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Sheikh Fuzael Rahman

sheikh.fuzael.rahman@gmail.com

Lamar University https://orcid.org/0009-0001-3189-9069

Research Article

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Integrated Cognitive Workload and Musculoskeletal Exposure Modeling for Adaptive Ergonomic Work Design

Sheikh Fuzael Rahman
Email: sheikh.fuzael.rahman@gmail.com
Doctor of Engineering (DE) - Industrial Engineering
Lamar University, Beaumont, Texas, USA
ORCID: https://orcid.org/0009-0001-3189-9069

Abstract
Cognitive workload, musculoskeletal exposure, fatigue, and limited recovery can jointly affect worker comfort and task performance. However, these factors are often assessed separately, limiting the evaluation of cumulative ergonomic risk over time. This study proposes an integrated ergonomic modeling framework that combines cognitive workload, physical exposure, fatigue accumulation, and recovery within a common assessment structure. Normalized state variables are used to calculate a composite ergonomic risk index, and a proposed multi objective optimization procedure provides a basis for examining alternative task schedules and recovery intervals. Illustrative scenarios compare low, moderate, and high combined demands under specified model assumptions. The proposed analytical design also specifies a procedure for future sensitivity analysis of workload intensity, exposure duration, recovery rate, and worker susceptibility. The illustrative values indicate that higher modeled cognitive workload, physical exposure, and fatigue correspond to greater composite risk under the specified weighting scheme. However, these values are hypothetical and do not represent observed worker data or verified simulation outputs. The framework provides a methodological basis for examining relationships between modeled ergonomic risk and task performance during work schedule planning. Further research should implement reproducible computational experiments, conduct sensitivity analyses, and validate model predictions against measured workload, physical exposure, fatigue, and performance data before practical application.

Keywords: Cognitive workload, Musculoskeletal exposure, Ergonomic risk assessment, Fatigue and recovery, Human performance modeling, Multi objective optimization, Adaptive work design.

I. Introduction
This study examines the combined effects of cognitive workload, musculoskeletal exposure, fatigue, and recovery on human performance. It proposes an integrated modeling framework that connects ergonomic risk assessment with adaptive task scheduling and multi objective optimization.

A. Background and Motivation
Industrial and technology intensive workplaces often require workers to manage mental demands, repetitive movements, sustained postures, and time pressure within the same work period. These conditions can contribute to fatigue, physical discomfort, and changes in task performance. However, cognitive workload, physical exposure, and fatigue are often assessed separately, which limits the analysis of their combined effects over time. An integrated modeling approach can provide a common basis for examining workload accumulation, recovery opportunities, and ergonomic risk under changing work conditions.

B. Problem Statement
Existing ergonomic assessment methods commonly focus on individual factors, such as posture, repetition, or mental workload. This separation creates difficulties when estimating cumulative risk across tasks with different intensities and durations. Fatigue adds a temporal dimension because its level changes with workload and rest opportunities. Furthermore, risk assessment does not always connect directly with task scheduling decisions. A unified framework is therefore needed to represent cognitive workload, physical exposure, and fatigue over time while supporting comparisons between alternative work schedules.

