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Intelligent factory layout design framework through collaboration between optimization, simulation, and digital twin

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Abstract
In the era of the fourth industrial revolution, various internet and communications technologies (ICTs) are being applied to manufacturing systems. Based on these technologies, many companies utilize smart manufacturing systems to optimize the design and operation of their lines and to diagnose failures. To build and/or improve production lines, various computer-aided engineering (CAE) tools such as optimization solvers and simulation tools for validation are required. In addition, experts depend on their experience or utilize numerous trial and error processes, implying that a large time investment is required obtain the best layout design, without any guarantee that the result is in fact the best. Therefore, the paper proposes an integrated intelligent layout design framework that automatically derives an optimal layout according the requirements of the layout. The proposed framework uses mixed integer linear programming, simulation-based optimization, and digital twin to perform processes such as assembly line balancing, cell/buffer optimization, and layout planning sequentially and repeatedly to derive an optimal layout. By applying this, it is possible to automatically derive the optimal layout design considering limited resources and physical constraints. In addition, it can contribute to improving productivity and work efficiency at manufacturing sites.

Keywords Assembly line layout · Digital twin · Integer linear programming · Intelligent manufacturing systems · Simulation-based optimization

Introduction

As internet and communication technologies (ICTs) such as big data, machine learning, digital twins, and edge computing develop in the era of the fourth industrial revolution, the manufacturing industry is becoming more advanced by applying them in a variety of ways (Lim et al., 2020; Zhuang et al., 2021). Various manufacturing companies are attempting to build their own smart manufacturing system by combining ICTs (Redelinghuys et al., 2020; Kim et al., 2020). These technologies can be used to discover failure causes, optimize product performance outcomes, and enhance production efficiency (Kusiak, 2017).

Meanwhile, certain companies are facing situations such as unsteady demand and shortened time-to-market outcomes in recent years, leading to new requirements in factory design (Tao et al., 2018; Tao & Zhang, 2017). For example, as a way to address the above situations, high flexibility is required at production facilities, as are rapid improvements of assembly lines. To respond flexibly to market conditions during the production planning process, flexible changes and improvements in factory layouts are required to suit the circumstances (Tliba et al., 2022). At this time, new designs or redesigns of factory layouts must consider various future situations to ensure profitability in all cases, as shown in Fig. 1 (Dombrowski & Ernst, 2013).

In general, to design or improve an assembly line, companies use various types of tools suitable for each stage, such as optimization solutions and simulation environments for verification, and rely on the experience of experts at each stage, as shown in Fig. 2 above (Kim et al., 2019). These

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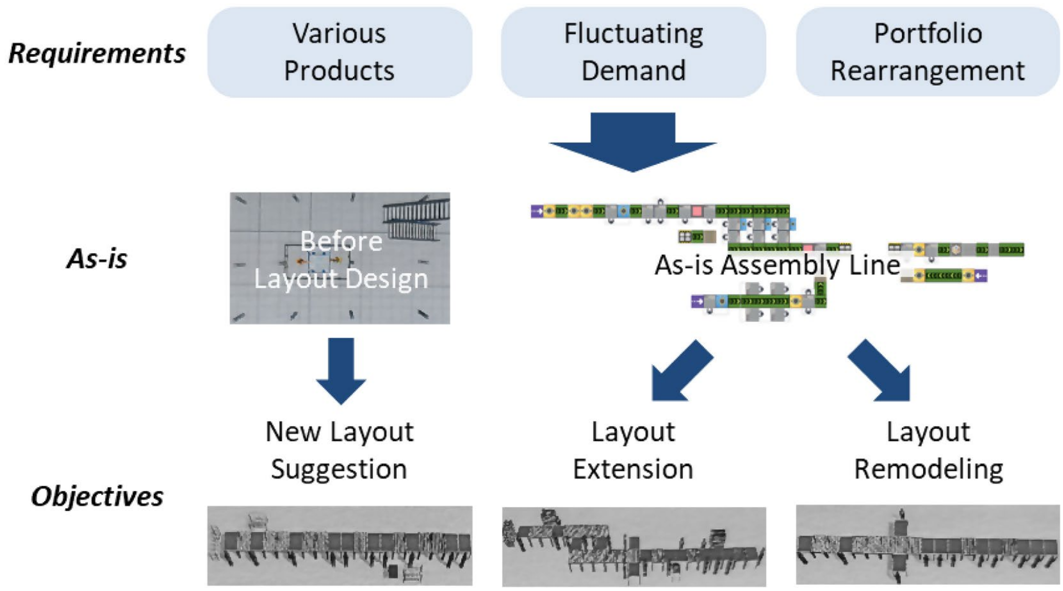


Fig. 1 Various layout design requirements

tools support them by testing different variants in different scenarios, such as discrete-event simulations of the logistics (Dombrowski & Ernst, 2013). Therefore, much time and effort are required to derive the optimal layout, and there is no guarantee that the results will be the optimal case suitable for production planning or the actual environment.

If we look at the scope of layout design broadly, it can encompass all logical and physical steps of assembly line balancing, cell/buffer optimization, and physical layout planning, as shown in Fig. 2 above. Although many studies of layout designs have been conducted in the past, the focus is mostly on solving only one problem among the overall steps above. In other words, researchers have yet to define an overall layout design process that is not standardized and that organically integrates each step. Therefore, an integrated design framework that encompasses the entire factory layout design phase is required.

Therefore, this paper proposes an intelligent factory layout design framework that automatically derives an optimal layout according to the conditions of an assembly line or a goal of production planning. The proposed framework automatically creates and optimizes layouts by repeating the steps of alternative design, validation, and improvement by integrating the tasks previously performed by each expert using individual solutions, as shown in Fig. 2. The alternative design includes three stages in detail: assembly line balancing, cell/buffer optimization, and the physical layout arrangement. In addition, corresponding strategies of linear optimization, discrete event simulation, and digital twin techniques are utilized to complete these steps. Through the proposed research, anyone can easily and quickly design a layout by standardizing and automating the layout design process of the factory assembly line, a process that requires much time and effort.

The remainder of the paper is organized as follows. Section "Preliminaries" describes the preliminaries and Section "Intelligent layout design framework" proposes the intelligent factory layout design framework. A case study that applies the proposed framework is described in Section "Application". Finally, Section "Conclusion" concludes the study.

Preliminaries

Prior to describing the proposed approach, this section briefly deals with preliminaries and related works on the topic of layout design. As mentioned earlier, several powerful commercial tools already exist in the production domain, such as PlantSim (Siemens, 2022), Automod (Rohrer and McGregor, 2002), FlexSim (Nordgren, 2003), and DELMIA (Dassault Systèmes, 2022). The tools have convenient and advanced libraries for productivity analyses and visualization tools using 3D. Many studies are being conducted on factory layout planning using them (Lin et al., 2014, Leiber et al., 2022, Kovács & Kot, 2017, Hadi-Vencheh & Mohamadghasemi, 2013). As well as the theoretical research, various application cases such as simulation-based digital shipyard construction (Woo & Oh, 2018), assembly line optimization (Ben-Arieh & Grabill, 2008), and facility layout optimization (Roux et al., 2008) are also being studied. The optimal layout was modeled by reflecting the physical constraints of the actual factory, and the optimal results were derived through simulations in the studies.

