Optimization Framework for Assembly Line Design Problem with Ergonomics Consideration in Fuzzy Environment

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Abstract. This paper presents a framework for solving assembly line design problems by considering ergonomics aspects. Although ergonomics factors have been ignored in conventional optimization problems in this area, in the long term, ergonomics risks and work-related injuries can impose considerable expenses on production systems. Moreover, in the design stage, different types of uncertainty in operational and ergonomics aspects can affect the optimization model. Therefore, the optimization framework in this study includes the results of ergonomics assessment tools and employs fuzzy logic to tackle imprecise factors. In the context of our problem, the sources of imprecision are twofold: environmental uncertainty and system uncertainty. Environmental uncertainty is related to demand uncertainty derived from market variations and customers' behavior. System uncertainty includes the uncertainties within the production process that partially relate to human aspects, such as uncertainty in task execution time and the physical capacity of the operators.

Keywords: Assembly Line Balancing Problem, Ergonomics, Fuzzy Set Theory.

1 Introduction

The main goal of planning assembly lines (ALs) is to increase productivity and efficiency. This is achieved through optimization problems called assembly line balancing problems (ALBP) [1]. However, market fluctuations and changing customer needs introduce uncertainty and require flexible production systems. Manual tasks in ALs contribute to system flexibility but also pose risks to operators' ergonomics and line efficiency. Therefore, Ergo-ALBP considers both operational and ergonomics factors in optimizing the AL system. Manual tasks also introduce variability due to workers' physical characteristics, gender, age, experience, and skills, impacting the optimization model [2-4].

There are two critical research gaps in Ergo-ALBP literature. Firstly, traditional optimization models have overlooked human factors and ergonomics (HFE) in favor of operational factors like cost and time. Additionally, most studies have considered ergonomics aspects in existing ALs rather than in the design stage. However, considering ergonomics parameters in the design stage (Ergo-ALDP) is strategic planning that can prevent future costs for redesigning and taking corrective actions to solve ergonomics problems [5]. Secondly, vague and imprecise factors, such as market uncertainty and varying worker characteristics, need to be included in the optimization problem. This includes accounting for variable takt time, inconsistent ergonomics risk levels, and task times that depend on individual workers. Notably, no previous Ergo-ALBP studies have addressed both uncertain conditions and HFE aspects during the design phase of ALs.

This study contributes by proposing a framework to optimize Ergo-ALDPs in uncertain conditions. Fuzzy logic is used to handle imprecise parameters and variables. The framework is applicable to any type of AL in the design step and beneficial for engineers and ergonomics practitioners in production systems.

This manuscript is organized as follows: In Section 2, a brief introduction to Ergo-ALBP is provided. Section 3 and Section 4 present the optimization model and solution approach, respectively. In Section 5, the practical perspective of the proposed framework is discussed. Finally, Section 6 presents the concluding remarks.

2 Background

In the early 1900s, Ford's car manufacturing plants were a good example of assembly lines used in the context of mass production. Since then, this crucial element of mass and lean production systems has significantly evolved and transformed into a more agile system. Assembly lines are the final stage of most production systems and are the closest part to customers. Thus, optimizing them involves balancing them and eliminating any issues that prevent them from working smoothly. In the following subsections, the main aspects of these optimization problems are explained.

2.1 Assembly Line Balancing Problem (ALBP)

Optimization models ALs aim to eliminate unbalanced points, such as bottlenecks, that decrease efficiency and worsen Key Performance Indicators (KPIs). Balancing ALs involves optimizing them with respect to productivity and efficiency goals [1]. The formulation of ALBPs as linear programming (LP) models dates back to 1955 [6]. While a solution approach was introduced in 1961 [7], trial-and-error techniques have been the primary solving method for several decades. ALBPs are NP-hard combinatorial optimization problems (COPs) that require finding an optimal solution from a finite set of feasible solutions (FSs). ALBPs are categorized into simple (SALBP) and general (GALBP) problems [8]. SALBPs consider one-sided straight ALs with deterministic operation times, optimizing one or two objectives. They are classified into four types: Type 1 minimizes the number of workstations based on a given cycle time, Type 2 minimizes the cycle time based on a fixed number of workstations, Type F checks the feasibility of the problem with a fixed number of workstations and cycle time, and Type E minimizes both the cycle time and the number of workstations. GALBPs encompass more complex conditions, such as multiple product types, multiple sides, or non-straight assembly lines.

