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Article

Integrating data-driven mechanisms for enhancing efficiency in business administration through biomechanics and bio-inspired modeling

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Abstract: This paper explores integrating biomechanics data and bio-inspired models to enhance efficiency in business administration, focusing on task scheduling, resource allocation, and workflow optimization. Biomechanics, traditionally applied in fields such as healthcare and sports, is used to analyze human movement and physical strain in business processes, particularly in physically demanding environments like manufacturing and logistics. Bio-inspired models, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), are applied to solve complex optimization problems in resource management and task scheduling. The study presents three case studies to demonstrate the practical application of these methodologies: (1) workflow optimization in a manufacturing environment using biomechanics data to reduce physical strain and improve task completion times; (2) resource allocation in Supply Chain Management (SCM) using PSO to minimize transportation and labor costs while improving warehouse utilization and delivery times; and (3) task scheduling in an office environment using GA to enhance task efficiency, workload distribution, and employee satisfaction. The case study results demonstrate the practical application of these methodologies: (1) a 21.6% reduction in shoulder joint strain and an 18.2% improvement in task completion time in a manufacturing setting; (2) a 16.1% reduction in transportation costs and an 18.6% improvement in warehouse utilization in SCM using PSO; and (3) a 17.6% decrease in makespan and a 29.8% improvement in workload distribution through GA-based task scheduling in an office environment. These findings underscore the potential of combining human-centered biomechanics data with bio-inspired optimization models to improve operational efficiency, employee well-being, and cost-effectiveness significantly.

Keywords: biomechanics; bio-inspired models; employee well-being; shoulder joint strain; human movement

1. Introduction

In the rapidly evolving landscape of business administration, efficiency and optimization are critical for maintaining competitive advantage and ensuring sustainable growth [1,2]. Modern businesses face many challenges, from Resource Allocation (RA) and workflow management to employee well-being and operational costs [3]. While effective to some extent, traditional approaches to solving these challenges often fall short in addressing the complexities of dynamic business environments [4,5]. As businesses increasingly adopt data-driven strategies, there is a growing interest in integrating advanced technologies such as biomechanics and bio-inspired models to enhance decision-making, streamline operations, and improve human and organizational performance [6,7].

Biomechanics, traditionally rooted in sports and healthcare, involves studying human movement, posture, and physical interactions with the environment [8,9]. Its application in business environments, particularly in physically intensive manufacturing, logistics, and services sectors, has shown significant promise [10,11]. By analyzing employee movements, repetitive tasks, and ergonomic factors, businesses can optimize workflow design, minimize physical strain, reduce the risk of work-related injuries, and ultimately increase productivity [12,13]. Integrating biomechanics into business processes introduces a human-centered approach to operations management, prioritizing employee health and performance alongside operational goals [14].

In parallel, bio-inspired models such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have emerged as powerful tools for solving complex optimization problems in business settings [15]. These models, which draw inspiration from natural processes like evolution and swarm intelligence, are particularly effective in resource management, Task Scheduling (TS), and process optimization. For example, GA simulates the natural selection process to identify optimal solutions in environments with numerous constraints and variables [16]. Similarly, PSO mimics the collective behavior of organisms to find solutions to multi-objective problems such as RA and inventory management. Both approaches offer the flexibility and scalability needed to address the growing complexity of business operations in an increasingly data-driven world [17–19].

This paper explores integrating biomechanics data and bio-inspired models as a comprehensive approach to enhancing business efficiency [20–22]. Businesses can develop solutions that optimize human performance and operational processes by leveraging the insights gained from human movement analysis and the computational power of bio-inspired algorithms. The study presents three case studies to illustrate how these methodologies can be applied in different business contexts: Workflow optimization in manufacturing using biomechanics data, RA in Supply Chain Management (SCM) using PSO, and TS in office environments using GA. Each case study demonstrates the practical benefits of integrating biomechanics and bio-inspired models in improving task completion times, reducing operational costs, and enhancing employee satisfaction and safety [23–27].

The remainder of this paper is organized as follows: Section 2 presents the theoretical framework, discussing the role of biomechanics in business processes and the application of bio-inspired models for optimization. Section 3 introduces data-driven mechanisms, including data collection and feature engineering techniques, and the application of machine learning models for business analytics. Section 4 focuses on the specific bio-inspired modeling techniques used in business optimization, with detailed discussions on GA, PSO, and hybrid models for decision-making. Section 5 provides the case studies, highlighting real-world applications of these models. Section 6 evaluates the results, demonstrating the tangible benefits of integrating biomechanics data and bio-inspired models in business administration. Section 7 concludes the work.

2. Theoretical framework

2.1. Biomechanics in business processes

Biomechanics, traditionally applied in sports and healthcare to analyze human movement, can be pivotal in optimizing business processes, especially those involving physical tasks. In business environments such as manufacturing, warehousing, and service industries, employee efficiency is heavily influenced by ergonomics, physical strain, and motion patterns. By employing biomechanics, businesses can analyze worker posture, repetitive motions, and task-specific activities to identify inefficiencies and potential risks for injury [28–32]. For instance, motion capture systems like Vicon or Xsens can gather precise data on employee movements during manual tasks, allowing for the development of ergonomic solutions to reduce physical strain and improve productivity.

