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INTELLIGENT LAYOUT RECONFIGURATION FOR RECONFIGURABLE ASSEMBLY SYSTEM: A GENETIC ALGORITHM APPROACH

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ABSTRACT

The ever-evolving automotive industry landscape, driven by shifting customer demands, necessitates flexible manufacturing solutions. Reconfigurable Manufacturing Systems (RMS), integrating modular facilities and Automated Mobile Robots (AMRs), emerge as pivotal alternatives to inflexible dedicated conveyor systems. This study delves into optimizing layout reconfiguration within automotive assembly, with a specific focus on the Reconfigurable Assembly System (RAS) inheriting the traits of RMS. We are focused on addressing scenarios characterized by frequent production schedule changes, necessitating frequent layout reconfiguration. Our approach prioritizes maintaining high area utilization without compromising throughput. In this study, we modified the NSGA- II algorithm, one of advanced Genetic Algorithms (GA) and proposed a layout reconfiguration algorithm to concurrently optimize two key objectives: (1) area utilization and (2) throughput, crucial facets of layout optimization. The proposed algorithm, integrated with discrete event simulation models spanning six layout scenarios, demonstrates significant enhancement in area utilization without compromising throughput integrity, by confirmed simulation studies.

1 INTRODUCTION

The conventional automotive assembly process is traditionally organized around in-line conveyors (Verma et al. 2022; Oh et al. 2022). However, the modern automotive industry continues to focus on customization and personalization, leading to a shift towards customized production (Verma et al. 2022; Oh et al. 2022; Kabasakal et al. 2017). In order to quickly respond to these increasingly diverse customer demands, it is necessary to move from the dedicated inflexible conveyor-centric system to a more flexible system (Oh et al. 2022).

The Reconfigurable Manufacturing Systems (RMS) is one of the most suitable solutions to respond to rapidly changing market conditions (Yelles-Chaouche et al. 2021). This concept, first defined by Prof. Koren in 1999, aims to improve the responsiveness of manufacturing systems to unexpected changes in product demand (Koren et al. 2018). The RMS, which refers to a system designed from the ground up for this purpose, has six core features: Modularity, Integrability, Diagnosability, Convertibility, Customization, and Scalability (Bortolini et al. 2018). The Reconfigurable Assembly System (RAS), which is the target manufacturing system of this study, has the features of RMS and is a more flexible and efficient system than conventional assembly systems because of modular facilities and AMRs (Verma et al. 2022; Löcklin et al. 2022; Bergmann 2022).

The RAS needs rapid reconfiguration of its capacity and layout depending on the production schedule change, and it needs to be flexible enough to respond to unpredictable changes, which requires faster decision-making. In addition, the RAS must be able to efficiently utilize the given plant floor area to prevent the occurrence of space waste while considering the travel distance of Automated Mobile Robots (AMRs) and the possibility of adding new workstations. Therefore, this study aims to develop a layout reconfiguration algorithm to optimize the layout for the RAS rapidly in such a way that the area utilization and the throughput (calculated by Units Per Hour (UPH)) are simultaneously enhanced. For this purpose, we first formulated the problem in a traveling salesman problem (TSP) and then developed a metaheuristic algorithm based on NSGA-II, one of the competitive genetic algorithms solve the problem where the discrete-event simulation is used to validate the proposed algorithm.

The paper is organized as follows: Section 2 provides a definition and overview of TSP and NSGA-II, followed by a more detailed problem definition and the implementation of the algorithm and simulation in Section 3. Then, in Section 4, we apply the implemented algorithm to six different scenarios and discuss the results. Section 5 concludes the paper with the outlook on this research.