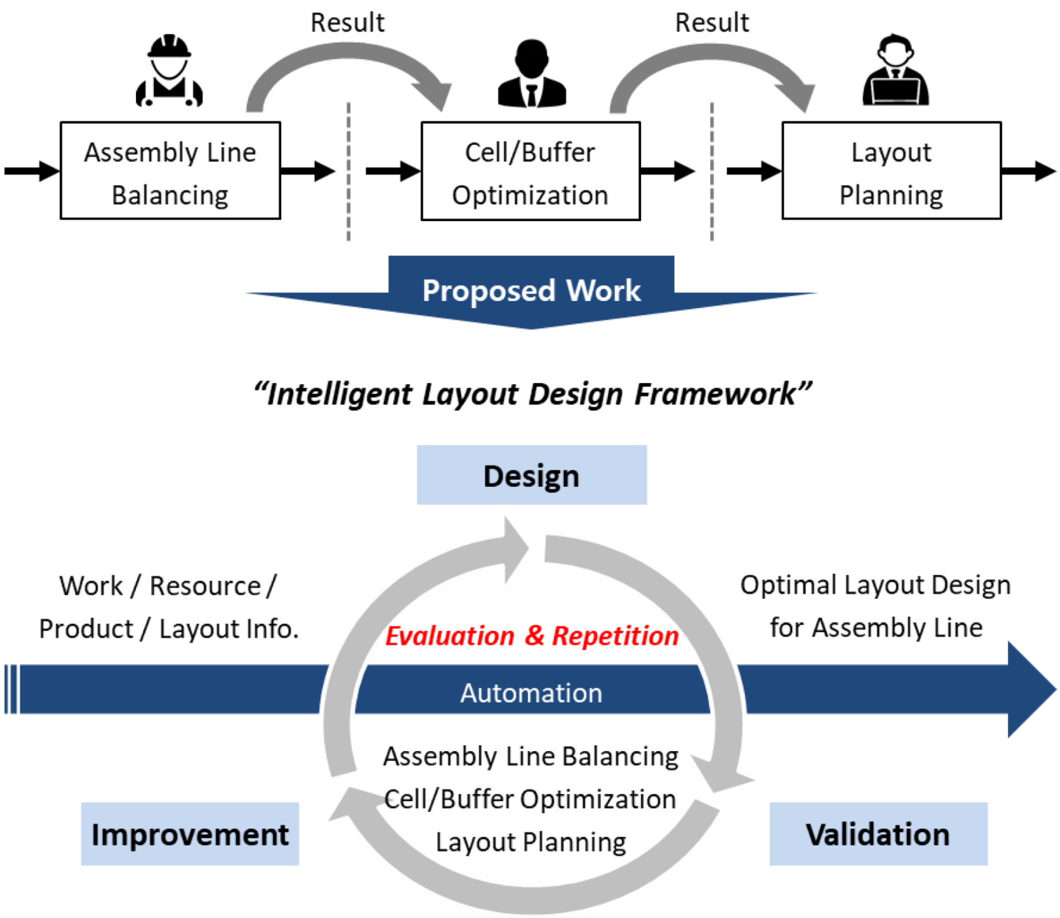


Fig. 2 Concept of the intelligent layout design framework

However, only physical factors were considered, assuming that assembly line balancing and the logical arrangement have already been completed. Therefore, it is not possible to consider the aspect of assembly line balancing with the initial information. In addition, because the stage before cell/buffer optimization required for the assembly process is not considered, the usability is significantly reduced in the early line design stages.

That is, it is essential to solve the assembly line worker assignment and balancing problems with work and resource information (e.g. worker, task, work station) in the initial stage of layout design. This is also one of the traditional production optimization problems and has long been studied by many researchers (Miralles et al., 2007, Shin et al., 2019, Araújo et al., 2012). Generally, mixed-integer linear programming (MILP) and heuristics are used to develop mathematical models for the optimal balancing of the assembly line to suggest line candidates. The established models can be analyzed with commercial or open-source solvers for linear optimization problems. However, because these studies focus on logical optimal arrangements, physical aspects such as the buffer length, cell shape, and layout arrangement are not considered.

Meanwhile, the optimal arrangement of available resources within the available space of the factory is the final step of the layout design. This step, called facility layout planning (FLP), has also been studied using various techniques. The purpose of FLP is to arrange the layout optimally in consideration of adjacency and obstacle avoidance aspects as well as resource arrangement rules, while also minimizing logistics costs (Esya and Santoso, 2020). Many researchers have studied this using techniques such as genetic algorithms (Azadivar & Wang, 2000; Besbes et al., 2020; Ye et al., 2023) and other algorithms (Azevedo et al., 2017, Banerjee et al., 1994, Guan et al., 2019, Ariafar & Ismail, 2009), depending on the type of problem to be solved. In addition, with the development of machine learning in recent years, many cases applying it have been conducted (Klar et al., 2021; Sun, 2022). However, contrary to the previous studies mentioned above, they only focus the physical aspects of the factory for the optimal arrangement and do not consider the logical optimization phase.

In addition, there are papers that utilized the digital twin for factory design (Guo et al., 2019, 2021). They used the digital twin to design the interior and layout of the factory, but it was used simply for physical arrangement with the logical design already completed. Also, a study was conducted that applied not only physical design using digital twin but also logical design in Zhang et al. (2017). Logical optimization and even physical optimization using digital twins were performed, but only a case study for a specific line were performed, and a framework for general assembly lines was not provided.

As noted above, previous studies are focused on solving and improving one problem at each stage. However, to the best of our knowledge, there has been no study that defines the overall layout design process and that organically integrates each step. Also, it is not easy to graft and organically connect each technique by reflecting the actual factory situation. Therefore, this paper proposes an intelligent layout design framework that encompasses all design stages by reflecting all product, work, resource information, and factory information. This strategy can advance the factory layout design problem through the complementary cooperation of digital twin models, a core technology in Industry 4.0, as well as traditional linear optimization and simulation-based optimization with a discrete-event simulation environment. Through this, it is possible finally to complete a framework that integrates the layout design process from the beginning to the end.

Intelligent layout design framework

Figure 3 shows the overall structure of the proposed intelligent layout design framework. It is largely composed of three steps: assembly line worker assignment/balancing, cell optimization, and the layout arrangement. The design alternatives produced through this framework are evaluated according to various evaluation criteria, and all steps are sequentially and iteratively performed until the criteria are achieved. Then, optimal layouts are automatically derived. This section describes the details of the proposed framework, including the applied techniques, the input/output of each step, and the interface for integrating all steps.

