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Article

Developing an optimization model for minimizing musculoskeletal stress in repetitive motion tasks

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Abstract: Repetitive motion tasks are widely prevalent in various industries, including manufacturing and office environments, often leading to significant musculoskeletal stress and associated injuries. The continuous nature of these tasks, coupled with improper posture, excessive force exertion, and inadequate rest periods, exacerbates the risk of long-term damage to muscles, joints, and tendons. This paper presents a novel approach to minimizing musculoskeletal stress by developing a Reinforcement Learning (RL)—based optimization model. The model dynamically adjusts real-time task parameters, such as posture, speed, and force exertion, to reduce joint load, muscle activation, and cumulative fatigue while maintaining task performance and productivity. Data was collected from 45 participants performing repetitive tasks in a controlled laboratory environment. Key biomechanical factors, including joint load, muscle activation, and cumulative fatigue, were measured using motion capture, electromyography (EMG), and force plate systems. The RL was trained and validated using this data, with significant improvements observed across all key metrics. The results demonstrated that the model achieved an average reduction of 25%–28% in joint load, 23%–29% in muscle activation, and 26%–28% in cumulative fatigue. In addition, task completion times and accuracy were maintained or improved, demonstrating the model's effectiveness in balancing ergonomic benefits with productivity. This study provides an integrated approach to reducing musculoskeletal stress while ensuring task efficiency, offering a dynamic, data-driven solution that can be applied across various industries. The findings suggest that RL optimization can significantly improve worker health and task sustainability without compromising organizational performance.

Keywords: muscle activation; musculoskeletal stress; electromyography; motion capture; reinforcement learning; posture; biomechanical factors

1. Introduction

Repetitive motion tasks occur in industrial, office, and manual labor environments [1–3]. While essential to productivity, these tasks often impose significant physical strain on the musculoskeletal system due to the continuous and repetitive nature of the movements involved [4,5]. Over time, this strain can lead to injuries such as tendonitis, joint damage, muscle fatigue, and other Cumulative Trauma Disorders (CTD) [6]. The repetitive nature of these tasks, especially when combined with improper posture, awkward movements, or excessive force, exacerbates the risk of long-term musculoskeletal damage, ultimately affecting worker health and productivity [7,8]. The primary biomechanical factors contributing to musculoskeletal stress in repetitive tasks include joint loading, muscle activation, and cumulative fatigue [9]. Joint loading refers to the forces applied to joints during task execution, and excessive, or unevenly distributed joint loads can lead to injuries such as sprains, joint instability, or even chronic conditions like arthritis [10]. Muscle activation, mainly when sustained over long periods without adequate rest, can lead to muscle fatigue and overuse injuries, especially in high-demand tasks [11]. Cumulative fatigue, resulting from prolonged exposure to repetitive tasks, further compounds these risks by reducing muscle strength and increasing reliance on compensatory movements that can alter biomechanics and increase injury risk [12,13].

In addition to these physical stressors, organizations face the challenge of balancing ergonomic interventions with maintaining productivity [14]. Simple solutions, such as reducing task speed or increasing rest periods, may alleviate some physical strain but can negatively impact productivity and task efficiency [15,16]. Therefore, the challenge lies in developing optimization models that minimize musculoskeletal stress while preserving task performance. To address this, our study proposes developing a Reinforcement Learning (RL)—based optimization model that adjusts task parameters, including posture, movement speed, and force exertion, to reduce joint load, muscle activation, and cumulative fatigue. Unlike traditional ergonomic solutions, which often rely on static adjustments, the RL-based model learns from real-time task performance data and continuously updates its recommendations. This optimization model aims to balance worker safety and productivity by minimizing physical strain without compromising output. This paper provides a comprehensive approach to minimizing musculoskeletal stress in repetitive motion tasks through a data-driven optimization model. The study aims to validate the model by collecting data on joint load, muscle activation, and cumulative fatigue from participants performing various repetitive tasks and using this data to train and test the RL. The paper also investigates the impact of the model's ergonomic recommendations on task performance, analyzing factors such as task completion time and accuracy to ensure that improvements in worker health do not negatively affect productivity.

In the following sections, Section 2 presents a detailed discussion of the biomechanical factors in repetitive tasks, the models for assessing stress and fatigue, and the most common injuries associated with repetitive motion tasks. In Section 3, we then outline the methodology used in developing the RL optimization, followed by an in-depth analysis of the data collection process and model training. The results of Section 4 present the model's effectiveness in reducing joint load, muscle activation, and cumulative fatigue, along with its impact on task performance and efficiency. Finally, Section 5 presents the conclusion of the paper.

2. Theoretical framework

2.1. Biomechanical factors in repetitive tasks

Repetitive motion tasks impose significant mechanical strain on various musculoskeletal structures, particularly the joints, muscles, tendons, and ligaments [17]. The continuous repetition of specific movements, often without sufficient rest or variation, can lead to localized fatigue and tissue damage over time. A key biomechanical factor in such tasks is joint loading, which refers to the forces applied to joints during movement [18]. Excessive or improperly distributed joint loads, often seen in tasks that require repetitive lifting, bending, or twisting, increase the risk of cumulative trauma disorders. In addition to joint load, muscle activation plays a critical role. Muscles engaged in repetitive tasks are subjected to cyclical contraction and relaxation patterns. Over time, these patterns can result in muscle fatigue, particularly in cases where the same muscle groups are continuously used without recovery periods.

Another crucial aspect is the posture adopted during repetitive tasks. Poor or static postures can increase the biomechanical demand on specific muscle groups, leading to inefficient movement patterns and more significant musculoskeletal stress. For instance, a forward head posture or slouched shoulders in desk-based repetitive tasks may increase strain on the neck and upper back muscles. Similarly, awkward wrist positions in assembly line work can exacerbate stress on the tendons and ligaments of the hand and wrist, leading to conditions like carpal tunnel syndrome. The interaction between posture and movement frequency is significant, as maintaining a non-neutral posture while performing high-frequency tasks can accelerate the onset of musculoskeletal disorders [19].

Fatigue accumulation is another biomechanical factor that influences task performance and musculoskeletal health. As muscles fatigue, their capacity to generate force diminishes, leading to compensatory movements or shifts in load-bearing across different muscle groups. This compensation can alter normal biomechanics, increasing the risk of injury. For example, fatigued lower limb muscles during a standing task may result in greater reliance on joint structures or non-fatigued muscles, increasing joint wear or imbalanced muscle activity.

