Minimizing Production Time and Worker Fatigue: A Bi-Objective Mathematical Formulation for Job Scheduling

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Abstract

Production schedules that minimize completion time can concentrate physically demanding tasks on individual workers. This study presents a small bi-objective mixed-integer linear programming model that balances makespan and cumulative ergonomic exposure in manual job assignment. The model is demonstrated using an explicitly synthetic instance comprising five independent jobs and three identical workers. Each job has a processing time and an illustrative exposure score on a 1-10 scale. The formulation minimizes normalized makespan and the maximum cumulative exposure assigned to any worker. All $3^5 = 243$ possible assignments were enumerated, which provides an exact check for this small instance and makes the results independently reproducible without a proprietary solver. The time-only solution achieved a makespan of 4.5 h and a peak exposure of 14 points. With equal normalized weights, the selected solution increased makespan to 5.5 h but reduced peak exposure to 10 points, corresponding to changes of +22.2% and -28.6%, respectively. Four nondominated solutions formed the Pareto frontier: (4.5 h, 14), (5.0 h, 12), (5.5 h, 10), and (6.5 h, 9). The results demonstrate the mathematical trade-off between production efficiency and exposure balance but do not establish a reduction in fatigue, injury, or cost because the input scores are hypothetical and not biomechanically validated. The formulation is intended as a reproducible proof of concept that can later be calibrated with observational assessment, wearable sensing, or plant-specific exposure data.

Keywords: ergonomic scheduling; human-centered manufacturing; mixed-integer linear programming; multi objective optimization; parallel machines; synthetic case study; workload allocation

1. Introduction

Digital manufacturing has increased the capacity to monitor equipment, coordinate production, and optimize throughput. Industry 4.0 research has largely emphasized connected machines, cyber-physical systems, data exchange, and automated decision support [1]. The subsequent Industry 5.0 perspective places greater emphasis on collaboration between people and technology and on the design of production systems around human needs [2,3]. This change in emphasis does not remove the requirement for productivity; rather, it makes worker well-being an explicit design criterion alongside time, cost, and quality.

The relationship between operational efficiency and ergonomics is not necessarily antagonistic, but it is strongly affected by how work is divided. Production-system design can change both output and physical

loading, so ergonomic consequences should be considered when planning work rather than assessed only after a schedule has been implemented [4]. In manual and mixed manual-automated environments, a time-efficient assignment may repeatedly allocate long or demanding tasks to the same person. The resulting imbalance is invisible to an objective function that measures only completion time.

Work-related musculoskeletal disorders have multifactorial origins. Epidemiological research associates physical exposure with musculoskeletal outcomes, while also recognizing individual, psychosocial, and organizational influences [5]. A systematic review identified repetition, awkward posture, heavy physical work, and related biomechanical exposures among commonly supported risk factors [6]. These findings justify including exposure information in production planning, but they do not imply that a simple numerical score can predict injury. A scheduling model should therefore distinguish an ergonomic exposure proxy from a clinical fatigue or injury outcome.

Several established methods can provide task-level ergonomic information. The revised NIOSH lifting equation evaluates selected manual lifting conditions [7]. RULA and REBA provide observational screening of upper-limb and whole-body postural risk, respectively [8,9]. Dynamic muscle-fatigue models represent loading and recovery more directly when the required biomechanical inputs are available [10]. The appropriate measure depends on the task, body region, duration, recovery, and purpose of the assessment. In the present proof of concept, the exposure score is intentionally generic so that the optimization logic remains transparent. In a real application, it must be replaced by a validated measure selected by an ergonomist.

This paper develops a compact mathematical model for assigning independent manual jobs to parallel workers while limiting the highest cumulative exposure. The contribution is deliberately modest: it provides a complete formulation, objective normalization, an exact synthetic case, a Pareto analysis, and a reproducible reporting structure. The study asks three questions. First, how does an exposure-aware objective change the optimal assignment relative to time-only scheduling? Second, what nondominated time-exposure alternatives are available to a decision maker? Third, how sensitive is the selected solution to the relative objective weights? The study does not use factory observations and does not claim injury prevention. Its purpose is to establish a defensible computational foundation for later empirical work.

