Graph-based Optimization for Assembly Line Balancing Incorporating Metabolic Restrictions

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Abstract— **Manual assembly processes remain a fundamental aspect of the manufacturing industry, primarily due to the dexterity and adaptability of human workers. However, the repetitive and physically demanding nature of these tasks highlights the need for an ergonomic and well-balanced workload, as poor ergonomics can also contribute to errors. This paper aims to automate the assembly line balancing process for a real-world case study. A new multi-objective Assembly Line Balancing Problem (ALBP) formulation is proposed, minimizing both workload variance and variance in workers' energy expenditure across workstations while accounting for daily fluctuations in the number of operators. The proposed metabolic and time-sensitive assembly line balancing method integrates caloric considerations to reduce long-term risks of Work-Related Musculoskeletal Disorders (WMSDs). Using a graph-based approach, the framework ensures that precedence constraints are met while optimizing task assignments to minimize cycle time and metabolic cost per operator. To improve accuracy in estimating energy expenditure, this study employs the Methods-Time Measurement - Universal Analyzing System (MTM-UAS), which decomposes tasks into standardized motion elements. The methodology is validated through a real-world case study at Bosch Thermotechnology in Portugal, assigning tasks while minimizing the trade-offs between worker fatigue and production goals. The code to validate this study is publicly available at `https://github.com/joaorafaelalmeida/line-balancing-algorithm`.**

I. INTRODUCTION

In every production line, the Assembly Line Balancing Problem (ALBP) seeks to optimally assign tasks to workstations while considering constraints such as cycle time and task precedence. This problem is one of the most critical challenges in manufacturing systems due to its combinatorial complexity and the significant impact it may have on productivity parameters [1]. However, traditional ALBP formulations often overlook the physical effort exerted by operators, which can result in significant disparities in workload distribution. This imbalance poses risks of fatigue and long-term health issues, such as Work-Related Musculoskeletal Disorders (WMSDs), particularly when repetitive tasks or heavy loads are involved in daily production operations. As a solution, ergonomic stress on workers should be kept below a predefined threshold to minimize the impact of repetitive activities [2].

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The inclusion of ergonomic considerations adds complexity to the ALBP by introducing constraints related to operators' physical effort. One effective way to quantify and balance these efforts is by measuring the energy expenditure of operators performing different tasks [3]. Energy expenditure, often expressed in kilocalories (kcal), is based on the maximum calorie expenditure of workers related to the maximum number of calories the human body can stand during cycle time [4]. The method calculates the fatigue generated by manual procedures as a function of oxygen consumption during specific tasks. Alternatively, energy expenditure can be estimated through macro- and micro-studies that use standardized table values to approximate the metabolic workload of an average worker [5].

The need for more accurate and predictive models of metabolic energy expenditure has led to the development of task-specific equations that account for individual effort and task characteristics [6]. In this work, we propose a multi-objective ALBP model that incorporates these predictive equations for energy expenditure with Methods-Time Measurement (MTM-UAS) in a task allocation model for assembly line balancing. Unlike traditional approaches that focus only on cycle time or basic ergonomic constraints, this study proposes a dual-objective optimization that balances productivity and operator workload more effectively. A dynamic workforce adjustment mechanism is also introduced, allowing the line to adapt to varying operator availability. The model is validated using real industrial data, demonstrating its applicability in a practical setting.

The remainder of the paper is structured as follows. In Section II, we present a review of previous works addressing the assembly line balancing problem considering energy expenditure as measure to ergonomic risks. In Section III, we describe the proposed problem and formulate the multi-object model, explaining the metabolic cost estimation employed in this study using the predetermined motion-time systems MTM-UAS. In SectionIV, we present both quantitative and qualitative results of our method using a dataset from a hot water boiler assembly line. Finally, in Section V, we summarize the main results of our study and suggest possible future research directions.

II. LITERATURE REVIEW

The Assembly Line Balancing Problem (ALBP) has been extensively studied in the literature, with research progressively adapting the problem to address the complexities of real-world industrial settings [7]. Traditional ALBP models focus primarily on minimizing cycle time, workstation, or production costs under ideal working conditions. However, when dealing with manual assembly activities, the omission of ergonomic considerations can lead to negative effects. There is a clear relationship between poor ergonomics requirements and quality errors [8], due to the direct link between the well-being of workers and their performance. Therefore, adjusting for performance variations related to operator fatigue is a major concern.