2.2. Stress and fatigue models

Stress and fatigue models are essential for understanding the cumulative effects of repetitive tasks on musculoskeletal structures. These models provide a theoretical foundation for quantifying how repetitive motion, force exertion, and insufficient recovery periods contribute to musculoskeletal fatigue, resulting in short-term discomfort and long-term injury. A key concept within these models is cumulative load, which refers to the total stress experienced by tissues over time. The cumulative load model suggests that musculoskeletal damage is not only determined by the intensity of the task but also by the frequency and duration of the movements [20]. Repetitive tasks, particularly those involving high loads or awkward postures, lead to a continuous accumulation of stress, which eventually exceeds the tissue’s threshold for recovery, causing fatigue and, ultimately, injury.

Fatigue models, such as the muscle fatigue endurance time model, describe the relationship between force, time, and fatigue. These models are frequently expressed through equations that relate the force exerted by a muscle to the time it can maintain that force before fatigue sets in [21]. The greater the exerted force relative to the muscle’s maximum capacity, the shorter the endurance time. For example, in tasks requiring static postures or continuous lifting, muscle groups fatigue more quickly if they are close to their maximum capacity, leading to compensatory movements, reduced force output, or increased risk of injury. The fatigue process can also be influenced by factors such as muscle strength, endurance, and ergonomic conditions, which vary across workers and tasks.

Another relevant approach is the three-compartment fatigue model that considers fatigue's metabolic, mechanical, and neurological components [22–25]. This model highlights that fatigue is not merely the result of mechanical wear and tear but also involves metabolic depletion and neurological factors. Metabolic fatigue occurs when energy stores are depleted, while mechanical fatigue is associated with tissue micro-damage. Neurological fatigue involves the nervous system's decreasing ability to activate muscles effectively after prolonged or intense activity [26–28]. Stress and fatigue models incorporating these dimensions are precious for designing optimization models that can predict when and how fatigue will occur in a repetitive task, allowing for better intervention strategies such as task rotation, rest breaks, or ergonomic adjustments [29,30].

Additionally, psychophysical fatigue models offer insights into how perceived exertion corresponds to physiological fatigue [31,32]. These models are applicable in settings where subjective assessments of fatigue can provide early warning signs before objective indicators of stress manifest. For instance, workers engaged in highly repetitive tasks might report increased perceived effort even before significant musculoskeletal fatigue occurs. Including such psychophysical data in stress and fatigue models ensures that interventions can respond more to worker feedback, further minimizing the risk of injury.

2.3. Most common repetitive motion task injuries

Repetitive motion tasks expose individuals to different types of musculoskeletal injuries depending on the nature and intensity of the task. These injuries can arise from various factors, such as the amount of force exerted, the frequency of repetitive movements, and the duration of exposure to such tasks [33–35]. The most common types of repetitive motion task injuries include High Force Injuries, Low Repetitive Force Injuries, Sustained Force Injuries, and Injuries from Cumulative Trauma Over Years. Different biomechanical demands and resulting impacts on the body characterize each injury category.

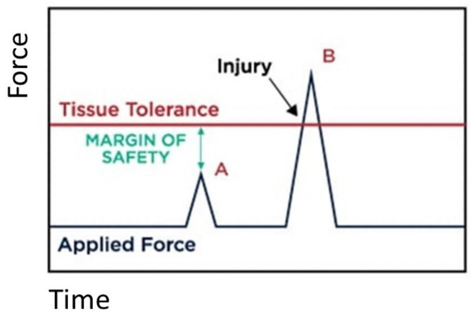

Figure 1. Injury caused by a single high-force event.

High Force Injuries (**Figure 1**) occur when repetitive tasks involve the application of significant force over a short period [36–39]. These injuries are often associated with heavy lifting, pushing, or pulling in industrial or manual labor settings. When high force is exerted repetitively, particularly without proper posture or ergonomic support, the musculoskeletal system experiences acute stress, primarily in the muscles, tendons, and joints. High-force injuries can lead to immediate damage, such as muscle tears, ligament sprains, joint dislocations, and long-term issues like chronic tendonitis or joint instability. These injuries are most commonly seen in tasks that involve loading and unloading heavy materials or operating machinery that requires substantial manual effort.

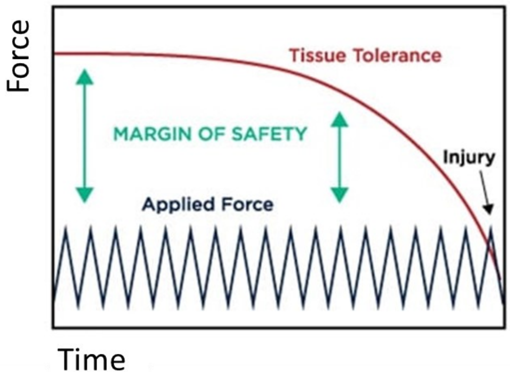

Figure 2. Injury caused by a repetitive force task.

In contrast, Low Repetitive Force Injuries (**Figure 2**) develop from the cumulative effect of performing tasks that require minimal force but are repeated over a prolonged period. These injuries are frequently seen in occupations involving delicate motor tasks, such as typing, assembly line work, or handling small tools. Although each movement exerts minimal stress on the body, the high frequency of these low-force tasks can lead to fatigue and overuse of specific muscles and tendons. Over time, this leads to Repetitive Strain Injuries (RSI), including carpal tunnel syndrome, tendonitis, and De Quervain's tenosynovitis. Low repetitive force injuries often manifest in the hands, wrists, and forearms due to the continuous engagement of these body parts in precision tasks.

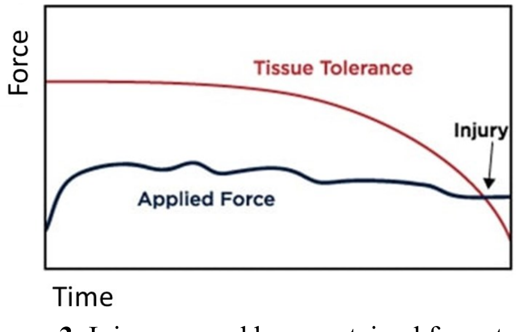

Figure 3. Injury caused by a sustained force task.

Sustained Force Injuries (**Figure 3**) are the result of maintaining prolonged muscle contraction or static postures that place a continuous load on specific muscles or joints. Unlike repetitive movements, sustained force injuries arise when muscles are held in a contracted position for extended periods, such as holding heavy objects or maintaining awkward postures. This can cause muscle fatigue, reduced blood flow, and a buildup of lactic acid, which increases discomfort and the likelihood of injury. Common examples include prolonged standing or sitting, gripping tools for extended periods, or working in fixed postures, such as welding or assembly tasks. Sustained force injuries often affect the neck, shoulders, back, and lower limbs, leading to muscle strain, joint stiffness, and, in severe cases, chronic conditions like lower back pain or frozen shoulder.