2 LITERATURE REVIEW

As research on layout optimization continues to be actively pursued, various methodologies targeting diverse systems are proposed and utilized (Maganha et al. 2019; Naik and Kallurkar 2016; Pérez-Gosende et al. 2021). One such approach is to apply the TSP to address the layout optimization challenge (Lam and Delosme 1988). TSP involves combinatorial optimization, aiming to find the shortest distance to visit all listed cities, given their respective distances (Goyal 2010). This problem is widely recognized as one of the NP-Hard problems, where the expected time to find the optimal solution increases exponentially with the increase in the number of solutions (Raman and Gill 2017; Akhand et al. 2020). Optimization algorithms, which attempt all possible solutions, employ exhaustive search techniques. Therefore, as the number of solutions increases, the computational and time resources required also increase, making it impractical to consider such methods for this problem (Tao et al. 2016). On the contrary, metaheuristics operate by finding approximate solutions for NP-Hard problems, rendering them more practical approaches (Verma et al. 2021; Sörensen & Glover 2013). Consequently, research utilizing various metaheuristics such as Simulated Annealing (SA), Ant Colony Optimization (ACO), hybrid ACO, Genetic Algorithms (GA), continues to address the TSP, with studies conducted by Sun and Teng (2002); Hasan, Mohammed, Ţăpuş and Hammood (2017); Tahery and Kucuksari (2020) serving as examples.

NSGA-II, as one of the competitive GA methods, is widely utilized for solving diverse multi-objective problems and has been actively applied as an enhanced genetic algorithm in TSP (Raman and Gill 2017; Verma et al. 2021; Deb et al. 2002; Dong et al. 2022; Azadivar and Wang 2000). It inherits key elements such as crossover, mutation, evaluation, and selection from GA (Bergmann 2022; Mirjalili 2019; Lambora et al. 2019). Additionally, it incorporates crucial features like Fast Non-dominated Sorting Approach, Density Estimation, and Crowded Comparison Operator (Deb et al. 2002). NSGA-II is actively utilized in various layout optimization-related studies aiming to enhance the flexibility of the target system. For instance, Izui et al. (2013) utilized NSGA-II for multi-objective layout optimization of Robotic Cellular Manufacturing Systems (RCMSs), conducting research based on criteria such as robot operating time, maneuverability, and layout area design. Erfani, Ebrahimnejad and Moosavi (2020) implemented NSGA-II and two local search algorithms to simultaneously optimize facility layout and scheduling problems, validating the results. Li, Chen, Song, Li and Yu (2023) performed research on optimizing logistics-based workshop layouts with the goal on carbon emission reduction using modified NSGA-II. These algorithms, such as NSGA-II, are often combined with discrete-event simulations (Bergmann 2022). Azadivar and Wang (2000) proposed a method for optimizing the layout of manufacturing systems by integrating simulations into the procedures of the GA algorithm. RazaviAlavi and AbouRizk (2017) applied this method to derive optimal layouts in construction sites. When combined with metaheuristic methods, the discrete-event simulations help algorithms make clear decisions by reflecting the complexity of manufacturing sites that are difficult to represent solely through mathematical models (Azadivar and Wang 2000; RazaviAlavi and AbouRizk 2017; Mourtzis et al. 2014; Lee et al. 2022). In this study, we aim to incorporate simulation models into the NSGA-II algorithm based on existing research to consider the complexity of the target system, RAS.

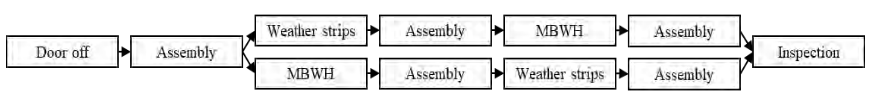
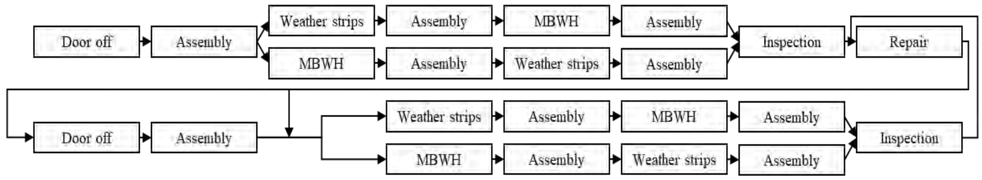
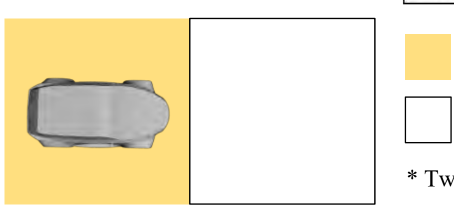
3 GENETIC ALGORITHM AND SIMULATION BASED INTELLIGENT LAYOUT RECONFIGURATION METHOD