The evaluation of metabolic energy expenditure of manual material handling jobs helps to establish limits of the worker's capacity to prevent excessive fatigue. The prediction equations proposed by Garg *et al.* [6] allows to estimate the energy expenditure of each single task execution, such as lowering or lifting an object with a certain weight, picking an item from a certain distance and walking or standing in a specific position.

Energy expenditure evaluations share similarities with predetermined motion-time systems (PMTS), used to set production time standards. One of these computerized systems is Methods-Time Measurement (MTM), which is a detailed system that divides any operation into single motions, that are used to describe manual activities [9]. MTM-UAS is part of the MTM family, which uses special codes and time values corresponding to seven basic motion elements: get and place, place, handle equipment, operate, motion cycles, body motions (e.g., walking, bending, sitting, standing), and visual control [10]. It applies to manufacturing processes characterized by experienced workers, well-defined work content and workflow and high job organization.

Battini *et al.* [11] introduced a new technique, called Predetermined Motion Energy System, that helps to estimate the energy expenditure rates, based on predefined motion data. In a subsequent study, Battini *et al.* [12] expanded on this by proposing the Integrated Assembly Line Balancing and Parts Feeding Problem (IALBFP), which aims to reduce inventory levels and minimize time losses due to unproductive activities while also addressing worker fatigue.

Finco *et al.* [13] introduced heuristic methods to incorporate rest allowances into the assembly balancing problem, emphasizing the role of human energy expenditure in optimizing work processes. Their study highlights the importance of considering rest periods to improve overall productivity and worker well-being.

In a related vein, Tiacci and Mimmi [14] proposed an approach that integrates ergonomic risk evaluation through the OCRA index with balancing and sequencing decisions for mixed model stochastic asynchronous assembly lines. Their application in the agricultural equipment sector illustrates the practical relevance of ergonomic assessments in designing compliant assembly lines.

Building upon the energy expenditure-based ergonomic estimation, Mura and Dini [15] developed a genetic algorithm that minimizes both station count and the number of qualified workers required while accounting for operators' technical and physical capabilities. Later, Giridhar and Panicker [16] used the same formulation to minimize the number of workstations, overall skill level required, and variance in workers' energy expenditure across workstations.

Finco *et al.* [17] continued this line of inquiry by integrating human energy expenditures into the assembly line balancing problem type 2, focusing on rest allowance evaluation. Their computational experiments validate the proposed mathematical model and compare various methodologies, contributing to the understanding of workload smoothing in assembly lines.

Weckenborg and Spengler [18] incorporated ergonomics through constraints, solving line balance problems with collaborative robots alongside human resources. They considered economic factors, adjusting processing times with rest intervals to limit energy expenditure. Alfaro-Pozo and Bautista-Valhondo [3] also examine the economic and productive implications of considering ergonomic risk and space constraint to maximize the line efficiency. Using observation techniques, they evaluated risk levels associated with postural loads, repetitive movements, and manual handling.

Despite these contributions, few studies incorporate real motion-time systems such as MTM for precise energy estimation, and even fewer validate their models in industrial settings. Our study aims to fill this gap by integrating MTM-based metabolic modeling with task allocation in a real-world ALBP scenario, optimizing both workload distribution and ergonomic sustainability. The proposed approach introduces a dynamic workforce adjustment mechanism, enabling the re-balancing of production steps according to the number of available operators.

III. METHODOLOGY

This section presents the hierarchical modeling used to estimate energy expenditure in assembly line tasks. It details the problem structure, notation, and the proposed multi-object model.

A. Problem modeling

The methodology for calculating energy expenditure across assembly line tasks is structured hierarchically into three distinct levels: basic motion (level 1), movement (level 2), and task (level 3). The relationships between these levels are visually represented in Figure 1. The MTM-UAS system provides standardized codes for basic motions, each calculated using the Garg model [6], based on the characteristics of the movement (the distance/height or the weight of the load lifted).