Assembly line worker assignment & balancing

The first step of layout design is to assign and balance assembly line workers optimally by utilizing the initial information. First, to configure an assembly line that produces products, information about precedence, process times, and resources is required as the initial information. Precedence refers to the preliminary task that must be done before proceeding with the main task, and process time is the working time required to complete the task. Resource information such as resource types and the number of detailed subtasks required to perform each main task is also required. Using this information, line designers must initially determine the number of physical stations constituting the line and the resources to be put into the work (worker/machine). Then,

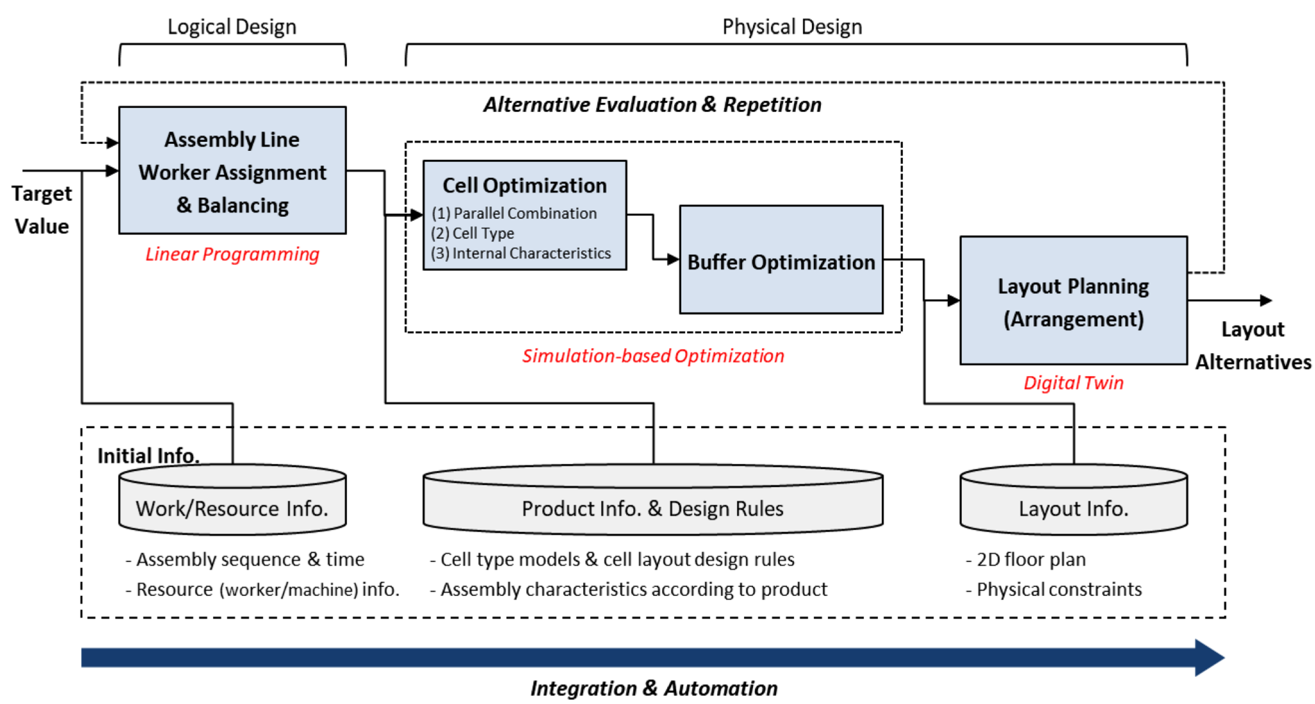


Fig. 3 Overall structure of the intelligent layout design framework

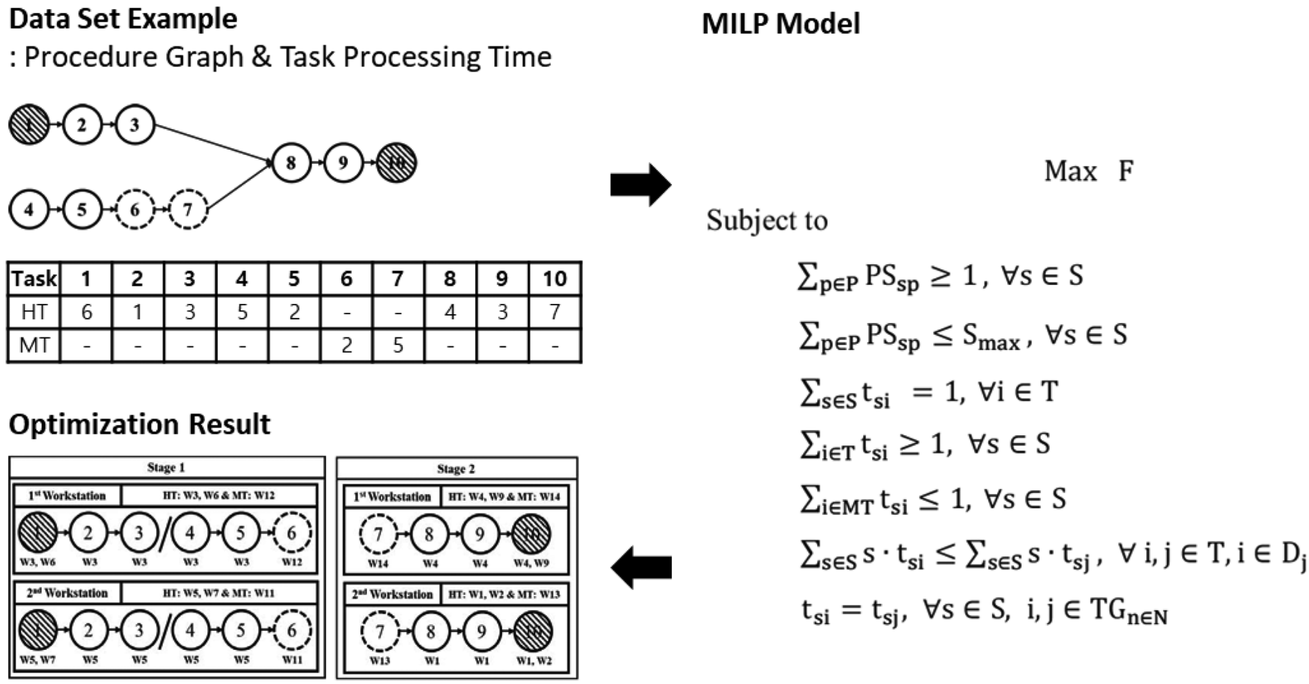


Fig. 4 Process of assembly line worker assignment & balancing

Table 1 Initial work information for a refrigerator assembly task

No	Task	Task time (sec)	Precedence	# of resource	Task group
1	Task 1	34.4	-	1 worker	-
2	Task 2	38.6	1	2 workers	-
3	Task 3	64.6	2	1 worker	-
4	Task 4	65.4	3	1 worker	-
5	Task 5	62.0	4	1 worker	-
6	Task 6	9.5	5	1 machine	-
7	Task 7	14.6	6	1 worker	-
8	Task 8	10.8	7	1 worker	-
9	Task 9	68.3	8	1 worker	-

tasks within the station must be allocated and the number of resources required for each task must be specifed (Kim et al., 2019). Subsequently, the expected throughput and line of balance (LOB) can be calculated according to the cycle time of the entire line by checking the cycle time per station according to the resources allocated to each task. Originally, the line designer repeats this process empirically to determine alternatives with shorter cycle times and higher LOBs as the initial solution. This manual work takes a long time, and it is difficult to derive the most optimal alternative. In addition, there is some difficulty in performing the line design step in consideration of work-time deviations between processes that contain a task bundle.

Therefore, it is necessary to develop a mathematical model that minimizes the cycle time so as automatically to provide an optimal alternative (Miralles et al., 2007). This model can assign each task and worker to a workstation within an assembly line considering line balancing aspects to meet the required production conditions. The established model can be analyzed with commercial or open-source solvers such as Gurobi or CPLEX for mixed-integer linear programming (MILP). Figure 4 shows the overall process of solving the assembly line worker assignment and balancing problem. This includes examples of a simple initial dataset, a MILP model, and the optimization process result.