Table 1 illustrates the RAS designed for the beginning part of the trim area in the automotive assembly process. The target trim area includes Door off, Weather strips, and Main Body Wire Harness (MBHW), with its layout configured in a 4 by 4 area, totaling 16 sizes. There are four types of facilities:

- Facility A is dedicated to handling the Door off process because it requires special tooling.
- Facility B can handle both Weather strips and MBHW processes as they do not require any special tooling and can be performed using common torque tools. There is no specific precedence order between Weather strips and MBHW.
- Facility C is designated for repair products. Note that all products undergo inspection before transferring to the next trim area. Defective products are directed to Facility C for repair.
- Facility D provides space for AMRs to wait for jobs and be recharged if necessary.

Within Facility B, the processing sequence begins with the random selection of either the BMHW or weather strips operation at the outset. If BMHW is chosen initially, the product undergoes the weather strips process within the next Facility B. Subsequently, all products proceed to the inspection facility for quality checks. In the event of a defect, the product is sent for rework and redirected to either Facility A or B, depending on the type of defect. Once again, one of the two tasks (weather strips or BMHW) is randomly selected for initial execution. Following the completion of all processes, another inspection is conducted again. The precedence order in Table 1 presents all possible process sequences. Furthermore, both Facility A and B consist of two modules: the part-setting module and the assembly module.

Table 1: Information of target assembly system.

Type	Description
Area	16 (4x4)
Facility	A : Door off B : Weather strips & MBHW(Main Body Wire Harness) C : Inspection D : Repair shop
Precedence Order	Case1) Defective product does not occur  Case2) Defective product occurs 
Module	 Setting Assembly * Two types of facilities are defined into one module

We optimized the layout of the target system by modifying NSGA-II, one of the advanced genetic algorithms, and developed a reconfiguration algorithm. To employ a genetic algorithm, the layout information derived from the list of facilities must be initially encoded as genetic information. In this study, the position of facilities is assumed to be destinations in the TSP and is substituted as genetic information for utilization. The information for each facility, designated as A, B, C, and D as depicted in Figure 1, corresponds to the colors red, orange, yellow, and green, respectively. The resulting chromosome information represents the entire layout of one facility, with each number constituting one gene in the chromosome.

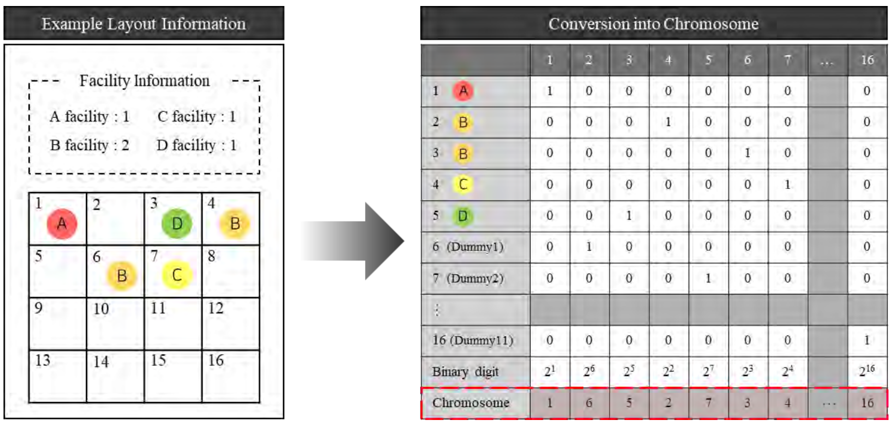


Figure 1: Conversion example of layout information into chromosome.