While SALBPs have been extensively studied, there is a need for more research on GALBPs to tackle sophisticated real-world problems [9]. The past decade has seen a positive trend towards considering these general problems to address complexity.

2.2 Assembly Line Balancing Problem with Ergonomics Aspect (Ergo-ALBP)

Assembly tasks pose ergonomics risks and work-related musculoskeletal disorders (WMSDs) due to their repetitive and prolonged nature. Considering ergonomics and operational factors together is crucial for preventing injuries, and Gunther et al. were the first to consider ergonomics risks in the ALBPs in 1983 [10]. Since then, there have been few contributions in this domain until 2011 when Otto and Scholl included an ergonomics objective in the optimization model [11]. Their study motivated other scholars to focus on Ergo-ALBPs.

Although many research studies have examined the balancing of different types of ALs, limited research has been conducted in Ergo-ALBPs. It is proved that neglecting ergonomics factors in the design stage can lead to health-related issues for workers in the long run, which may require corrective measures that cost 9.2 times more than preventive actions taken during the design phase [5]. However, in the case of Ergo-ALBPs, few studies have focused on design problems (Ergo-ALDPs). Baykasoğlu et al. [2] addressed a SALBP in the design phase and developed a heuristic solution to solve it. Finco et al. [12] modeled an optimization problem for designing a semi-automatic AL. They attempted to minimize the design cost and ergonomics risks by analyzing the vibration of automatic hand-held tools. In recent years, collaborative human-robot assembly line design problems (CALBPs) or (RALBPs) that integrate ergonomics aspects with assigning exoskeletons and robots have become more common. For instance, Abdous et al. [13] examined a CALDP and developed an optimization model to reduce the overall equipment cost (design cost of AL) and minimize the ergonomics risk level.

Based on the definition by the International Ergonomics Association (IEA), human factors and ergonomics (HFE) is a scientific discipline that examines interactions between humans and system components, aiming to enhance operator safety and system performance. Numerous ergonomics assessment tools (EATs), such as OCRA, REBA, RULA, OWAS, and NIOSH's RNLE, have been developed to evaluate ergonomics risk factors in workspaces. Some of these methods serve as foundations for national and international ergonomic standards, including EN1005-2, EN1005-5, ISO11228-1, and ISO11228-3. While no method is universally superior [14], EATs categorize ergonomics risk levels into ranges from low to high [3].

2.3 Uncertainties

168: Limited research has incorporated ergonomics aspects into optimization models for ALBPs, particularly in the design stage (Ergo-ALDP). Most studies have focused on deterministic problems, overlooking the impact of uncertainty. However, in the design phase, uncertainty affects the assembly design in some way. In general, there are two types of uncertainty: environmental and system uncertainty [15]. In the context of the problem under study, environmental uncertainty includes uncertainties in demand variations resulting from market fluctuations. Moreover, system uncertainty is related to any imprecision in the manufacturing process. It partially consists of human aspects, such as uncertainty in system reliability, task time, and the physical capacity of the workers. In addition, Golabchi et al. [16] found that the inputs of EATs are often imprecise, which could significantly impact the results. To model these uncertainties, researchers employ stochastic programming models when historical data is available to identify the probability distribution of imprecise factors. Otherwise, fuzzy programming is helpful.

To the best of the authors' knowledge, only Tiacci and Mimmi [17] have included uncertainty in their Ergo-ALBP model. They incorporated stochastic task times and introduced penalties for cases where ergonomics constraints and/or predicted cycle times were not addressed. To evaluate ergonomics parameters, they utilized OCRA, and for cost minimization, they employed a genetic algorithm (GA).

2.4 Fuzzy Approaches in Balancing Problems

Ergonomics aspects and operational parameters in optimization problems of ALs represent conflicting objectives. To overcome the vagueness in multi-objective models with ergonomics and operational functions, some articles such as Cheshmehgaz et al. [18] and Ozdemir et al. [4] employed fuzzy goal programming. Although considerable research studies in ALBPs have employed fuzzy set theory (FST) to address uncertain and imprecise conditions in ALs, only Mutlu and Özgörmüş [19] considered ergonomics risks as fuzzy numbers among Ergo-ALBPs literature. They applied Bellman and Zadeh's approach [20] to minimize the number of workstations and perceived workload.