2. Literature Review

2.1 Parallel machine and multi-objective scheduling

Scheduling theory provides a standard language for allocating jobs to limited resources. Classical surveys formalized machine environments, processing constraints, and performance criteria, and established the computational difficulty of many scheduling problems [11]. Parallel-machine scheduling assigns jobs to two or more machines or workers that can operate simultaneously, and the conventional objective is often to minimize the maximum completion time [12]. Complexity results show that even apparently simple machine-scheduling classes can be computationally difficult as the number of jobs and constraints increases [13]. Comprehensive scheduling texts describe exact, approximation, and heuristic approaches for these problem families [14].

Real planning problems rarely have only one objective. Multicriteria optimization distinguishes efficient or Pareto-optimal solutions from dominated alternatives [15]. Weighted-sum methods are attractive because they convert several criteria into one scalar objective, but weights are meaningful only if objective magnitudes are made comparable. Normalization also does not remove the decision maker's responsibility to justify priorities, and nonconvex parts of a Pareto frontier may require epsilon-constraint or other methods [16]. For the discrete case used here, complete enumeration identifies every nondominated objective pair and avoids ambiguity about solver convergence.

2.2 Ergonomic considerations in assignment and rotation

Operations-research studies have incorporated ergonomic or safety measures into job assignment and rotation. Carnahan et al. used optimization and heuristic search to design job-rotation schedules with reduced biomechanical stress [17]. Tharmmaphornphilas and Norman formulated a quantitative method for choosing rotation intervals [18]. Diego-Mas et al. developed a multicriteria genetic algorithm that considered several ergonomic criteria when generating rotation schedules [19]. These studies show that exposure can be represented within a formal planning model rather than treated solely as a post-processing assessment.

Related work has integrated ergonomic risk into assembly-line balancing [20] and developed specialized job-rotation methods that distribute risks among workers [21]. Asensio-Cuesta et al. designed rotations for repetitive work to reduce musculoskeletal exposure [22]. Mossa et al. explicitly examined the productivity-ergonomics trade-off in a job-rotation scheduling model [23], while Yoon et al. sought to eliminate consecutive high workloads and reduce between-worker variability in cumulative daily workload [24]. Collectively, the literature provides more sophisticated formulations than the present five-job example. The remaining value of a small example is pedagogical and diagnostic: every feasible assignment can be checked, normalization effects can be shown directly, and unsupported claims are easy to identify.

The gap addressed here is therefore not the absence of ergonomic scheduling research. It is the need for a minimal, fully transparent demonstration that can be reproduced by students or small manufacturers before plant-specific data are available. The model separates assignment logic from the choice of exposure metric and reports the complete frontier rather than presenting only one weighted result. This separation allows the same formulation to accept RULA, REBA, NIOSH-based, energy-expenditure, force-time, or wearable-derived task measures after suitable validation and scaling.

3. Mathematical Formulation

3.1 Problem definition and assumptions

Let $I = \{1, \dots, m\}$ denote workers and $J = \{1, \dots, n\}$ denote independent jobs. Each job j has a deterministic processing time p_j and a nonnegative ergonomic exposure score e_j. Workers are assumed to be identical with respect to eligibility and processing speed. Every job is assigned to exactly one worker, jobs are nonpreemptive, and a worker process assigned jobs sequentially. Release dates, due dates, precedence relations, setup times, learning, recovery, skill differences, and worker availability are omitted. These assumptions define an identical-parallel-resource load-assignment problem, not a general job-shop problem. Because sequence does not affect either objective under these assumptions, start-time and pairwise non-

overlap variables are unnecessary. A feasible sequence can be constructed after assignment by placing each worker's jobs consecutively.

Table 1. Synthetic job characteristics used in the illustrative case study.

Job	Illustrative task	Processing time (h)	Exposure score (1-10)
J1	Heavy lifting assembly	2.0	9
J2	Precision soldering	4.0	3
J3	Component transport	1.5	7
J4	Quality inspection	3.0	2
J5	Machine calibration	2.5	5

3.2 Decision variables and load measures

The binary assignment variable is defined as follows:

$$x_{ij} = \begin{cases} 1, & \text{if worker } i \text{ performs job } j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Each job must be assigned exactly once:

$$\sum_{i \in I} x_{ij} = 1, \quad \forall j \in J \quad (2)$$

The total processing time assigned to worker i is:

$$T_i = \sum_{j \in J} p_j \, x_{ij} \quad (3)$$

and the cumulative exposure assigned to worker i is:

$$E_i = \sum_{j \in J} e_j \, x_{ij} \quad (4)$$

The additive exposure assumption is a simplification. It treats a point assigned for one job as commensurate with a point assigned for another job and does not model body-region specificity, duration-response nonlinearity, or recovery. It is used only to demonstrate minimax load balancing.