Incorporating biomechanics into business operations can lead to better task allocation and workplace design. Ergonomically optimized workstations, developed through biomechanical analysis, can decrease fatigue and the risk of injury, thereby improving employee well-being and efficiency. Furthermore, analyzing data on movement patterns can help businesses streamline workflows by eliminating unnecessary physical motions and reducing the time needed to complete tasks. This is particularly valuable in industries where manual labor forms a significant part of operations, such as assembly lines or logistics. Biomechanics offers a data-driven approach to enhancing human-centered processes, directly impacting operational efficiency and safety.

2.2. Bio-inspired models in business optimization

Bio-inspired models, derived from natural systems, offer innovative solutions for complex optimization problems in business. These models mimic biological processes such as evolution, swarm behavior, and neural activity to develop algorithms capable of solving tasks like RA, TS, and process optimization more efficiently. Inspired by the natural selection process, GA is beneficial for solving optimization problems involving numerous variables and constraints. In business settings, GAs can be used to optimize workflow design and TS by identifying the best combination of tasks, resources, and personnel to minimize downtime and maximize output.

Another powerful bio-inspired model is PSO, which simulates the collective behavior of birds flocking or fish schooling to find optimal solutions. PSO can be applied in dynamic business environments where resource management, inventory control, and logistics decisions require continuous adaptation to changing conditions. By using PSO, businesses can optimize resource utilization by dynamically adjusting the allocation of resources based on real-time data, leading to more flexible and efficient operations.

Bio-inspired models are particularly effective in solving problems with high complexity or uncertainty, where traditional linear programming or heuristic methods fall short. The ability of these models to explore a wide range of possible solutions and adapt to changes in the business environment makes them a valuable tool in decision-making processes. For example, in SCM, bio-inspired models can optimize routes, minimize transportation costs, and ensure timely deliveries by dynamically responding to fluctuations in demand and supply. The adaptability and scalability of bio-inspired algorithms allow businesses to handle large datasets and complex scenarios, offering a more robust and flexible approach to business optimization.

3. Data-driven mechanisms for business efficiency

3.1. Data collection and feature engineering

Effective data collection and feature engineering are essential components in integrating data-driven mechanisms for business process optimization. In the context of biomechanics and bio-inspired modeling for business efficiency, data collection must encompass both human-centered and operational metrics. The first step in this process involves gathering relevant data from diverse sources such as motion capture systems, employee performance tracking tools, and enterprise resource planning (ERP) systems. In a manufacturing or logistics environment, for example, data on employee movements, task completion times, and resource usage can be captured using motion-tracking technologies like Vicon or Xsens and sensors embedded in machinery or workstations. These systems provide real-time, high-resolution data on worker postures, physical motions, and task-specific activities, which are vital for optimizing ergonomic conditions and minimizing workplace injuries.

Simultaneously, operational data related to business functions—workflow efficiency, RA, and inventory levels—can be extracted from ERP platforms like Systems, Applications, and Products (SAP) or Oracle. This data, which includes key performance indicators (KPIs) such as task completion rates, employee productivity, machine uptime, and resource utilization, provides a broader context for understanding how physical tasks contribute to overall business efficiency. Collecting this data in real-time allows businesses to analyze performance trends and make informed decisions to enhance process flows and minimize inefficiencies.

Once the data is collected, feature engineering becomes crucial in transforming raw data into meaningful inputs for machine learning models. In this stage, various techniques are applied to create relevant features that capture key patterns and insights from the data. For instance, in a business process involving repetitive physical tasks, features such as joint angles, time per task, frequency of movements, and task duration can be engineered from motion capture data. These features provide insights into the physical demands placed on workers and help identify inefficiencies, such as redundant motions or suboptimal postures, that may lead to decreased productivity or increased injury risk.

Feature engineering also extends to the operational side, where data points like task handoff times, resource consumption rates, and workflow bottlenecks can be engineered into predictive variables. Feature selection techniques such as Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE) can be used to identify the most critical variables, reducing dimensionality and improving model performance. For example, engineered features like machine downtime intervals, resource utilization rates, and task completion orders in optimizing a production line can significantly influence predictions for efficiency improvements.

To enhance the quality of features, preprocessing steps like data normalization, handling missing values, and addressing outliers must be conducted. Tools such as Python's pandas, NumPy, and sci-kit-learn libraries offer potent capabilities for cleaning and transforming datasets. Data augmentation techniques, such as adding noise to the training data or generating synthetic data points, can also enhance model robustness, mainly when working with small or imbalanced datasets.

3.2. Machine learning models for business analytics

Machine learning (ML) models have become indispensable in business analytics, offering powerful predictive modeling, optimization, and decision-making tools. In enhancing business efficiency through biomechanics and bio-inspired modeling, machine learning models enable businesses to analyze vast amounts of data, uncover hidden patterns, and predict outcomes that improve operational processes. The choice of machine learning models is critical, as it depends on the type of data collected and the business problem being addressed. For this purpose, supervised learning models such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting are commonly applied in business analytics.

