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A Simulation Hyper-heuristic Method for Multi-floor AGV Delivery Services in Hospitals

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Abstract*—Automated Guided Vehicles (AGVs) enhance transportation efficiency in different domains such as warehouses, factories, and container ports. Much research has been done into optimal scheduling and routing of multiple AGVs to improve the overall efficiency of the systems. However, more research efforts are required when addressing more complex real-life systems where the mobility of AGVs is highly constrained due to special geometric shapes and dimensions. Focusing on a real-world hospital AGV routing problem, this paper tackles the additional complexity arising from space capacity constraints long narrow corridors and lifts for cross-floor deliveries. A simulation optimisation approach is introduced to accurately model complex interactions of AGVs under conditions like floor switching, charging, and passing narrow corridors. To tackle the underlining vehicle routing problems with pickup and delivery (VRPPD) which is NP-Hard, this paper presents a simulation-based hyper-heuristic optimization approach to minimize the makespan of all tasks. A surrogate model is integrated to expedite the search process, and several experiments are conducted to properly evaluate the performance of our method. Based on the results, our method exhibits great potential in improving efficiency while maintaining the excellent practicality of AGV routing for complex environments like hospitals.

***Index Terms*—simulation-based optimization, hyper-heuristic, pickup and delivery problem, multi-floor AGV routing, AGV congestion.**

I. Introduction

Automated Guided Vehicles (AGVs) have emerged as one of the front-runners in the automation landscape, with applications spanning a wide spectrum of industries, from manufacturing floors to container ports [1]. As artificial intelligence technology continues its rapid progression, the application of AGVs in these domains is no longer just an innovation but an imperative. Among the myriad of fields benefiting from AGVs, hospitals stand out as a particularly salient application area [2]. In such a critical environment, the introduction of AGVs has the potential to revolutionize operations, presenting a multitude of benefits such as enhanced healthcare services, heightened safety and cleanliness standards, cost reductions, and end-to-end traceability of operations.

The advantages offered by AGVs are hard to overstate. In hospitals, where promptness and precision are paramount, AGVs can ensure timely transportation of vital equipment, medications, test samples, meals, and other essential items. This predictability not only enhances operational efficiency but also contributes to improved patient care [3]. As a consequence, an increasing number of healthcare facilities are integrating AGVs into their logistical framework.

However, the incorporation of AGVs into the multifaceted infrastructure of hospitals presents distinct challenges. The nuanced architecture of hospitals, characterized by their diverse departments, varied floor levels, and specialized units, poses intricate dilemmas for AGV scheduling. Conventional routing techniques, including the first-come-first-serve-based shortest-path algorithms, may exhibit efficacy in more straightforward environments but are insufficient in guaranteeing quality AGV functionality within hospital settings where narrow corridors and capacity-constrained lifts could cause AGV deadlocks and long queues. Our modeling experiments highlight the limitations of these traditional methodologies, suggesting a notable decline in AGV operational efficiency when implemented in the context of a hospital's intricate framework.

In light of the complexities associated with AGV routing in hospitals, this paper undertakes a rigorous examination of the underlying challenges. Firstly, we introduce and elaborate on simulation hyper-heuristic-based optimization methodologies. Central to our innovative contributions is the development of a novel simulation model for hospital AGV routing, which explicitly accounts for nuances such as elevator lift usage, inter-floor transitions, and AGV charging considerations. Furthermore, we assess the efficacy of diverse AGV scheduling techniques, along with their interactions within confined spaces. In response to these observations, we introduce a surrogate-based hyper-heuristic approach for AGV routing. Lastly, we present comparative analyses between conventional routing strategies

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and our proposed method, offering compelling evidence of the superior efficacy of our hyper-heuristic approach for real-life applications in hospitals.

The rest of this paper is organized as follows. Section II presents a review of related works and provides background information on the hospital AGV routing problem. Section III introduces and formulates this hospital AGV routing problem. The proposed hyper-heuristic-based method is delineated in Section IV. Section V presents the experimental results. Finally, conclusions are drawn in Section VI.

II. Background and Literature Review

The landscape of AGVs has undergone significant transformation over the years. From their humble beginnings as rudimentary guided vehicles, AGVs have transitioned into sophisticated systems equipped with advanced functionalities. Their ubiquity across various sectors, ranging from manufacturing [4], [5] to container terminals [6], [7]. With the growing emphasis on efficiency and automation in healthcare, AGVs are now being considered integral components within hospital infrastructures. Several studies have underlined their potential in such specialized settings, elucidating how they address the unique operational challenges innate to healthcare environments [3].