Table 2. Sets, parameters, variables, and performance measures.

Symbol	Type	Definition
I	Set	Workers $i = 1, \dots, m$
J	Set	Jobs $j = 1, \dots, n$
p_j	Parameter	Processing time of job j
e_j	Parameter	Illustrative ergonomic exposure score of job j
x_{ij}	Binary variable	1 when worker i is assigned job j
T_i	Derived value	Total processing time assigned to worker i
E_i	Derived value	Cumulative exposure assigned to worker i
C_{max}	Objective value	Maximum assigned processing time
F_{max}	Objective value	Maximum assigned cumulative exposure

3.3 Objectives

Makespan is bounded by every worker's assigned time:

$C_{max} \geq T_i, \quad \forall i \in I$ (5)

Peak cumulative exposure is bounded in the same way:

$F_{max} \geq E_i, \quad \forall i \in I$ (6)

Directly adding hours and exposure points makes the outcome depend on arbitrary units. The two objectives were therefore normalized using the payoff-table anchors. Let C_{min} be the minimum makespan, C_{atF} the makespan of the minimum-exposure solution, F_{min} the minimum peak exposure, and F_{atC} the peak exposure of the minimum-makespan solution. The normalized criteria are:

$\hat{C} = \frac{C_{max} - C_{min}}{C_{atF} - C_{min}}; \quad \hat{F} = \frac{F_{max} - F_{min}}{F_{atC} - F_{min}}$ (7)

The weighted objective is:

Minimize $Z(w) = w\hat{C} + (1 - w)\hat{F}, \quad$ with $0 \leq w \leq 1$ (8)

Here w is the priority assigned to production time. Scenario A uses $w = 1$ and ignores exposure. Scenario B uses $w = 0.5$ and gives equal importance to the two normalized criteria. The normalization is specific to the feasible set and should be recomputed if jobs, workers, or constraints change.

3.4 Solution and verification procedure

The instance has three possible worker assignments for each of five jobs, giving $3^5 = 243$ labelled assignments. A Python script enumerated all assignments, calculated worker-level time and exposure totals, and retained nondominated pairs. The weighted objective was then evaluated for each candidate. Worker-label permutations produce equivalent schedules; a lexicographic rule was used only to display one representative assignment. Complete enumeration is exact for this instance and verifies the mathematical logic independently of a mixed-integer solver. For larger instances, Equations (1)-(8) can be entered directly in an open-source modelling package such as Pulp, which expresses linear and integer programs in Python [25].

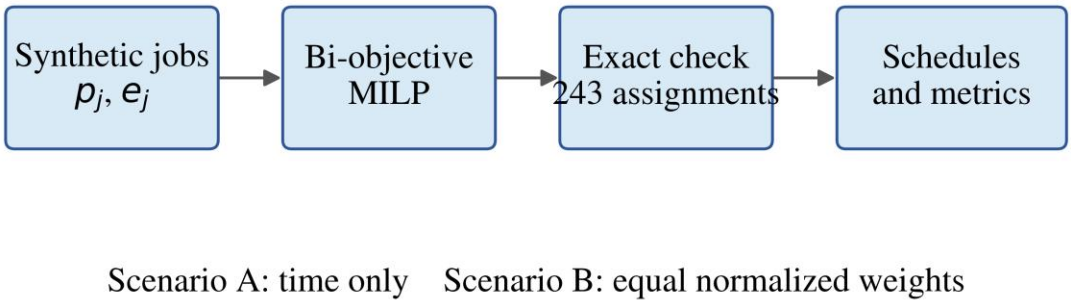

Figure 1. Reproducible workflow for the synthetic case study. Exact enumeration verifies the mixed-integer formulation for the 243 possible labeled assignments.