3.2.1. Random forest for task and workflow optimization

Random Forest is a robust ensemble learning method that can be applied for classification and regression tasks, making it suitable for various business applications. In business administration, Random Forest models can predict task completion times, identify key factors affecting employee productivity, and recommend task allocations that optimize workflow. For instance, in a manufacturing environment, Random Forest can be trained on historical data such as task duration, worker motion data, and machine utilization. Once trained, the model can predict which factors are most likely to cause delays and suggest strategies for improving efficiency, such as reassigning workers to different tasks or adjusting workflow sequences. The advantage of Random Forest lies in its ability to handle large, complex datasets while minimizing overfitting, ensuring reliable predictions even in dynamic business environments.

3.2.2. Support vector machines (SVM) for predictive analytics

Support Vector Machines (SVM) are another powerful tool for predictive analytics in business settings, mainly when the goal is to classify data. SVM works by finding the optimal hyperplane that separates different classes in a dataset, making it ideal for tasks like employee performance classification, customer segmentation, or product demand forecasting. For example, in a sales department, SVM can classify employees based on their performance data, identify high performers, and predict which employees may need additional training or support. This helps businesses allocate resources more efficiently by focusing training efforts where needed most. Additionally, SVM's capacity to handle non-linear relationships is beneficial when the data is complex, and patterns are not easily discernible through linear models.

3.2.3. Gradient boosting for RA and demand forecasting

Gradient Boosting is another machine learning technique that is highly effective for predictive analytics, especially regarding RA and demand forecasting. Gradient

Boosting builds models incrementally, combining the predictions of weaker models to create a more robust and accurate overall model. This can be applied to optimize RA, such as inventory management or staffing in business contexts. For instance, in a logistics company, Gradient Boosting can analyze historical shipping data, customer demand, and supply chain efficiency to predict future demand patterns. These predictions can then be used to optimize inventory levels, reduce stockouts, and ensure that resources are allocated to the areas where they will be most effective. The incremental nature of Gradient Boosting makes it particularly useful when working with real-time or frequently updated data.

3.2.4. Integrating machine learning with biomechanics data

Machine learning models can further enhance decision-making and efficiency when biomechanics data is integrated into business processes. For example, combining motion capture data with machine learning algorithms can provide predictive insights into worker fatigue, posture-related productivity issues, or the likelihood of repetitive strain injuries. By training models on features such as joint angles, task duration, and movement frequency, businesses can predict when workers will likely experience fatigue and adjust workflow or task assignments to mitigate these risks.

Additionally, machine learning models can be used to analyze the impact of ergonomics on business performance. Models such as Gradient Boosting can predict how ergonomic changes—such as workstation redesigns or new task workflows—will impact productivity and employee satisfaction. By analyzing biomechanics data and operational metrics, businesses can create holistic strategies that optimize human and machine performance.

3.2.5. Tools and implementation

For implementing these machine learning models, Python's sci-kit-learn library offers a range of tools for model development, training, and evaluation. Libraries like XGBoost can be employed for Gradient Boosting, while Random Forest and SVM can be implemented using sci-kit-learn's built-in functions. Preprocessing tools such as pandas and NumPy prepare data before feeding it into the models, ensuring it is clean, normalized, and suitable for analysis. Additionally, model evaluation metrics such as accuracy, precision, recall, and F1-score can be applied to assess the performance of these models in predicting business outcomes.

3.3. Integrating biomechanics data for business solutions

Integrating biomechanics data into business solutions is an innovative approach to optimizing human performance and operational processes. Biomechanics data traditionally analyzes human motion, posture, and physical interactions with the environment and can offer valuable insights when applied to business operations. This data allows businesses to optimize workflows, reduce physical strain on employees, enhance task performance, and minimize workplace injuries, ultimately leading to greater efficiency and productivity. Businesses can develop comprehensive, data-driven solutions that address human and operational factors by combining biomechanics data with machine learning and bio-inspired models.

3.3.1. Human-centered optimization

Human-centered optimization is one of the primary areas where biomechanics data can be leveraged in business. Many industries rely heavily on manual labor, where worker efficiency is directly tied to physical performance. By capturing and analyzing motion data using tools such as motion capture systems (e.g., Vicon, Xsens) or wearable sensors, businesses can gain deep insights into how workers perform tasks and interact with their environment. For example, in a manufacturing environment, motion capture can analyze how workers move, bend, lift, and reach while performing tasks on an assembly line. By understanding these movements, businesses can redesign workstations, tools, and workflows to minimize unnecessary movements and reduce physical strain on employees.

This type of data integration can also help prevent work-related injuries. For instance, repetitive strain injuries (RSIs) are common in jobs that involve repeated motions, such as typing, lifting, or assembly tasks. By analyzing biomechanics data, businesses can identify which movements are causing strain and adjust workflows accordingly. Machine learning models can be applied to predict when workers are likely to experience fatigue or injury based on motion patterns, allowing businesses to implement preventive measures such as rotating tasks or adjusting break schedules. This enhances worker safety and well-being and reduces downtime and associated costs.

