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Assembly line Optimization: A systematic review of various algorithms, applications & drawbacks

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Abstract

One of the most popular production methods is assembly line manufacturing. The assembly line balance problem, which is used to quickly build large quantities of a consistent product, is focused on decreasing the number of workstations, lowering cycle time, maximizing work cohesion, and maximizing workload uniformity. The initial purpose of assembly lines was to produce standardized goods in large quantities at a reasonable cost. A production unit's assembly line consists of a number of employees and equipment. An assembly line is used to produce the components in a production unit. During processing, the product travels along this line. In a flexible manufacturing system, assembly lines have changed throughout time from straight lines with a single model to mixed lines with numerous models, U-shaped lines, and lines with parallel workstations. Reducing the number of work stations and balancing the assembly line based on the intended production volume each shift are the primary goals of system assembly line planning. Various assembly line balance difficulties (ALB) have been examined and described in this paper. Researchers can greatly benefit from the creation of a mathematical model to address the assembly line balancing and sequencing difficulties.

Keywords: Productivity; Assembly line optimization, Manufacturing process, Random Start of Shortest Distance Permutation algorithm

1. Introduction

1.1. Background:

As large-scale manufacturing techniques developed to meet the demand for more affordable and accessible goods, assembly lines were born [4]. For this, a number of workstations are set up along a conveyor belt or other comparable material handling apparatus. As the semi-finished goods are moved along the assembly line, each of these workstations completes one or more duties. The final product is assembled at each workstation by a series of steps based on an assembly order. These processes are broken down into elementary operations, or tasks, that are carried out on the assembly line's workstations.

A company that now purchases its goods from assembly lines faces many difficulties. First, their production lines need to build a sizable number of product models and their variations because of the market's desire for variety. Because a certain level of diversity is required by the market. Another difficulty is allocating resources and ensuring a sufficient workforce. This example demonstrates the act of reconciling activities. The purpose of workstation equilibrium jobs is to increase assembly line productivity and lower operating expenses. These goals can be accomplished using a variety of ways, including simulation, heuristic, meta-heuristic, and exact approaches. The importance of frequent assembly line changes is what many businesses do to overcome these problems. Allocating tasks to terminals is an issue known as manufacturing facility 6] or reconfiguration, though, if one wishes to make changes or redesign an already-existing assembly line. This rearrangement of current lines is the outcome of the ongoing shift toward mass customization [1] ,[2], [9], [26] often referred to as the "accessible production paradigm" [5]. Eliminating waste and recycling present-day producing resources is a crucial aspect of modern production, and reorganization can result in enhanced sustainable manufacturing [6].

Assembly lines were initially created to produce standardized goods in large quantities at a low cost, allowing for high worker specialization and the learning benefits that come with it. Assembly line balancing (alb), on the other hand, takes advantage of modern manufacturing techniques like mass customization and offers effective assembly line solutions for the manufacture of small quantities [15]. This in turn guarantees that, for the foreseeable future, meticulous assembly system planning and implementation will remain highly relevant to practice. Allocating various jobs to workstations while optimizing one or more goals while adhering to assembly line constraints is another aspect of the assembly line balance challenge. Various objectives are taken into consideration in 2alb problems.

If efficient methods and instruments for solving problems have been created for many years, the SALBP research is in the mature stage. In contrast, a growing amount of work has been done in recent years to expand the GALBP to represent actual industrial issues, particularly by combining a number of useful limitations and features in a coordinated way. This creates a significant non-homogeneity throughout the GALBP's extensive publications. There have also been several noteworthy classification schemes put forth [16]. However, because the review brought together many ALBP situations, such as disassembly, machining, etc., their classification schemes were too detailed for novice researchers and practitioners to understand. The primary layout was either a straight line or, if slightly more sophisticated, a U-shaped line (U-line). The U-line concept was still relatively new in the industry at the time and had just recently been developed to facilitate JIT production. It follows that while conducting literature surveys, the classification of the ALBP using SALBP and GALBP was sufficient to distinguish unique features between the two groups [16]. However, the number of articles on the SALBP is currently starting to reach saturation, whereas the number of articles on the GALBP is significantly growing due to the emergence of new layout types, such as two-sided assembly lines (2SAL) and parallel assembly lines (PAL).

