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FROM COORDINATION TO EFFICIENCY: BOOSTING SMART ROBOT USE VIA HYBRID INTRALOGISTICS CONCEPTS

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ABSTRACT

Automated guided vehicles (AGVs) and Autonomous mobile robots (AMRs) are widely used in intralogistics for material delivery and product transport. As manufacturing evolves with Industry 5.0, the integration of autonomous systems, particularly in complex shop floor layouts, plays a crucial role in improving efficiency and reducing human intervention. This study explores various intralogistics concepts for AGVs and AMRs collaborating on an assembly line. We define an online dispatching rule for AGVs and benchmark it against previous implementations on high-mix-low-volume production. All proposed concept-related decisions are analyzed via a simulation model under a real-world case study, with sensitivity analyses varying system parameters. We observe an improvement of up to 51% in the hourly throughput rate and a significant drop in AGV utilization rates of up to 88% compared to benchmark instances. The results also show that pooling AGV/AMR resources achieves a higher throughput rate, and consequently reduces investment costs.

1 INTRODUCTION

Companies are progressing toward Industry 4.0 and, more recently, Industry 5.0, which centers on human well-being within technological advancements (Leng et al. 2022). Consequently, machines are expected to become more intelligent and assume more responsibilities. Businesses are striving for more autonomous manufacturing processes to adapt to these changes. This requires careful resource planning to improve production efficiency while reducing human involvement in daily operations.

In line with these revolutions, the integration of autonomous robots in manufacturing settings is becoming popular, adding flexibility to traditional production lines with constant-paced conveyors. Automated guided vehicles (AGVs) and autonomous mobile robots (AMRs) are the leading robots in intralogistics. Previous studies commonly use them for material delivery and product transport tasks. Unlike AGVs, AMRs are intelligent robots that navigate in free space rather than following grid lines (see Figure 1). Both have capacity limitations for loads, batteries, and speeds. In addition, they must operate under safety restrictions alongside process requirements. For different shop floors, e.g., job shops, challenges increase due to diverse product flows and types. Their working principles, i.e., intralogistics concepts, should be wisely chosen to prevent traffic conflicts between and within the fleets, as well as in the flow of the assembly line. Due to these challenges, our study discovers different intralogistics concepts for AGV and AMR fleets collaborating on an assembly line. AGVs are responsible for product transport between the stations, while AMRs provide material and tools. In some cases, these responsibilities overlap in the current manufacturing setting. We demonstrate the performance of new concepts through computational experiments for AGVs and AMRs under varying process times, product types, and fleet sizes.

We review the related literature in two categories: AGV and AMR use in manufacturing. AGVs, which are widely used in comparison to AMRs, are reviewed first. AGVs were introduced as delivery devices in manufacturing in the late 20th century (Ulusoy and Bilge 1993; Bilge and Ulusoy 1995). These studies scheduled machines and AGVs simultaneously to achieve a flexible manufacturing system. More recently, De Ryck et al. (2020) provides a comprehensive review of AGVs, highlighting their key role in enhancing

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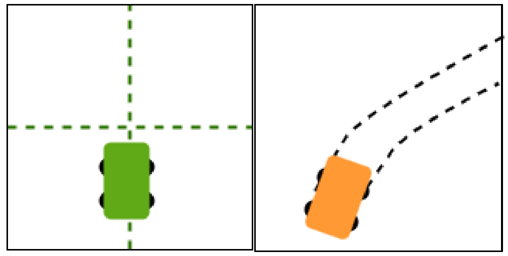


(a) (b)

Figure 1: Smart Robots: (a) AGV following grid lines, (b) AMR doing curved moves

flexibility and automation in manufacturing systems. They detail the integrated scheduling of AGVs and machines within production environments. Singh et al. (2022), Dang et al. (2021), and Singh et al. (2024) represent recent work that considers AGVs in their problem formulations and solution methodologies, addressing real-time requests through mixed-integer linear program and metaheuristics.

Second, the use of AMR in manufacturing is reviewed. Kim et al. (2021) study an AMR traffic control problem, which is solved using a mixed-integer programming model. The resulting paths are dynamically tested in a simulation representing a warehouse. Skapinyecz and Landschützer (2022) study AGVs with free-space navigation ability similar to AMRs. Their simulation model analyzes collision and obstacle detection scenarios. Similarly, Turhanlar et al. (2024) create a simulation model to evaluate the efficiency of the proposed warehouse layout. The warehouse is organized to help AMRs avoid deadlocks, thereby minimizing traffic congestion. Likewise, the AMR path planning problem is investigated with a simulation model in the work of Cadete et al. (2024). Their algorithm is tested in both industrial and urban areas with the main objective of maximizing efficiency by minimizing collisions with obstacles.

We scarcely see studies addressing the joint problem of AGVs and AMRs. Silva et al. (2024) conduct a comparative study between AGVs and AMRs using a simulation model to analyze the performance of two robot types with respect to travel time and collisions within a shop floor. Their study concludes that AGVs are more reliable in task completion, whereas AMRs exhibit higher flexibility and speed. Erdogan et al. (2024) present one of the other problems in this literature stream. Our work in this paper extends the work in Erdogan et al. (2024) in such a way that AMRs can be used between stations within an assembly line. This extension creates a more complex problem, as the integration between AMR and AGV increases. In addition, shop floor expansion scenarios are analyzed to utilize both robots more efficiently. Our aim is to achieve enhanced throughput rates by leveraging recently proposed intralogistics concepts.