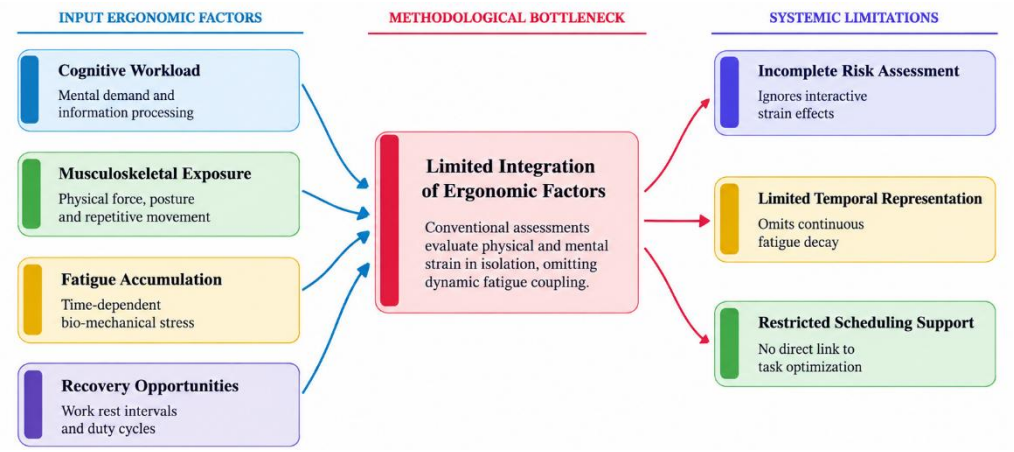


Fig. 1. Conceptual representation of the research problem.

C. Proposed Solution

This study proposes an integrated ergonomic modeling framework in which cognitive workload, physical exposure, and fatigue are represented as normalized, time dependent states. These states contribute to a composite ergonomic risk index that describes modeled changes throughout a work session. A multi objective optimization component evaluates task allocation, task duration, and recovery timing against two competing goals: reducing cumulative ergonomic risk and preserving task performance. Scenario based simulations and sensitivity analyses are intended to examine the effects of workload intensity, posture exposure, recovery rate, and worker susceptibility. The numerical examples are illustrative and do not represent observed worker data; computational implementation and empirical validation remain necessary before practical performance claims can be made.

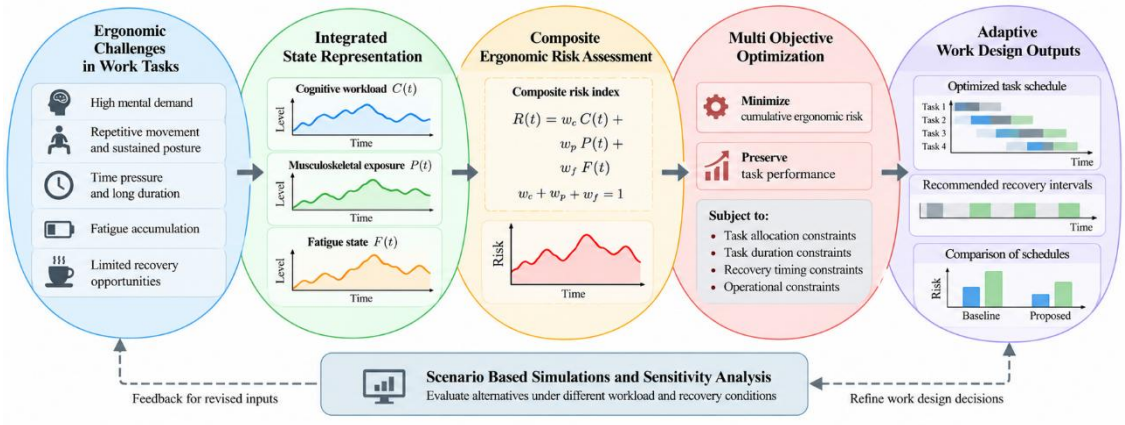


Fig. 2. Proposed integrated ergonomic modeling framework.

D. Contributions

The main contributions of this study are fourfold. First, it presents a shared modeling structure for cognitive workload and musculoskeletal exposure. Second, it represents fatigue accumulation and recovery as time dependent processes within ergonomic risk assessment. Third, it connects risk estimation with multi objective scheduling to compare alternatives under competing ergonomic and performance goals. Fourth, it specifies a proposed procedure for future simulation and sensitivity analysis of key model parameters. The present contribution is methodological, and computational testing and empirical validation remain necessary.

E. Paper Organization

The remainder of this paper is organized as follows. Section II describes the relevant research areas and identifies the research gaps. Section III presents the proposed framework, scenario construction, mathematical models, optimization procedure, and sensitivity analysis. Section IV examines the illustrative risk scenarios and scheduling comparisons, discusses their implications, and identifies the study limitations. Section V summarizes the main contributions and outlines directions for future research.