Traditional AGV routing mechanisms, particularly the First-Come-First-Served (FCFS) approach and the Shortest-Path algorithm, have long been the cornerstone of AGV deployment strategies [8]. While these methodologies have showcased efficacy in relatively straightforward contexts, their limitations become pronounced in more complex terrains. Specifically, when applied within the intricate maze of hospital infrastructures, these conventional strategies often fail to deliver optimal outcomes [9].

Hospitals, with their varied departments, multiple floor transitions, and the exigencies of patient care, present a set of challenges that are seldom encountered in typical industrial applications of AGVs. The challenges associated with elevator lift coordination and floor transitioning have been a recurrent theme in the existing literature, with several researchers emphasizing their impact on AGV routing efficiency [8]. Compounding these challenges is the critical aspect of AGV charging. Given the round-the-clock operational demands typical of hospitals, ensuring the uninterrupted functioning of AGVs without compromising on their routing efficiency is a conundrum that has been touched upon in recent studies [10].

The introduction of hyper-heuristic optimization [11] techniques has opened new avenues in AGV scheduling. These methods, characterized by their inherent adaptability and the amalgamation of diverse heuristics, are increasingly being recognized for their suitability in addressing non-traditional challenges. There have been inklings in the literature hinting at the potential of these techniques for AGV scheduling in hospitals, but a comprehensive exploration of this niche remains conspicuously absent.

Simulation, as a tool for research, has steadily gained traction in the realm of AGVs. By crafting realistic replications of real-world scenarios, simulation models facilitate a more nuanced evaluation of AGV routing strategies. Such empirical frameworks offer researchers a controlled setting to rigorously test the boundaries of proposed methodologies, thereby honing their applicability and efficiency [12].

Given this backdrop, the current study endeavors to bridge the gaps identified in the extant literature. Our emphasis is not merely on the articulation of a novel hyper-heuristic method for hospital AGV routing but extends to its empirical validation through an intricate simulation model that captures the multifaceted nature of hospital environments.

III. Problem Formulation

A. Problem Description

The real-world challenge considered in this paper is a combinatorial optimization problem of multi-AGV routing within an involved hospital environment, which can be conceptualized as a multi-depot Vehicle Routing Problem with Pickup and Delivery (VRPPD) with additional constraints. A multi-depot AGV fleet is employed to transport vital materials, including blood samples and medicines, across various hospital departments and wards. For hygiene reasons, each AGV must complete the current delivery before proceeding to the origin of the subsequent task. All these delivery tasks preplaced by medical staff are conducted every morning, which transforms the problem into an offline optimization challenge. This scenario provides an opportunity to compute a high-quality solution in advance without being constrained by tight computational time.

Due to hygiene requirements, the current setting of our problem permits one order per each AGV delivery, as illustrated in Figure 1. Conceptually, if we abstract each delivery task as a node, this problem can be modeled as a multi-vehicle Travel Salesman Problem (m-TSP). However, this way of modeling does not help solve the problem because the complex interactions between AGVs in congested areas are overlooked and therefore existing m-TSP methods are not directly applicable.

The battery level of the AGV is affected by the distance it has traveled, therefore planning AGV charging is crucial to ensure the AGV completes the tasks as expected. The temporal cost for charging tasks is determined by the battery status, which is affected by the trip distance.

In addition, within a complex hospital encompassing multiple floors, we must take time cost into account as well. Given fluctuating delivery requests across different floors, lifts become an indispensable and expensive resource to transport AGVs vertically, which often leads to congestion and queues. Moreover, some narrow corridors in the hospital accommodate only one AGV at a time, forcing other AGVs going through a same corridor to wait outside these corridors. In such instances, the travel cost is no longer measured by distance only. Factors such as waiting time for lifts, duration for charging, and time spent in congested areas must be integrated into the overall cost calculation within the hospital VRPPD, as shown in Figure 2. Considering these complexities, we propose to use agent-based simulation to model the problem, as opposed to relying on mathematical models which would be exceedingly challenging (if not impossible) to accurately formulate the problem.