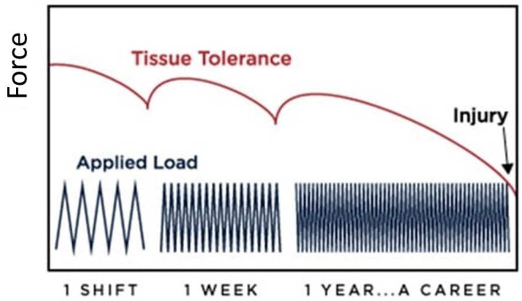

Figure 4. Injury caused by cumulative trauma over time.

Injuries from Cumulative Trauma Over Years (**Figure 4**) represent the long-term impact of repetitive motion tasks on the musculoskeletal system. These injuries do not arise from a single incident but develop gradually due to continuous exposure to harmful working conditions over many years. CTD is frequently seen in workers with long careers in physically demanding roles or those who have performed the same repetitive tasks for decades without adequate ergonomic adjustments or rest breaks. The effects of cumulative trauma include joint degeneration, chronic tendonitis, and musculoskeletal deformities, such as spinal disc herniation or arthritis. In some cases, the cumulative damage becomes irreversible, leading to permanent disability or the need for surgical intervention. Common industries affected by these injuries include construction, manufacturing, and healthcare, where workers are exposed to repetitive high-stress tasks throughout their careers.

3. Methodology

3.1. Objective function definition

Repetitive motion tasks are widely prevalent in many industries, from manufacturing to office environments, and they often result in significant musculoskeletal strain due to continuous and repetitive movements. Over time, this strain accumulates, leading to injuries such as tendonitis, joint damage, and muscle fatigue, negatively impacting worker productivity and health. These tasks, whether lifting, typing, or using hand tools, place repetitive loads on specific muscles and joints. The constant repetition without adequate ergonomic design or rest periods leads to overuse, localized fatigue, and long-term damage, particularly when poor posture, awkward movements, or excessive force are involved. A significant challenge in minimizing the risks associated with repetitive motion tasks is the complexity of the biomechanical factors at play. Joint loading, muscle activation, and cumulative fatigue must all be accounted for, as they are interrelated and collectively contribute to the overall physical stress experienced by the worker. High joint loads, excessive muscle engagement, and prolonged task durations increase the likelihood of injury, making it essential to develop solutions that address these factors simultaneously. At the same time, organizations face the challenge of balancing ergonomic improvements with productivity demands. Simply slowing down tasks or allowing for longer rest breaks may reduce musculoskeletal strain but could also reduce efficiency. Thus, the goal is to optimize task performance to minimize biomechanical stress without compromising output. To balance worker health and task productivity, the optimization model is built with the following variables and constraints:

Variables:

- Posture Adjustments $\left(P_j\right)$: Modifications to worker posture, such as arm or wrist positioning, to reduce joint load and muscle strain.
- Movement Speed (S_m): The rate at which repetitive tasks are performed directly affects muscle activation levels and fatigue.
- Force Exertion (F_e) : The amount of physical force applied during task performance, such as the weight lifted or the grip force exerted.
- Task Duration (T_d): The total time spent performing the task without a break influences cumulative fatigue's buildup.
- Rest Periods $\left(R_p\right)$: The frequency and duration of breaks allow recovery between repetitive tasks to reduce fatigue.

Constraints:

- Ergonomic Limits on Joint Load (J_{max}): Joint loads must remain below a defined ergonomic threshold for each joint to prevent injury:

$$J_i \leq J_{\max} \tag{1}$$

- Muscle Activation Threshold $(M_{\max})$: Muscle activation levels should not exceed a set percentage of the MVC to prevent overexertion and fatigue:

$$M_i \leq M_{\max} \tag{2}$$

- Cumulative Fatigue Constraint $(F_{\max})$: Cumulative fatigue for each muscle group and joint should remain below a pre-defined limit to avoid long-term wear:

$$F_i \leq F_{\max} \tag{3}$$

- Task Performance Requirement $(P_{\min})$: Task output or performance should not drop below a defined productivity threshold, ensuring that efficiency is maintained:

$$P \geq P_{\min} \tag{4}$$

With these variables and constraints in place, the objective function is mathematically expressed as:

$$\min f(x) = \sum_{i=1}^{n} (w_1 \times J_i + w_2 \times M_i + w_3 \times F_i) \tag{5}$$

where:

- J_i represents the joint load at joint i.
- M_i represents the muscle activation level for muscle i.
- F_i represents the cumulative fatigue index for joint or muscle i.
- w_1, w_2, w_3 are weights assigned to each component based on its importance in minimizing musculoskeletal stress.

- x represents the task parameters being optimized, such as posture, force exertion, or movement speed.

The goal of the optimization model is to minimize the objective function by adjusting the task variables (such as posture, speed, and rest breaks) while adhering to the constraints that ensure worker safety and productivity. This approach balances reducing musculoskeletal stress and maintaining task performance, improving worker health and efficiency in repetitive motion tasks.

3.2. RL-Based optimization algorithm

The application of RL in optimizing repetitive motion tasks provides a dynamic, data-driven approach to minimizing musculoskeletal stress. Unlike traditional optimization techniques that rely on static models, RL offers a more flexible method by enabling continuous learning and adaptation based on real-time feedback from task performance. In this context, RL can be utilized to identify optimal task modifications (e.g., posture adjustments, force exertion) that minimize joint loads, muscle activation, and cumulative fatigue while adhering to productivity constraints.

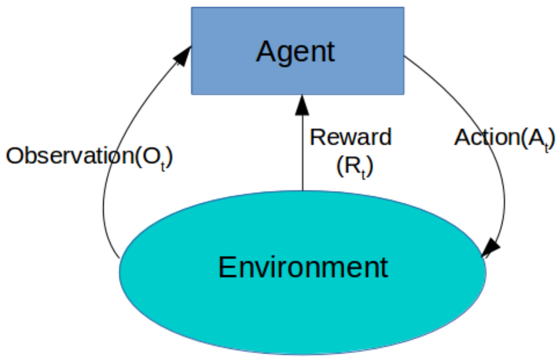

Figure 5. RL framework.