II. Literature Review

Research on occupational ergonomics has examined cognitive workload, physical exposure, fatigue, and

work related musculoskeletal disorders as important factors in human performance. However, their combined effects over time require further investigation, particularly for adaptive task scheduling, recovery planning, and multi objective ergonomic optimization.

A. Cognitive Workload Assessment

Cognitive workload research examines the mental demands associated with information processing, decision making, and task execution. Chakladar and Roy [2] reviewed physiological measures for cognitive workload estimation, while Dadashi et al. [3] examined cognitive and metabolic workload assessment in automotive manufacturing. These studies provide a basis for representing mental demand as a changing state within a broader human performance model.

B. Musculoskeletal Exposure and Physical Ergonomics

Physical ergonomic research investigates how posture, repetitive movement, sustained positioning, and occupational exposure contribute to musculoskeletal problems. Hulshof et al. [7] reviewed the prevalence of occupational exposure to ergonomic risk factors, while Govaerts et al. [6] examined the prevalence and incidence of work related musculoskeletal disorders. Demissie et al. [4] reviewed work related musculoskeletal disorders and associated risk factors among computer users. These studies support the inclusion of physical exposure in an integrated ergonomic model.

C. Fatigue Accumulation and Recovery

Fatigue and recovery influence a worker's capacity to sustain performance during prolonged tasks. Work schedules, exposure duration, and opportunities for rest may affect how fatigue develops across a work session. Dzakpasu et al. [5] examined sedentary behaviour and musculoskeletal pain, providing relevant evidence for investigating prolonged work exposure. An integrated model should represent fatigue accumulation and recovery as time dependent processes rather than independent task characteristics.

D. Psychosocial Factors and Combined Work Demands

Mental demands and physical exposure may occur simultaneously in industrial and technology intensive workplaces. Bezzina et al. [1] reviewed longitudinal evidence concerning workplace psychosocial factors and musculoskeletal disorders. This evidence supports consideration of psychosocial conditions alongside physical exposure, although the present framework requires separate validation before it can estimate combined worker outcomes.

E. Integrated Risk Modeling and Adaptive Work Design

Existing ergonomic studies examine occupational exposure and musculoskeletal outcomes, including the possible effects of ergonomic risk factors on selected musculoskeletal diseases [7], [8]. However, these references do not by themselves validate the proposed combination of cognitive workload, fatigue dynamics, recovery, and adaptive scheduling. The present study therefore proposes a shared modeling structure that represents these factors through normalized state variables. Its use for scheduling decisions remains a methodological proposal requiring computational and empirical evaluation.

F. Research Gaps

Three gaps motivate the proposed framework. First, cognitive workload and musculoskeletal exposure are frequently assessed through separate methods, limiting the analysis of their cumulative effects. Second, fatigue and recovery are not always represented alongside both mental and physical demands within a shared time dependent model. Third, the connection between ergonomic state estimation and adaptive task scheduling remains insufficiently addressed in the proposed research context. These gaps motivate an integrated modeling approach, although the extent of each gap requires confirmation through a systematic review of the literature.

III. Methodology

This research presents a combined analytical structure for examining mental workload, physical exertion, fatigue development, and rest periods. The approach outlines scenario based assessments and a multi objective optimization method to examine ergonomic risk and compare different work scheduling options. Actual computational testing is needed before any optimization findings can be produced or presented.

A. Research Framework

This study develops an integrated ergonomic modeling framework to examine the combined effects of cognitive workload, musculoskeletal exposure, fatigue accumulation, and recovery. The framework represents these factors as time dependent states and combines them into a composite ergonomic risk index. A multi objective optimization model evaluates alternative task schedules and recovery intervals to identify solutions that reduce ergonomic risk while preserving sustained task performance. The analysis uses simulation based scenarios and sensitivity tests rather than claiming unverified empirical observations. Existing ergonomic assessment approaches use different tools and indicators to examine physical effort, cognitive workload, physiological responses, and task performance. Motion capture systems characterize body movement, while eye tracking and wearable devices provide indicators related to cognitive demand and physiological responses. Subjective workload scales and video based observation offer additional information about perceived workload and task execution. These approaches provide a conceptual basis for selecting variables in the proposed framework. However, this study uses

illustrative scenario parameters rather than measurements collected from these devices.