The remainder of this paper is organized as follows. Section 2 describes the manufacturing setting considered in our study. Section 3 then presents the solution methodology and the experimental design. In Section 4, the results of the computational experiment for a real-world case study are discussed. Finally, conclusions and future research directions are given in Section 5.

2 SYSTEM PROPERTIES

We define a shop floor including an assembly line with manual, automated, and semi-automated stations, illustrated in Figure 2. Each station performs different types of processes. The assembly line begins with a preparation station. In addition, the shop floor includes warehouses for finished products and material/tools. To support robotic operations, the shop floor also includes charging stations for AGVs and AMRs.

AGVs and AMRs perform product transport tasks between any of the circular nodes inside each station. In addition, AMR has the responsibility of performing material supply tasks between any of the rectangular nodes inside each station and the material/tooling warehouse. The stations have designated areas for different AMR tasks at each station, separated by a physical wall. Sensors help identify the correct area for each task. When an AMR is assigned to sequential tasks that require different areas within the same

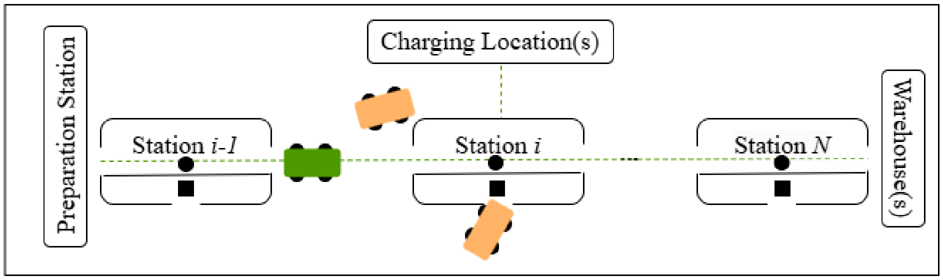


Figure 2: Illustration of a shop floor with N stations.

station, it cannot move directly between areas due to wall separation. Instead, it must complete the first task, exit the station via the product entry/exit point, and re-enter the station through the material entry point to perform the next subsequent task.

The first type of task, assembly, takes place at various stations (manual, automated, or semi-automated) without interruption, with sequences depending on the product type. The assembly line operates on a pull principle, where a product moves forward only when the next station is available, and a new product enters only when the first station becomes free. The second type of task, product transport, can be performed by either AGVs or AMRs. This task is initiated upon completion of an assembly. Each transport task has a source and destination nodes, connected by predefined paths. AGVs follow grid lines using the Manhattan distance, while AMRs utilize Euclidean distances when traveling between stations and the tooling/material warehouse. The third type of task, material supply, is performed only by AMRs. They use designated parking spots at stations for material pick-up and delivery. The levels of material inventory at the stations are checked after each assembly, initiating a supply task when the levels fall below the thresholds. When material supply is requested, the nearest available AMR is assigned. Material supply utilizes two different tools: trolleys for multiple simultaneous material deliveries, or scarts for single material kit if a scart is used. AMRs also return empty scarts/trolleys to the tooling/material warehouse. For product transport, both AGVs and AMRs use skids. An assembly task depends on material supply and product transport, ensuring that the necessary product and materials are available before the assembly starts.

Moreover, both AGVs and AMRs operate within battery limits and must be recharged when their state of charge (SoC) drops below a predetermined threshold. The charging tasks are prioritized over the other tasks to ensure that the robots reach the charging station after completing their current transport. The robots return to the parking area when they are idle. Both robots feature obstacle detection capabilities that allow them to navigate around objects, although this may cause delays. Therefore, we assume that a shop floor is a conflict-free environment.

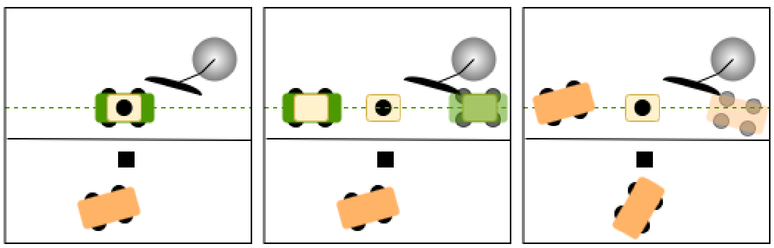
For AGVs and AMRs during product transport tasks, we use the concepts defined in Sections 2.1 and 2.2. Both concepts are developed based on our previous study to maximize the throughput rate (see Erdogan et al. (2024)). We also evaluate the utilization rates of AGVs and AMRs, defined as the proportion of the average active time of all vehicles over the total time horizon length.