3.3.2. Ergonomic design and workflow improvements

Biomechanics data also plays a crucial role in improving ergonomic design and workflow efficiency. Poor ergonomics in workstations or tools can lead to decreased productivity, higher error rates, and increased worker discomfort. Businesses can design ergonomically optimized workstations that reduce physical stress and increase comfort by analyzing data from worker movements and postures. For example, in an office environment, analyzing data from sitting postures, keyboard usage, and mouse movements can help design workstations that promote better posture and reduce the likelihood of repetitive strain injuries.

Additionally, in logistics and warehousing, where workers are frequently required to lift, move, or carry heavy items, biomechanics data can inform the design of lifting aids or other ergonomic tools that reduce the physical burden on workers. For instance, wearable devices that monitor joint angles and muscle activity can provide real-time feedback to workers on proper lifting techniques, preventing injuries and improving task performance. These solutions can significantly enhance worker efficiency while minimizing injury risks and boosting productivity.

3.3.3. Predictive analytics for task allocation and resource management

Another powerful application of biomechanics data in business solutions is using predictive analytics for task allocation and resource management. By integrating biomechanics data with machine learning algorithms, businesses can develop predictive models that anticipate worker fatigue, performance drops, or injury risks. These models can be used to optimize TS and RA, ensuring that workers are assigned tasks that match their physical capabilities and current fatigue levels.

For example, in a warehouse setting, biomechanics data from wearable devices can monitor worker movements throughout the day. This data can then be fed into machine learning models that predict when workers will likely experience fatigue, allowing managers to adjust task assignments or offer rest breaks before performance declines or injuries occur. Similarly, in service industries, where employees must stand for long periods or engage in repetitive motions, predictive analytics can help optimize shift schedules and task rotations, improving employee well-being and customer service quality.

3.3.4. Tools and technologies for biomechanics integration

Integrating biomechanics data into business solutions requires hardware and software tools. On the hardware side, businesses can use motion capture systems, wearable sensors (e.g., accelerometers, gyroscopes, and electromyography devices), and smart workstations equipped with sensors to collect data on worker movements, postures, and physical interactions with the environment. These devices can capture real-time, high-resolution data critical for understanding how workers perform tasks and identifying areas for improvement.

On the software side, machine learning tools like sci-kit-learn, TensorFlow, and PyTorch can be used to build predictive models that analyze biomechanics data and provide actionable insights. Based on historical and real-time data, these models can be trained to predict fatigue, injury risks, or performance declines. Additionally, MATLAB or Python's NumPy and pandas libraries can be used for data preprocessing, feature extraction, and data analysis, enabling businesses to derive meaningful insights from complex biomechanics datasets.

3.3.5. Impact on business performance

Integrating biomechanics data into business operations significantly benefits performance optimization, cost reduction, and employee well-being. By designing work environments that align with human physical capabilities, businesses can reduce errors, speed up task completion, and minimize downtime caused by injuries or fatigue. Moreover, ergonomically optimized workflows improve employee satisfaction and retention by reducing the physical demands of their jobs, boosting overall productivity.

In high-stakes industries such as healthcare, manufacturing, and logistics, the ability to predict and prevent worker injuries through biomechanics data analysis has far-reaching implications. Reducing injury rates leads to lower medical costs, fewer lost workdays, and a more engaged workforce. Furthermore, integrating biomechanics data with bio-inspired models for optimizing resource management and task allocation ensures that human resources are utilized most efficiently, contributing to long-term operational excellence.

4. Application of bio-inspired modeling in business optimization

4.1. GA for TS

GA is a bio-inspired optimization technique that mimics the process of natural selection to solve complex optimization problems. In business administration, GAs can be effectively applied to TS, where the objective is to allocate tasks to resources (e.g., employees, machines, or teams) to minimize overall completion time, balance workloads, or reduce operational costs. GAs are particularly well-suited for solving such scheduling problems because they can handle large, complex solution spaces with multiple constraints and objectives. The iterative process of GAs allows for exploring numerous possible solutions and the gradual improvement toward an optimal or near-optimal schedule. Using a for TS involves several key steps: Initialization, selection, crossover, mutation, and termination.

The basic structure of the GA can be described as follows:

1) Initialization: The algorithm starts by generating an initial population of potential solutions, where each solution is represented as a chromosome (a sequence of tasks assigned to specific resources). Each chromosome corresponds to a possible task schedule, and the quality of each solution is evaluated using a fitness function.

$$\text{“}Chromosome\text{”} = \{C\_1, C\_2, C\_3, \dots, C\_\mathrm{n}\}$$

where C_i represents the assignment of tasks to a particular resource.

2) Fitness Function: The fitness function evaluates how well each chromosome satisfies the optimization criteria, such as minimizing makespan (the total time required to complete all tasks), balancing workloads, or minimizing idle time. The fitness function $f(x)$ is a mathematical representation of the objective. For example, if the goal is to minimize makespan, the fitness function could be expressed as:

$$f(x) = \frac{1}{\text{Makespan } (x)}$$

The makespan is the total time required to complete all tasks in the schedule x. The higher the fitness score, the better the schedule.

3) Selection: In the selection phase, the fittest chromosomes (schedules with the highest fitness scores) are chosen to propagate to the next generation. This step uses selection mechanisms such as roulette wheel selection or tournament selection. In the roulette wheel selection, the probability of selecting a chromosome is proportional to its fitness:

$$P(C_i) = \frac{f(C_i)}{\sum_{j=1}^{N} f(C_j)}$$

where $P(C_i)$ is the probability of selecting a chromosome C_i, and $f(C_i)$ is its fitness score. Chromosomes with higher fitness values are more likely to be selected.