Table 1 presents several parts of a sample dataset showing the task time, precedence, and required resources for each task of an assembly line that produces refrigerators. In this paper, the detailed roles of the tasks are omitted. After the number of stations to configure and the number of workers to allocate are set using this dataset, the MILP model proposed above is analyzed using Gurobi. Table 2 shows the simple results of the first step through the optimization process with only sample input data. This represents the result of configuring three to nine stations for the task in Table 1 and assigning the maximum number of workers, which is ten in this case. The result shows that the optimal assembly consists of two parallel jobs at seven stations, requiring a total of eleven resources. At this time, the product cycle time of the line is determined to be the value having the longest cycle time at the configured stations, and the LOB of the line is calculated according to the common LOB formula. Figure 5 presents the result of this first step using a procedure graph.

Table 2 Work assignment & balancing result

No	Station	# of Stations	# of Resource	Task	Total time	Cycle time
1	Station 1	1	1	Task 1	34.4	34.4
2	Station 2	1	2	Task 2	38.6	38.6
3	Station 3	2	1	Task 3	64.6	32.8
4	Station 4	2	1	Task 4	65.4	34.7
5	Station 5	2	1	Task 5	62.0	31.0
6	Station 6	1	1	Task 6	9.5	34.9
				Task 7	14.6	
				Task 8	10.8	
7	Station 7	2	1	Task 9	68.3	34.2

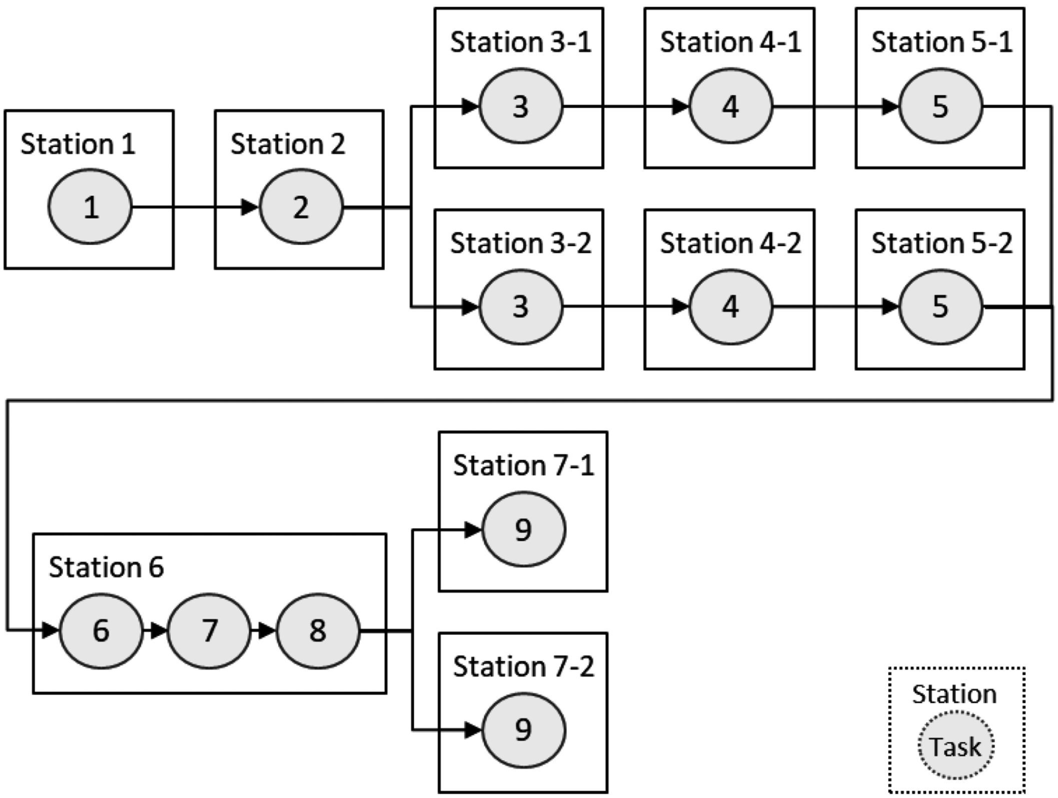


Fig. 5 Procedure graph of worker assignment & balancing

Cell/buffer optimization

Cell optimization

After the first optimal worker assignment is completed, the second step is carried out using this result as the input. This is the stage of optimally arranging the logical assignment result in a concrete form that can be placed on an actual line including conveyors, converters, workstations, etc. For the actual arrangement of an assembly line, a range of variables must be considered according to the characteristics of the product. These variables include not only the cell type but also variables related to several characteristics within the cell, such as the call method, the standby positions of the parts, the length of the buffer inside the cell, and the cell assignment priority levels, among others.

Among them, the cell type is one of the most important factors to consider. With regard to a parallel cell as a result of the first step above, it can actually have various forms depending on the characteristics of the task. In other words, it is necessary to model the parallel process by reflecting the rules related to the characteristics of the process, product, equipment, and other factors.

For example, in the results of Fig. 5, station 3 to station 5 can be composed of two-stage parallel cells. It can be built as a single parallel cell containing all three tasks from task 3 to task 5 but can also be devised as three parallel