2.1 Improved Concepts with AMR Backup

A product transport task for a robot, whether AGV or AMR, comprises a source (pick-up) and a destination. Upon reaching the destination, we previously defined two different concepts for AGVs: Concept (I) and Concept (II) (Erdogan et al. 2024). In Concept (I), an AGV remains at the destination station until the assembly task is complete. Once the subsequent destination is free, a new transport task is generated, and the AGV moves the product to this location. Conversely, in Concept (II), the AGV can execute different product transport tasks in parallel to the assembly task at the current destination. After an assembly task is completed, a new transport task is generated, and any available (nearest) AGV retrieves the product for the next assembly. Beyond these concepts, we propose the following two new concepts:

- Concept (III): Derived from Concept (I), AGVs primarily manage product transport unless all AGVs are currently occupied, in which case the task is assigned to the nearest idle AMR. The AMR carries the product throughout its production cycle and can execute material supply tasks in parallel. If all robots are busy, the task is queued up for the nearest AGV upon its transport completion.
- Concept (IV): Based on Concept (II), AGVs and AMRs share the same dispatching rule for product transport tasks. AMRs function similarly to AGVs, serving the earliest assigned task in their queue, without differentiating between task types.

Figure 3 represents all four different concepts, with AGVs depicted in green and AMRs in orange. The predefined AGV paths are shown as green grid lines. In Figure 3(a), an AGV carries a product (yellow) to the station and remains there throughout the production cycle (Concept (I)). In Figure 3(b), an AGV carries a product to the station, drops it there, and departs to perform other tasks (Concept (II)). In both concepts, an AMR may simultaneously supply material to the designated area below the assembly execution zone. Figure 3(c) illustrates the AMR backup capabilities applicable for Concepts (III) and (IV). The AMR is free to make any curved movement within the station if space permits. It drops the product and proceeds to other tasks. In this way, we expect to utilize AMRs more efficiently with the dual-tasking approach.



(a) (b) (c)

Figure 3: (a) Concept I, (b) concept II, and (c) improved concepts III and IV with AMR backup.

2.2 Hybrid Robot Dispatching

At the end of each assembly task, a signal is sent to the fleet manager to assign one of the AGVs according to the hybrid dispatching concept, named Concept (V). In this concept, we first look for idle AGVs within a predefined radius r that covers the surroundings of the current station i where the product is being processed. Among the available AGVs, we choose the one nearest to station i. If no AGVs within radius r are available at that time, we dispatch the nearest AGV, which will become free after completing its current transport task, to pick up the product at station i. The radius r must be carefully chosen to use nearby AGVs more and minimize the waiting time to pick up the product at station i. In this way, we can better utilize AGVs that would otherwise remain idle during product processing periods at other stations. We expect that this concept would free up the AGV capacity; in other words, reduce AGV occupation considerably compared to Concept (I). In addition, as AGVs support product flow across other stations, more products can enter the assembly line, potentially increasing the throughput rate. An illustration of Concept (V) is provided in Figure 4. The figure shows a battery pack being assembled at Station 3. Within radius r of Station 3, two AGVs (labeled 1 and 2) are available for dispatch. As AGV 2 is located closer to Station 3 than AGV 1, and no other AGVs are within radius r, we dispatch AGV 2 to collect the battery pack at Station 3.

3 SIMULATION MODEL

This section introduces a simulation model that incorporates five different intralogistics concepts discussed in Section 2. A simulation model is built to handle system uncertainties, such as varying product arrivals, process times, or delays caused by obstacles encountered by AGVs and AMRs.

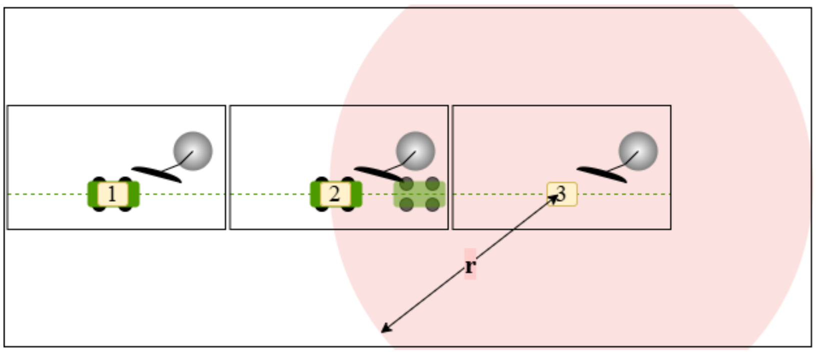


Figure 4: Concept (V) within a shop floor with 3 stations.