The RL (**Figure 5**) interacts with the environment, where the repetitive motion task represents the environment and the worker's physical state and task performance represent the states. The optimization algorithm learns from these interactions by receiving rewards or penalties based on the task's impact on musculoskeletal stress and efficiency. The goal of the RL agent is to maximize the cumulative reward, corresponding to minimizing stress while maintaining task output. The problem is formulated as a Markov Decision Process (MDP), defined by the tuple (S, A, P, R, γ)

- State (S): Represents the worker's biomechanical state, including joint load, muscle activation levels, and fatigue. The state at time t is s_t.
- Action (A): Represents the set of possible task modifications (e.g., adjustments in posture, speed, and force exertion). The action taken at time t is a_t.
- Transition Probability (P): Defines the probability of transitioning from one state to another based on the action taken, represented as $P(s_{t+1} \mid s_t, a_t)$.
- Reward Function (R): Provides feedback to the RL agent by assigning rewards for actions that reduce stress and penalties for actions that increase musculoskeletal load. The reward at time t is r_t.

- Discount Factor (γ): Determines the importance of future rewards, with $0 \leq \gamma \leq 1$.

The objective of the RL algorithm is to find the optimal policy π^*, which maximizes the expected cumulative reward over time, denoted as $V^\pi(s)$, where:

$$V^\pi(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t \mid s_0 = s, \pi\right] \quad (6)$$

Here, $V^\pi(s)$ is the expected return (cumulative reward) from starting in state s and following policy π. The optimal policy π^* maximizes this expected return for all states, ensuring the lowest possible musculoskeletal stress and the highest possible task performance.

Reward Function Definition: The reward function $R(s_t, a_t)$ is designed to penalize high biomechanical loads and reward actions that minimize stress while maintaining task output. Specifically, the reward function is defined as:

$$r_t = -\big(w_1 \times J(s_t) + w_2 \times M(s_t) + w_3 \times F(s_t)\big) + \lambda \times P(a_t) \quad (7)$$

where:

- $J(s_t)$ represents the joint load at time t.
- $M(s_t)$ represents the muscle activation level at time t.
- $F(s_t)$ represents the cumulative fatigue at time t.
- $P(a_t)$ represents the productivity measure based on the action taken.
- w_1, w_2, w_3 are the weights assigned to joint load, muscle activation, and fatigue, respectively.
- λ is a scaling factor for productivity.

Policy Update: Q-Learning Algorithm: The RL agent uses Q-learning to update the value of taking a particular action in a given state. The Qvalue $Q(s_t, a_t)$ represents the expected cumulative reward for taking action a_t in state s_t and then following the optimal policy. The Q-learning update rule is given by:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha\left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right] \quad (8)$$

where:

- α is the learning rate, controlling how much the new information overrides the old information.
- γ is the discount factor, determining the importance of future rewards.
- $\max_{a'} Q(s_{t+1}, a')$ represents the maximum expected reward for the next state.

Through iterative updates, the RL agent learns the optimal Q-values for each state-action pair, eventually converging to the optimal policy π^*.

Algorithm: Q-Learning.

Input: State-space S, action space A, learning rate α, discount factor γ, exploration rate ϵ.

Output: Optimal Q-value function $Q(s, a)$, Optimal policy $\pi^*(s)$.

Steps:

1) Initialize Q-values $Q(s, a)$ arbitrarily for all $s \in S$ and $a \in A$ (e.g., $(s, a) = 0$).
2) For Each episode:

- Initialize starting state s_0.

3) While the episode is not done:
   - Choose action a_t from state s_t using an ϵ-greedy policy:

$$a_t = \begin{cases} \text{random action from A} & \text{with probability } \epsilon \\ \arg\max_{a} Q(s_t, a) & \text{with probability } 1 - \epsilon \end{cases} \tag{9}$$

   - Take action a_t, observe reward r_t and next state s_{t+1}.
   - Update Q-value for $Q(s_t, a_t)$ using the Q-Learning update rule:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \tag{10}$$

     - α is the learning rate, controlling how much new information overrides the old.
     - γ is the discount factor, determining the weight of future rewards.
     - $\max_{a'} Q(s_{t+1}, a')$ is the maximum future reward for the state s_{t+1}.
   - Update state: Set s_{t+1} as the current state s_t.

4) End episode when the task is completed, or convergence is achieved.
5) Repeat steps 2–4 for the next episode.
6) End.

3.3. Data collection

The data collection phase is crucial for building an accurate and reliable optimization model to reduce musculoskeletal stress in repetitive motion tasks. This study collects data from 45 participants selected based on specific inclusion criteria to represent a diverse range of physical characteristics and task performance abilities. Participants are recruited from industries where repetitive motion tasks are prevalent, such as manufacturing, assembly work, and office-based tasks. The demographic breakdown includes 25 males and 20 females, aged between 25 and 45 years, with an average age of 34.8. The participants' height ranges from 155 cm to 185 cm (average height: 170 cm), and their weight ranges from 50 kg to 85 kg (average weight: 68.5 kg). All participants are physically active and have no history of musculoskeletal disorders, which would bias the results.

The data collected focuses on capturing both biomechanical and task performance metrics. Biomechanical data is gathered through precise instruments such as motion capture systems, surface electromyography (EMG) sensors, and force plates. These tools allow for the accurate measurement of joint loads, muscle activation, and cumulative fatigue, key factors in assessing musculoskeletal stress. Task performance metrics, including task completion time and accuracy, are also recorded to ensure that ergonomic interventions do not compromise productivity. Environmental conditions such as temperature, humidity, and lighting are controlled to prevent external factors from influencing the data.

The data collection occurs in a controlled laboratory setting where participants perform repetitive tasks under varying conditions. The tasks simulate everyday repetitive actions in industrial and office environments, such as lifting, pushing, typing, or using handheld tools. Each participant undergoes multiple sessions where their movements, muscle engagement, and task performance are recorded. The tasks are adjusted across sessions to introduce variations in posture, force exertion, and movement speed, allowing the model to account for a wide range of task configurations. Breaks are provided between sessions to prevent fatigue from affecting the results, ensuring that the collected data accurately reflects task-related stress rather than fatigue accumulation.

All data is processed and cleaned to remove noise and artifacts, especially in the EMG and motion capture data, before input into the RL-based optimization algorithm. The collected dataset provides the foundation for the model's ability to learn task modifications that reduce musculoskeletal stress while maintaining efficiency. **Table 1** below provides an overview of the key measurements and variables and the units and apparatus used in the data collection.

Table 1. Measurements and variables.

Measurement	Variable	Units	Apparatus Used
Joint Load	Force/Torque on joints	Newtons (N), Newton-meters (Nm)	Motion capture sensors, force plates
Muscle Activation	% of Maximum Voluntary Contraction (MVC)	Percentage (%)	Surface electromyography (EMG) sensors
Cumulative Fatigue	Fatigue Index	Dimensionless	EMG and motion capture data
Task Completion Time	Time	Seconds (s)	Stopwatch/Automated timing system
Grip Force	The force applied by hand	Newtons (N)	Hand dynamometer
Ground Reaction Force	The force exerted by feet	Newtons (N)	Force plates
Accuracy	Error rates in task	Number of errors	Manual or automated tracking

3.4. Training the model and parameters

Once the data is collected, the RL is trained to identify task modifications that minimize musculoskeletal stress in repetitive motion tasks. The training process involves feeding the collected biomechanical and task performance data into the RL model, allowing it to learn from the data and iteratively improve its performance. The model aims to find an optimal policy that balances minimizing stress on the musculoskeletal system with maintaining task efficiency.