To respond to market changes, manufacturing today needs to be more competitive than ever, which means the production line needs to be resilient to ongoing changes. Manufacturers are compelled to provide a wide range of products due to more demanding customers, necessitating the construction of suitable mixed-model assembly lines. A production line that launches unfinished goods through a series of stations connected by a material handling system is known as an assembly line. Accordingly, a precedence connection is assigned to the many tasks needed for each product, which are carried out using a variety of techniques, including robots, operators, or operators with supporting robots [38].

In an effort to increase output and quality, some businesses have started to make improvements to assembly line layouts. The U-shaped assembly line differs from a simple linear assembly line in that it has cross workstations to complete duties on both the entrance and exit sublines in addition to standard workstations to complete tasks on either the entrance or the exit subline. More specifically, a task can be allocated as long as its immediate predecessors or successors have been assigned. This increased flexibility leads to a far better degree of productivity.To assist the decision maker in setting up an effective assembly system, a variety of optimization models are used to depict the assembly line balancing and optimization problem. A few assembly line balance issues and fundamental techniques are covered in [50]

1.2. Motivation:

Increased demand for customized products and decreased production costs with improved quality has necessitated the need to adopt efficient assembly line optimization strategies. An assembly line is a complex system containing several variables, constraints, and uncertainties and is considered a challenging process for optimization. Although many different algorithms have been developed for optimizing different types of problems, most lack a comprehensive review of what their strengths and limitations are in these applications. The paper aims to bridge this gap by providing a comprehensive overview of assembly line optimization algorithms, their applications, and drawbacks, hence helping industry practitioners and researchers to come up with more efficient and effective optimization strategies.

1.3. Objectives:

- To minimize production time and reduce lead times.
- To maximize assembly line throughput and capacity utilization.
- To improve product quality and reduce defect rates.
- To optimize resource allocation and assignment.
- To reduce production costs and improve profitability.

1.4. Scope:

The pre-assembly and assembly facilities in the latter buildings will be combined into a single, continuous assembly line as part of the planned assembly system restructuring operation. The foundation of this procedure is the pre-assembly line's transition to single-line production. The goal of this work is to rebuild a more effective pre-assembly line and reorganize the production system by taking the required steps. This involves analyzing activities at these pre-assembly locations while taking line balancing and lean assembly principles into account. The anticipated work to be completed within this research includes addressing/readdressing operations to stations, removing/replacing stations, performing modifications in the sequence of operations at stations, layout planning, operator planning, and line balancing.

1.5. Structure of the Paper:

This survey's content is arranged as follows. Section I provides background information on graphs and GNN models. The state-of-the-art in Assembly Line Optimization is reviewed in Sections III Methodology and IV Assembly Line Optimization. Section V Drawbacks and Limitations of Assembly Line Optimization. Sections VI and VII, finally, are devoted to suggestions for further research and their conclusions.

2. Methodology

2.1. Data Sources:

This systematic literature review (SLR) precisely follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) criteria in order to methodically study the Assembly line Optimization into various algorithms, its application and drawbacks. The review, which was done using dependable sources like Google Scholar, IEEE Xplore, Scopus, and PubMed, covers all works published between 2018 and 2024. The abundance of Random Start of Shortest Distance Permutation algorithm material in these groups led to their selection. Furthermore, the abundance of information accessible allows for the analysis of related ideas and usage trends of the term comprehensibility.

2.2. Search Strategy:

A complete set of papers was included following an extensive selection process that adhered to the PRISMA principles for systematic examinations. PRISMA principles were adhered to, and a systematic and exhaustive search technique was employed. Predefined search phrases, such as Assembly line Optimization, Assembly line optimization automotive, Drawbacks of assembly line optimization algorithms, production planning optimization, manufacturing optimization, Analysis of industrial optimization were checked, such as IEEE Xplore, PubMed, Google Scholar, and Scopus.

2.3. Selection Criteria:

In the process of information research, the Assembly line Optimization into various algorithms, its application and drawbacks. The first source of articles used was Google Scholar, followed by IEEE Xplore, Scopus, PubMed, and thousand seven hundred sixty and six fifty from Google Scholar. Following a comprehensive screening procedure that included identifying relevant papers and eliminating duplicates, one fifty articles were determined to be eligible for further assessment (Figure 1). The final selection of 50 papers adhered to PRISMA principles, ensuring a comprehensive and uniform examination based on preset selection criteria.