4 Computational Case Study

The synthetic instance represents a short set of manual support activities rather than observations from a particular company. Table 1 lists five jobs with a total processing requirement of 13.0 h and a total exposure score of 26 points. Three identical workers are available at time zero. Processing times and scores were chosen to create a visible conflict: J1 has a high exposure score but moderate duration, J2 has the longest duration but a low score, and J3 is short but relatively demanding. J4 and J5 provide lower-exposure combinations that can be used to balance assignments.

The score range of 1-10 is ordinal in origin but is treated as cardinal and additive for the optimization. This is a strong modeling assumption. The values should therefore be interpreted as synthetic exposure points, not as RULA, REBA, NIOSH lifting-index, metabolic, force-time, or injury-risk values. Scenario comparisons indicate what the mathematical model does with the supplied numbers; they do not validate the numbers themselves.

For reporting, jobs assigned to a worker were sequenced in ascending job-number order. Since no release dates, due dates, precedence constraints, recovery effects, or sequence-dependent setup times are present, any no-idle sequence of the same assigned jobs has the same completion time and cumulative score. The Gantt chart is consequently a visualization of one feasible sequence, not evidence that this order is ergonomically superior.

5 Results and Discussion

5.1 Exact Pareto frontier

The exact enumeration produced four nondominated objective pairs (Figure 2). The minimum-makespan point P1 was (4.5 h, 14 points). Reducing peak exposure to 12 points required a makespan of 5.0 h at P2. Point P3 achieved 10 points with a 5.5 h makespan, and the minimum-exposure point P4 achieved 9 points with a 6.5 h makespan. Every other feasible objective pair was dominated by at least one of these four alternatives.

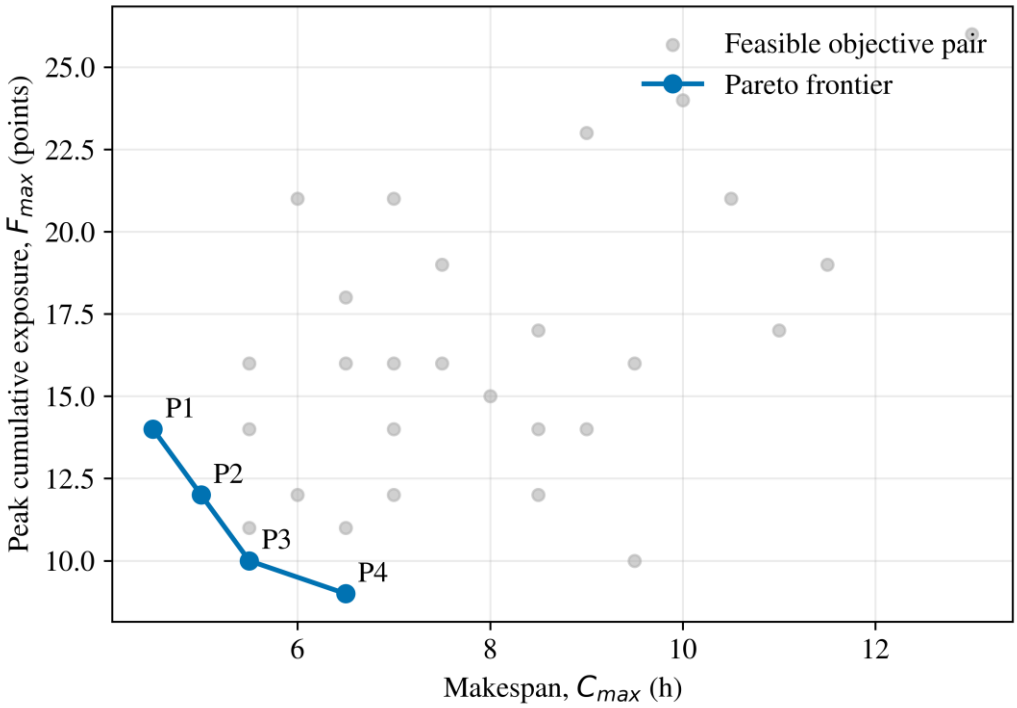

Figure 2. Feasible makespan-exposure pairs and the exact Pareto frontier. P1-P4 denote nondominated solutions; gray points are dominated feasible objective pairs.