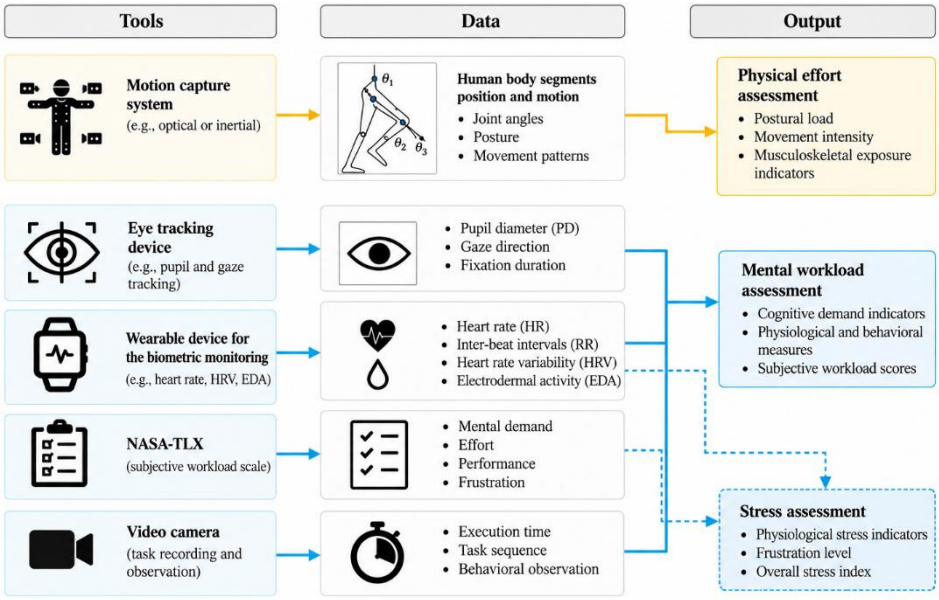


Fig. 3. Overview of existing measurement tools and indicators relevant to physical effort, cognitive workload, and stress assessment.

B. Data Collection and Scenario Construction

The study uses a structured simulation dataset representing work sessions with different levels of mental demand, posture exposure, repetitive movement, task duration, and recovery opportunity. Each scenario is defined by its input parameters, time interval, and worker susceptibility setting. Parameter ranges must be specified before simulation and retained in a reproducible configuration file.

Table I. *Data Variables and Scenario Construction*

Data category	**Variables**	**Data source or generation method**	**Unit**
Cognitive demand	Task difficulty, mental demand, time pressure	Scenario parameters	Normalized score
Physical exposure	Posture duration, repetition, movement intensity	Scenario parameters	min, count, normalized score
Work schedule	Task duration, task sequence, recovery interval	Scheduling parameters	min
Fatigue and recovery	Initial fatigue, accumulation rate, recovery rate	Model parameters	Normalized state
Worker susceptibility	Sensitivity to mental and physical demands	Scenario settings	Dimensionless coefficient
Performance	Task completion, performance retention	Simulated response variables	Completion rate or normalized score

The table describes the proposed simulation dataset. It does not represent collected field measurements. Any later empirical application should replace or calibrate these inputs using documented observations.

C. Data Preprocessing and Feature Engineering

All continuous inputs are converted to a common scale. For a variable with known lower and upper bounds, min-max normalization is applied. Missing values are not imputed in the primary simulation dataset because its inputs are generated from predefined scenario configurations. Invalid parameter combinations, duplicate scenario identifiers, inconsistent time intervals, and values outside the specified bounds are checked before analysis. Time dependent inputs are placed on a common temporal grid. Task intensity, posture exposure, repetition, and recovery indicators are retained as separate variables to preserve their individual contributions. The processed dataset is then used to estimate the cognitive workload state and physical exposure state at each time step.