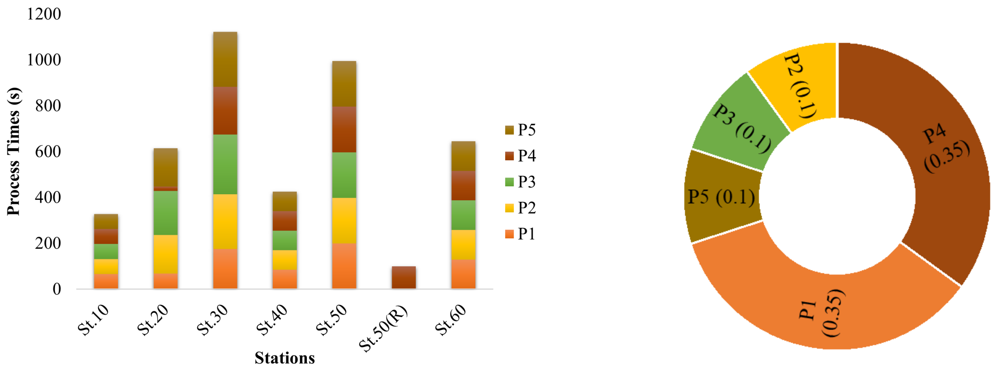
Our simulation model combines three approaches: discrete event simulation (DES), agent-based modeling (ABM), and system dynamics (SD), using AnyLogic 8.9.4 (AnyLogic 2025). DES models battery pack assembly, product transport, and material supply tasks.ABM defines agents within the system, such as battery packs, AGVs, AMRs, and charge tasks. SD is used within AGV and AMR agents to manage battery SoC, with discharge as an outflow and recharge as an inflow. The model encompasses four flows: (1) battery packs and AGVs for assembly and product transport, (2) battery packs and AMRs for assembly and product transport, (3) AMRs, scarts, and trolleys for material supply, and (4) charging tasks for AGVs and AMRs, which take priority. The SD mechanisms embedded within the AGV and AMR agents operate continuously through a *statechart*, running in parallel with the other flows.

3.1 Case Study

In this section, we present a real-world case study inspired by VDL Nedcar in the Netherlands, with details available in the study of Erdogan et al. (2024). The assembly line begins with a preparation station on the shop floor and ends with separate warehouses for finished products and material & tools. Between these endpoints, the line comprises six stations, numbered 10 to 60. Each station contains a single parking spot that accommodates an AGV/AMR during product loading/unloading. Each station also features an entry and an exit points used by both robots. For AGVs, the parking spots inside the stations are connected via grid lines, in addition to the grids between the finished product warehouse and the AGV charging location.

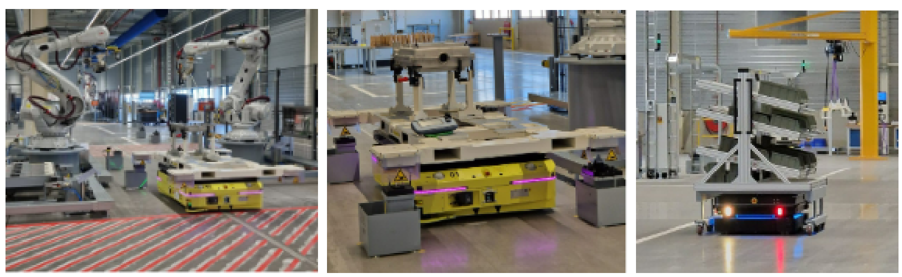
Material supply requirements vary between stations: Stations 10 and 30 require trolley-based supply, while Stations 20 and 50 require scart-based supply. Similarly to production transport, AMRs use designated parking spots within each station. Stations 10, 20, and 30 each contain 3 AMR parking spots, while Station 50 has 4 parking spots. The remaining stations do not have AMR spots as they do not require material supply. For trolley deliveries, we implement an inventory policy (s,S), where a material supply task is generated whenever the material inventory level drops to $s = 2$, with replenishment up to $S = 10$. For scart deliveries, each AMR can carry one scart at a time, with a new material supply task created whenever one of the parking spots at Stations 20 and 50 becomes available.

The assembly line handles diverse product types typical of high-mix-low-volume production environments. Five different product types, P1–P5, are presented in Figure 5. These products vary not only in process times, but also in their required processing sequences. In particular, Product 4 (P4) visits Station 50 twice as indicated by revisit (R) in Figure 5a. This revisit necessitates buffers at Stations 30 and 50. In Concepts (I) and (III), robots serve as buffers, while Concepts (II), (IV), and (V) use physical storage spaces at these stations. Apart from that, all other products visit the stations in the sequence of 10-20-30-40-50-60. Work orders arrive randomly in the system, following the product type distribution shown in Figure 5b. For concept (V), after conducting preliminary experiments, we establish radius r at 50 m to involve only the adjacent stations. Radius r can be adjusted to include the neighbors of the adjacent stations if desired.



(a) (b)

Figure 5: Experiment Setup: (a) Process times for different product types, (b) Arrival Probabilities for different product types.



(a) (b) (c)

Figure 6: (a) AGV operating within the restricted area of the assembly line, (b) AGV waiting for a process to end at a station, and (c) AMR doing material supply with trolley.

4 COMPUTATIONAL EXPERIMENTS

This paper presents experimental setups beginning with one AGV and one AMR, progressively increasing the fleet sizes up to six AGVs and three AMRs, respectively. We first focus on one product type, which is product type 1 with process times and station configurations detailed in Section 3.1. Performance is evaluated over 10 shifts of 8 hours each, with results presented in Section 4.1.