The frontier is more informative than a single weighted result because it shows the marginal sacrifice required for progressively lower peak exposure. Moving from P1 to P2 adds 0.5 h and removes 2 exposure points. Moving from P2 to P3 has the same changes. Moving from P3 to P4 adds 1.0 h for only one additional point of reduction. For this synthetic instance, P3 is therefore a plausible compromise, but a real decision would require validated exposure thresholds, shift constraints, and economic values.

5.2 Time only and equal weight scenarios

Scenario A assigned J1 and J5 to W1, J2 to W2, and J3 and J4 to W3. Worker times were 4.5, 4.0, and 4.5 h, so the makespan was 4.5 h. The corresponding exposure totals were 14, 3, and 9 points. The time loads were balanced, but W1 received the highest-exposure combination. This is not a solver failure: exposure was absent from the objective, so the time-only formulation had no reason to distinguish assignments with different exposure distributions.

Scenario B assigned J1 to W1, J2 and J3 to W2, and J4 and J5 to W3. Worker times were 2.0, 5.5, and 5.5 h, and exposure totals were 9, 10, and 7 points. Relative to Scenario A, makespan increased by 22.2%, from 4.5 to 5.5 h, while peak cumulative exposure decreased by 28.6%, from 14 to 10 points. Figure 3 shows that the equal-weight solution reduced the highest score and its spread across workers, but it also produced a more uneven time assignment.

Table 3. Comparison of the two principal scenarios.

Measure	Scenario A time only	Scenario B equal weights	Change from A
Weight on time, w	1.00	0.50	-
Weight on exposure	0.00	0.50	-
Displayed assignment	W1: J1,J5; W2: J2; W3: J3,J4	W1: J1; W2: J2,J3; W3: J4,J5	-
Worker times (h)	4.5; 4.0; 4.5	2.0; 5.5; 5.5	-
Worker exposures	14; 3; 9	9; 10; 7	-
C_max (h)	4.5	5.5	+22.2%
F_max (points)	14	10	-28.6%

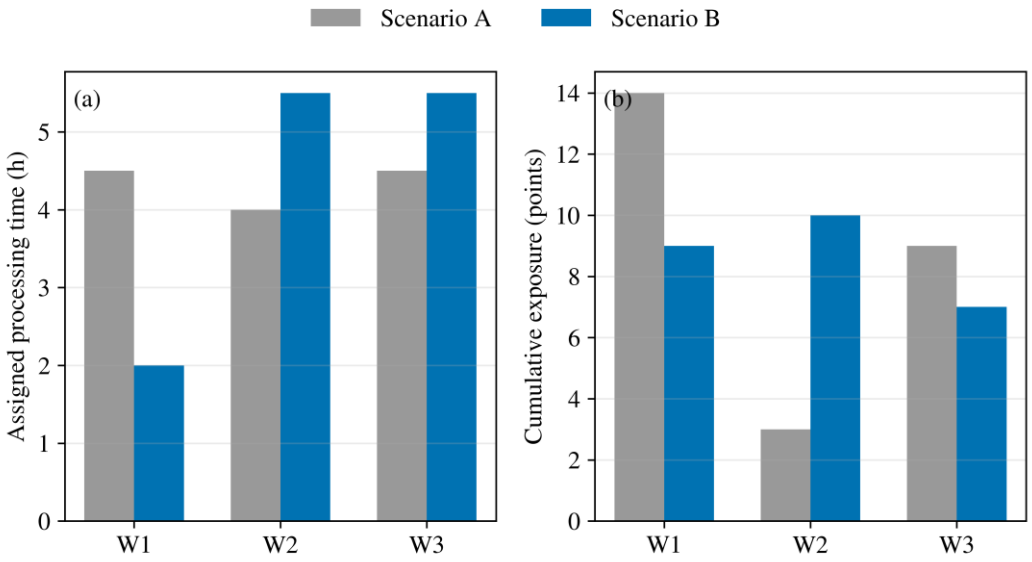

Figure 3. Worker-level comparison of Scenario A and Scenario B. (a) Assigned processing time. (b) Cumulative synthetic exposure score.