4) Crossover (Recombination): The crossover step generates new offspring (task schedules) by combining parts of two parent chromosomes. A standard crossover method is a one-point crossover, where a random point is selected in the chromosome, and the task assignments of the parents are swapped at that point. For example, if two parent chromosomes P_1 and P_2 are as follows:

$$P_1 = \{T_1, T_2, T_3, T_4\},\ P_2 = \{T_4, T_3, T_1, T_2\}$$

After performing a crossover at a random point, the offspring O_1 and O_2 would be:

$$O_1 = \{T_1, T_2, T_1, T_2\},\ O_2 = \{T_4, T_3, T_3, T_4\}$$

This process creates diversity in the population and helps the algorithm explore new parts of the solution space.

5) Mutation: Mutation introduces random changes to individual chromosomes to maintain diversity in the population and prevent premature convergence to a local optimum. In TS, a mutation might involve swapping the assignment of two tasks or changing the task allocation for a resource. For example, if a chromosome is $\{T_1, T_2, T_3, T_4\}$, a mutation might result in $\{T_1, T_3, T_2, T_4\}$. The mutation rate p_m Controls how often mutations occur, with a typical value between 0.01 and 0.05.
6) Termination: The algorithm repeats the selection, crossover, and mutation steps for a fixed number of generations or until a termination condition is met, such as when the fitness of the best solution stabilizes, or a predefined number of iterations is reached. The final output is the chromosome with the highest fitness, which represents the optimal or near-optimal task schedule.

The TS problem can be formulated as follows: Suppose we have a set of tasks $T = \{T_1, T_2, \dots, T_\mathrm{n}\}$ that need to be assigned to resources $R = \{R_1, R_2, \dots, R_\mathrm{m}\}$, and each task T_i has a processing time p_i. The goal is to find a schedule that minimizes the makespan, which is defined as:

$$\text{Makespan} = \max_{j=1}^{m} \left(\sum_{i \in S_j} p_i \right)$$

where S_j represents the set of tasks assigned to a resource R_j, and p_i is the processing time of the task T_i. The objective is to minimize the makespan by finding an optimal allocation of tasks to resources.

4.2. PSO for resource management

PSO is a bio-inspired algorithm modeled after the social behavior of birds flocking or fish schooling to find food. It is a powerful technique for solving optimization problems in various fields, including resource management in business operations. PSO is beneficial for dynamic, multi-objective resource management tasks where businesses must efficiently allocate resources (e.g., labor, machinery, inventory, or time) under varying constraints and requirements. The algorithm’s strength lies in its ability to explore the solution space collectively while retaining the flexibility to adapt to changing business conditions.

In PSO, each potential solution to the resource management problem is represented as a particle in a multi-dimensional space. Each particle has a position and velocity, which are iteratively adjusted based on the particle’s experience and neighboring particles’ experience. The particles “fly” through the search space, guided by two main influences: The best solution each particle has found (personal best) and the best solution found by the entire swarm (global best). These iterative adjustments enable the particles to converge toward optimal or near-optimal solutions.

Let’s define some of the key components of PSO:

1) Particle: Each particle represents a potential solution in the search space. A particle might represent a specific RA (e.g., labor hours, equipment, or inventory) in resource management.

2) Position: The position of a particle corresponds to a particular RA. For a problem with n resources, the position of a particle can be represented as a vector $x_i = (x_{i1}, x_{i2}, \dots, x_{\text{in}})$, where each x_{ij} represents the amount of resource j allocated by particle i.
3) Velocity: Each particle has a velocity $\mathrm{v}_i = (v_{i1}, v_{i2}, \dots, v_{\text{in}})$, which determines how its position is updated in each iteration. The velocity is influenced by the particle's personal best position and the global best position discovered by the swarm.
4) Personal Best and Global Best: At each iteration, each particle records its personal best position p_i, and the global best position g is determined by the best-performing particle in the swarm.

The basic PSO update rules are as follows:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1 \left[p_{ij} - x_{ij}(t)\right] + c_2 r_2 \left[g_j - x_{ij}(t)\right]$$
$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$

where $v_{ij}(t)$ is the velocity of particle i in the j-th dimension at iteration t, $x_{ij}(t)$ is the position of particle i in the j-th dimension at iteration t, ω is the inertia weight that controls the influence of the previous velocity on the current velocity, c_1 and c_2 are cognitive and social acceleration coefficients, respectively, which control the influence of personal and global best positions, r_1 and r_2 are random values between 0 and 1 to add stochasticity to the movement. The parameters c_1 and c_2 dictate how strongly a particle is influenced by its own experience and the swarm's collective knowledge, and ω controls the trade-off between exploration and exploitation in the search space.

In business resource management, PSO can be applied to optimize how resources such as labor, materials, machinery, or capital are allocated across different tasks or operations. Resource management problems often involve multiple conflicting objectives, such as minimizing costs while maximizing productivity or balancing workloads among teams while adhering to time constraints. PSO's ability to handle multiple objectives and constraints makes it a powerful tool for resource optimization.