3 Problem Context

As mentioned in previous sections, in the design stage of Ergo-ALBP, two types of uncertainty must be addressed in the optimization model. Since takt time, derived from the demand rate, is not deterministic in the design phase, cycle time is imprecise. Task execution times also vary based on the worker's skill and experience level. Furthermore, ergonomics risk factors are vague because, in the planning step, the works situations are not precisely determined nor who will perform the task in each workstation. Various characteristics of workstations (e.g., the force required to use tools or lift parts to be assembled, types of tools used, physical dimensions of workstation components, repetition and frequency of sub-tasks, thermal environment) and of operators (e.g., gender, age, skill level, experience, and physical and work capacity, prior training), can impact the ergonomics risk level of each task. Therefore, this section defines the optimization problem by taking some steps and developing the model from an initial mathematical problem, SALBP-Type1, to the final state by identifying fuzzy time and ergonomics parameters.

3.1 Initial Model

In the design stage, the optimum number of workstations should be identified, thus the mathematical problem is the same as SALBP-Type1. The notations of the initial optimization model are as follows:

<u>Sets & Indexes</u>:

N Set of tasks (i,j = Indices for tasks: $i,j \in \{1, \ldots, n\}$)

S Set of workstations (s = Index for workstations: $s \in \{1, \ldots, m_{max}\}$

P_i Set of immediate predecessors of task i

<u>Parameters</u>:

n = number of tasks m = number of workstations
t_i = execution time of task CT = cycle time
Decision variables:
x_{si} = Binary variable, if task i is assigned to station s, it will be equal to 1 otherwise 0
y_s = Binary variable, if at least one task is assigned to station s, it will be equal to 1 otherwise 0
Then the initial mathematical model for the proposed ALDP is the same as SALBP-Type1:

$$\text{Min} \sum_{s=1}^{m_{max}} y_s \tag{1}$$

$$\text{Subject to: } \sum_{s \in S} x_{si} = 1 \text{ , } \forall i \in N \tag{2}$$

$$\sum_{s \in S} s.x_{si} \leq \sum_{s \in S} s.x_{sj} \text{ , } \forall\ i, j \in N | i \in P_j \tag{3}$$

$$\sum_{i \in N} x_{si}.t_i \leq CT \text{ , } \forall\ s \in S \tag{4}$$

$$\sum_{i \in N} x_{si} \leq M.y_s \text{ , } \forall\ s \in S \ \&\ \sum_{i \in N} t_i < M \tag{5}$$

$$x_{si},\ y_s \in \{0,1\} \text{ , } \forall\ s \in S;\ \forall\ i \in N \tag{6}$$

In equation (1), the objective function minimizes the number of workstations. The constraint in equation (2) guarantees that every task i is assigned to a single workstation. Equation (3) checks that the assigned stations satisfy precedence relations between tasks i and j. Equation (4) ensures that the total stations' time cannot exceed the cycle time. Equation (5) guarantees the utilization of a workstation when any task is assigned to it. The last equation indicates that decision variables x_{si} and y_s are binary variables.

3.2 Fuzzy Ergo-ALDP

As mentioned before, in the design step, time-related parameters are imprecise. Cycle time depends on takt time (available time divided by demand) and the execution time of tasks. Thus, according to inconstant demand and variable task times, cycle time is imprecise and varies to some extent (α). As a result, fuzzy logic can help us to define this parameter's variability. Fig. 1(a) illustrates the membership function of cycle time (CT) by considering α as an acceptable increase in CT which imposes some overtime in the production system, and it should be minimized.

Based on the output of most EATs and considering the imprecise input of these tools which brings uncertainty to our model, fuzzy sets can define the results in the best way. Fig. 1(b) depicts the membership function for a typical EAT. In this function, if the result of EAT is between ER_L and ER_U, it is interpreted as a moderate risk. While the results lower than ER_L show a low-risk level, the outputs upper than ER_U entail a high ergonomics risk. Taking advantage of the research done by Cheshmehgaz et al. [18], ergonomics risks can be evaluated as accumulated factors. As a result, various EATs can be applied to assess desired ergonomics parameters in the final optimization model. Some studies employed fuzzy set theory in literature to tackle the uncertainty in assessing ergonomics parameters. For instance, Ghasemi and Mahdavi [21] developed a new REBA scoring system based on fuzzy sets and several fuzzy membership sets. Furthermore, Wang et al. [22] integrated a 3D automated posture-based ergonomics risk assessment with a specialized rule-based fuzzy inference algorithm to solve the issue derived from the imprecise nature of inputs.