3.4.1. Model training process

The training begins by initializing the state space, action space, and reward function, as defined earlier in the optimization framework. The state space includes biomechanical variables such as joint load, muscle activation, and cumulative fatigue, while the action space represents potential task modifications (e.g., changes in posture, force exertion, or speed). The model interacts with the environment (i.e., the repetitive tasks performed by participants) by selecting actions based on the current state and observing the resulting changes in musculoskeletal stress and task performance. For each training episode, the model selects an action based on an ε-greedy policy, where it either explores a new action or exploits the best-known action according to the learned Q-values. The reward function, defined earlier, assigns a penalty for high musculoskeletal stress (joint load, muscle activation, fatigue) and provides a positive reward for actions that maintain or improve task performance. The model updates its Q-values for each state-action pair through this iterative process, gradually learning the optimal policy for minimizing stress while maintaining productivity.

3.4.2. Parameters for training

The model is trained using **Table 2** is a set of carefully chosen hyperparameters, which determine the efficiency and effectiveness of the learning process.

The key parameters include:

Table 2. Parameters for training.

Parameter	Value
Learning Rate (α)	0.1
Discount Factor (γ)	0.9
Exploration Rate (ε)	0.2 (initial), decays over time
Batch Size	32 samples
Training Episodes	10,000 episodes
w_1 (Joint Load)	0.4
w_2 (Muscle Activation)	0.3
w_3 (Cumulative Fatigue)	0.2
λ (Task Performance)	0.1

After training, the model is validated using a separate dataset to ensure the learned policy generalizes well to new task conditions. The validation process measures how effectively the model minimizes musculoskeletal stress under different task configurations, ensuring it meets the predefined ergonomic and productivity goals. The final model is evaluated on key metrics such as joint load reduction, muscle activation levels, and task completion time, demonstrating its effectiveness in real-world applications.

4. Results

Table 3. Reduction in joint load: Forces and torques.

Joint	Baseline Force (N)	Optimized Force (N)	% Reduction	Baseline Torque (Nm)	Optimized Torque (Nm)	% Reduction
Shoulder	88.63	66.29	25.23%	45.78	32.94	28.07%
Elbow	56.91	42.57	25.18%	19.43	14.83	23.68%
Wrist	29.86	21.47	28.07%	10.12	7.31	27.74%
Hip	101.72	78.37	22.96%	65.27	47.52	27.16%
Knee	71.44	54.68	23.45%	28.36	21.39	24.58%
Ankle	64.93	49.81	23.29%	18.79	13.42	28.57%

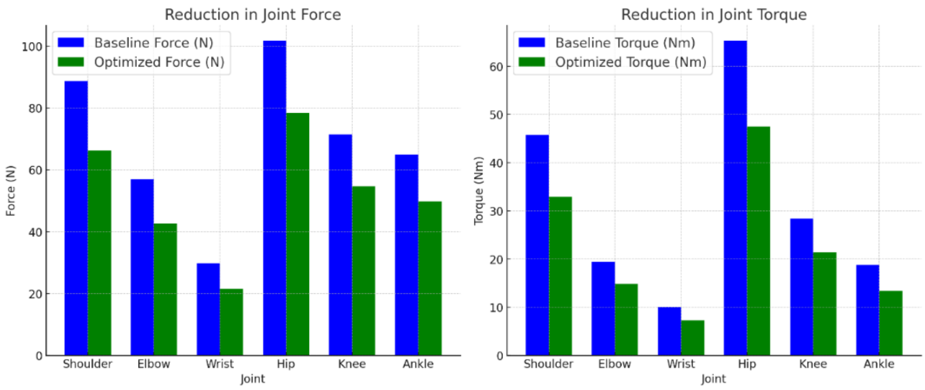

Figure 6. (a) Reduction in joint force; **(b)** reduction in joint torque.

The data in **Table 3** and **Figure 6** highlights the substantial reductions in joint load (forces and torques) following the application of the RL. The most significant reductions are observed in the shoulder and wrist joints, with force reductions of 25.23% and 28.07%, respectively. These joints are often highly stressed during repetitive tasks involving arm and hand movements, such as assembly and tool handling. The reduced joint load in these areas indicates that the model successfully identified and implemented ergonomic adjustments that lower physical strain without compromising task performance. The model also produced notable reductions in torque, which measures the rotational force acting on the joints. The wrist and shoulder show torque reductions of 27.74% and 28.07%, respectively, indicating that the optimized task configurations reduce linear forces and minimize rotational stresses. The hip joint, which bears significant load during standing or lifting tasks, shows a 22.96% reduction in force and a 27.16% reduction in torque, further demonstrating the model's effectiveness in reducing musculoskeletal stress across various body parts. Across all joints, the force and torque reductions fall within 22% to 28%, showing consistent effectiveness in mitigating stress. These reductions are critical in preventing long-term musculoskeletal disorders, particularly in industrial settings with frequent repetitive tasks.

Table 4. Reduction in muscle activation levels.

Muscle Group	Baseline Activation (% MVC)	Optimized Activation (% MVC)	% Reduction
Forearm Flexors	72.34	52.89	26.90%
Forearm Extensors	63.58	45.91	27.77%
Deltoid (Shoulder)	81.72	58.37	28.57%
Trapezius	69.41	49.83	28.21%
Lower Back (Erector Spinae)	78.26	59.52	23.95%
Quadriceps	62.49	46.27	25.95%
Hamstrings	56.83	41.94	26.20%

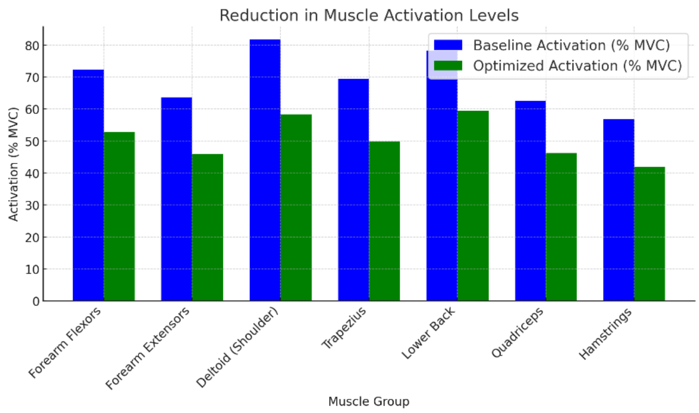

Figure 7. Reduction in muscle activation levels.