For instance, in a manufacturing plant, PSO can allocate machine usage hours and labor shifts to minimize downtime and maximize throughput. Each particle in the swarm represents a potential schedule of machine and labor assignments. The fitness function for PSO would be designed to minimize operational costs while ensuring that production deadlines are met. The fitness function could be defined as:

$$f(x) = \alpha \times \text{Cost}(x) + \beta \cdot \text{ Penalty for Deadline Violations } (x) + \gamma \times \text{Resource Utilization } (x)$$

where:

- Cost (x) is the total cost of the RA,
- Penalty for Deadline Violations (x) accounts for penalties due to unmet deadlines,
- Resource Utilization (x) measures how efficiently resources (machines, labor) are utilized,
- α, β, and γ are weighting factors that reflect the relative importance of each objective.

PSO iteratively adjusts the RA, improving the solution with each generation until an optimal or near-optimal schedule is found.

4.3. Hybrid model for decision-making

A hybrid model for decision-making integrates PSO for global resource optimization with Decision Trees for local decision refinement. This combination optimizes RA in business processes by leveraging the exploration power of PSO and the interpretability and predictive capabilities of Decision Trees. The model dynamically adapts resource management strategies in real time, balancing multiple objectives such as cost minimization, resource utilization, and task completion time.

The hybrid decision-making model can be structured into three components: Global search via PSO, local decision-making via Decision Trees, and real-time adaptation using predictive models. PSO initializes a swarm of particles in the RA process, each representing a different RA plan. For example, consider a business where the resources to be allocated are machine hours, labor shifts, and raw materials. The particles in the swarm represent different combinations of these resources assigned to various tasks.

Let x_i represent the position of particle i, which corresponds to a particular RA strategy across multiple departments. For example, $\mathrm{x}_i = (x_{i1}, x_{i2}, \dots, x_{\mathrm{in}})$ where x_{ij} represents the allocation of resource j by particle i to a specific task.

The goal is to optimize multiple objectives, such as minimizing costs $C(x)$, reducing delays $D(x)$, and maximizing resource utilization $U(x)$. The PSO fitness function could be defined as:

$$f(x) = \alpha \times C(x) + \beta \cdot D(x) - \gamma \times U(x)$$

where:

- $C(x)$ represents the total operational costs of the allocation strategy x,
- $D(x)$ is the delay penalty associated with incomplete tasks,
- $U(x)$ measures how effectively resources are utilized,
- α, β, and γ are weighting factors reflect the business's prioritization of cost, delays, and resource efficiency.

The velocity and position of each particle are updated iteratively using:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1 \left[p_{ij} - x_{ij}(t)\right] + c_2 r_2 \left[g_j - x_{ij}(t)\right]$$
$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$

where:

- $v_{ij}(t)$ is the velocity of particle i in dimension j at iteration t,
- p_{ij} is the personal best position found by particle i,
- g_j does the entire swarm find the global best position,
- ω, c_1, c_2, r_1, and r_2 are the inertia weight, cognitive and social acceleration coefficients, and random factors, respectively.

Once PSO generates an optimized global solution, a Decision Tree refines this solution by making local adjustments based on specific business rules or real-time data. For instance, in a warehouse RA problem, PSO may allocate forklifts and workers across different sections. The Decision Tree can then refine these allocations by classifying sections based on factors like workload intensity, shipment urgency, and traffic flow within the warehouse.

Consider a Decision Tree that classifies each warehouse section s based on features such as:

- W_s (workload),
- T_s (traffic congestion),
- D_s (shipment urgency).

The Decision Tree is trained on historical data to predict the best RA strategy for each section:

$$y_s = \text{DecisionTree}\,(W_s, T_s, D_s)$$

where y_s is the recommended adjustment in RA (e.g., increasing forklifts or reallocating workers). The Decision Tree refines the allocation suggested by PSO to account for real-time operational conditions, ensuring that resources are optimally distributed based on local demands.

The hybrid model can incorporate real-time predictive models to adjust RA in response to changing conditions dynamically. For example, in a retail business, a Random Forest model can predict fluctuations in customer demand based on external factors like seasonality, weather, or promotions.

The predictive model is trained on historical data with features such as:

- d_t (customer demand at time t),
- s_t (seasonal trends),
- p_t (promotional activity).

The model predicts future demand:

$$\hat{d}_{t+1} = \text{RandomForest}\,(d_t, s_t, p_t)$$

Based on the predicted demand $\hat{d}_{t+1}$, the hybrid model adjusts inventory levels or labor schedules in real-time. For example, if an increase in demand is predicted, the model may reallocate more workers to the sales floor or adjust inventory replenishment schedules to avoid stockouts.

5. Case studies

5.1. Case study 1: Workflow optimization using biomechanics data

In this case study, biomechanics data was used to optimize the workflow of a manufacturing assembly line, aiming to enhance productivity and reduce the physical strain experienced by workers. The manufacturing facility specialized in producing automotive parts, where workers performed repetitive tasks such as lifting, reaching, and assembling components. Over time, these repetitive tasks led to a decline in productivity, increased work-related errors, and increased musculoskeletal injuries among employees. The study's primary goal was to redesign the workflow by incorporating insights derived from biomechanics data, ultimately improving efficiency and reducing the risk of injury.