2.4. Data Extraction:

All works published between 2018 and 2024 are included in the review, which was conducted using credible sources such as Google Scholar, IEEE Xplore, Scopus, and PubMed. Their selection was prompted by the large number of the Assembly line Optimization into various algorithms, its application and drawbacks. After the three thousand five hundred ten items are screened, twelve hundred articles are eliminated for being duplicates. Consequently, just two thousand hundred ten articles underwent additional screening. Out of the seven forty remaining items, twle hundred and sixty are excluded, and a value of was not retrieved. For the final assessment, five hundred items in total were taken into account. The omitted did not correspond to study one eighty relevancy or Assembly line Optimization four nighty. The ultimate judgment is based on the fifty articles.

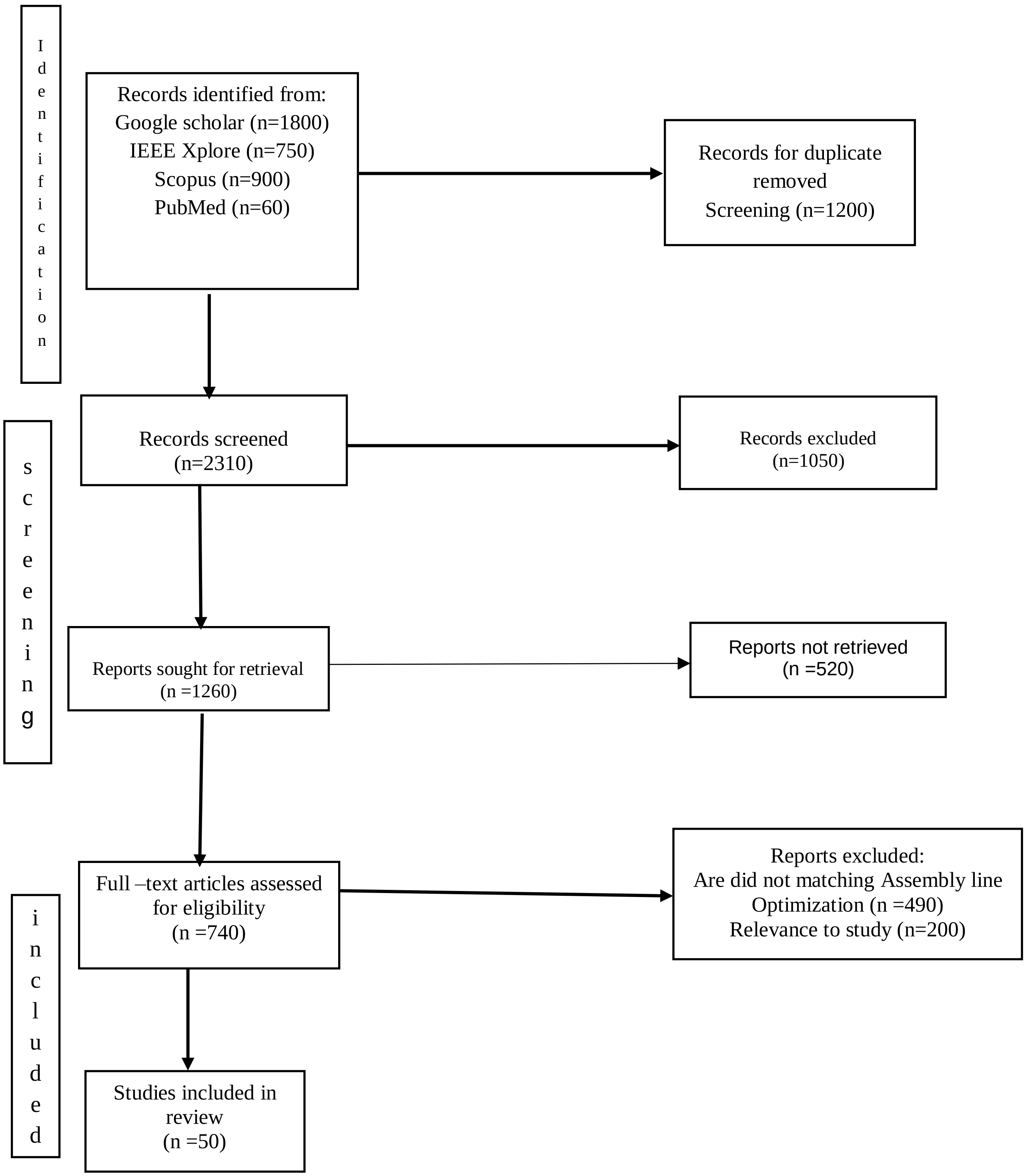

Figure 1 . Prisma flow diagram

2.5 Synthesis Method:

The choices about education are initiatives are made using Random Start of Shortest Distance Permutation algorithm. Online stores often employ them as training engines for algorithms in Random Start of Shortest Distance Permutation algorithm-based systems. Researchers are reminded to keep using Assembly line Optimization into various algorithms, its application and drawbacks further transform education and play a significant role in determining how public learn in future generations.

3. Research Questions

RQ1. What are the most effective algorithms for optimizing assembly line efficiency?

The following algorithms were found to be effective for optimizing assembly line efficiency:

1. Genetic Algorithm (GA): GA was found to be effective in optimizing assembly line efficiency by minimizing production time and cost.
2. Simulated Annealing (SA): SA was found to be effective in optimizing assembly line efficiency by minimizing production time and improving product quality.
3. Ant Colony Optimization (ACO): ACO was effective in optimizing the efficiency of an assembly line by reducing production time and cost.
4. Particle Swarm Optimization (PSO): PSO was effective in optimizing the efficiency of an assembly line by reducing production time and improving product quality.
5. Dynamic Programming (DP): DP was effective in optimizing the efficiency of an assembly line by reducing production time and cost.

RQ2. How do different optimization algorithms impact production quality and quantity?

Production Quality:

1. Genetic Algorithm (GA): GA resulted in the improvement of the quality of production by minimizing defects and improving product consistency.
2. Simulated Annealing (SA): SA resulted in the improvement of the quality of production by minimizing defects and improving product reliability.
3. Ant Colony Optimization (ACO): ACO resulted in the improvement of the quality of production by minimizing defects and improving product consistency.