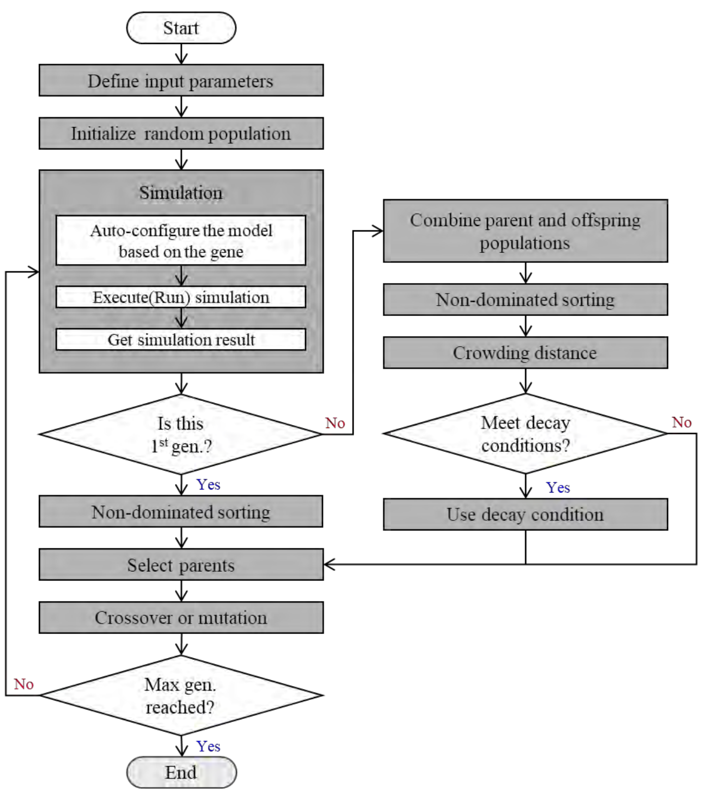


Figure 2: Sequence diagram of proposed reconfiguration algorithm derived from NSGA-II (Deb et al. 2002; Azadivar and Wang 2000).

Our reconfiguration algorithm depicted in Figure 2 aims to simultaneously optimize two metrics: Area Utilization and UPH values, which are in a trade-off relationship. The algorithm begins by randomly generating 10 initial solutions. Each genetic information undergoes simulation based on the gene information to derive Area Utilization and UPH values as results. Subsequently, the objective function values of the 10 solutions are sorted, and subsequent generations derive solutions using crowding distance values based on their objective function values. Cross probability (5%) is applied to each of the 16 genes, while for mutation, a 1% probability is used to randomly select two genes for swapping their placement order. The algorithm gradually decreases crossover and mutation probabilities based on decay conditions, defined through trial and error, when the sum of two objective function values is above 9.4 and the number of generated generations exceeds 20. The iteration sequence concludes when the number of generations reaches the maximum generation value of 30.

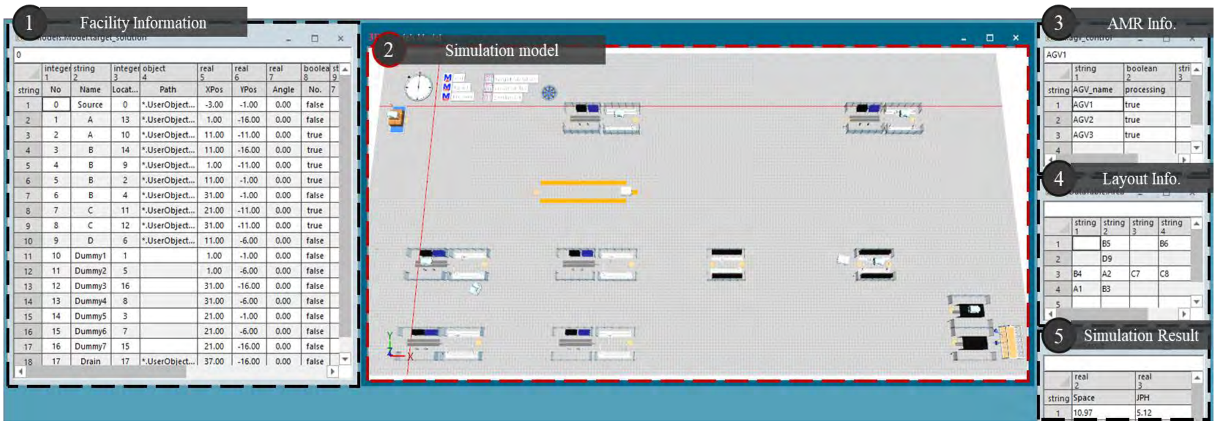


Figure 3: Simulation model of target system.