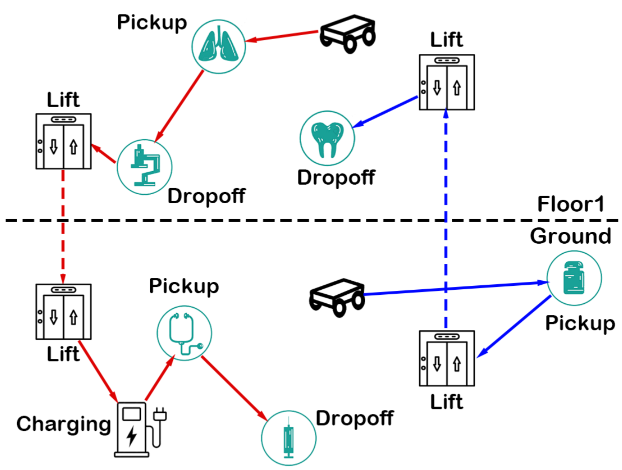

Fig. 1. An overview of the AGV Pickup and Delivery Problem with floor switching and charging in hospitals.

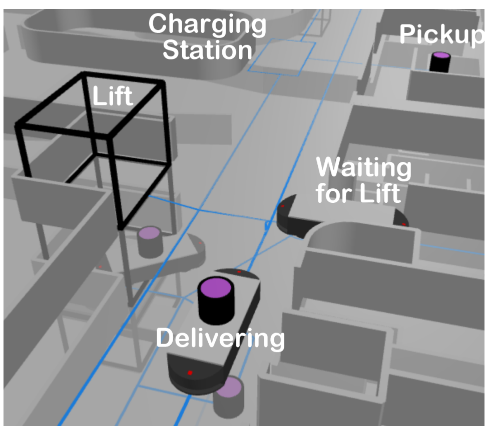

Fig. 2. The 3D view of the simulation model of the AGV Pickup and Delivery Problem with floor switching and charging in hospitals, captured in AnyLogic.

B. Encoding and Representations

The problem considered in this paper can be formally abstracted as follows. The system consists of an undirected graph denoted as $G = (V \cup D, E)$ and a collection of delivery orders, denoted as O [13]. V is the set of physical locations, including the origins and destinations of all orders, AGV charging stations as well as the depots on each floor. The set of edges E encodes the connections between different nodes in V by traveling agents set A. Therefore, graph G serves as the guide-path network for AGV agents, denoted as A.

We denote vertex set D to be `charging` or `depot` locations for AGVs. Each order $o \in O$ has an origin (designated as $s \in V$) and a corresponding destination (denoted by $e \in V$). The paper adopts an integer-based and multi-chromosome representation to encode the order sequence due to the steady performance of the multi-chromosome encoding strategy in routing problems [14]. Given a total of n delivery orders and a fleet containing m AGVs, the solution is a m-list permutations denoted as π, each list sketching the order execution sequence of each AGV. Formally, a solution to our problem can be encoded as a set $S = S_1, S_2, \dots, S_m$, where each $S_i, i = 1, ..., m$ represents an ordered sequence of orders to be completed by AGV i.

C. Objective Function

The distance measurement of traditional VRPPD can be transformed to time cost given an average AGV speed v_{avg} such that objectives can incorporate lift waiting, charging, and congestion-related time costs. Therefore, the objective of our problem is to minimize the makespan of all delivery orders, which represents the time from the start to the completion of the final order. For a given solution $< S_1, \dots, S_i, \dots, S_m >$, the objective function jointly considers sequence-dependent setup times, s_{jk}, between order $order_j$ and $order_k$, the processing time of $order_j$ assigned to agent a_i (denoted as p_{ij}) to compute the completion time C_{max}. Since both the setup time and the processing time involve possible lift waiting and congestion time, we rely on our simulation for the objective evaluations, as opposed to analytical functions which are difficult to compute.

D. Constraints

There are several constraints that must be satisfied to ensure the feasibility of individual solutions. First, the union of the AGv task lists satisfies $\uplus S_i = O$, ensuring complete coverage of all orders and the intersection of the subsets remains disjoint, symbolized by $S_1 \cap S_2 \cdots \cap S_i = \phi$, underscoring the exclusive execution of orders by individual AGVs. Another constraint is the capacity limit of lifts and narrow corridors, which are implemented as hard constraints in our simulation, forcing AGVs that require these bottleneck resources to wait their turn in a queue until the resources become available.

