. The simulation results with the different data sets are shown in Table II. Each data set consists of the average number of products and the SKUs in order at the same time.

The total distance travelled by the robots while picking up the orders in the system is called the picking time (hour). The distance travelled during the transport of the products in the system to the places where they are to be found is called time spent for re-arrangement (hour). The distance travelled when the products arrive in the warehouse to the corresponding places is called loading time (hour). The total distance travelled in these three processes is called simulation time (hour). In any given data set, the sum of the three performance criteria in terms of healing and re-arrangement will give the value of the simulation duration.

The picking time criteria range from 125 to 309 hours with the existing approach. However, with the re-arrangement, the picking time is reduced to 104 and 218 hours. The re-arrangement or healing reduces the time for picking – nevertheless, the time required for re-arrangement or healing increases in the simulation. Therefore, simulation time is an appropriate performance criterion for the system under study. The simulation time is also reduced by re-arrangement or healing.

The time spent for re-arrangement or healing time is 10.1 hours – 38.9 hours. When the healing approach is applied so that only the robots re-arrange some parts of the warehouse, the time spent for re-arrangement time decreases to 5.6 hours and 25.7 hours.

The loading time increases when the re-arrangement approach is applied to the warehouse. Since the re-arrangement approach transports the empty slots to the backyard of the warehouse, there is a better settlement for picking in the warehouse when the re-arrangement approach is applied to the warehouse. Loading time is a very important performance criterion because if an order picker is waiting for a product to arrive at its place, this affects the efficiency of the entire system. Some parts of the warehouse can be re-arranged according to working time constraints. The results are summarised in Table II.

Table II: Computational results.

		Set 1	**Set 2**	**Set 3**	**Set 4**	**Set 5**	**Set 6**	**Set 7**	**Set 8**	**Set 9**	**Set 10**
The part number in an order		127	113	172	141	158	161	142	132	175	143.8
The SKU number in an order		21.2	13.4	30.1	27.6	32.5	31.8	26.6	27.5	45.1	36.2
Picking time (hour)	Existing	168	125	147	188	293	215	182	187	309	247.3
	50 % (Healing)	155	108	126	163	233	171	136	142	234	174.6
	100 % (Re-arr.)	149	104	118	156	208	165	128	137	218	178.2
Loading time (hour)	Existing	128	137	143	150	150	149	151	170	166	185.5
	50 % (Healing)	128	139	146	154	156	156	161	184	181	204.8
	100 % (Re-arr.)	129	139	147	157	159	161	166	190	189	214.4
Time spent for re-arrangement or healing (hour)	50 % (Healing)	5.6	6.5	8.8	11.3	21.1	16.5	14.2	15.7	25.7	20.6
	100 % (Re-arr.)	10.1	10.6	14.1	15.2	38.9	21.7	22.4	20.6	37.2	26.4
Simulation duration (hour)	Existing	296	262	290	338	443	364	333	357	475	432.7
	50 % (Healing)	289	254	281	329	410	344	311	341	441	400
	100 % (Re-arr.)	288	254	279	328	406	348	317	348	444	419

To verify our analytical model, a simulation platform was developed in Matlab on a computer equipped with an Intel$^{(R)}$ Core $^{(TM)}$ i5-9300H CPU @ 2.40 GHz and 8GB of RAM, with the Windows 10 Professional OS. We conduct several numerical experiments to explore the performance of RCBSS.

An analytical technique for contrasting two or more versions, such as versions A and B, is A/B testing. It assesses whether any difference between the two versions is statistically significant and which version performs well.

As companies operate in this way today, they need to adopt a data-driven strategy. A common problem for businesses is that they think they understand their customers but behave differently than you might suspect. Users often act without knowing why they are doing it. However, something unexpected may be discovered when an experiment or A/B test is conducted. The results are often startling, and customers may behave differently than you predict. Therefore, it is better to run tests than rely on intuition. For example, two different landing pages or two different marketing or web design newsletters could be compared. Then half of the visitors will see the original version of the page (called the control), while the other half will see the updated version (the variation).

Four distinct criteria – referred to as performance criteria in Table II – were examined in this work. The re-arrangement strategy was the variation group, and the current approach served as the control group. If the variant is successful, a new A/B test will be run using a new healing variant. The outcomes are repeated 20 times in our real-world scenario, and the average values are presented.

H_0 : There is no difference between the existing and re-arrangements approaches.

H_1 : There is a significant difference between the existing and re-arrangements approaches.

$p < 0.001$ is considered significant in hypothesis testing at a 95 % significance level. There is, therefore, enough evidence to disprove hypothesis H_0 and accept hypothesis H_1. The test shows that the simulation study's findings are statistically significantly different. Making practical decisions is possible with A/B testing. The re-arrangement strategy has not gained popularity throughout the past fifty years. From a budgetary standpoint, this strategy was previously impractical. The re-arrangement strategy is much more practical now, thanks to recent technological advancements from both a cost and client pleasure standpoint.

5. CONCLUSION

This study presents a dynamic strategy to solve the problems of SLAP and OPP in a compact storage system using a re-arrangement or healing approach. The re-arrangement and healing approaches are tested with a proposed simulation on different example sets. The simulation comparing re-arrangement and the healing approach on CSS is proposed. A series of examples illustrated the design and assignment of a storage and re-arrangement model. The performance comparison of the different approaches is observed on a real problem.

The approach is tested according to different performance criteria. One of the important criteria simulation duration is always reduced by re-arrangement or healing. So, re-arrangement and healing should be planned whenever there is an opportunity in the working plan.

Consequently, the re-arrangement and healing approach is tested on different example sets using the proposed simulation method, and the results are statistically proven. This study minimizes throughput time, order delays, busy time of stations, and robot congestion. Moreover, system throughput and customer satisfaction are increased. We are planning that the re-arrangement approach can be applied to different compact storage systems as a future study.

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