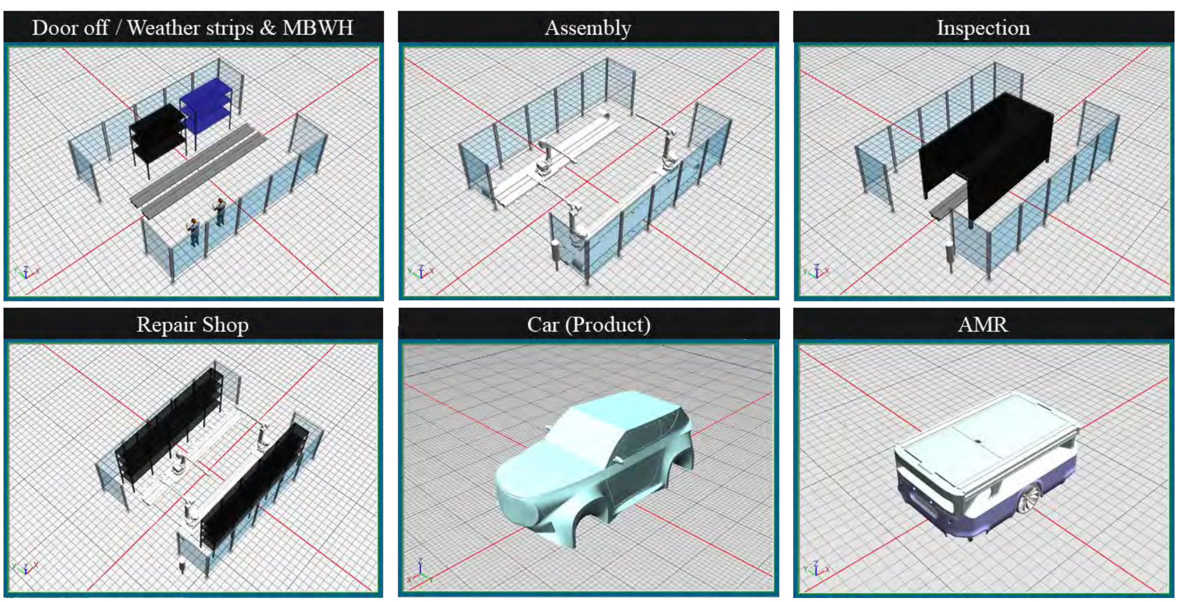


Figure 4: 3D models of each facility, product, and AMR.

Figure 3 illustrates the simulation model employed to derive the objective function values for each layout solution. In Figure 3, components 1, 3, 4, and 5 present the facility, AMR, layout information, and simulation results, while component 2 depicts the simulation model generated and executed based on this information. Figure 4 presents 3D models of facilities, product (Car), and AMR. The models are strategically placed and utilized within the simulation model according to the layout information defined prior to simulation execution. All assembly facilities are positioned behind the Door off or Weather strips & Main Body Wire Harness (MBWH) equipment. It is assumed that AMRs will operate individually, each consisting of three units. The simulation model is used to determine the objective function values, namely Area Utilization and UPH, for each solution, calculated with the following formulas.

$$Area\ Utilization = \frac{1}{n} * \sum_{i=1}^{n} \sqrt{(x_{center} - x_i)^2 + (y_{center} - y_i)^2} \quad (1)$$