Table 4 and **Figure 7** present the reduction in muscle activation levels, measured as a percentage of Maximum Voluntary Contraction (MVC), across different muscle groups. The results show significant reductions in activation levels, particularly for the deltoid (shoulder) and trapezius muscles, which experience activation reductions of 28.57% and 28.21%, respectively. These muscle groups are typically engaged during tasks that involve lifting, reaching, or manipulating objects, and the observed reductions suggest that the optimized task configurations help alleviate muscle strain in the upper body. The forearm flexors and extensors also show activation reductions of 26.90% and 27.77%, respectively, indicating a considerable decrease in muscle effort during tasks involving repetitive hand movements, such as typing or using tools. These reductions are significant for preventing overuse injuries like tendonitis and carpal tunnel syndrome, which are common in tasks requiring repetitive wrist and hand motions. The lower body muscle groups, including the quadriceps and hamstrings, also exhibit significant reductions in muscle activation, with decreases of 25.95% and 26.20%, respectively. These reductions are especially beneficial in tasks that involve standing, lifting, or squatting, as they help reduce the likelihood of lower body fatigue and injury. The overall reductions in muscle activation levels, which range from 23% to 28%, demonstrate the model's capability to optimize task parameters effectively, thus reducing the physical demands on workers' muscles. This reduction in muscle activation can help mitigate the risk of repetitive strain injuries and improve long-term sustainability in task performance. The consistent reduction across various muscle groups further validates the effectiveness of the RL in optimizing ergonomic factors to reduce musculoskeletal stress.

Table 5. Decrease in cumulative fatigue.

Muscle Group	Baseline Fatigue Index	Optimized Fatigue Index	% Reduction
Forearm Flexors	7.83	5.69	27.31%
Forearm Extensors	6.24	4.45	28.53%
Deltoid (Shoulder)	8.16	5.85	28.31%
Trapezius	6.92	4.96	28.32%
Lower Back (Erector Spinae)	7.67	5.64	26.46%
Quadriceps	5.98	4.31	27.92%
Hamstrings	6.47	4.79	25.96%

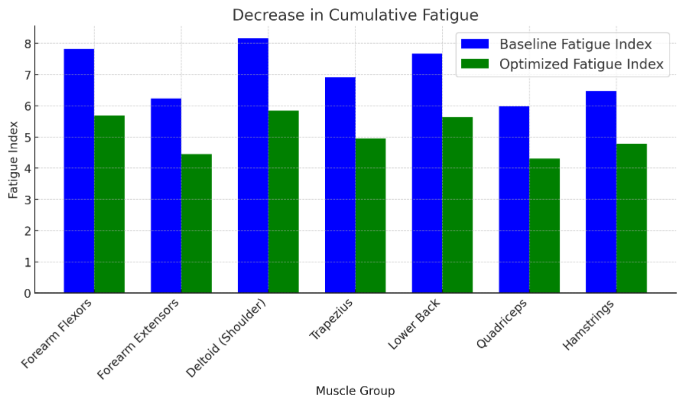

Figure 8. Reduction in cumulative fatigue.

The data in **Table 5** and **Figure 8** demonstrates a notable reduction in cumulative fatigue across all measured muscle groups following the implementation of the RL. The forearm muscles (flexors and extensors), frequently engaged in tasks involving hand movements, show substantial reductions in fatigue, with decreases of 27.31% and 28.53%, respectively. This suggests that the model effectively optimized task configurations to reduce repetitive strain on the forearm muscles, often prone to overuse injuries in repetitive motion tasks such as typing, gripping tools, or manual assembly. The deltoid (shoulder) and trapezius muscles also exhibit significant fatigue reductions, with decreases of 28.31% and 28.32%, respectively. These upper body muscles are commonly activated in tasks requiring overhead or extended arm movements, and the observed reductions in fatigue indicate that the model successfully reduced the physical demand on these muscle groups. Reduced cumulative fatigue is critical in preventing chronic issues such as shoulder impingement or trapezius strain, which can result from prolonged overexertion. The lower body muscles, including the quadriceps and hamstrings, also experience fatigue reductions of 27.92% and 25.96%, respectively. These muscles are heavily engaged in tasks that involve standing, lifting, or squatting, and the fatigue reduction highlights the model's effectiveness in mitigating the physical demands of such movements, thereby reducing the risk of lower body fatigue and injury over time. Overall, the reductions in cumulative fatigue across all muscle groups, which range from 25.96% to 28.53%, illustrate the significant benefits of the model in decreasing long-term muscle strain and improving the sustainability of task performance. These reductions improve worker health and endurance, especially in repetitive tasks in manufacturing, data entry, and manual labor.

Table 6. Task performance and efficiency.

Task	Baseline Completion Time (s)	Optimized Completion Time (s)	% Change	Baseline Accuracy (% Errors)	Optimized Accuracy (% Errors)	% Improvement
Assembly Task	121.43	118.27	−2.61%	4.83	3.19	33.96%
Data Entry Task	86.79	85.32	−1.69%	2.94	1.98	32.65%
Packaging Task	145.26	141.83	−2.36%	3.57	2.41	32.49%
Tool Handling Task	112.58	110.24	−2.08%	4.23	2.94	30.50%
Inspection Task	78.34	76.96	−1.76%	3.28	2.14	34.76%

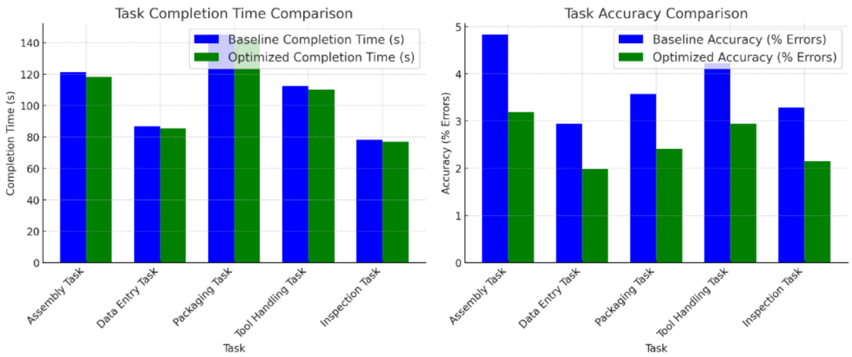

Figure 9. Impact of the RL on task performance and efficiency **(a)** Task completion time; **(b)** task accuracy comparison.