Motion capture technology was employed to collect biomechanics data from the workers on the assembly line. The workers wore body-worn sensors from the Xsens motion capture system, which tracked joint angles, postures, and movements during their shifts. The data captured included critical metrics such as shoulder, elbow, and wrist joint angles, the frequency of repetitive movements like lifting and bending, the forces exerted during lifting tasks, and the time taken to complete each task in the assembly process. Additional information, including task completion times and error rates, was recorded using digital monitoring systems integrated into the production process.

The collected data was then analyzed using OpenSim biomechanics software, which provided detailed insights into how workers' movements and postures affected their efficiency and contributed to physical strain. The analysis revealed specific inefficiencies in the workflow, such as frequent overextension of the arms when reaching for components, leading to shoulder strain, and excessive bending during assembly tasks, which caused lower back fatigue. Additionally, repetitive lifting motions were found to exceed recommended ergonomic thresholds for joint angles and force exertion, increasing the risk of injury.

Armed with this data, the company initiated a workflow redesign. One of the first changes implemented was rearranging the workstation layout to minimize unnecessary movements. Components and tools were repositioned to be within the workers' natural range of motion, significantly reducing the need for overextension and repetitive reaching motions. This adjustment addressed the primary cause of shoulder strain. Height-adjustable workstations were also introduced, allowing workers to customize their workstation height based on their individual needs, thereby reducing lower back strain caused by prolonged bending. This change enabled workers to alternate between sitting and standing positions, improving ergonomic comfort.

In addition to the layout changes, new ergonomically designed lifting tools were introduced. These tools were based on the analysis of lifting forces and joint angles and were specifically designed to help workers perform repetitive lifting tasks without exceeding ergonomic safety thresholds. These tools contributed to a safer and more efficient working environment by reducing the physical strain on the back and knees. The company implemented a task rotation system to mitigate the risk of repetitive strain injuries. Workers rotated between tasks requiring varied physical movements, allowing their muscles to recover from overuse and preventing the onset of fatigue-related injuries.

The tools and technologies used in this case study played a crucial role in achieving these results. The Xsens motion capture system provided detailed data on joint angles and movement patterns, while the OpenSim biomechanics software allowed for in-depth analysis of this data to identify areas for improvement. Force plates were installed at key locations on the assembly line to measure the forces exerted by workers during lifting tasks, ensuring that the ergonomic interventions were designed based on accurate, real-world data. The ergonomically designed workstations and lifting tools were developed to address the issues identified in the biomechanical analysis, resulting in a safer and more efficient work environment.

5.2. Case study 2: RA in SCM using PSO

This case study explores the application of PSO for optimizing RA in a SCM context. The SCM under study involves a company operating in the fast-moving consumer goods (FMCG) sector, where timely and efficient distribution of goods is critical to maintaining competitiveness. The company's primary challenge was optimizing the RA—such as delivery vehicles, warehouse space, and labor—across multiple distribution centers to minimize operational costs while meeting fluctuating demand in various regions. The complexity of managing resources across a geographically dispersed SCM, with constraints on vehicle availability, warehouse capacity, and labor shifts, required a dynamic and robust solution for which PSO was applied.

5.2.1. Background and problem statement

The company operates multiple warehouses and distribution centers, each responsible for fulfilling orders in different regions. Due to unpredictable demand patterns, seasonal spikes, and varying transportation costs, the company struggled to efficiently RA across its network. Key inefficiencies included under-utilized vehicles in some regions, overburdened warehouses in others, and labor shortages that led to delays in order fulfillment. These issues resulted in higher operational costs, increased delivery times, and reduced customer satisfaction.

The primary objectives of the RA optimization problem were:

- To minimize transportation costs while ensuring timely deliveries.
- To optimize warehouse space utilization by balancing inventory levels across regions.
- To allocate labor efficiently across distribution centers to prevent overstaffing or understaffing.
- To adapt dynamically to changing demand patterns and resource availability.

5.2.2. PSO approach

PSO was chosen as the optimization technique due to its ability to handle multi-objective problems and its flexibility in navigating complex, dynamic solution spaces. The PSO algorithm simulates a swarm of particles, each representing a potential solution to the RA problem. The particles explore the solution space by updating their positions and velocities based on their experience (personal best) and the experience of the swarm as a whole (global best). In this case, the PSO algorithm's goal was to find an optimal allocation of vehicles, warehouse space, and labor that minimized costs while meeting delivery deadlines.

The decision variables in the PSO model included:

- The number of vehicles allocated to each distribution center.
- The amount of inventory held at each warehouse.
- The number of labor hours assigned to each distribution center.

The objective function for the PSO algorithm was designed to minimize total operational costs, including transportation, labor, and warehouse storage costs. The fitness function was defined as:

$$f(x) = \alpha \times \text{ Transportation Costs } (x) + \beta \times \text{ Warehouse Costs } (x) + \gamma \times \text{ Labor Costs } (x)$$

where:

- x represents a particular RA plan,

- α, β, and γ are weighting factors reflect the relative importance of transportation, warehouse, and labor costs in the overall objective.