Firstly, the formula for area utilization employs the Euclidean method, which divides the sum of distances from the center coordinates to each facility by the number of facilities (n). In this context, the central coordinates of the layout are denoted as (x_{center}, y_{center}), and the center coordinates of facility i are represented as (x_i, y_i). Since the target system may frequently implement new facilities or warehouses depending on the circumstances, it is essential to maximize the utilization of available area. This aspect is evident in the movement range of the AMR within the simulation model, thus establishing the degree of dispersion of each facility as the primary objective function.

$$UPH = \frac{Total\ Count\ of\ finished\ Products}{Simulation\ Duration} \quad (2)$$

Secondly, UPH represents the production throughput (units) per hour, calculated by dividing the total number of finished products obtained during simulation by the total simulation time. These two values serve as objective function values to assess each solution. Production throughput analysis is a crucial factor in the design and operation of every production system. Therefore, it was selected as the second objective function for the proposed algorithm.

Figure 5: Interface procedure within the proposed system.

Our reconfiguration algorithm and simulation model were implemented using Python and Siemens Plant Simulation 23.02, respectively. An interface between them was established using the xlwings library and Excel VBA. This interface facilitates the transfer of solutions generated by the proposed reconfiguration algorithm to the simulation. The solutions enable the derivation of results, which are then fed back as objective function values to the reconfiguration algorithm, aiding its progress.

4 RESULTS

The implemented algorithm is validated by defining scenarios and analyzing their results. Each scenario is defined in Figure 6 by varying the number of facilities. Furthermore, each scenario is redefined based on the results of the previous scenario according to user decisions. Scenarios 4 and 5, aimed at alleviating the AMR shortage issue from Scenario 3, apply two different approaches respectively. These scenarios are simultaneously applied to Scenario 6, as defined in Figure 6.

The generational objective function values of our proposed reconfiguration algorithm include (1) Area Utilization, (2) UPH, and (3) Total value, which integrates the two metrics. The Total value is calculated by assigning an equal weight of 0.5 to each of the Area Utilization and UPH values and then summing them. Area Utilization gradually improves in all scenarios. UPH does not exhibit as dramatic changes as Area Utilization; however, despite being in a trade-off relationship with Area Utilization, it consistently shows slight improvements across all scenarios, with no instances of degradation in value. This suggests that the proposed algorithm in this study is effectively operational. Furthermore, in the Total value combining both metrics, all scenarios show improvement, as depicted in Figure 7 below, with Scenario 5 producing the best result.

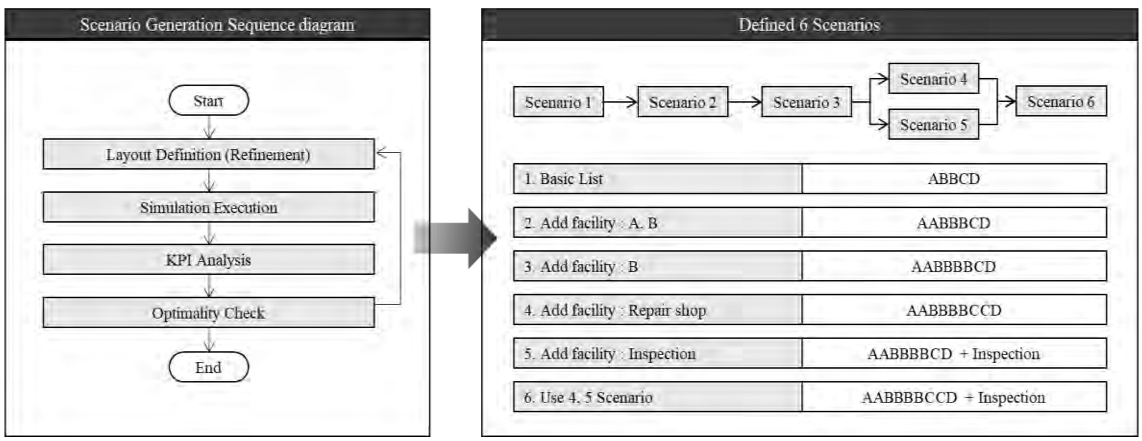


Figure 6: Sequence diagram of scenario generation and defined scenarios information.