Level 1 - Basic Motion: Each basic motion in the MTM-UAS system is assigned a specific energy expenditure value (kcal), denoted as Ebm. The set of 77 basic motions represents fundamental physical actions performed by the worker, such as grasping, lifting, or reaching. These values are predetermined and calculated based on specific parameters, namely motion type (mt), duration (τ), intensity/effort (e), body part (bp), and load weight (lw). For each basic motion i, the energy expenditure is computed as:

$$Ebm_i = f(mt, \tau, e, bp, lw) \tag{1}$$

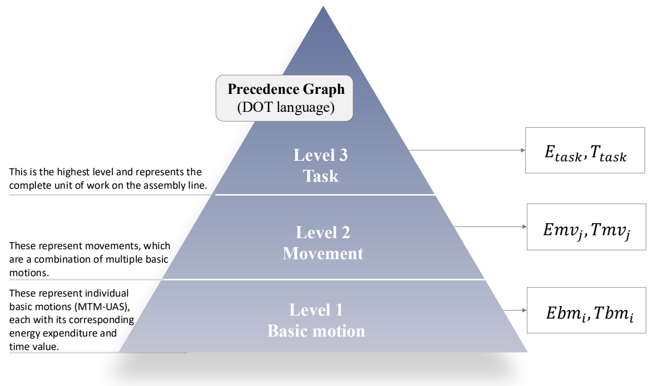

Fig. 1. Hierarchical representation of cycle time and energy expenditure.

where f is a function that returns the kcal expenditure for the motion type i. Each basic motion also has a standard time, denoted as Tbm_i, associated with it. This time value is predefined and is used in the MTM-UAS system.

Level 2 - Movement: A movement represents a combination of multiple basic motions. For example, lifting an item may involve a grasp, lift, and place motion. The total energy expenditure for a movement j is the sum of the energy values of the constituent basic motions:

$$Emv_j = \sum_{i=1}^{n} Ebm_i \tag{2}$$

where Emv_j is the total energy expenditure for a specific movement j, and n represents the number of basic motions involved in that movement. The total time for a movement is also the sum of the times associated with the constituent basic motions:

$$Tmv_j = \sum_{i=1}^{n} Tbm_i \tag{3}$$

where Tmv_j is the total time for the movement, and Tbm_i is the time associated with each basic motion i.

Level 3 - Task Level: A task is composed of multiple movements, and its energy expenditure is the sum of the energy expenditures of the movements involved:

$$E_{task} = \sum_{j=1}^{m} Emv_j \tag{4}$$

where E_{task} is the total energy expenditure for the task, and m is the number of movements. The total time for a task is similarly the sum of the times for each movement:

$$T_{task} = \sum_{j=1}^{m} Tmv_j \tag{5}$$

where T_{task} is the total time, and Tmv_j is the time for each movement. Precedence relationships between tasks can be represented in a task dependency graph.

In this study, the task dependency graph was implemented using the DOT language, which was processed with Graphviz to visualize and manage the precedence relationships between tasks (level 3).

B. Mathematical model

The definitions and notations presented in Table I are used to solve the model.

TABLE I
MATHEMATICAL NOTATION AND DEFINITIONS

Notation	Description
$T = \{t_1, t_2, \ldots, t_n\}$	Set of tasks in the assembly process
C_{t_i}	Cycle time required to complete task t_i (seconds)
M_{t_i}	Metabolic cost of task t_i (kcal)
CT_{limit}	Maximum allowed cycle time per operator
MC_{limit}	Maximum allowed metabolic cost per operator
P	Set of precedence constraints between tasks
G	Directed acyclic graph representing task dependencies
$d[t_i]$	Indegree of task t_i in the precedence graph G, where d is a mapping from tasks to their number of predecessors.
$O = \{O_1, O_2, \ldots, O_k\}$	Set of operators
AT	Set of available tasks with no unmet precedence ($d[t_i] = 0$)
Ebm_i	Energy expenditure of basic motion i
Tbm_i	Time duration of basic motion i
Emv_j	Total energy of movement j ($\sum_i Ebm_i$)
Tmv_j	Total time of movement j ($\sum_i Tbm_i$)
E_{task}	Energy of task ($\sum_j Emv_j$)
T_{task}	Time of task ($\sum_j Tmv_j$)
α, β	Weighting factors for time and metabolic cost in objective function
SI_C	Smoothness Index for cycle time
SI_M	Smoothness Index for metabolic cost
$\dot{E}_k$	Energy expenditure rate of operator O_k

Step 1: Build the precedence graph and initialize indegree values. A directed graph G representing the precedence constraints between tasks is constructed as seen in Algorithm 1.