IV. METHODOLOGY

This section describes our integrated solution framework that encompasses both a simulation model and a hyper-heuristic approach, utilized as the objective evaluator and solution optimizer for our problem. A surrogate model is also used to expedite the convergence of the iterative hyper-heuristic method.

A. Simulation Model

The creation of a simulation model is essential to emulate the everyday logistics operations within the hospital, including AGV operations, lift usage, charging, and the potential occurrence of congestion. As representing congestion arising from lifts or narrow corridors in a mathematical format is exceedingly difficult, simulation offers an alternative approach to model this complex VRPPD scenario and evaluate the quality of candidate solutions. By representing the mathematically intricate VRPPD constraints through an agent-based simulation, the simulator can provide the predicted behavior of this system based on different inputs. Our simulation, built in the state-of-the-art simulation suite, AnyLogic, requires three key inputs: AGV fleet size, orders, and a permutation of order execution sequence. As the simulation is stochastic, the objective function must be estimated using the statistical estimation API of this simulator rather than a human-readable formula. Given the simulation's complexity, the objective function becomes difficult and expensive to evaluate. To attain optimal solutions with minimum cost, a well-designed heuristic method with rapid convergence is indispensable as a simulation-based optimization approach. For this reason, we chose to use a hyper-heuristic method, which we describe in the next sub-section.

B. Modified Choice Function and Simulated Annealing Hyper-heuristic

This section describes the implementation details of a modified choice function-based hyper-heuristic method with simulated annealing (MSHH), inspired by works in [15], [16]. Our hyper-heuristic adopts a modified choice function, a tabu mechanism, and simulated annealing in the hyper-level. The choice function is a heuristic selection approach, donated as F, which scores heuristics based on three different measures and picks the best heuristic to apply. In each iteration, every low-level operator is evaluated based on its previous performance, cooperating performance with the last operator and the eclipsed duration since the last call. We donate the score of each heuristic j as h_j and the calculation function as f.

$$F_t(h_j) = \phi_t f_1(h_j) + \phi_t f_2(h_k, h_j) + \delta_t f_3(h_j) \tag{1}$$

Each parameter in this choice function at iteration t is parameterized with ϕ and δ which are set as follows:

$$\phi_t = \begin{cases} 0.99 & \text{if quality improves} \\ max\{\phi_{t-1} - 0.01, 0.01\} & \text{otherwise} \end{cases} \tag{2}$$

$$\delta_t = 1 - \phi_t \tag{3}$$

Besides, a tabu-list is added to prevent this selection function from repeatedly selecting certain low-level heuristics.Simulated annealing with a geometric cooling schedule and reheating strategy is used as the move acceptance method for this approach. As the temperature T decreases from a high level, the probability of accepting worsening moves decreases. While the search gets stuck at a poor local optimum, the reheating is triggered to increase the temperature at a certain level and a ruin-recreate heuristic is applied. Algorithm 1 describes the main steps of MSHH.

Low-Level operators used in this heuristic to find neighborhood solutions are maintained as same as all neighborhoods in VNS. All low-level operators are parameterized with IOM (Intensity of Mutation) or DOS (Depth of Search).

1) Random Bit Insertion and Deletion: This mutational heuristic randomly chooses a bit and then inserts this task into a task list randomly.

Algorithm 1 MSHH

```
s ← initialSolution
T ← θ          // initialize temperature
ChoiceFunction ← lowlevelOperatorList
while time limit not exceeded do
  operator ← ChoiceFunction.getBestOperator()
  if needs reheating then
    operator ← ruin-recreate, T ← θ
  end if
  s′ ← s.apply(operator)
  Δ ← Simulate(s′) − Simulate(s)
  ChoiceFunction.updateOperatorScore(Δ)
  if Δ < 0 or rand(0,1) < e^(−Δ/T) then
    s ← s′
  end if
  T ← coolTemerature(T)
end while
```

2) Inner 2-opt Swap: Two bits are randomly chosen from a task list associated with a single AGV, and their values are swapped. This action effectively alters the sequence of node visits for delivery within a single AGV.

3) Outer 2-opt Swap: This mutational heuristic selects two bits from two distinct AGVs and exchanges their values, effectively swapping a task from one AGV with a task from another.

4) Best Bit Insertion and Deletion: In this heuristic, a bit is randomly chosen, and the corresponding task is inserted into a random task list. Meanwhile, an exploiting search is conducted within the task list to find the optimal insertion position for the selected task.