We then extended the computational experiments to five different product types (given in Section 3.1), again starting with one AGV and AMR, scaling up to six and five, respectively. Performance measures are analyzed over five replications of a 20-work-day production cycle, including three 8-hour shifts per day with a one-week warm-up period for statistical reliability. The results are then presented in Section 4.2. In addition, we simulate a second production line directly next to the existing layout. This new line mirrors the original in terms of arrival probabilities and product types. Both lines share the same fleets of AGVs and AMRs for product transport and material supply. The results are detailed in Section 4.3.

All experiments are performed on a computer with an 11^{th} Gen Intel(R) Core(TM) i5-1135G7 CPU @ 2.40 GHz, 16 GB RAM, and Windows 11 operating system.

4.1 Output Analysis on Deterministic Setup

We compare all concepts by evaluating three different performance measures: hourly throughput rate, AGV utilization, and AMR utilization presented in Figure 7. The first column shows the hourly throughput rates, the middle column displays the average AGV utilization rates, and the third column presents the average AMR utilization rates. In all the graphs, the Y-axis represents the performance measure, while the X-axis indicates the AMR fleet size n_R. The AGV fleet size n_V is indicated at the beginning of each row. Within each graph, the five different concepts are distinguished by colored lines. The detailed results are here (Erdogan, B. 2025).

In all concepts, increasing fleet sizes for both AGV and AMR contribute to an increased hourly throughput rate. AGV increments show significantly higher contributions compared to AMRs. For Concepts (I) and (II), increasing fleet sizes to six AGVs and three AMRs continues to improve the throughput rate, a pattern that can also be observed in the other concepts. For material supply, the benefit of larger AMR fleet sizes increases with expanding AGV fleet sizes due to higher production rates. However, for product transport under Concepts (III) and (IV), the benefit of additional AMRs diminishes with a higher number of AGVs. Across all concepts, we see a significant increase in the throughput rate from one to two AMRs. The throughput rates range between three and 16, with the highest rate of 15.95 achieved with Concept (V) using six AGVs and three AMRs. Notably, Concept (I) performs almost equivalent to Concept (V) with more than three AGVs, though with higher AGV utilization rates.

We see improvements in the performance of Concepts (I) and (II) when supplemented with backup plans provided by Concepts (III) and (IV). Although the throughput rates are occasionally the same for both, the AGV utilization rates are lower in Concepts (III) and (IV). We do not observe the best performance with Concept (III) in any case. Concept (IV) performs best with one and three AGVs, indicating that backup plans provide greater benefits under Concept (II) than Concept (I). This occurs because the AGVs are fully attached to the product, minimizing the waiting time at each station. However, this is not the case for AMRs when performing product transport tasks. Hence, their presence does not provide a significant benefit under Concept (I). For larger fleet sizes exceeding three AGVs, Concept (V) is the best. The hybrid AGV dispatching method minimizes the waiting time of a product at the station in two ways. First, the waiting time after the assembly is complete is minimum if an AGV is waiting at that station. Second, we call the nearest AGV within the radius when no robot is waiting, and thereby minimizing the waiting time of the product at that station compared to calling any idle AGV waiting at the parking/charging location as in other concepts. The greatest improvement occurs when AGVs are scarce. When the AGV fleet size is equal to one with three AMRs, the throughput rate increases by 51% compared to the maximum values observed in Concepts (I) and (II).

Looking at the middle and last columns of Figure 7, the AMR utilization rates show a consistent declining trend as the AMR fleet size increases. However, AGV utilization either decreases or remains the same when AMRs exceed two. For Concepts (I) and (II), this occurs because the maximum number of AMRs needed has been reached. Concepts (III) and (IV), however, benefit from additional AMRs, which reduce AGV utilization as AMRs support the product transport flow. We observe this reduction across all rows for both Concepts (III) and (IV). When the size of the AGV fleet exceeds three, this reduction becomes slower. On the other hand, Concept (V) behaves differently from all other concepts in terms of AGV utilization. AGV utilization increases up to two AMRs in all rows, since AMRs provide enough material on time to improve the production rate. Beyond two AMRs, material supply tasks are executed even faster, which decreases the AGV utilization rates. With three AMRs, AGVs on the assembly line become more active, and because of the radius rule, they mainly serve the nearest stations. This decreases the travel times of AGVs, and hence the utilization rates. The lowest utilization rate, almost 10%, is reached under Concept (V) with six AGVs and one AMR, coinciding with higher throughput. Implementing Concept (V) reduces AGV utilization from 56% to 34% with increasing AGV fleet sizes compared to Concepts (I) and (II). The highest improvement in AGV utilization occurs with six AGVs and three AMRs, which is a drop from 94% to 10%.