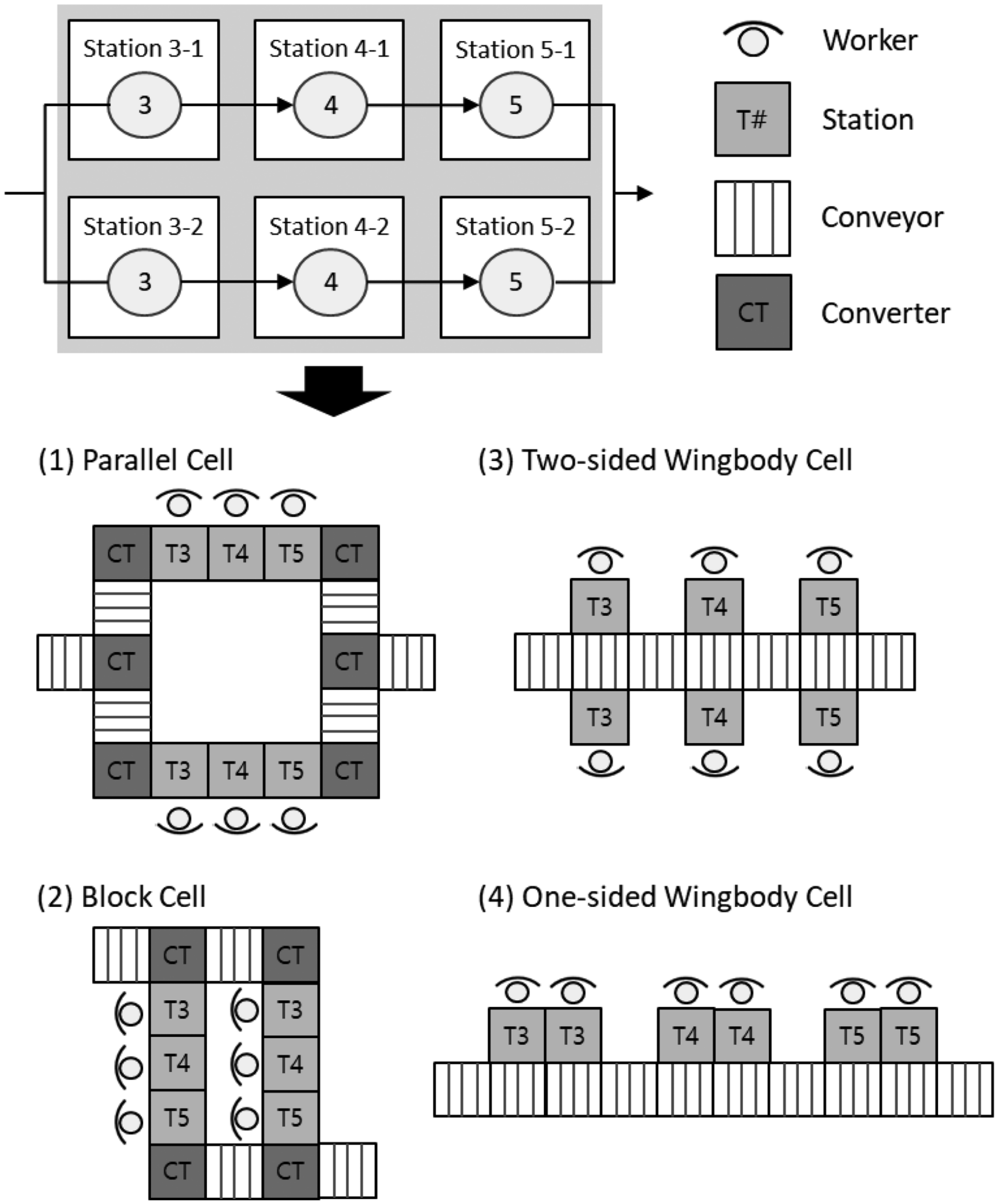


Fig. 6 Examples of various cell types

cells containing only one task each. Alternatively, it can be composed of a combination of a parallel cell with two tasks and a parallel cell with one task. In this way, because the result of the worker assignment can consist of various combinations of parallel cells, all of these combinations must be considered in the cell type optimization stage. Among these combinations, let's check out a parallel cell containing all three tasks in one cell. Although it has a single logical arrangement, it can use various forms for the physical arrangement in a factory. Figure 6 shows examples of cell types in which a two-stage parallel cell can be placed. As shown in the figure, in addition to the common parallel cell, there are various cell types, such as a block cell, a one-sided wingbody cell, and a two-sided wingbody cell, among others. In other words, by simulating and analyzing all possible combinations for all parallel cells, it is possible to derive an optimal cell type among them. Because the assembly cells can be modified into various forms by reflecting the characteristics of the company/business/product, it is necessary to model appropriate cell types after identifying these characteristics for improved cell type optimization. It is also necessary to manage various modeled cell libraries through the database.

Meanwhile, for each cell type, it is necessary to optimize the characteristics inside each cell mentioned above. One of the variables inside the cell is the call method, which determines whether to use the push or the pull strategy when each station requests a product. The location where the product is waiting before entering the station, the length of the conveyor between the stations in a parallel cell, and the presence or absence of each station's buffer are also variables to consider. In this paper, only the call method and the conveyor inside the cell are reflected; all others will be considered in future work. Cell optimization is completed by undertaking the optimization of all cell types and variables for all combinations of parallel cells with the worker assignment results.

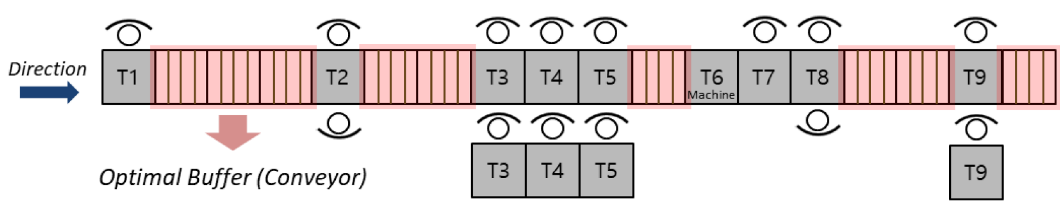
Buffer optimization

After the optimization of individual parallel cells is completed, it is necessary to assign the buffers between the stations across the entire line. At this time, it is important to optimize the physical characteristics of the buffer, i.e., the length of the buffer, and the cell type and the shape of the entry/exit conveyor should also be considered. To reflect the actual field in the simulation, it is important to consider deviations in the working time, and in this case, allocating the optimal buffer greatly affects the performance. Figure 7 illustrates the necessity of buffer optimization through the previously assigned assembly line. The assembly line in Fig. 5 is a logical design that assumes no buffer and does not take into account deviations. At this time, if the deviation of the working time for each task is considered, a buffer is essential to prevent blocking between stations. Therefore, a buffer with an appropriate length should be positioned between the stations to maximize productivity. To do this, simulation-based optimizations are undertaken by adjusting the buffer length between all stations based on the product size.

The table inside Fig. 7 shows how the performance changes depending on the presence or absence of buffers when the deviated working time is taken into account at this line. Due to congestion in the absence of a buffer between stations, it has a high tact time and shows a low capacity. Conversely, when assigning unlimited buffers, good performance can be realized theoretically, but because it is impossible actually to arrange the tasks due to a physical limitation, it is important to find an optimum level with the highest efficiency given the minimum amounts of resources. As shown in the table, with the optimal buffer, the productivity is very high compared to when there is no buffer despite not adding a small buffer compared to an unlimited case.

To obtain the optimum solution in the minimum amount of time, the problem should be solved iteratively where, during each iteration, the solution moves closer to the optimum solution (Nguyen et al., 2014). Such methods are referred to as simulation-based optimizations, and the second step described above uses them as a solution. They include ranking and selection methods (Choi & Kim, 2017), heuristic methods, and response surface methodologies depending on the problem to be solved (Wortmann, 2019). In this study, heuristic methods, specifically genetic algorithms, are used to find a good solution in less time compared to traditional methods. This method is a metaheuristic approach inspired by the process of natural selection, relying on operators such as mutation, crossover and selection (Mitchell, 1998). The simulation model required for the application of such an algorithm can be modeled using PlantSim, a powerful manufacturing modeling and simulation tool for discrete-event simulations.

In this paper, a simulation model that can reflect various cell types and their characteristics is created, and a



	No deviation	Considering deviation (10%)		
	Ideal	No buffer	Optimal buffer	Unlimited
Capacity (EA)	719	547	**714**	716
Tact Time (s)	38.39	50.46	**38.66**	38.55
LOB (%)	68.66	68.66	**68.66**	68.66

Fig. 7 Example of a productivity increase through buffer optimization

module that automatically executes a genetic algorithm is built using the model. Then, this module is run to create several near-optimal layout alternatives preferentially. Among them, several proper layouts are automatically derived by comparing the layout constraints and performance indexes. Figure 8 shows the results after the execution of the second step using the results of the first step. These results are used as input for the final step.