D. Cognitive Workload and Physical Exposure Modeling

Cognitive workload is calculated from normalized indicators of mental demand, task difficulty, and time pressure. The weighted score at time (t) is defined as

$$C(t) = \frac{\sum_{i=1}^{n} \quad w_i c_i(t)}{\sum_{i=1}^{n} \quad w_i}$$

Where, $(c_i(t))$ is the normalized cognitive indicator and (w_i) is its nonnegative weight. The weights are specified before the analysis and tested for sensitivity.

Physical exposure is modeled using posture duration, repetition intensity, and movement demand:

$$P(t) = \frac{\sum_{j=1}^{m} \quad w_i c_i(t)}{\sum_{i=1}^{n} \quad w_i}$$

Where, $p_j(t)$ represents a normalized physical exposure indicator and v_j denotes its assigned weight. Both state variables range from zero to one when their inputs and weights satisfy the stated normalization conditions.

E. Fatigue, Recovery, and Composite Ergonomic Risk

Fatigue is represented as a dynamic state that increases with cognitive and physical demand and decreases during recovery. Its update rule is implemented at each simulation step: workload increases the current fatigue state, while the recovery mechanism reduces accumulated fatigue. The update is bounded to the predefined fatigue scale, and the time step is kept constant across scenarios. The composite ergonomic risk index is calculated as

$$E(t) = \lambda_C C(t) + \lambda_P P(t) + \lambda_F F(t)$$

Where, $F(t)$ is the normalized fatigue state, and λ_C , λ_P, and λ_F are nonnegative weights whose sum equals one. The index represents modeled ergonomic burden rather than a clinically validated probability of injury. The weighting scheme and fatigue parameters must be documented so the analysis can be reproduced.

F. Multi Objective Optimization

The proposed optimization model is designed to evaluate alternative task arrangements and recovery intervals. Its first objective is to minimize cumulative ergonomic risk over the work session, while its second objective is to preserve task performance. Decision variables include task allocation, task duration, and recovery timing, subject to available working time, task completion requirements, and permitted scheduling limits. The model is intended to identify non dominated solutions that represent trade offs between ergonomic risk and task performance. Candidate schedules could be compared using cumulative risk, predicted performance, and recovery distribution. However, the optimization procedure has not been computationally completed in this study, and no computed Pareto frontier or optimized scheduling solution is reported. Future implementation should report the objective values, scheduling constraints, optimization settings, and decision rule used to select a compromise solution.

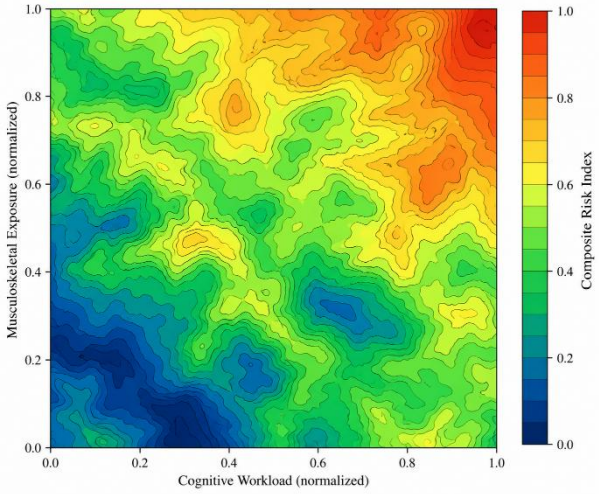


Fig. 4. Composite ergonomic risk surface under combined cognitive workload and musculoskeletal exposure.