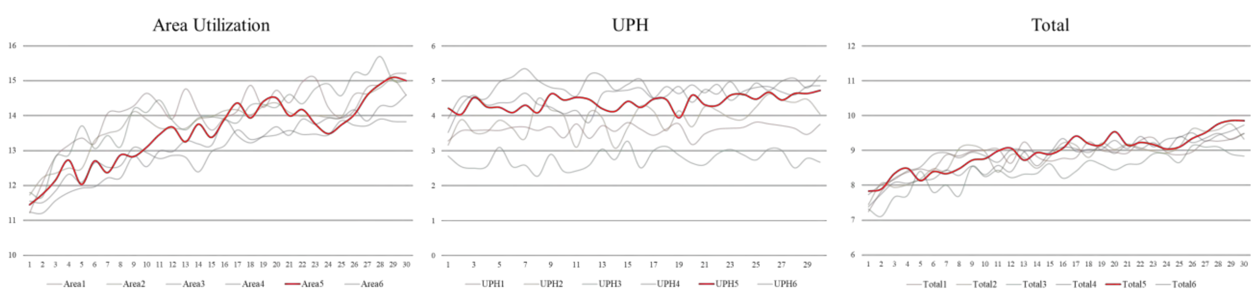


Figure 7: Simulation results of the proposed reconfiguration algorithm.

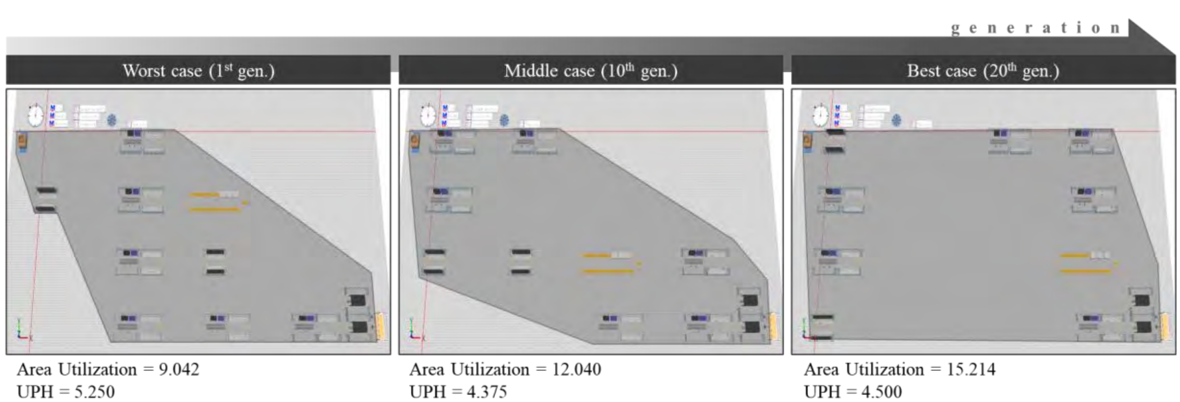


Figure 8: Area Utilization improvement through evolutions in Scenario 6.

Figure 8 displays how Area Utilization is improved across three different generations derived from Scenario 6, which the algorithm progresses. Changes in UPH are also observed along with Area Utilization. The diagram shows that the proposed algorithm effectively improves the area utilization without degrading the throughput. Meanwhile, Figure 9 illustrates the proposed algorithm's results for Scenario 5, including the layout transformation for a single solution. It is evident that as generations progress, all chromosomes gradually converge, with each representing a distinct solution layout. In this case, a solution encompasses facilities A, B, C, D, and Dummy, as delineated in Figure 1. Each facility is numbered and positioned according to its defined gene information, as depicted in Figure 9. Overall, common observations were identified across all scenarios in the simulation results.

- Because Area Utilization and UPH are competing with each other, our proposed reconfiguration algorithm rather increases Area Utilization with priority while preventing degrading of UPH instead of improving both Area Utilization and UPH simultaneously. This shows that the proposed reconfiguration algorithm is intelligent enough to identify the trading-off relationship between two objectives and prioritize which objective.
- Facility A, performing the first process, is primarily located in the first column close to the product input position.
- Facility B, performing two processes, tends to be placed close to each other and near the last column close to the product output position.
- Facility C is positioned closer to Facility A and B, enabling faster rework.