5) Ruin and Recreate: This algorithm randomly designates a subset of solution variables to be reset to random values. The number of ruined variables affected is determined by the IOM parameter.

6) First Gradient Hill Climbing: This local search technique employs a random 2-opt swap operator. The process halts after encountering several improvements or no improvement for a long time, ensuring the search remains focused on rapidly optimizing solutions.

C. Surrogate Assisted MSHH

Our MSHH relies on expensive simulation to evaluate solutions. To speed up the algorithm, we introduce a surrogate model (denoting the new algorithm as SMSHH, see 2). SMSHH aims to reduce the computational burden of simulator evaluations during the search [17]. Instead, the surrogate employs a simplified road network extracted from complex scenarios to evaluate solutions with a certain degree of inaccuracy. The core idea is to employ an assistant evaluator that widens the step size from a solution to its neighborhood without ignoring potential improvements. Each solution undergoes k iterations using a surrogate model before being applied to our simulation, which accelerates the exploitation process by a factor of nearly k. Though the surrogate model may not be completely accurate and may miss some good-quality solutions, it effectively filters out most poor-quality solutions. The structure of the algorithm is shown in Figure 3.

Regarding the internal structure of the surrogate model, the distance between edges is easy to model in our implementation. However, complex factors such as lift waiting times and random congestion can only be provided by simulation. Therefore, we used a statistical approach to obtain the mean value as a static threshold. For instance, any AGV traversing these specialized nodes and lifts is subjected to an average penalty value associated with these nodes and lifts.

This hybrid approach retains the core mechanisms of MSHH while introducing agent-guided decision-making to simplify the optimization process, allowing for more efficient and faster exploration of the solution space.

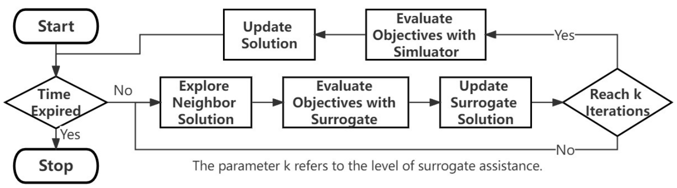

Fig. 3. The framework of proposed surrogate-assisted (hyper-)heuristic

Algorithm 2 SMSHH

$s \leftarrow initialSolution,\ s_s \leftarrow surrogateSolution$
$ChoiceFunction \leftarrow lowlevelOperatorList,\ T \leftarrow \theta$
while time limit not exceeded **do**
  for each surrogate episode **do**
    $operator \leftarrow ChoiceFunction.getBestOperator()$
    $s' \leftarrow s_s.apply(operator)$
    $\Delta \leftarrow Surrogate(s') - Surrogate(s_s)$
    $ChoiceFunction.updateOperatorScore(\Delta)$
    if $\Delta < 0$ **or** $rand(0,1) < e^{\frac{-\Delta}{T}}$ **then**
      $s_s \leftarrow s'$
    end if
    $T \leftarrow coolTemerature(T)$
  end for
  $\Delta \leftarrow Simulate(s_s) - Simulate(s)$
  if $\Delta < 0$ **or** $rand(0,1) < e^{\frac{-\Delta}{T}}$ **then**
    $s \leftarrow s_s$
  else
    $s_s \leftarrow s$ // reject
  end if
  $T \leftarrow coolTemerature(T)$
  if needs reheating **then**
    $s.apply($ruin-recreate$),\ T \leftarrow \theta$
  end if
end while

V. Experiment Design and Results Analysis

This section is dedicated to evaluating the effectiveness of the proposed simulation hyper-heuristic method in addressing a complex vehicle routing problem within hospital settings. The baseline method adapts the AGV dispatching algorithm from a real-world hospital system, which combines a nearest distance dispatch strategy with an A* routing strategy. Since the AGV strategy used in our collaborator hospital follows a First-in and First-out approach with A* routing, it is adopted as the benchmark in this experiment. Furthermore, to assess the performance of our MSHH, we employ a standalone VNS as a comparison group, based on its stable performance in vehicle routing problems as indicated by reference [18]. Notably, the hyper-heuristic is based on the same group of low-level operators as the VNS, ensuring a coherent experimental setup. Additionally, we introduce surrogate-assisted versions of both heuristics to measure the surrogate model's impact on simulation-based optimization.