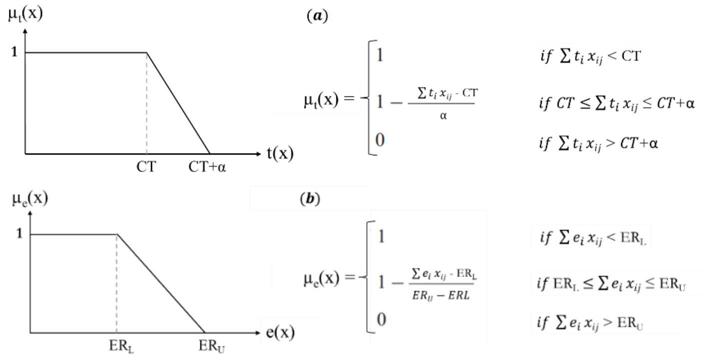

Fig. 1. The membership functions: (a) For cycle time (b) For ergonomics risk factor

4 Proposed Optimization Framework

In Ergo-ALBP literature, Mutlu and Özgörmüş [19] were the only ones to consider fuzzy ergonomics risks in their research and solve their model using the Bellman-Zadeh method. However, in their approach [20], the constraints and objectives are treated together, even though they convey different meanings. Therefore, the proposed solution procedure in this paper employs a bipolar view [23]. In this perspective, negative preferences play the role of constraints and restrict the number of FSs. In contrast, positive preferences act as the objective function(s) and evaluate FSs to find the best one. Fig. 2 shows the procedure of the proposed heuristic method for solving the fuzzy Ergo-ALDP. This heuristic approach combines the COMSOAL (Computer Method of Sequencing Operations for Assembly Lines), Fuzzy goal programming, and a fuzzy inference system.

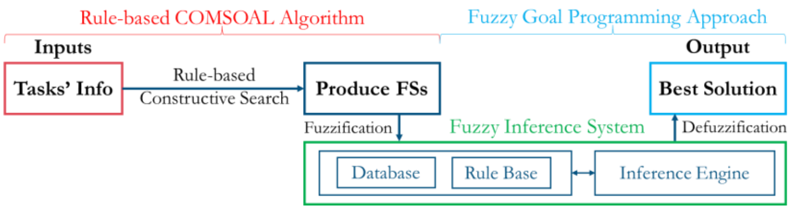

Fig. 2. Schematic of the proposed heuristic solution approach

The first step involves identifying FSs based on time and precedence constraints, using the mathematical model developed in the previous section. The task assignment rules for this step are consistent with those proposed by Baykasoglu et al. [2], and the pseudocode for the first part is presented in Fig. 3. It is worth noting that FSs can be generated using different CTs by varying the value of α. Moreover, tasks' execution times vary in a range of $[t_i , t'_i]$, t_i is the average time of executing the task and t'_i is the maximum duration for doing it by the lowest skill operator.

```
Input: The set of tasks and their information
Output: Feasible solutions
BEGIN
Create a set of assignable task(s)
WHILE set of assignable task(s) ≠ Ø
    Consider a workstation for allocation,
    FOR each assignable task
        Calculate the probability according to task selection rules,
    END FOR
    Select a task by applying the Roulette Wheel Selection method,
    Assign the selected task to the current workstation,
    IF the total execution time of assigned tasks for the current workstation ≥ CT
        Assign the selected task to a new workstation,
    ELSE
        Assign to the current workstation,
    Update the opened workstation(s) and assignable task(s) sets,
END WHILE
```

Fig. 3. Pseudo code of the rule-based COMSOAL approach

The solution method's second part involves applying a fuzzy inference system, as illustrated in Fig. 2. In this stage, ergonomics considerations are expressed as rules, and FSs are evaluated based on these rules, including the membership function defined in Section 3.2.

5 Application Perspective

The fuzzy optimization framework is advantageous for real-world scenarios due to its ability to handle complex and uncertain information that is challenging to quantify precisely. It is particularly useful in ergonomics risk prediction during the design phase, where data may be incomplete or uncertain. The proposed framework can incorporate multiple objectives and constraints, enabling a more balanced approach to decision-making and comprehensive analysis of the optimized system. This framework is suitable for various industries, including the automotive sector, which is prominent in Ergo-ALBP literature. Incorporating realistic uncertain conditions in planning and designing production systems is a challenge. Thus, addressing uncertainty in optimization problems is expected to become more prevalent in the future to identify robust solutions.

As mentioned before, the proposed optimization approach consists of two steps. In the first step, FSs are identified based on technical parameters and constraints, making it useful for different configurations of assembly lines (e.g., 2-sided, U-shape lines). The second step involves considering ergonomics aspects by developing fuzzy rules to evaluate FSs and determine the best among them. Various ergonomics fuzzy rules can be applied, such as the assessment methodology developed by [21], which uses fuzzy sets and REBA, or the fuzzy REBA and RULA risk rating proposed by [22].