Layout planning

The final step is for layout planning, in which the physical information of the factory is received and the alternatives derived in the previous stage positioned in the actual factory. This physical arrangement of the assembly line can significantly affect the productivity. At this time, it is necessary to consider the physical constraints of the plant,

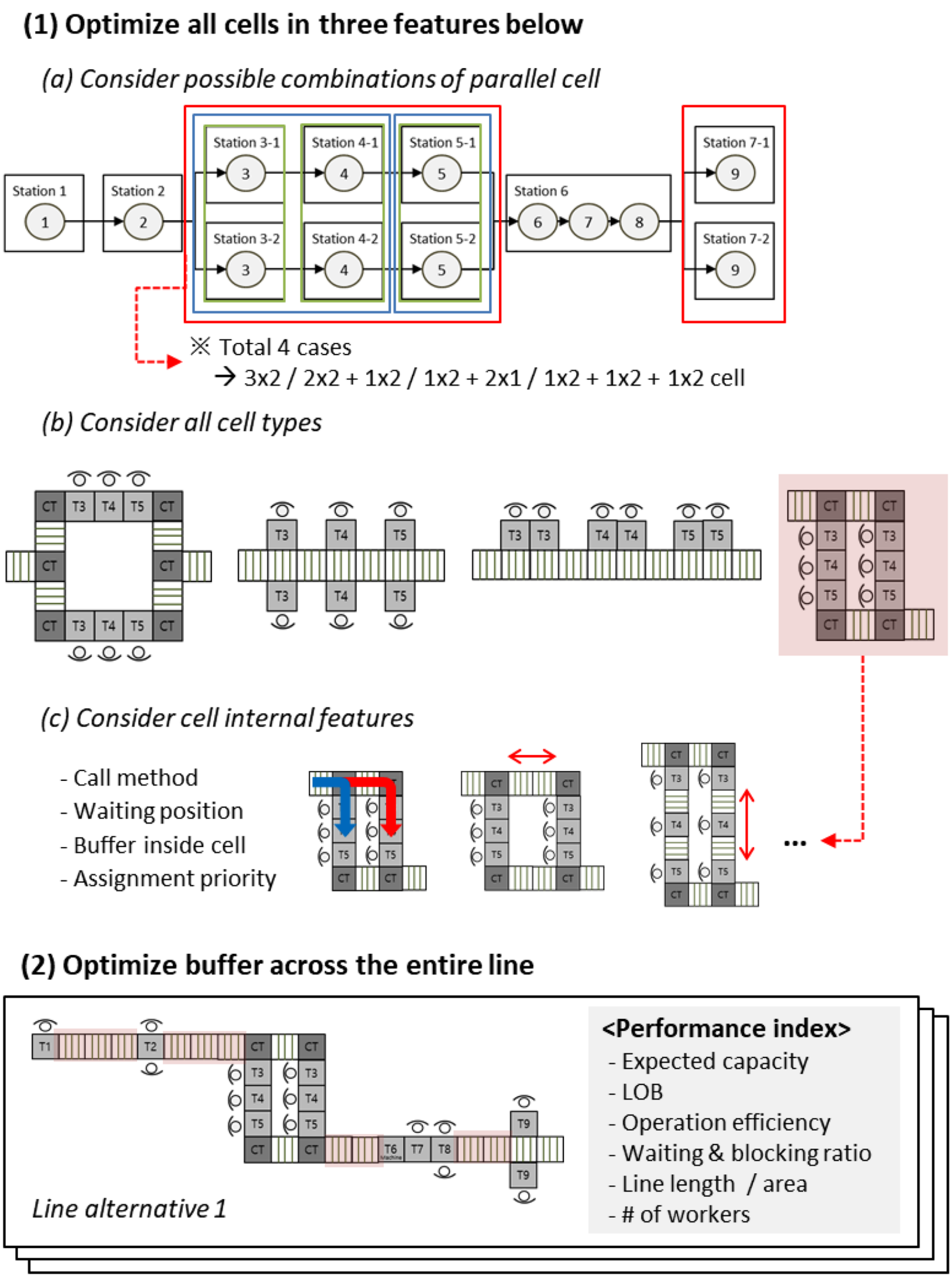


Fig. 8 Detailed process and cell/buffer optimization result

such as obstacles, columns, unused spaces, free space for workers, and passageways. Also, various characteristics such as adjacency between resources, fixed locations of specific equipment, and logistics flows can be considered. For layout planning, as mentioned above, in-depth studies are being conducted to improve efficiency rates, including those focusing on nesting algorithms and machine learning. However, because this paper proposes an overall framework, it focuses solely on avoidance planning on the assembly line rather than increasing the performance by considering a range of variables in this layout planning stage using digital twin model of actual factory layout. Factors other than avoidance planning will be considered in future work. When undertaking layout planning, information about alternative lines, which are the results of the second step, is needed. This information includes not only the optimized line structure but also physical information about the station/conveyor/product size required for actual planning. In addition to this, layout information, including the size of the layout to be placed and the aforementioned physical constraints, is required. After that, it is necessary to build a digital twin model for the factory layout using this information.

First, in the layout planning stage, in order to use the optimized line as the input, it is converted into attribute data tables including the sequence number, object sizes, object types, input/output locations, and safety areas, as shown in Fig. 9. At this time, the aforementioned physical information is also reflected in the attribute data. Also, with regard to parallel cells, the assumption is that they form a single unified object. Through this process, a table including both logical and physical information about alternative lines is completed. Next, based on the completed input table, the first to last objects are sequentially placed in the factory digital twin until all objects are placed. At this time, the input layout can be gridded in terms of the unit size and can be divided into usable spaces and unusable spaces including obstacles.

The first object is placed at a random starting point; after the current object is placed, placement is basically attempted in the current direction. After the current object is placed, the next object is placed in the current direction by default. At this time, by checking the overlap between the expected position of the next object and the unused spaces in the layout, it is decided whether the next object should be placed as it is or in a different direction. Nevertheless, if it is not possible finally to arrange all objects in the current layout, the placement step is repeatedly attempted while changing the starting point. Through this process, the result of the physical arrangement of the assembly line is automatically derived in the layout, as shown in Fig. 9. It basically reflects the avoidance of unusable spaces and the securing of a safety area. Figure 10 also shows that the layout planning results can vary depending on changes in the factory layout. First, Fig. 10(a) and Fig. 10(b) show the initial factory layout and planning results to be placed in that layout, respectively. At this time, if a rack is added to the initial layout, the layout planning result as shown in Fig. 10(c) is derived, in which the direction of the line is changed because the same arrangement used before is impossible. Next, if an unused space is added to this layout, a valid planning result cannot be derived, as shown in Fig. 10(d), as logical line results cannot be physically placed in the current layout.

Additionally, in addition to this simulation-based optimization method, faster layout planning is possible using reinforcement learning (Kaelbling et al., 1996). In order to apply this approach to layout planning, the environment for reinforcement learning is defined as the placement area and unusable spaces are designated as they were before. Also, the agent is defined as objects to be placed, such as stations, buffers, and cells, and the action is defined as where from among four directions to place the next object in the current state. The reward is received after each object is placed. If the object is placed in an unusable space, it will receive a negative infinite reward and will also receive a low reward when the adjacency is high or the direction of the line is changed. The defined model is repeatedly learned through an algorithm such as Q-learning (Sutton & Barto, 2018) until the cumulative reward is maximized. At this time, it can be seen that this is an optimal layout, because maximizing the reward means minimizing overlap with unusable spaces, the degree of adjacency, and the bending of lines.

Application

Usage analysis

In this section, a simple assembly process is applied to the framework proposed in Section "Intelligent layout design framework", and the results are analyzed. Also, the contributions of the proposed work are explained. As mentioned in Section "Introduction", according to the various requirements of manufacturing sites, use cases of this framework can be divided into three types: new layout suggestions, layout extensions, and layout remodeling cases, as shown in Fig. 11. Depending on the use case, the framework can be applied in the following way.