The experimental datasets were derived from real-world hospital scenarios with slight modifications. Four instances of typical scenarios are extracted from daily logistics service records, ranging from 80 orders to 243 orders. Factors like agent travel time and parcel load/unload duration were calculated using actual operational time distributions, rendering them uncertain variables. A time limit of 2 hours is applied to all algorithms except the baseline. For each solution, 10 independent runs were conducted with distinct random seeds and average results are reported. The results of VRPPD with floor switching only and VRPPD with floor switching and charging are reported in Table I, along with the improvement ratio versus the baseline time costs.

From Table I, it is clear that all four algorithms offer significant improvements over the original strategy in the baseline. In the case of the floor switching problem, most algorithms show enhancements ranging from 10% to 15% compared to the original approach. However, Instance 3 displays a more modest improvement, potentially because larger datasets lead to improved computations, resulting in a narrower search area. Within each instance, all algorithms with surrogate assistance outperform algorithms without such assistance under the same runtime duration. Moreover, our hyper-heuristic-based algorithms tend to exhibit slightly better performance than those built on VNS.

For the floor switching and charging problems, significant improvements are evident in most instances. Among these instances, SMSHH demonstrated the most remarkable improvement, achieving a substantial 33.6% reduction in makespan for Instance 3. Furthermore, when considering the heuristic variable exclusively, SMSHH showcased significant progress over SVNS, while MSHH exhibited marked improvement over VNS. VNS emerged as the least effective among the four algorithms. Hence, both MSHH and SMSHH demonstrated commendable performance in addressing this problem. Notably, the optimal solution doesn't include a charging task due to the dataset's small size, resulting in consistent data for Instance 1 across both tables.

In summary, the simulation-based SMSHH successfully amalgamates the advantages of MSHH and surrogate models, showcasing superior performance in addressing VRPPD challenges involving floor switching and charging. This in-

TABLE I
COMPUTATIONAL RESULTS FOR FLOOR SWITCHING (FS) ONLY AND WITH CHARGING (C)

Problem	Instance	Baseline(A*)	VNS		MSHH		SVNS		SMSHH	
		C_{max} (s)	C_{max} (s)	Imp.	C_{max} (s)	Imp.	C_{max} (s)	Imp.	C_{max} (s)	Imp.
FS	1-82	5891	5102	13.4%	5067	14.0%	5060	14.1%	4976	**15.5%**
	2-150	10054	9334	7.2%	9267	7.8%	8953	11.0%	8926	**11.2%**
	3-243	14250	14210	0.3%	14058	1.3%	13064	**8.3%**	13066	**8.3%**
	4-181	11846	10847	8.4%	10655	10.1%	9748	**17.7%**	9756	17.6%
FS + C	1-82	5891	5102	13.4%	5067	14.0%	5060	14.1%	4976	**15.5%**
	2-150	47051	32465	31.0%	24676	47.6%	36360	22.7%	23648	**49.7%**
	3-243	139692	63069	54.9%	58489	58.1%	54732	60.8%	46909	**66.4%**
	4-181	69311	45815	33.9%	45669	34.1%	40463	41.6%	40266	**41.9%**

* A time limit of 2 hours is applied to all algorithms except the baseline.

tegrated framework, encompassing both simulation modeling and heuristic approaches, effectively addresses hospital AGV scheduling problems, indicating a promising avenue for future applications and advancements in this domain.

VI. CONCLUSION

This paper introduced an innovative simulation hyper-heuristic method to tackle a complex multi-floor AGV routing problem faced by a real-life hospital. Through the integration of multiple techniques and mechanisms, we effectively addressed a new problem, namely multi-depot, multi-floor AGV routing encompassing pickup, delivery, lift-queuing, and charging tasks. The simulation model accurately replicates the core constraints of real-world hospital logistics and enables predictive behavioral analysis and optimization. Our proposed methods, namely modified choice function simulated annealing hyper-heuristic with and without surrogates, MSHH and SMSHH, exhibit considerable performance enhancements over the baseline strategy. Particularly, SMSHH's integration of MSHH with surrogate optimization demonstrates noteworthy gains. This integrated approach holds the potential to optimize healthcare logistics operations and offers pragmatic insights for enhanced resource allocation. Subsequent research avenues could explore further refinements to these hybrid strategies, specifically focusing on more effective surrogates to cater to the dynamic and evolving nature of complex environments.