Algorithm 1: Precedence graph and initialize indegree values.

```
foreach t ∈ T do
    G[t] ← [ ] ;          // Initialize empty adjacency list
    d[t] ← 0 ;  // Set initial indegree to 0
foreach (a, b) ∈ P do
    G[a].append(b)
    d[b] ← d[b] + 1
```

Step 2: Identify tasks with no predecessors. These are tasks whose indegree value is zero, meaning no other tasks need to be completed before them. The set of available tasks, denoted as AT, is determined by selecting all tasks t from the set of tasks such that the indegree of t is zero, as described in Formula 6.

$$AT = \{t \in \text{tasks} \mid \text{indegree}(t) = 0\} \tag{6}$$

These tasks are the first candidates for assignment to operator, as they can be started immediately without any dependency on other tasks.

Step 3: Assign tasks to operators. In this step, tasks are allocated to operators O_k, where $k \in \{1, 2, \ldots, k_{\text{max}}\}$, with k_{max} being the total number of operators available, based on available daily resources. The total number of tasks N is distributed among the operators such that each operator may be assigned multiple tasks at a given workstation. The task assignment process considers both the cycle time and the metabolic cost constraints for each operator, ensuring that the workload is balanced across all available operators. Tasks are assigned sequentially to operators as long as these constraints are satisfied, with priority given to minimizing both the cycle time per workstation and the metabolic cost per operator. The objective function is defined as:

$$\min \left(\alpha \cdot \max_{k \in O} \sum_{t_i \in O_k} C_{t_i} + \beta \cdot \max_{k \in O} \sum_{t_i \in O_k} M_{t_i} \right) \tag{7}$$

α and β are weighting factors that control the importance of time versus metabolic effort in the objective.

The conditions for assigning tasks to operators are the following:

1) The sum of cycle times for tasks assigned to each operator O_k does not exceed the cycle time limit.
2) The sum of metabolic costs for tasks assigned to each operator O_k does not exceed the metabolic cost limit.
3) Precedence constraints between tasks are respected.

When either condition 1 or condition 2 is satisfied, the algorithm assigns one more task to the operator. If the condition $\text{current\_time} + C_{t_i} > \text{CT}_{\text{limit}}$, the algorithm selects the task t_i with the shortest cycle time C_{t_i}:

$$t = \arg\min_{t \in AT} C_{t_i} \tag{8}$$

Otherwise, if the condition is not satisfied, the algorithm selects the task t_i with the smallest metabolic cost M_{t_i}:

$$t = \arg\min_{t \in AT} M_{t_i} \tag{9}$$

This formulation ensures that when constraints are violated, the method attempts to assign a task that minimally impacts the violated constraint, either by choosing the task with the smallest cycle time or the smallest metabolic cost, depending on which constraint is exceeded.

To analyze the workload distribution balance across workstations, the Smoothness Index (SI) is computed for both cycle time and metabolic cost. This index quantifies workload variability, where a lower value indicates a more evenly distributed workload, thereby reducing inefficiencies. The Smoothness Index for Cycle Time (SI_C) and Smoothness Index for Metabolic Cost (SI_M) are calculated as follows:

$$SI_C = \sqrt{\sum_{k=1}^{K} \left(C_k - \max_{k \in O} \sum_{t_i \in O_k} C_{t_i} \right)^2} \tag{10}$$

$$SI_M = \sqrt{\sum_{k=1}^{K} \left(M_k - \max_{k \in O} \sum_{t_i \in O_k} M_{t_i} \right)^2} \tag{11}$$

A lower Smoothness Index indicates a more balanced distribution of workload, minimizing inefficiencies. Finally, to assess the physiological workload imposed on each operator O_k, the Energy Expenditure rate is defined as:

$$\dot{E}_k = \frac{\sum_{i=1}^{n_k} M_{t_i}}{\sum_{i=1}^{n_k} C_{t_i}} \tag{12}$$

IV. RESULTS AND DISCUSSION

This section presents the case study of a hot water boiler assembly process at Bosch Thermotechnology in Portugal. The dataset comprises a large number of tasks and a complex precedence diagram, with limited flexibility for reconfiguring the overall workflow since the production process is already established.