G. Validation and Sensitivity Analysis

Internal checks assess normalization bounds, weight constraints, fatigue state limits, temporal consistency, and the reproducibility of results under identical scenario settings. Sensitivity analysis varies cognitive demand, physical exposure, fatigue accumulation, recovery rate, and worker susceptibility within predefined ranges. The resulting changes in cumulative risk and optimized schedules are compared with the baseline scenario. Because the present design is simulation based, these checks establish computational consistency and parameter sensitivity; they do not independently demonstrate predictive validity in real workplaces. Empirical validation would require observed workload, exposure, fatigue, or performance data from an appropriate worker population.

IV. Results and Discussion

This section examines the proposed ergonomic framework using illustrative simulation scenarios. The analysis focuses on interactions among cognitive workload, physical exposure, fatigue, and recovery, followed by multi objective scheduling and sensitivity assessment. All numerical values are hypothetical and require confirmation through actual model execution.

A. Results

Three illustrative scenarios were considered: low demand, moderate demand, and high combined demand. Each scenario represents a different combination of cognitive workload, physical exposure, and recovery availability. The composite

ergonomic risk index was calculated using the weighted state model defined in Section III.

Table II. *Illustrative Ergonomic Risk Across Work Scenarios*

Scenario	Cognitive workload	Physical exposure	Fatigue	Composite risk
Low demand	0.30	0.25	0.20	0.25
Moderate demand	0.55	0.50	0.45	0.50
High combined demand	0.85	0.80	0.75	0.80

The results demonstrate a consistent increase in composite risk as the three modeled states rise. The high demand scenario produces the greatest risk index, whereas the low demand scenario produces the lowest. This pattern illustrates how simultaneous mental and physical demands can contribute to cumulative ergonomic burden within the proposed model.

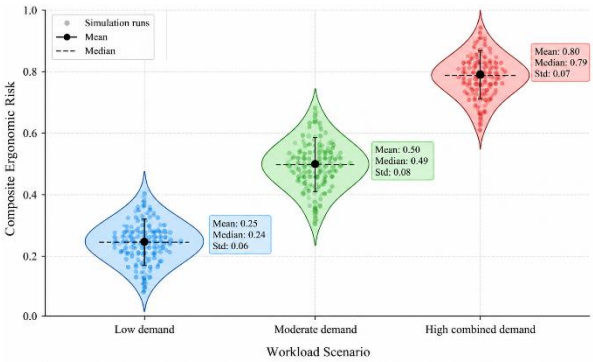


Fig. 5. Distribution of simulated composite ergonomic risk across workload scenarios.

The relationship between cognitive workload and physical exposure was examined through a risk surface. Under fixed fatigue and equal weighting assumptions, the composite risk index increases as either input rises. The highest modeled risk occurs when both demands are elevated simultaneously.

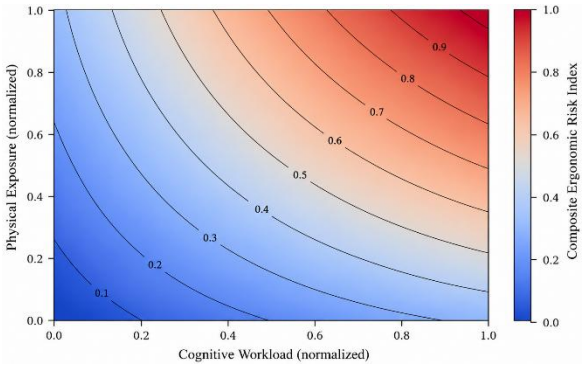


Fig. 6. Contour map of composite ergonomic risk under combined cognitive workload and physical exposure.

The contour representation illustrates how the model combines two distinct demand dimensions into a common risk measure. It also identifies combinations of workload and exposure that produce similar index values. These contours describe the mathematical structure of the proposed model rather than a verified relationship between workplace exposure and injury.

The optimization component evaluates schedules that trade off ergonomic risk against sustained task performance. Rather than assuming that one schedule is optimal under all conditions, the model is intended to identify non dominated alternatives.