When the AMR fleet size is one, AMR utilization reaches its maximum of 90% in all concepts. AMR utilization increases between 2% and 47% as AGV fleet size expands if we use the best concept compared to Concepts (I) and (II), because AMRs support product transport tasks. With AGV fleet size of two and

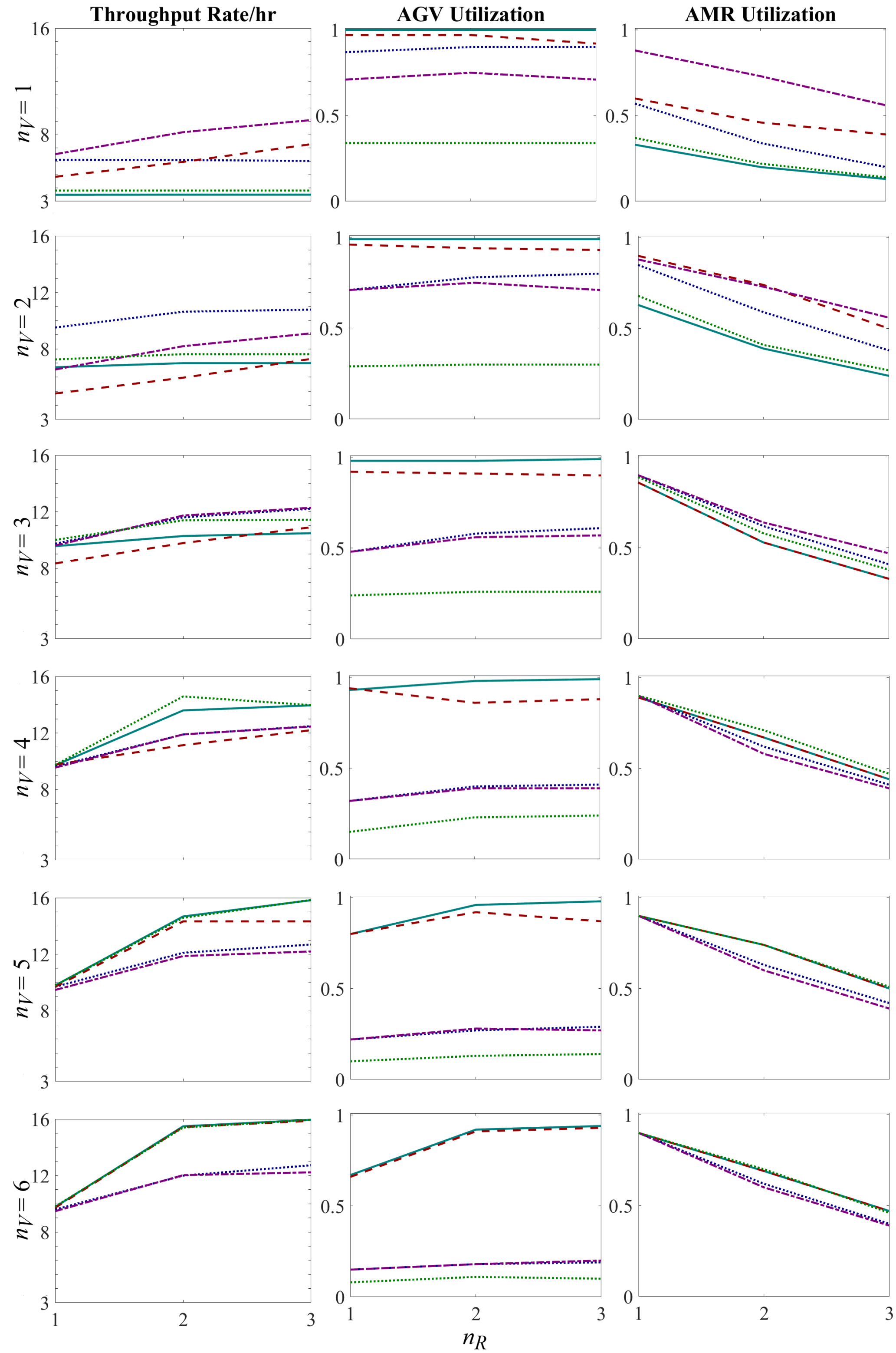


Figure 7: Deterministic Experiments: Hourly throughput rate (on the left), AGV utilization (at the middle), AMR utilization (on the right); C(I) (—), C(II) (· · ·), C(III) (- - -), C(IV) (- · -), C(V) (· · ·).

AMR fleet size of three, Concept (IV) achieves a significant 47% increase in the AMR utilization rate compared to Concept (II). The increase in AMR utilization observed with 5 AGVs and 2 AMRs is due to the more active usage of AMRs in product transport tasks, which constitutes 55% of those tasks.

4.2 Output Analysis on Stochastic Setup

Figure 8 displays three performance measures: mean hourly throughput rate (the first column), mean AGV utilization (the second column), and mean AMR utilization (the third column) with 95% confidence intervals. Across all graphs, the Y-axis shows the performance measure, while the X-axis shows the AMR fleet sizes. The variation in the AGV fleet size is indicated at the beginning of each row. Each graph shows five different concepts, illustrated with colored lines. The complete results can be found here (Erdogan, B. 2025).

Our findings here parallel those of the deterministic experiment in terms of the marginal contributions of both AGVs and AMRs. In all graphs, there is a more significant increase in the throughput rate when the AMR fleet size changes from one to two. This increase matters even more when the AGV fleet sizes are at low levels, below three, due to the support of AMRs in product transport. Mean throughput rates ranges between three and 14, with the highest throughput rate of 13.63 ± 0.11 under Concept (V) with six AGVs and three AMRs. Unlike the deterministic setup, we do not see any close results in terms of the throughput rate.