The result should not be summarized as a reduction in worker fatigue. F_max is the maximum of assigned synthetic scores, and no physiological fatigue state is calculated. The valid conclusion is narrower: under the additive scoring rule, the equal-weight objective redistributes the high-scoring jobs and lowers the maximum assigned score. This distinction is essential because a scheduling model cannot compensate for an invalid ergonomic metric.

5.3 Weight sensitivity

Table 4 reports a simple sensitivity analysis. When exposure received all or most of the weight (w = 0 or 0.25), the model selected P4, with a 6.5 h makespan and 9-point peak exposure. Equal weights selected P3. When time received 75% or all of the weight, P1 was selected. The discrete changes arise because only a

finite number of assignments exist. A small change in weight may leave the selected schedule unchanged until a breakpoint is crossed.

Table 4. Sensitivity of the selected solution to normalized objective weights.

Time w	weight	Exposure weight	C_max (h)	F_max	Makespan change	Exposure change
0.00		1.00	6.5	9	+44.4%	-35.7%
0.25		0.75	6.5	9	+44.4%	-35.7%
0.50		0.50	5.5	10	+22.2%	-28.6%
0.75		0.25	4.5	14	0.0%	0.0%
1.00		0.00	4.5	14	0.0%	0.0%

The sensitivity results also show why raw weights such as 0.5 h plus 0.5 exposure points are difficult to interpret. A change in the units of processing time from hours to minutes would alter the schedule even though the physical problem was unchanged. Payoff-range normalization prevents this particular unit artifact. It does not determine the correct organizational preference, which should be established through stakeholder input, regulatory requirements, and validated risk thresholds.

5.4 Schedule interpretation

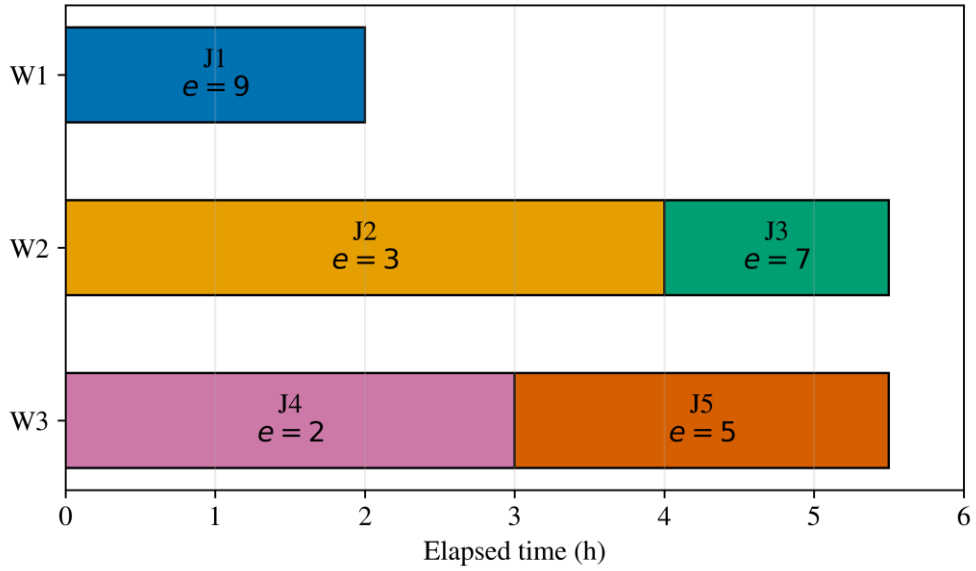

Figure 4. One no-idle sequence for the equal-weight assignment. The label e gives each job's synthetic exposure score. Sequence does not affect the objectives in the present model.

Figure 4 illustrates the equal-weight assignment. W1 completes J1 in 2.0 h. W2 performs J2 followed by J3 and finishes at 5.5 h. W3 performs J4 followed by J5 and also finishes at 5.5 h. The higher-scoring jobs J1 and J3 are allocated to different workers. The chart makes the non-overlap assumption visible, but it does not include breaks or recovery. If exposure depends on task order, the model must introduce sequence variables and a time-dependent fatigue-recovery relation.