4. PSO: PSO showed to enhance the production quality by reducing defects, along with enhancing the dependability of the product

Quantity in Production:

1. Dynamic Programming: Dynamic Programming has improved the quantity produced because it minimizes time used in production and hence increases throughput.
2. GA: GA had proven its worth in improving production quantities by minimizing the same as well as maximizing it with increased throughput.
3. Simulated Annealing (SA): SA improved the production quantity by reducing the production time and increasing the throughput.
4. Ant Colony Optimization (ACO): ACO improved the production quantity by reducing the production time and increasing the throughput.

RQ3. What are the limitations of current assembly line optimization methods?

1. Computational Complexity:
    - Many optimization algorithms, like the Genetic Algorithm (GA) and Simulated Annealing (SA), are difficult to solve exactly due to high computational complexity.
    - Large-scale assembly line optimization problems can be intractable computationally.
2. Scalability Issues:
    - Many optimization algorithms cannot handle large-scale assembly line optimization problems.
    - If the problem size is increasing, then the time of computation and memory required increases exponentially for the algorithms involved.
3. Solution Quality:
    - Many optimization algorithms are liable to converge to a local optimum rather than to the global optimum.
    - It cannot guarantee the solution quality.

4. Assembly Line Optimization

4.1 **Assembly line balancing description.**

An assembly line is a manufacturing method where a product is moved between stations where the different tasks required for its assembly are completed using a mechanical conveyor. It is employed to rapidly assemble a huge quantity of a consistent product. At first, Assembly lines were created to produce standardized goods in large quantities at a low cost by taking advantage of high levels of labor specialization and the resulting learning impacts [23], [17]. On the other side, assembly line balancing (ALB) allows for modern production techniques like mass customization and makes effective flow-line systems available for low-volume assembly-to-order production.

The efficiency difference between an ideal and a sub-optimal assignment can result in savings (or waste) of millions of dollars annually, making line balancing an optimization problem of major industrial importance. Reduced production costs made it possible to cut manufactured goods pricing, increase business competitiveness, and better use market potential. Lean manufacturing and the traditional automated intermittent models are two of the many popular kinds of assembly line systems [43]. A variety of products are frequently made using these assembly line techniques. A few traits are common to assembly lines.