Concepts (III) and (IV) present higher throughput rates compared to Concepts (I) and (II) in all cases. Concept (IV) achieves the highest throughput rate with fewer than three AGVs, followed by Concept (II). Concept (IV) shows 49% improvement compared to Concept (II) with the same fleet size of one AGV and three AMRs, similar to the improvements in the deterministic setup. Again, we observe higher improvements when the AGVs are limited and the AMRs are idle. For AGV fleet sizes larger than three, Concept (V) achieves the best performance, reflecting the positive effects of minimizing waiting time after the process is completed at all stations.

The second and third columns of Figure 8 show the utilization rates for both fleet sizes. The AGV and AMR utilization rates decrease with increasing fleet sizes in all concepts. Concept (V) consistently shows the lowest AGV utilization rate regardless of the AGV fleet size, demonstrating significant improvements over Concepts (I) and (II). For example, when we have one AGV and three AMRs, throughput rates are almost the same under Concepts (I) and (V). However, Concept (V) achieves the same performance with 67% less AGV utilization ($32\% \pm 0.003$). The highest drop 88% in mean AGV utilization occurs when there are six AGVs and three AMRs under Concept (V).

When the AMR fleet size is equal to one, the mean AMR utilization rate peaks at $90\% \pm 0.01$, with more than three AGVs. The AMR utilization rate is affected by increasing the AGV fleet size, as they feed the assembly process. When AGVs become more active, AMRs must also match this, which increases the throughput rate and AMR utilization. In addition, when AMRs back up AGVs in Concepts (III) and (IV), we again observe an increase in their utilization compared to Concepts (I) and (II). For example, Concept (IV) shows an increase of 52% in the mean AMR utilization rate with two AGVs and three AMRs.

4.3 Output Analysis on Line Expansion

In this section, we extend the experiments by adding a second production line with the same capacity as the original, sharing the same AGV/AMR resources. Figure 9 shows the mean hourly throughput and AGV utilization for Concepts (III–V), tested with four AGVs and two AMRs under the stochastic setup.

With this fleet size, all these concepts achieve a higher throughput than a single line can deliver. With four AGVs and two lines, the highest throughput rate is achieved with Concept (V), reaching 14.19 ± 0.14, representing a 24% improvement from the additional production line. Concept (IV) follows, offering the second-highest throughput rate, representing a 40% improvement compared to a single line. Concept (III)