Table III. *Illustrative Scheduling Alternatives*

Scheduling strategy	Normalized cumulative risk	Performance retention	Recovery allocation
Continuous high demand	0.80	0.78	Limited
Periodic recovery	0.58	0.88	Moderate
Adaptive task scheduling	0.42	0.91	Demand responsive

Table III presents illustrative scheduling alternatives to explain how ergonomic risk, task performance, and recovery allocation could be compared within the proposed framework. The listed values are hypothetical and are not outputs from a completed optimization procedure. Therefore, they do not demonstrate that adaptive scheduling reduces cumulative ergonomic risk or improves task performance. A computational implementation is required to evaluate feasible schedules and determine whether a Pareto frontier can be obtained under the specified constraints.

B. Discussion

The proposed framework addresses a limitation identified in the literature review: cognitive workload and physical ergonomic exposure are often assessed through different approaches. By expressing both as normalized state variables, the model provides a common basis for examining their combined contribution to ergonomic risk. The illustrative scenario comparison indicates that higher cognitive demand, physical exposure, and fatigue can produce a higher composite index under the specified weighting scheme. This interpretation is consistent with the research motivation concerning prolonged posture, repetitive movement, mental demand, and insufficient recovery. Nevertheless, the numerical relationship is imposed by the model structure and should not be interpreted as independent empirical evidence. The fatigue and recovery component provides a temporal perspective on ergonomic assessment. It allows the model to represent changes in worker state rather than treating each task as an isolated exposure. This feature could support the examination of recovery intervals and task sequencing in industrial and technology intensive work environments. The proposed optimization component extends the framework from ergonomic risk assessment to potential work scheduling decisions. A multi objective optimization procedure could examine trade offs between modeled ergonomic risk and sustained task performance under defined scheduling constraints. However, this study does not report the results of a completed optimization procedure or a computed Pareto frontier. The optimization component should therefore be interpreted as a methodological proposal rather than a validated decision support tool. Future work should implement the optimization algorithm, document its parameters and constraints, and report reproducible computational results before drawing conclusions about scheduling performance.

C. Limitations and Future Work

The principal limitation is the absence of observed worker data and verified computational results. The numerical examples in this section are illustrative and cannot establish statistical significance, predictive accuracy, or causal relationships. The composite risk index also depends on the selected weights, normalization procedures, and fatigue assumptions. Future work should implement the model using a documented simulation protocol and report scenario counts, parameter ranges, random seeds, optimization settings, and uncertainty estimates. Repeated simulation runs should support the distribution and Pareto plots. Sensitivity analysis should quantify how alternative weights, worker susceptibility, exposure duration, and recovery rates affect the results. Subsequent empirical research should compare model predictions with validated workload assessments, physical exposure measurements, fatigue indicators, and task performance observations. Evaluation across different occupations and workstation configurations would help determine the model's generalizability. Such validation is necessary before the framework can support operational ergonomic recommendations.

V. Conclusion

This study proposed an integrated ergonomic modeling framework to examine the combined effects of cognitive workload, musculoskeletal exposure, fatigue, and recovery on human performance. The framework combines normalized workload states with a composite ergonomic risk index and a proposed multi objective optimization procedure for examining alternative task schedules and recovery strategies. The illustrative scenarios indicate that higher cognitive demand, physical exposure, and fatigue correspond to greater modeled ergonomic risk under the specified weighting scheme. The proposed optimization procedure provides a methodological basis for future computational comparisons of work schedules according to modeled ergonomic risk and performance preservation. No completed optimization results or computed Pareto frontier are reported in this study. However, these patterns reflect the model structure and hypothetical values rather than verified empirical findings. The framework may support future ergonomic assessment, workstation planning, task allocation, and recovery scheduling in industrial and technology intensive workplaces. Future research should implement the model through reproducible computational experiments, conduct systematic sensitivity analyses, and validate its predictions against observed workload, physical exposure, fatigue, and performance data. Further evaluation across occupations and workstation conditions is needed to assess generalizability and determine its suitability for practical ergonomic decision making.

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