The first is when a new line is needed when developing a new product or building a new factory. In this case, new line alternatives should be proposed using work information and factory information. The example described previously while proposing a framework corresponds to this case. The second is a case where there is an existing line, but the line must be expanded because an increase in production

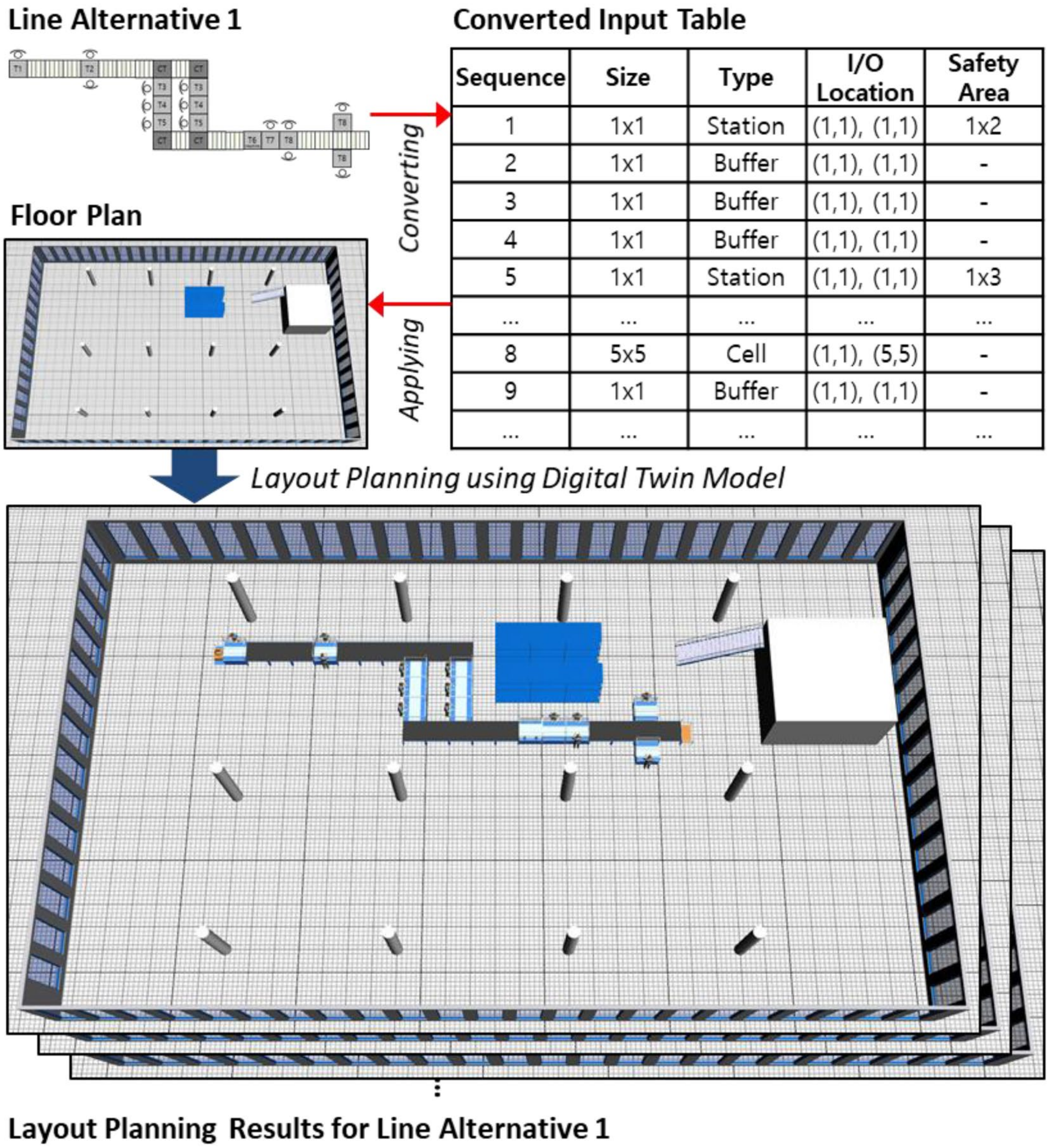


Fig. 9 Layout planning process

or an additional process is required. In this case, the first stage is performed only on the extended portion, and cell/buffer optimization is performed by integrating the existing line information with this result. The optimal layout can be completed by reflecting the physical constraints by performing layout planning of the third stage on the completed extension line through the previous process as shown in the middle of Fig. 11. The last case is one in which an existing line must be reorganized for LOB and productivity improvement, or the line must be modified due to a process improvement. Such cases can be performed again from the first stage of line balancing with modified work information, such as process changes as shown in the bottom of Fig. 11.

Table 3 shows the analysis results of each optimal layout derived for these three use cases based on the information used in Sect. "Intelligent layout design framework". In other words, after automatically deriving the optimal layouts only with the initial work information, expected capacity, LOB, operation efficiency and line structure can be easily predicted. In addition, it is possible to analyze how much productivity will increase when a line is expanded by adding a process like Case 2 or when a process is improved like Case 3.

Contribution and evaluation

The following is the contribution effect of the proposed framework. It can be seen that an optimal alternative can be generated through the optimization process within a short time using only the initial assembly information. Although