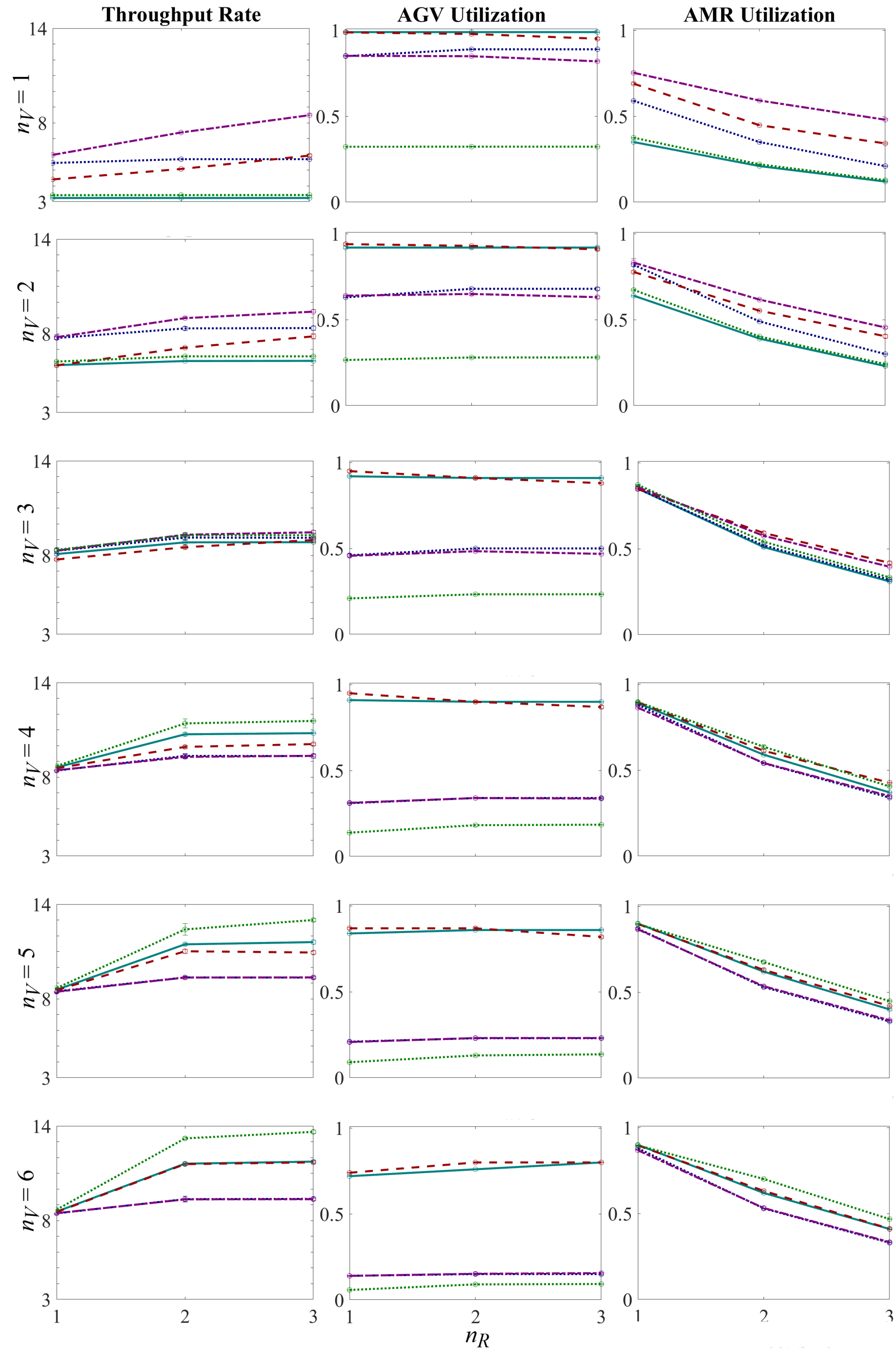


Figure 8: Stochastic Experiments: Hourly throughput rate (on the left), AGV utilization (at the middle), AMR utilization (on the right) with 95% confidence intervals; C(I) (—), C(II) (···), C(III) (- - -), C(IV) (-·-), C(V) (···).

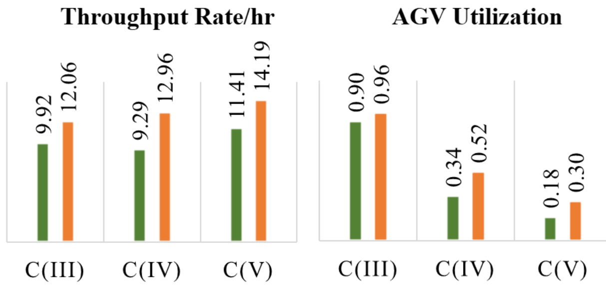


Figure 9: Hourly throughput rate (on the left) and AGV utilization (on the right) for Concepts (III–V) with 4 AGVs and 2 AMRs; single line ·, two lines ·.

shows the lowest throughput among the three, maintaining the same ranking behavior as in the single-line setup under stochastic conditions.

We further investigate a scenario where resources are doubled. For comparison, we use the results from stochastic experiments involving two AGVs and one AMR. Concepts (III) and (V) produce around six battery packs per hour in this configuration. When we double the number of lines, AGVs, and AMRs, the expected throughput rate should be approximately 12 packs per hour. However, with 2 lines under Concept (V), the mean throughput increases to 14.19, exceeding the expected 12.47 by 14%. In other words, we can achieve the same throughput of 12.47 with fewer AGVs. This supports the idea that pooling robot resources across similar production settings can reduce costs and improve efficiency.

Regarding AGV utilization rates, they increase with line expansion for all concepts as AGVs need to travel more. Concept (IV) shows the highest increase in the mean utilization from 33% to 52%. Similar increases also occur for the other concepts. We again observe the highest AGV utilization rate with Concept (III) as AGVs remain with the product throughout the entire process.

5 CONCLUSIONS

This study investigates the collaborative use of AGVs and AMRs in an assembly line setting, introducing three new intralogistics concepts, which are built on two existing baseline concepts, to improve throughput rates and reduce robot utilization. In baseline Concept (I), AGVs wait at destination stations until assembly tasks are completed before proceeding, while baseline Concept (II) enables AGVs to perform parallel transport tasks alongside assembly. Concepts (III) and (IV) extend (I) and (II), respectively, by dynamically involving AMRs in the product transport flow whenever all AGVs are busy. Finally, Concept (V) introduced a hybrid dispatching rule that assigned AGVs based on proximity within a limited radius, thus minimizing the waiting time for product pickup at the target destinations.

Through extensive simulation experiments using real-world data, we demonstrate that the proposed methods can significantly enhance system performance, achieving up to a 51% increase in hourly throughput in the deterministic setup. In the stochastic setup, we observe a 88% reduction in AGV utilization compared to the baseline scenarios using Concepts (I) and (II). The results show that Concept (V) performs much better with larger AGV fleet sizes. For less crowded setups, we suggest using concept (IV), an improved version of Concept (II). Additionally, the dual-line experiment allows us to analyze the impact of shared robot resources on system performance. By pooling the robots across both lines, we achieve a comparable throughput rate without the need for additional AGV or AMR investments, demonstrating the cost-efficiency of shared resources.

The results underscore the importance of flexible, integrated intralogistics systems, particularly as manufacturing moves toward Industry 5.0 paradigms that demand higher adaptability and efficiency. Overall, this study establishes a foundation for next-generation intralogistics systems where collaborative AGV-AMR operations drive higher efficiency, flexibility, and resilience in high-mix-low-volume manufacturing environments.

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