A numerical example is provided to exhibit the relevance of the suggested mathematical model and the efficiency of the proposed solution approach. The example is generated randomly and consists of 10 tasks with the precedence diagram that is shown in Fig. 4.

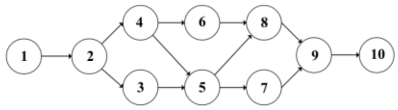

Fig. 4. Precedence diagram of the example

By applying the proposed heuristic algorithm, four FSs are found with the minimum number of workstations which is four stations. For each workstation, ergonomics risk factors are assessed by the model developed in the Gallagher and Heberger study [24]. They evaluated MSD risk factors by examining the interaction of force and repetition of tasks. Table 1 indicates the results of their model in the form of fuzzy rules. By applying four fuzzy rules, the ergonomics risk level of each workstation is calculated as shown in Fig. 5. In the next step, the FSs should be evaluated to find the best solution. For this final step, we can consider the following three approaches to detect the optimum solution:

1) Highly Conservative Approach: No red area task assignment is permitted.

2) Conservative Approach: Limiting the number of moderate-risk task assignments (minimize orange area).

3) Less Conservative Approach: Limiting the number of minor-risk task assignments (minimize yellow area).

Table 1. Ergonomics assessment fuzzy rules derived from [24]

Rule No.	Rule Statement
1	**IF** Repetition AND Force are low, **THEN** the Risk Level is Acceptable
2	**IF** Repetition is high AND Force is low, **THEN** the Risk Level is minor
3	**IF** Repetition is low AND Force is high, **THEN** the Risk Level is moderate
4	**IF** Repetition AND Force are high, **THEN** the Risk Level is high

Based on the first approach, the first FS is eliminated in finding the optimum solution. The second approach removes the third FS. Finally, the optimum solution, in this case, will be the fourth FS which does not have any high-risk level and the number of its moderate-risk and minor-risk workstations is minimum in comparison with other FSs.

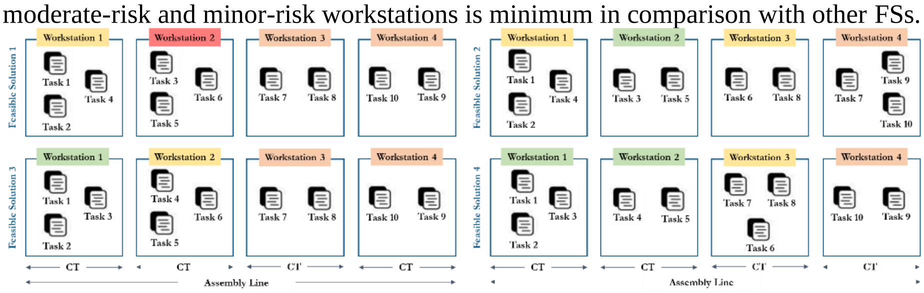

Fig. 5. Ergonomics assessment of workstations in each FS

This numerical example was developed just for explanation of our proposed optimization framework. However, it is expected that implementation of this algorithm on real case studies with proper fuzzy ergonomics rules and optimum detection approaches can find an effective solution in Ergo-ALDPs. The developed optimization framework is a versatile tool that can be customized to solve a wide range of problems under uncertain conditions, making it applicable to various domains.

6 Conclusions

Due to the importance of considering HFE in the design of manual assembly processes, as well as the vital role of ALs in manufacturing systems, this paper presents a practical procedure for optimizing the Ergo-ALDP. This study proposes a framework that integrates ergonomics factors with operational parameters to optimize the ALDP in uncertain conditions. The objective is to determine the optimal task assignments for a minimum number of workstations while adhering to time restrictions and minimizing the ergonomics risk level. To achieve this objective, the study adopts a bipolar view, where operational aspects are considered negative preferences for producing FSs, while ergonomics aspects are positive preferences for evaluating FSs and identifying the best one. The fuzzy set theory is employed through several membership functions and a fuzzy inference system that conveys various rules based on different ergonomics assessment techniques (EATs).

Based on the importance of considering inconsistent conditions in the design phase of ALs, future study directions can include stochastic optimization models for general industries with typical tasks and historical data. Furthermore, more sophisticated ALs can be considered, and more complicated optimization models can be developed to probe more realistic problems. This proposed fuzzy framework could be applied to some case studies to be verified and validated.

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