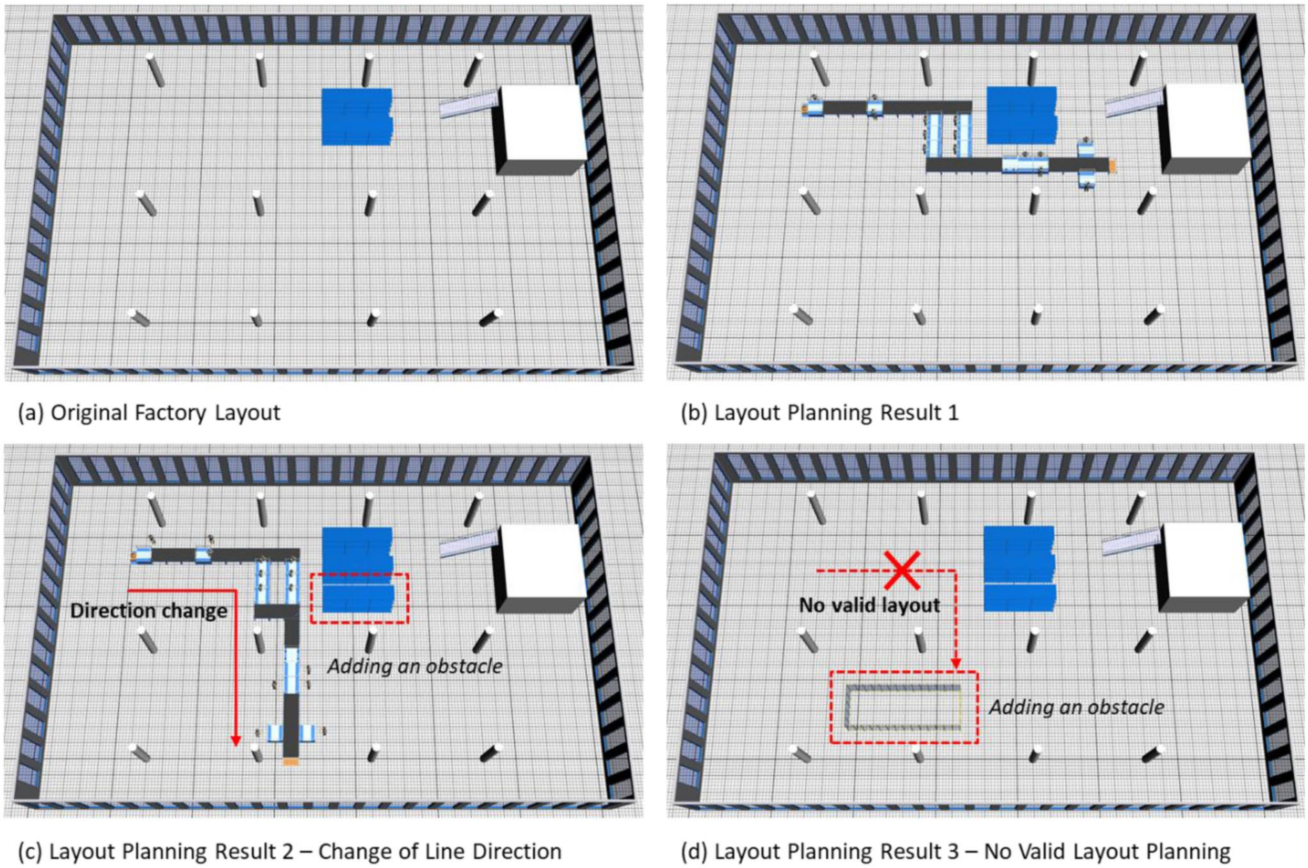


Fig. 10 Various planning results according to layout changes

it is not directly comparable to designing by experts, and given that the time can vary depending on the computing environment, this alternative can in general significantly reduce the time and effort required design an assembly line. It can also ensure sufficient production and efficiency through optimization. Hence, it can thus help with decision-making activities at actual manufacturing sites. In cases where it is difficult to apply the results directly due to various constraints, it is possible actually to apply them through additional modifications by experts depending on the situation.

Quantitative evaluation results for this are shown in Table 4. Because there is no method that can be compared directly, we simply compare the method of consignment to layout experts commonly used in the manufacturing company. This result is based on real data obtained in the company.

Conclusion

This paper proposes an integrated intelligent layout design framework that automatically derives an optimal layout according to the requirements of the layout. The proposed framework proceeds sequentially and repeatedly in three steps: assembly line balancing, cell/buffer optimization, and layout planning. Using this sequence, it is possible easily and automatically to design the optimal factory layout without entrusting it to experts. Moreover, it is also possible to improve the productivity because the framework derives the optimal design considering limited resources and physical constraints. In addition, it can be applied to manufacturing enterprises to support manpower for factory construction and design efforts, and it can be used to improve work efficiency by spreading not only to major companies but also to medium-sized manufacturing companies that do not have professional manpower for layout design tasks. Through this, the makespan for decision-making among various departments required for factory construction/operation will be reduced and reusability will increase, as it is easy to modify/manage the layout alternatives continuously. In other words, the framework can be utilized as a decision-support system.

This paper also demonstrates the effectiveness of the framework by showing an example of a simple line design for actual product assembly using the proposed framework. It provides several layout alternatives to users by sequentially proceeding with each of the two stages of physical design.

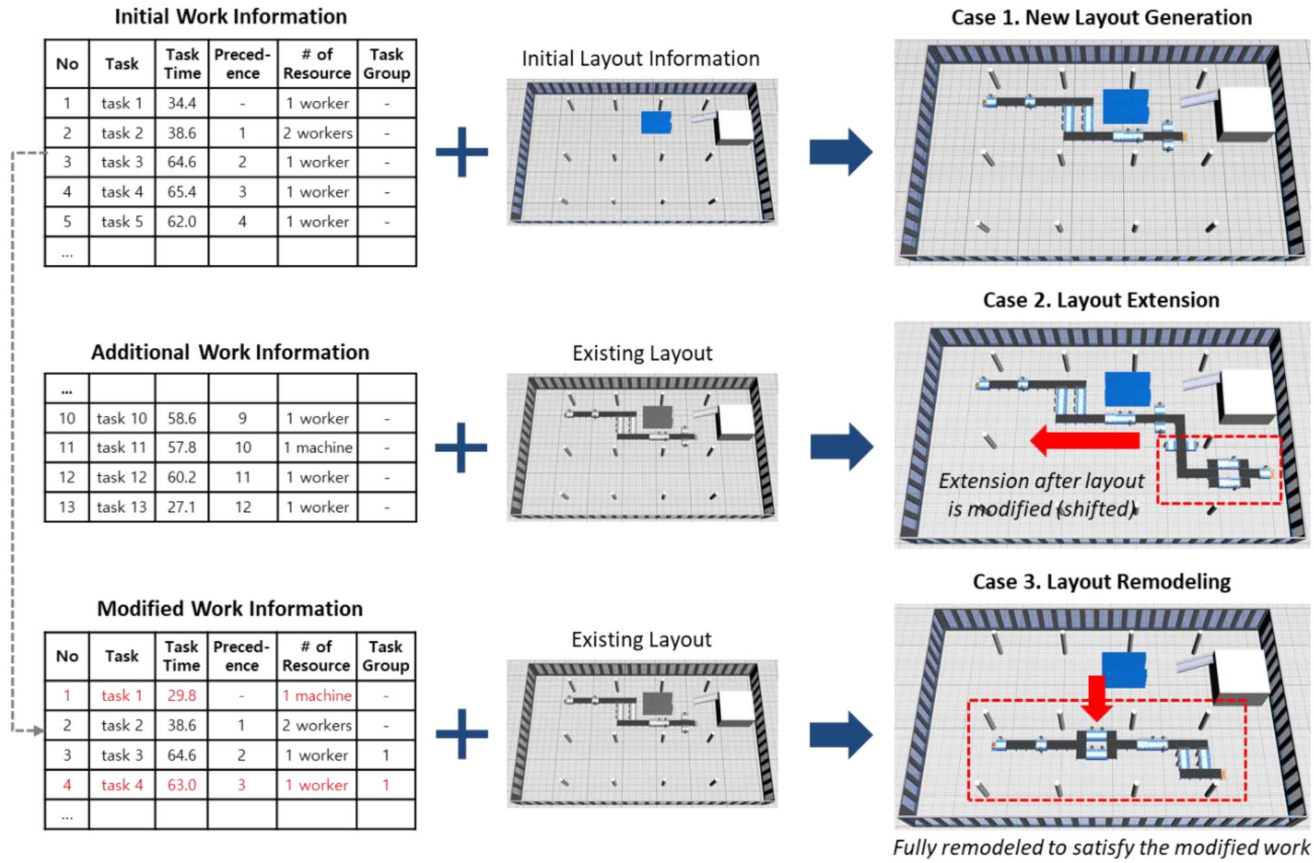


Fig. 11 Three types of use cases

Table 3 Experimental results of the use cases

Index	Case 1	Case 2	Case 3
Expected capacity	3400 EA/shift	3364 EA/shift	3412 EA/shift
LOB	68%	64%	70%
Operation efficiency	Average 78% (minimum 60%)	Average 73% (minimum 57%)	Average 79% (minimum 60%)
Waiting & blocking ratio	23%	26%	22%
Line length	22 m	29 m	25 m
Line area	176 m^2	435 m^2	175 m^2
# of workers	14	19	13

Table 4 Evaluation result of the proposed work

Index	Consignment to layout expert	Using proposed framework
Layout design period	Average 5 days	3 h (Case 1)
Training period	2 ~ 3 months (if it is required)	1 day
# of tools required	More than two	One
Optimal layout	Optimal layout not guaranteed	Providing optimal layout alternatives

However, in this case, the result may differ from those when optimizing by considering the second and third stages at the same time. Therefore, as future work, it is planned to study a new method that optimizes both steps at the same time to overcome this limitation. Also, it is planned to increase the performance of each stage by reflecting actual factors in the field more succinctly. For example, for layout planning in the third stage, algorithms that consider complex situations such as adjacency and logistics flows will be studied. In addition, the framework will be expanded to make it universally applicable to various manufacturing types.

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