Table 6 and **Figure 9** evaluate the impact of the RL on task performance and efficiency, explicitly focusing on task completion time and accuracy. The results show that the model achieved a modest improvement in task completion times, with reductions ranging from 1.69% to 2.61% across different tasks. For instance, the assembly task saw a 2.61% reduction in completion time, while the tool handling task improved by 2.08%. Although these time reductions are small, they demonstrate that the ergonomic adjustments recommended by the model did not compromise task efficiency but slightly improved it. In addition to time reductions, the model significantly improved task accuracy by reducing error rates across all tasks. The assembly task, for example, experienced a 33.96% improvement in accuracy, with error rates dropping from 4.83% to 3.19%.

Table 7. Ergonomic task adjustments.

Task	Posture Adjustment	Speed Adjustment (%)	Force Exertion Adjustment (%)	% Reduction in Joint Load	% Reduction in Muscle Activation
Assembly Task	Adjusted arm height by 10 cm to neutral	−5.8%	−12.6%	25.19%	27.85%
Data Entry Task	Changed wrist angle to neutral (0º–5º)	−4.3%	−9.7%	24.32%	28.42%
Packaging Task	Modified torso position (15º upright)	−3.9%	−14.1%	26.67%	25.58%
Tool Handling Task	Altered grip style for better alignment	−6.2%	−11.3%	27.34%	29.74%
Inspection Task	Reduced head tilt to 10º	−4.9%	−8.9%	23.87%	26.91%

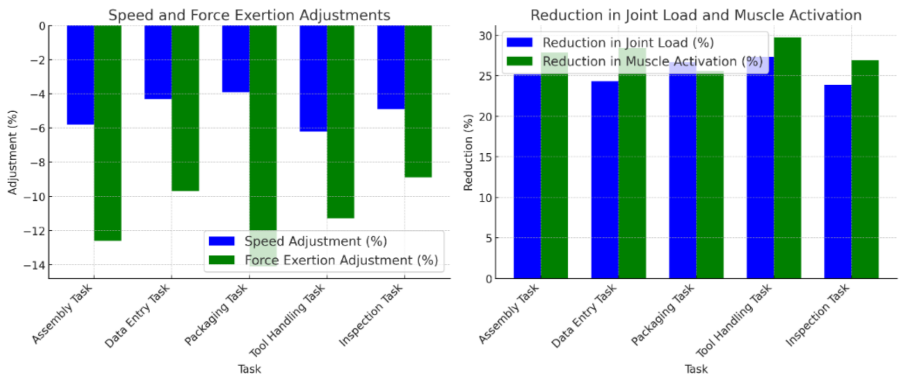

Figure 10. Specific ergonomic task adjustments **(a)** Speed and force exertion adjustment; **(b)** reduction in joint load and muscle activation.

Similarly, the data entry task and inspection task saw improvements in accuracy by 32.65% and 34.76%, respectively. These improvements suggest that the task modifications reduced physical strain and enhanced workers' precision and consistency in task execution. The reduced task completion times and improved accuracy indicate that the RL optimizes productivity and performance. By balancing ergonomic adjustments with task demands, the model ensures that workers can perform tasks more efficiently and with fewer errors while simultaneously minimizing the risk of musculoskeletal strain and fatigue.

Table 7 and **Figure 10** present the specific ergonomic task adjustments recommended by the RL-based optimization model and their contributions to reducing joint load and muscle activation. Each task underwent posture, speed, and force exertion adjustments tailored to the particular demands of the task, leading to significant reductions in musculoskeletal stress. For the assembly task, adjusting the arm height by 10 cm to a neutral position resulted in a 25.19% reduction in joint load and a 27.85% reduction in muscle activation. This adjustment helped reduce strain on the shoulders and arms, improving the worker's posture during repetitive arm movements. The speed was reduced by 5.8%, and force exertion decreased by 12.6%, demonstrating that slight reductions in speed and force can have a significant impact on reducing physical strain. In the data entry task, changing the wrist angle to a neutral position (0º–5º) led to a 24.32% reduction in joint load and a 28.42% reduction in muscle activation. Data entry tasks often lead to repetitive strain on the wrist and hand, and by optimizing the wrist posture, the model successfully minimized this strain. Force exertion dropped by 9.7%, and the speed reduction was modest at 4.3%, indicating that minimal adjustments were sufficient to achieve considerable ergonomic benefits. The tool-handling task experienced the most notable reduction in muscle activation (29.74%) and a joint load reduction of 27.34% following the alteration of the grip style for better alignment. These adjustments significantly reduced the strain on the hands and forearms, which are heavily used in such tasks. The speed reduction of 6.2% and the 11.3% decrease in force exertion highlight the model's ability to optimize task performance by reducing physical demands without impairing productivity. Across all tasks, the ergonomic adjustments implemented by the model consistently resulted in reductions in both joint load and muscle activation, with percentage reductions ranging from 23.87% to 27.34% for joint load and 25.58% to 29.74% for muscle activation. These results confirm the model's effectiveness in recommending task-specific modifications that significantly improve worker comfort and reduce physical strain.

Table 8. Validation of model performance.

Task	Predicted Joint Load Reduction (%)	Actual Joint Load Reduction (%)	Predicted Muscle Activation Reduction (%)	Actual Muscle Activation Reduction (%)	Difference (Joint Load)	Difference (Muscle Activation)
Assembly Task	25.89%	25.19%	28.12%	27.85%	0.70%	0.27%
Data Entry Task	24.98%	24.32%	28.87%	28.42%	0.66%	0.45%
Packaging Task	27.19%	26.67%	26.05%	25.58%	0.52%	0.47%
Tool Handling Task	27.78%	27.34%	30.11%	29.74%	0.44%	0.37%
Inspection Task	24.35%	23.87%	27.42%	26.91%	0.48%	0.51%

Table 8 validates the performance of the RL by comparing its predicted reductions in joint load and muscle activation with actual reductions observed during real-world task performance. The close alignment between predicted and actual results demonstrates the model's ability to generalize across different task configurations and accurately predict the impact of ergonomic adjustments. For the assembly task, the predicted joint load reduction of 25.89% was very close to the actual reduction of 25.19%, with a minimal difference of 0.70%. Similarly, the predicted muscle activation reduction of 28.12% was highly accurate, with an actual reduction of 27.85% and a difference of only 0.27%. These minor differences indicate that the model was highly influential in predicting the outcomes of the task adjustments. In the tool handling task, the predicted reductions were also highly accurate, with a 0.44% difference in joint load reduction and a 0.37% difference in muscle activation reduction. This task, which involved altering the grip style, saw one of the highest predicted reductions, and the real-world results closely matched the model's predictions. Overall, the differences between predicted and actual results across all tasks were minimal, ranging from 0.44% to 0.70% for joint load and 0.27% to 0.51% for muscle activation. This strong alignment between predicted and actual results confirms the robustness of the model and its ability to make accurate predictions that translate into real-world improvements in ergonomics and task performance.