Facility D tends to be placed closer to the center of the layout to efficiently improve UPH as the number of Facility A and B increases.

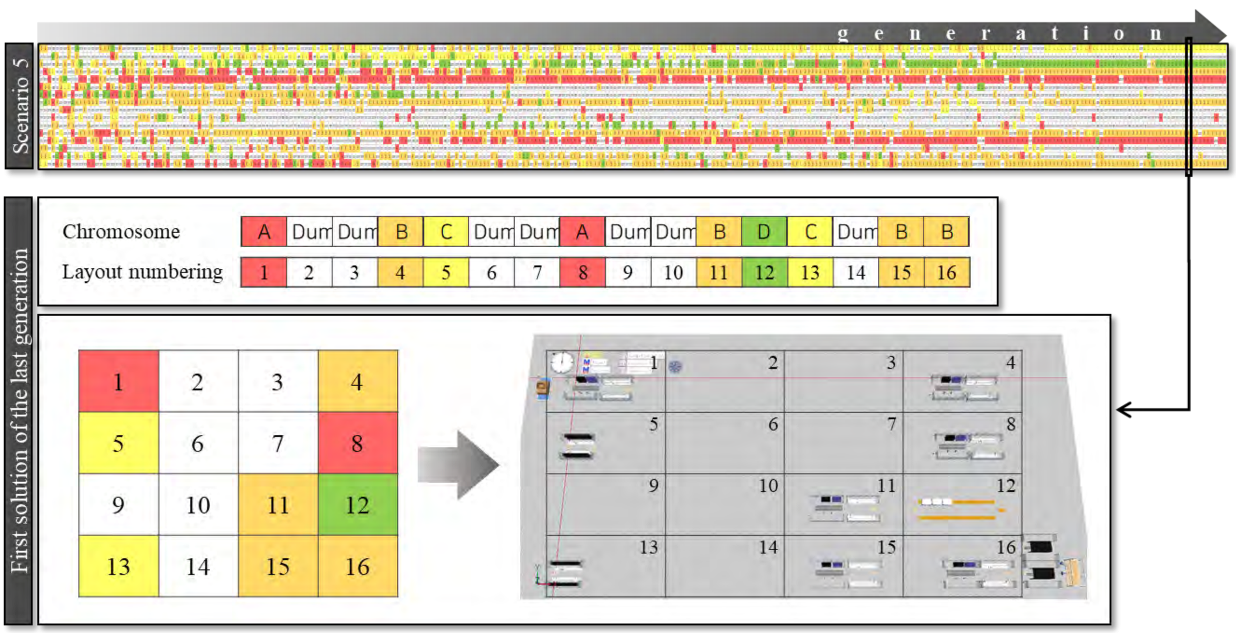


Figure 9: Gene information from Scenario 5.

5 CONCLUSION

In response to the growing demand to serve a variety of customers, the RAS employs reconfigurable modular facilities and AMRs instead of traditional in-line conveyors. This manufacturing approach, inheriting the traits of RMS, offers adaptability and responsiveness to unexpected dynamic manufacturing environments compared to dedicated manufacturing systems. In this study, we developed a layout reconfiguration algorithm modified from NSGA-II with a dual focus on optimizing area utilization and throughput. The implemented algorithm and simulation models are connected through an interface module and were executed for a total of six scenarios. As a result, the area utilization significantly improved in all scenarios, while the throughput (UPH), which is in a trade-off relationship with the area utilization, showed its slight improvement too. From the simulation results, it was observed that each facility was positioned optimally based on the relationships between facilities.

While the target RAS system in this study is designed to consider real-world automotive manufacturing processes, a broader application of the algorithm may yield richer insights. Additionally, while our proposed algorithm demonstrates efficacy, comparative research against alternative algorithms such as particle swarm optimization algorithms could provide valuable insights for future endeavors.

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