A. Assembly line process

The assembly process is a U-shaped layout and consists of 1324 basic motions (Level 1), which are grouped into 441 movements (Level 2) and ultimately form 160 tasks (Level 3) required for full assembly completion. The system is classified as a light production process, generally associated with low ergonomic risk. Most tasks involve handling small components weighing less than 2 kg, with moderate repetitiveness. Generally, it does not involve awkward postures except for bending positions to pick up assembly parts. The assembly process primarily involves standing workstations, where operators are required to move trolleys frequently to transport the assembly component between workstations. Although most tasks impose low to moderate energy expenditure, certain workstations demonstrate significantly higher energy demands due to increased motion frequency, repetitive handling, or extended durations of specific actions.

The optimization model was implemented in Python 3.12.0 using hardware featuring an Apple M1 processor with 8GB of RAM. In the following, the main results of the case study are presented, comparing the optimization impacts with and without considering metabolic cost.

B. Results

To better understand the impact of different operator configurations, multiple scenarios were simulated, allowing for a performance comparison. Three scenarios were considered: (1) time-based balancing, which optimizes task allocation to minimize cycle time disparities across workstations; (2) metabolic-cost-based balancing, which prioritizes equalizing workers' energy expenditure; and (3) a combined approach, which integrates both objectives with equal weighting. The performance of each scenario was assessed using the Smoothness Index for cycle time SI_C and metabolic cost SI_M, where lower SI values indicate a more balanced distribution. Table II summarizes the SI_C and SI_M values for operators k =3 to 12 for each scenario.

TABLE II
SMOOTHNESS INDEX (SI) VALUES FOR TIME, METABOLIC COST, AND BOTH.

k	Time		Metabolic cost		Both	
	SI_C	SI_M	SI_C	SI_M	SI_C	SI_M
3	29.4	1.8	48.9	0.9	46.4	1.4
4	33.5	3.8	74.5	1.1	67.6	3.5
5	21.7	3.2	113.9	1.6	66.6	2.4
6	49.6	3.0	146.8	1.9	57.2	2.6
7	76.4	7.6	135.4	2.3	97.6	6.0
8	49.4	7.1	148.6	3.7	102.3	4.4
9	33.4	6.7	169.4	3.7	77.9	4.2
10	65.9	8.8	117.0	4.8	73.7	5.6
11	33.0	11.6	145.6	7.6	63.7	8.1
12	56.7	7.3	174.4	4.4	97.3	5.0

In the time-balanced scenario, the lowest SI_C values were achieved, indicating a well-balanced distribution of work in terms of cycle time. However, this comes at the cost of significantly higher SI_M values, which means that while the workstations are temporally balanced, there is a substantial disparity in physical workload. This imbalance implies that some operators experience considerably higher levels of fatigue by the end of a shift, increasing the risk of WMSDs.

In the metabolic-cost-balanced scenario, SI_M values were minimized, resulting in a more equitable distribution of physical effort. However, this optimization leads to considerably higher SI_C values, which means that while workstations are temporally balanced, the line suffers from inefficiencies due to increased idle times and lower synchronization between workstations. This could lead to bottlenecks or underutilization of certain workstations, negatively impacting overall production efficiency.

The combined scenario, which integrates both time and metabolic balance with equal weighting, provides a more balanced trade-off between these two objectives. While SI_C is slightly higher compared to the time-only scenario, it remains significantly lower than in the metabolic-cost-based approach. Similarly, SI_M is substantially lower than in the time-based scenario, indicating a reduction in fatigue disparities among operators.

Figure 2 illustrates the evolution of the Smoothness Index for Cycle Time as the number of operators increases. The results suggest that achieving a well-balanced workload distribution becomes more challenging as the workforce size grows. This is largely attributed to the nature of task grouping in the problem formulation. Since tasks are grouped based on movements, they have different energy expenditures and cycle times, meaning some tasks take significantly longer to complete than others. When tasks with very different durations are grouped together and assigned to operators, it becomes harder to distribute them equally.