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REFERENCES

[1] E. A. Oyekanlu, A. C. Smith, W. P. Thomas, G. Mulroy, D. Hitesh, M. Ramsey, D. J. Kuhn, J. D. Mcghinnis, S. C. Buonavita, N. A. Looper, *et al.*, "A review of recent advances in automated guided vehicle technologies: Integration challenges and research areas for 5g-based smart manufacturing applications," *IEEE access*, vol. 8, pp. 202312–202353, 2020.

[2] S. Benzidia, B. Ageron, O. Bentahar, and J. Husson, "Investigating automation and agv in healthcare logistics: a case study based approach," *International Journal of Logistics Research and Applications*, vol. 22, no. 3, pp. 273–293, 2019.

[3] M. Pedan, M. Gregor, and D. Plinta, "Implementation of automated guided vehicle system in healthcare facility," *Procedia engineering*, vol. 192, pp. 665–670, 2017.

[4] V. A. Nunes and G. F. Barbosa, "Simulation-based analysis of agv workload used on aircraft manufacturing system: a theoretical approach," *Acta Scientiarum. Technology*, vol. 42, 2020.

[5] T. Ganesharajah, N. G. Hall, and C. Sriskandarajah, "Design and operational issues in agv-served manufacturing systems," *Annals of operations Research*, vol. 76, no. 0, pp. 109–154, 1998.

[6] X. Chen, R. Bai, R. Qu, and H. Dong, "Cooperative double-layer genetic programming hyper-heuristic for online container terminal truck dispatching," *IEEE Transactions on Evolutionary Computation*, 2022.

[7] X. Chen, R. Bai, R. Qu, H. Dong, and J. Chen, "A data-driven genetic programming heuristic for real-world dynamic seaport container terminal truck dispatching," in *2020 IEEE Congress on Evolutionary Computation (CEC)*, pp. 1–8, IEEE, 2020.

[8] L. Qiu, W.-J. Hsu, S.-Y. Huang, and H. Wang, "Scheduling and routing algorithms for agvs: a survey," *International Journal of Production Research*, vol. 40, no. 3, pp. 745–760, 2002.

[9] M. Antony, M. Parameswaran, N. Mathew, V. Sajithkumar, J. Joseph, and C. M. Jacob, "Design and implementation of automatic guided vehicle for hospital application," in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, pp. 1031–1036, IEEE, 2020.

[10] A. J. Moshayedi, L. Jinsong, and L. Liao, "Agv (automated guided vehicle) robot: Mission and obstacles in design and performance," *Journal of Simulation and Analysis of Novel Technologies in Mechanical Engineering*, vol. 12, no. 4, pp. 5–18, 2019.

[11] E. K. Burke, M. Hyde, G. Kendall, G. Ochoa, E. Özcan, and J. R. Woodward, "A classification of hyper-heuristic approaches," *Handbook of metaheuristics*, pp. 449–468, 2010.

[12] H. Neradilova and G. Fedorko, "Simulation of the supply of workplaces by the agv in the digital factory," *Procedia engineering*, vol. 192, pp. 638–643, 2017.

[13] G. Daugherty, S. Reveliotis, and G. Mohler, "Optimized multiagent routing for a class of guidepath-based transport systems," *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 1, pp. 363–381, 2019.

[14] X.-A. Dou, Q. Yang, P.-L. Xu, X.-D. Gao, and Z.-Y. Lu, "Comparative study on different encoding strategies for multiple traveling salesmen problem." In press.

[15] V. R. De Carvalho, E. Özcan, and J. Sichman, "Comparative analysis of selection hyper-heuristics for real-world multi-objective optimization problems," *Applied Sciences*, vol. 11, p. 9153, 10 2021.

[16] R. Bai, J. Blazewicz, E. Burke, G. Kendall, and B. McCollum, "A simulated annealing hyper-heuristic methodology for flexible decision support," *4OR*, vol. 10, pp. 43–66, Mar. 2012.

[17] D. Thiruvady, S. Nguyen, F. Shiri, N. Zaidi, and X. Li, "Surrogate-assisted population based aco for resource constrained job scheduling with uncertainty," *Swarm and Evolutionary Computation*, vol. 69, p. 101029, 2022.

[18] A. Imran, S. Salhi, and N. A. Wassan, "A variable neighborhood-based heuristic for the heterogeneous fleet vehicle routing problem," *European Journal of Operational Research*, vol. 197, no. 2, pp. 509–518, 2009.