The trade-off has an operational interpretation. A manager who accepts only P1 obtains the shortest completion time but also accepts the highest peak assigned score. P2 and P3 provide intermediate choices,

while P4 minimizes the peak score at a substantial time penalty. In practice, overtime, absenteeism, quality, worker skill, and injury-related cost may alter this comparison. None of those quantities is present in the synthetic instance, so statements that the compromise is profitable would be speculative.

5.5 Relation to prior ergonomic scheduling research

The observed redistribution is consistent with the logic of minimax ergonomic scheduling and job-rotation studies [17–24]. However, the current formulation is simpler in three important respects. First, it assigns each job once rather than generating repeated rotations over a shift. Second, it uses a single generic exposure score rather than body-region or risk-specific measures. Third, it omits worker heterogeneity. The model should therefore be viewed as an entry-level formulation that demonstrates objective conflict and normalization, not as an alternative to established ergonomic scheduling methods.

The formulation nonetheless provides a useful modular structure. Job-dependent scores e_j can be replaced by worker-job scores e_{ij} when workers differ in strength, skill, stature, or technique. Eligibility constraints can prevent unqualified assignments. Shift limits can cap T_i, and exposure thresholds can cap E_i. If a task affects several body regions, E_i can become a vector and the model can impose a maximum for each region. Recovery-aware models require start times and sequence-dependent state updates. These extensions preserve the central idea that human exposure should be represented explicitly rather than inferred from makespan.

6. Limitations and Validation Requirements

The main limitation is the absence of empirical data. All processing times, descriptions, and exposure scores are hypothetical. The study consequently demonstrates mathematical behaviour only. It cannot estimate fatigue, discomfort, musculoskeletal-disorder probability, absenteeism, quality loss, or financial benefit. Publication and reuse should identify the case as synthetic in the title, abstract, methods, tables, figure captions, and data statement. Presenting the values as observations from a factory would be misleading.

The exposure measure is also simplified. A 1–10 score is treated as linear, additive, independent of duration, and comparable across different tasks. Real ergonomic assessments may be ordinal, nonlinear, body-region specific, or sensitive to force, frequency, posture, duration, recovery, and individual capacity [7–10]. Summing scores may therefore be inappropriate without a defined measurement model. The term F_{max} is retained as a mathematical label for peak cumulative exposure, not physiological fatigue.

The scheduling assumptions limit operational realism. Workers are identical, every job is available at time zero, processing times are deterministic, and there are no precedence relationships, setups, breaks, skill requirements, learning effects, quality differences, or availability constraints. The example is too small to evaluate computational scalability because enumeration is trivial. A larger study should report solver, version, hardware, optimality gap, run time, and sensitivity to instance size.

A credible empirical extension should proceed in stages. First, select an ergonomic measure appropriate to each task and collect repeated assessments with trained raters or calibrated sensors. Second, obtain actual processing-time distributions and worker eligibility data. Third, validate exposure estimates against independent observations rather than optimizing and validating on the same scores. Fourth, compare the new schedule with current practice using preregistered operational and ergonomic outcomes. Finally, report

worker consent, privacy safeguards, and ethics review when identifiable wearable or health data are collected.

7. Conclusions

A transparent bi-objective model was formulated for assigning independent manual jobs to parallel workers while balancing completion time and cumulative ergonomic exposure. In the synthetic five-job, three-worker case, the time-only optimum had a makespan of 4.5 h and peak exposure of 14 points. Equal normalized weights selected a 5.5 h, 10-point solution, giving a 22.2% increase in makespan and a 28.6% reduction in the maximum assigned score. Exact enumeration identified four Pareto-efficient alternatives.

The study establishes a reproducible optimization result, not evidence of health or economic improvement. Its practical value is as a starting framework: a validated plant-specific exposure metric can replace the illustrative score, while worker skills, precedence, recovery, uncertainty, and shift rules can be added as constraints. Future research should test the extended model with real production and ergonomic data and evaluate whether exposure balancing improves worker-centered outcomes without unacceptable operational cost.

Data and Code Availability

All numerical inputs used in this study are reported in Table 1 and are explicitly synthetic. The complete solution can be reproduced by enumerating the 243 labeled assignments and evaluating Equations (2)-(8). The accompanying computational workflow generated the Pareto frontier, scenario assignments, tables, and figures from these values. No confidential company, worker, wearable, or health data were used.

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