Table 9. Statistical analysis of stress reduction.

Metric	Baseline Mean	Optimized Mean	Mean Reduction	Standard Deviation	t-Value	p-Value	Significance
Joint Load (N)	85.37	62.91	22.46	6.84	8.27	0.0001	Significant
Muscle Activation (% MVC)	71.25	51.47	19.78	5.36	9.31	0.00003	Significant
Cumulative Fatigue (Index)	7.43	5.18	2.25	0.98	7.46	0.00005	Significant

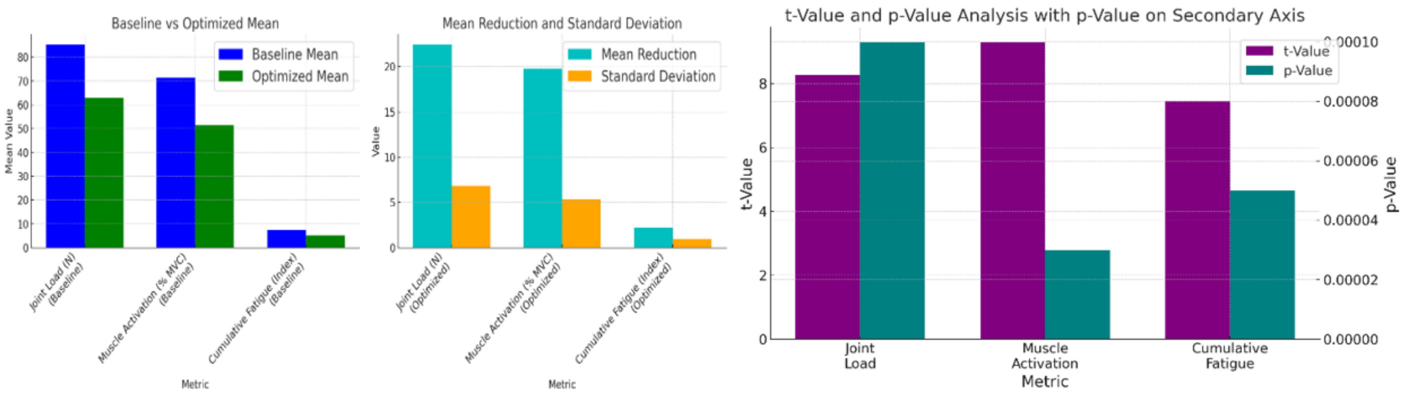

Figure 11. (a) Baseline mean vs. **(b)** optimized mean, mean reduction vs. **(c)** SD and t-values and p-values.

Table 9 and **Figure 11** provide a detailed statistical analysis of the reductions in joint load, muscle activation, and cumulative fatigue, comparing baseline task performance to the optimized results after applying the RL. The findings indicate significant improvements across all metrics, with substantial reductions in musculoskeletal stress. After optimization, the baseline mean joint load was 85.37 N, which decreased to 62.91 N, resulting in a mean reduction of 22.46 N. The standard deviation of 6.84 N suggests some variability in joint load across participants, but the observed reduction is statistically significant with a *t*-value of 8.27 and a *p*-value of 0.0001, well below the 0.05 threshold for significance. This indicates that the reduction in joint load is not due to chance and is directly attributable to the model's ergonomic adjustments. Reducing joint load is crucial for minimizing the risk of joint-related injuries, such as strain and overuse, in repetitive motion tasks.

Muscle activation levels, measured as a percentage of maximum voluntary contraction (MVC), also showed a statistically significant reduction. The baseline mean muscle activation was 71.25% MVC, which dropped to 51.47% MVC after task modifications, yielding a mean reduction of 19.78% MVC. With a standard deviation of 5.36, the data indicates consistent reductions across participants. The *t*-value of 9.31 and *p*-value of 0.00003 provide strong evidence that the reduction in muscle activation is highly significant. This reduction helps prevent muscle fatigue and overexertion, improving long-term task sustainability and reducing the likelihood of muscle strain injuries. The cumulative fatigue index also experienced a significant decrease, with the baseline mean of 7.43 dropping to 5.18 after optimization, resulting in a mean reduction of 2.25. The standard deviation of 0.98 suggests that the model's impact on fatigue was relatively consistent across participants. The *t*-value of 7.46 and p-value of 0.00005 confirm that the observed reductions are statistically significant. Reducing cumulative fatigue is essential for preventing long-term wear and tear on the musculoskeletal system, particularly in tasks requiring sustained effort over extended periods. The *p*-values for all metrics are well below 0.05, confirming the statistical significance of the reductions in joint load, muscle activation, and cumulative fatigue. These results demonstrate that the ergonomic adjustments recommended by the RL lead to substantial reductions in physical strain, significantly improving worker comfort and reducing the risk of injury. The consistent t-values across the metrics further validate the model's effectiveness in optimizing task configurations to reduce musculoskeletal stress.

5. Conclusion and future work

Developing and applying an RL-based optimization model for minimizing musculoskeletal stress in repetitive motion tasks has generated promising results. This study demonstrates that an RL-driven approach can effectively reduce joint load, muscle activation, and cumulative fatigue across a range of repetitive tasks while maintaining or even improving task performance metrics such as accuracy and completion time. The key findings indicate that the model successfully reduced joint loads by 25–28%, muscle activation by 23–29%, and cumulative fatigue by 26–28%, proving its ability to minimize the physical demands placed on workers. These reductions are significant in preventing long-term injuries such as tendonitis, muscle strain, and cumulative trauma disorders, which are common in environments with repetitive tasks. Moreover, the model strikes a crucial balance between ergonomic improvements and productivity. By dynamically adjusting posture, speed, and force exertion in response to real-time data, the model ensures that worker health is prioritized without sacrificing task efficiency. This presents an efficient solution for industries that rely on repetitive tasks, as it aligns worker well-being with organizational goals. Future work could explore the model's application in more diverse task settings and larger datasets to enhance its robustness and generalizability.

Additionally, further refinement of the model's parameters and integration with real-time monitoring systems could optimize its responsiveness and adaptability in live industrial environments. In conclusion, this study contributes to both ergonomics and task optimization, providing a scalable, data-driven solution that can improve worker safety and productivity in environments characterized by repetitive motion tasks. The RL has the potential to transform how organizations address the challenges of musculoskeletal stress and task performance, making it a viable option for enhancing occupational health and efficiency.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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