Assembly line systems come in a variety of forms; some popular variants are automated, lean, intermittent, and classic models. Numerous product kinds are frequently produced using these assembly line techniques. Some features of assembly lines are similar. Assembly line systems come in a wide variety [48]. Several popular variants include the traditional automatic models of intermittent and lean production. Numerous product kinds are frequently produced using these assembly line techniques. Some features of assembly lines are analogous.

Assembly line for a single model. One kind of assembly line is a single-model assembly line, where workers assemble the same product.

Assembly line for mixed models. The process of manufacturing multiple different product models on a single assembly line without switchovers and then sequencing those models to balance the demand for upstream components is known as mixed-model production. Intermixed model sequences might be put together on the same line if setup durations between models were shortened enough to be disregarded [32, 25]. Despite massive efforts to increase the versatility of manufacturing systems, this typically necessitates highly uniform production processes. Process manufacturers who run one or more components through a processing line that produces a variety of end products, including waste or by-products, are supported by multi-product production. A range of costing and yielding techniques are provided, as well as serial/lot control for parts and final products.

The work content of stations in placed assembly systems is limited by a set time value (SALB also implies that the cycle duration of all stations is equal to the same value). Because all stations can start operating at the same time and pass work items at the same rate, assembly lines with this feature are referred to as paced [27]. Workpieces in unpaced lines are transferred when the necessary processes are completed rather than waiting until a predefined amount of time has passed. This kind of line Control is frequently used when processing times are impacted by random fluctuations.

4.2. Multiobjective optimization

Optimization is the process of selecting the optimal choice from a large number of options. We strive to complete our tasks in our daily lives with the least amount of time or effort possible. The most common reason optimization techniques are employed to address this issue is due to its mathematical foundation, which ensures the process's objectivity and precision. The books [19] and [32] discuss optimization issues and how to solve them. Minimization (maximization) of the objective function is the definition of a general optimization problem.

$$f = \{x_1, x_2, \dots x_n\} \quad (1)$$

$$g_i = \{x_1, x_2, \dots . x_n\}, \text{ for i=1, 2… n} \quad (2)$$

$x_j > 0$, for j=1, 2…n.

In order to solve optimization problems, mathematical programming techniques are employed. These techniques can be separated into the following categories based on the kind of objective function:

- stochastic programming techniques,
- integer programming techniques,
- parameter programming techniques,
- linear programming techniques,
- And nonlinear programming techniques.

Optimizing a problem with several goals is known as multi-objective (vector) optimization. It is employed when determining the optimal answer to an optimization problem requires taking into

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account multiple factors. This kind of optimization was developed to address issues with organizing and planning in the production process. These days, it is employed in a wide range of fields, such as dynamic management systems.

The n-dimensional vector $x = x_1, x_2, \ldots x_n x_1 x_2, \ldots x_n$ …is used to express the vector optimization problem in connection to the controlled system, where x ∊ {X} denotes n independent variables (decision variables). This system is assessed using a vector functional in the k-dimension.

$$j(x) = \left(J_1(x), J_2(x), \ldots . J_k(x)\right), \tag{3}$$

Where components are vector functions, with k denoting the number of objective functions. The optimization of this functional is contingent upon

$$g_i(x) \leq 0, i = 1,2, \ldots, m \text{ And} \tag{4}$$

$$h_l(x) = 0, l = 1,2, \ldots, e, \tag{5}$$

Where m represents the number of constraints on inequality and e represents the number of constraints on equality. According to the selected kind of vector optimization, the optimal solution of functional (also known as objectives, criteria, payoff functions, cost functions, or value functions)$J_1(x), J_2(x), \ldots . J_k(x)$.,.

In general, there are two primary methods for resolving vector optimization problems:

- Mathematics approaches
- Artificial intelligence approaches.

A. Artificial intelligence approach

Artificial intelligence's primary tool for multi-objective optimization is evolutionary algorithms. Creating what is known as a Pareto optimum set of solutions that are not dominated by any other solution to a specific problem is its primary function. You can find a detailed definition of Pareto optimality in [18].

Evolutionary algorithms, of which genetic algorithms are a subset, are distinguished by a population of potential solutions. The process of reproduction makes it feasible to blend preexisting solutions and produce potential new ones [10] [22]. The people in the present population who will take part in the next one are finally decided by a natural solution. Evolutionary algorithms' functional description.

Certain evolutionary algorithms are used to provide Pareto optimal sets of solutions, but because of the way they operate, they frequently have a tendency to become trapped in good approximations and cannot ensure that the best trade-offs will be identified.