Figure 3 illustrates the evolution of the Smoothness Index for Metabolic Cost. In the metabolic-cost-balanced scenario,

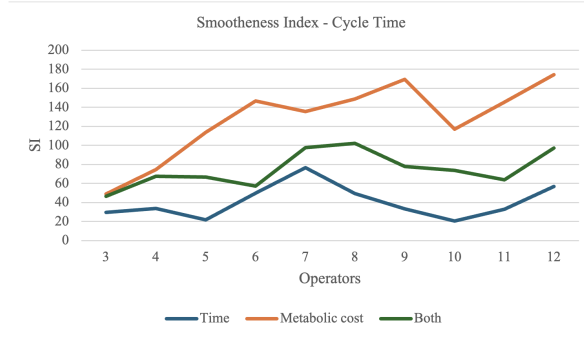

Fig. 2. Smoothness Index for Cycle Time for the 3 scenarios balanced.

SI_M values remain consistently lower than those of the other scenarios, confirming that the metabolic workload is more evenly distributed. The trend is similar across all three scenarios, with a general increase in SI_M as the number of operators grows. However, when considering 12 operators, the metabolic cost distribution improves, but at the cost of an increased time imbalance (as seen in Figure 2).

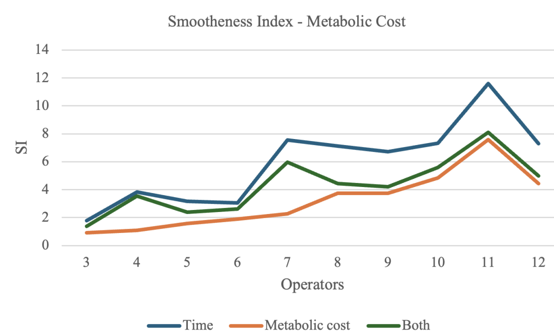

Fig. 3. Smoothness Index for Metabolic Cost for the 3 scenarios balanced.

C. Analysis

These results underscore the inherent trade-offs between optimizing for cycle time and for energy expenditure. Each approach—focusing solely on cycle time, metabolic cost, or a combination of both has distinct benefits and challenges.

Operators assigned to tasks with higher energy demands may experience greater fatigue, which could necessitate more frequent rest breaks, a factor that is not accounted for in the time-optimized scenario. The result is a potential ergonomic risk, as workers with higher metabolic demands may struggle to maintain performance without sufficient recovery time.

The average metabolic cost of the operators is 2,46 kcal/min, regardless of the scenario, which according to [19], is considered light effort. This matches the initial assumptions of the production line, which involve standing assembly tasks of small components.

The combined balance scenario emerges as the most robust solution to line balancing. Although it does not minimize either the time imbalance or metabolic cost to their lowest possible values, it manages both factors within acceptable ranges, preventing the extremes observed in the single-objective models. The method proposed is suitable not only for rebalancing an existing production line but also for designing a new production line from the outset. It requires an initial time and energy expenditure analysis for the assembly tasks without the need for additional information on production factors. It is suitable for every type of production type layout, including parallel stations, U-shaped lines or multi-manned assembly lines.

In terms of practical implications, the results suggest that the optimal choice for a company depends on its primary objectives. If a company prioritizes productivity, it may prefer the time balance approach, accepting the trade-off of increased variability in metabolic cost. However, when considering the long-term well-being of operators, the multi-objective approach offers better outcomes by preventing fatigue while maintaining acceptable levels of production efficiency.

V. CONCLUSIONS

This study proposes a new multi-objective metabolic and time-sensitive method designed to optimize both energy expenditure and cycle time in assembly line balancing, using the predetermined motion-time systems - MTM-UAS. The proposed framework adapts to fluctuating workforce sizes and enables dynamic rebalancing of production steps based on the number of operators available. This dual-objective modeling shows how repetitive physical tasks in assembly lines can lead to ergonomic risks if workloads are not evenly distributed, improving performance and reducing the likelihood of injuries.

Ergonomics is optimized by reducing and smoothing the energy expenditures of operators assigned to tasks in the production line. The results demonstrate that the proposed method effectively minimizes workload variance across all tested scenarios in a real-world production case. In an industrial context, this tool can be used to improve daily decision-making processes, enabling managers to evaluate the most efficient use of available operators while minimizing the risks of fatigue and ensuring that ergonomic considerations are met.

While this study focuses on physical workload and energy expenditure, it does not consider other important factors such as cognitive workload, psychological fatigue, or stress. The current method has limitations in fully addressing these factors. Future research could incorporate models for cognitive workload and psychological stress to provide a more complete understanding of worker health and productivity.

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