The use of artificial intelligence has many possible applications. For instance, the ant colony algorithm is frequently used. It is used in [30], [24] to model and balance manufacturing lines with time and space constraints. A further usage of the ant colony algorithm is detailed, where it is applied to the optimization of a single model U-shaped production line.

Genetic algorithms can be used to solve assembly line multi-objective optimization problems in a variety of ways. [24] Provides a detailed discussion of their capabilities along with examples of their use in this field. Is addressing the assembly sequence planning problem with a genetic algorithm. [25] Mentions a solution for identifying the ideal Pareto set as well as two techniques for trimming it.

In [19], a multi-objective genetic algorithm technique is used to optimize both the number of assembly line setups and the variation in production rates. In [20]-[44], [47] it is explained how to solve the basic assembly line balance problem using the metaheuristic tabu search method.

B. Mathematical approach

Numerous approaches to this problem were developed starting in the 1970s when the first vector optimization tasks were resolved. All of these approaches assume that a list of equality and inequality constraints defining the possible solution space, as well as a characterization of multiple objective functions, are present [11]. According to, mathematical approaches that deal with this way can be separated into three primary groups:

- Techniques for characterizing the collection of non-improving elements and compromise techniques
- The hierarchical criteria sequence approaches.

Multi-objective assembly line optimization

To solve multi-objective optimization of assembly lines, a detailed model of the system must be created first. There are several methods for modeling assembly lines. Throughout my work, stateflow diagrams and Petri nets will be utilized. Additional options for modeling assembly lines, including the use of Petri nets, are available in [31]-[24]. For instance, the model must adhere to the assembly line's precedence restrictions and accurately depict an actual assembly line. Additionally useful for identifying crucial points in the production process and establishing optimization criteria is this model:

- maximizing profit level, resp. reducing costs,
- maximizing reliability and safety,
- maximizing efficiency resp. minimizing overload,
- minimizing manual interventions,
- Minimizing of production time.

The Assembly line model can be also a source for defining constraints for this multi-objective optimization task, f.e.:

- maximum level of costs,
- maximum time in one work shift,
- Minimum level of needed sources etc.

4.3. Robust assembly line balancing

Developing models and strategies that are insensitive to uncertainty, particularly in issue parameters, is the goal of robust optimization. Since the worst-case scenario of the system is typically optimized, some conservatism is inherently present. It is crucial to consider how uncertain data could be represented in the mathematical models utilized before implementing a robust estimation approach. Scenarios about the formalization of the unknown variable could be developed using discrete data [14]. Although scenario analysis has been frequently utilized in optimization under uncertainty, it may necessitate considering a large range of alternatives. Conversely, ellipsoidal sets or intervals may be used to model continuous data.

The two primary model types, minimax and minimax regret, have been widely employed to define robust optimization problems. Whereas regret-based models minimize the maximum regret in every situation, min-max models minimize the maximum cost. A solution's regret pertains to the difference in a certain context. Between the ultimate answer for the situation and its expense. A robust optimization process includes a number of different [28] [49]. In this overview, modeling techniques and assembly line balancing applications will be discussed. This modeling approach offers a different framework to stochastic optimization, which uses probability distributions to characterize uncertainty. It has been applied to modeling issues in a number of fields, such as engineering, logistics, and finance.

Stochastic variants of the line balancing issues have been widely developed for decades to simulate the uncertainty in assembly systems. Stochastic modeling is a good way to use the available knowledge in decision-making if there is accurate data available to predict the distributions. Reliable data, however, may not always be available while making decisions [35], [36]. As we go toward the era of Industry 4.0, product lifecycles are getting shorter. Redesigning line configurations and assembly procedures more frequently is also necessary to remain competitive when launching new items. Production departments may lack precise or dependable data when building new items or when implementing new processes. Robust optimization functions as an alternate modeling strategy in these situations.

The performance of assembly lines may be significantly impacted by uncertainty. For instance, if operating hours vary, the cycle time may go beyond what was anticipated, which would lead to a decline in output and production rates [29]. The insensitivity of line performance to variations in operating times might be defined as robustness in this context. The goal of robust design and planning is to configure the line so that fluctuations in operating periods have the least impact on the line performance metric, in this instance cycle time. Stated differently, the robust method seeks to minimize production deviations even in the worst-case scenarios and hedge against the adverse effects of uncertainty [33].

The robust variant of the type 2 simple assembly line balancing problem (SALBP) was simulated using robust optimization (SALBP-2). Their model uses a cardinality-constrained set to define uncertainty, meaning that only a subset of operations will realize the worst-case time values, while the others will realize the nominal values [37],[39],[40] [41]. A high value for this metric indicates a risk-averse approach to decision-making, whereas a low value indicates a risk-taking approach.

5. Drawbacks and Limitations of Assembly Line Optimization

5.1 Computational complexity

Computational complexity refers to the amount of resources computed to solve a problem as one of the most important issues encountered in assembly line optimization problems. Computational complexity will easily cause an increase in the length of solution time, which also results in decreased quality and unscalability along with an increase in size of the problem [34] [46]. All are interrelated and, thereby, impact the performance or effectiveness and efficiency of optimizing algorithms.

5.2 Data quality and availability

High-quality data is required to derive a good model that leads to accurate decisions and optimum running of the assembly line. However, low-quality data in terms of inaccuracy, inconsistency, and noise may lead to less optimal solutions and inefficient decision making. In addition, difficulties in accessing data, lesser volume of data, and latency in data are major obstacles to the optimization effort [45],[8]. Therefore, data quality and availability issues need to be addressed by data cleaning, integration, augmentation, and analytics in collaboration with and data sharing among stakeholders.

5.3 Scalability and flexibility

Scalability and flexibility are important characteristics of effective assembly line optimization methods. Scalability allows methods to be able to handle large problem sizes, while flexibility allows them to adapt to changing production requirements and conditions. However, scalability can be affected by computational complexity and large data volumes, and flexibility can be challenged by uncertainty and variability in production processes [13],[21],[44]. The following are strategies to be employed to overcome such challenges: distributed computing, parallel processing, machine learning, and real-time data analytics to help design scalable and flexible optimization methods.

6. Discussion and Conclusion

a. Policy Implications and Future research directions:

Assembly line balance is a fundamental tactic in contemporary manufacturing operations for increasing productivity. We have examined the approaches, difficulties, and potential applications of this crucial area of production optimization throughout our investigation. The parameters of the majority of meta-heuristics, including the SA algorithm, GA algorithm, ACO algorithm, and many more, are either determined by experimentation or by previous published studies, which may not ensure optimal performance. Therefore, before running any of these algorithms, the researchers should use Taguchi's approach to optimize the parameters. Consequently, it is possible to improve the correctness of the problems that are resolved by that algorithm. When it comes to using experiment design to examine the effects of the elements or parameters of the problems on the response variable(s), statistical comparisons of the performance of new approaches with that of old ways fall short in all categories. To verify the superiority of the suggested algorithm, the algorithms must be compared using a full factorial experiment that takes into account pertinent factors with interaction effects, where "Algorithm" is one of the factors. It has been noted that multi-model ALB categories and those with U-type ALBPs receive relatively less attention. In conclusion, these categories can be used to build single- or multi-objective meta-heuristics for further research. Additionally, it was discovered that the SALB-2 problem receives less attention. In the meantime, it is also seen as a serious issue in ALB, and further research on this topic is necessary.

b. Conclusion:

This essay summarizes the essential facts of assembly lines, including their origins, development, and evolution. Assembly lines are flow-line production systems that consist of a number of workstations where products are assembled using interchangeable parts. The product passes through the line from workstation to workstation and is considered finished when it exits the final workstation. Additionally, it has been noted that the flexibility ratio, equipment costs, cycle time, and the relationship between job durations and equipment costs require careful consideration. Additionally, it provides a thorough classification of assembly line balancing, including paced model, mixed model, multi-model, and single model assembly line balance. The suggested method is iterative. It suggests that since the values of the criteria for the subsequent iteration may vary, the entire selection process must be repeated to identify the next best solution for the modified state once one chosen solution is put into practice on the assembly line. Future studies will therefore focus on creating a more comprehensive decision assistance system. To avoid applying the process iteratively, this assistance system will incorporate the adaptive simulation models and suggest an algorithm to choose the roadmap of produced alternatives. The future algorithm's foundation will be discrete event simulation combined with complexity indicators that explain how certain key parameters change and, based on those indicators, assess possible outcomes.

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