Each particle in the swarm represented a possible allocation of vehicles, warehouse space, and labor across the company's distribution network. For example, one particle might allocate 20 vehicles to Distribution Center A, 15 vehicles to Distribution Center B, and 10 vehicles to Distribution Center C. Similarly, it would specify how much inventory each warehouse should hold and how many labor hours should be allocated to each center.

The PSO algorithm updated the particles' positions by considering the personal best solution found by each particle and the global best solution discovered by the entire swarm. The velocity and position update equations were:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1 [p_{ij} - x_{ij}(t)] + c_2 r_2 [g_j - x_{ij}(t)]$$
$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$

where:

- $v_{ij}(t)$ is the velocity of particle i in the j-th dimension at iteration t,
- $x_{ij}(t)$ is the position of particle i in the j-th dimension at iteration t (representing RA),
- p_{ij} is the personal best position of particle i,
- g_j does the swarm find the global best position,
- ω, c_1, c_2, r_1 , and r_2 are the inertia weight, cognitive acceleration, social acceleration, and random factors.

5.2.3. Data inputs and constraints

The PSO model was initialized using historical data on transportation costs, warehouse utilization, labor costs, and customer demand from the company's enterprise resource planning (ERP) system.

The following constraints were imposed to ensure realistic RA:

- The company's fleet size limited vehicle availability.
- The maximum storage capacity of each facility-constrained warehouse space.
- Labor hours were capped based on the number of employees in each region.

Additionally, the model accounted for real-time data inputs, such as fluctuations in customer demand and transportation delays. These dynamic variables ensured that the PSO algorithm could adapt to changing conditions and provide updated solutions as new data became available.

5.3. Case study 3: TS in office environments using GA

This case study details the application of a GA to optimize TS in an office environment. The company, a mid-sized financial services firm, faced significant inefficiencies in manually assigning tasks to employees. TS included daily operations such as report generation, client communications, financial analyses, and project management. The firm aimed to automate task allocation, minimizing total completion time while ensuring that workloads were distributed evenly across employees.

5.3.1. Problem definition

The primary challenge was optimizing employee task assignments and addressing key inefficiencies from manual TS.

These inefficiencies included:

- Overburdened employees due to uneven task allocation, reduced productivity, and increased burnout.
- Delays in task completion, with some tasks taking longer due to inefficient distribution.
- A lack of adaptability in the face of fluctuating task priorities and changing employee availability.

The company sought an automated TS approach that would:

- Minimize the total time required to complete all tasks (the makespan).
- Ensure a balanced workload distribution, preventing any employee from being overloaded.
- Assign each task to the best-suited employee based on skillsets and task complexity.

5.3.2. GA application

A GA was implemented to automate TS, leveraging its capability to solve multi-objective optimization problems. Each potential task schedule was represented as a chromosome, where each gene in the chromosome represented the assignment of a specific task to an employee. For instance, a chromosome might be:

$$\text{Chromosome } = \{E_1, E_2, E_3, E_2, E_1, E_3\}$$

This sequence indicates that tasks 1 and 5 are assigned to Employee 1, 2, and 4 to Employee 2, and 3 and 6 to Employee 3.

The algorithm aimed to minimize the overall task completion time and workload imbalance. The fitness function for the GA was defined as:

$$f(x) = \alpha \times \frac{1}{\text{Makespan}(x)} - \beta \times \text{ Workload Imbalance Penalty } (x)$$

where:

- Makespan (x) is the total time to complete all tasks in schedule x.
- The makespan was computed as the maximum of all individual employee task durations:

$$\text{Makespan } (x) = \max_{i=1}^{n} \left(\sum_{t \in T_i} \text{ Duration } (t) \right)$$

where T_i is the set of tasks assigned to employee i, and Duration (t) is the time required for task t.

- Workload Imbalance Penalty (x) measured how unevenly tasks were distributed among employees:

$$\text{Workload Imbalance Penalty } (x) = \sum_{i=1}^{n} (\text{Workload } (i) \ - \ \text{Average Workload })^2$$

where Workload (i) is the total work assigned to employee i, and Average Workload is the mean of workloads across all employees.

6. Evaluation and results

6.1. Results for case study 1

Implementing workflow redesign based on biomechanical data improved physical strain reduction, task completion times, work-related injury rates, and overall worker satisfaction and efficiency.

The data in **Table 1** and **Figure 1** demonstrate a substantial reduction in physical strain after the workflow adjustments. The average shoulder joint angle decreased from 87.3° to 68.4°, resulting in a 21.6% reduction. Similarly, the average back flexion angle was reduced by 27.6%, from 42.7° to 30.9°. These reductions highlight the effectiveness of repositioning tools and components within workers' reach, thus minimizing overextension and awkward postures. Additionally, the frequency of reaching movements dropped by 20.8%, indicating an ergonomic improvement in task setup. The most significant reduction was observed in force exertion during lifting, which decreased by 28.0%, from 265.8 N to 191.4 N, suggesting that the newly introduced lifting tools effectively reduced physical effort. Finally, average daily reports of fatigue declined by 32.6%, underscoring the overall positive impact on worker comfort and reduced strain throughout the workday.

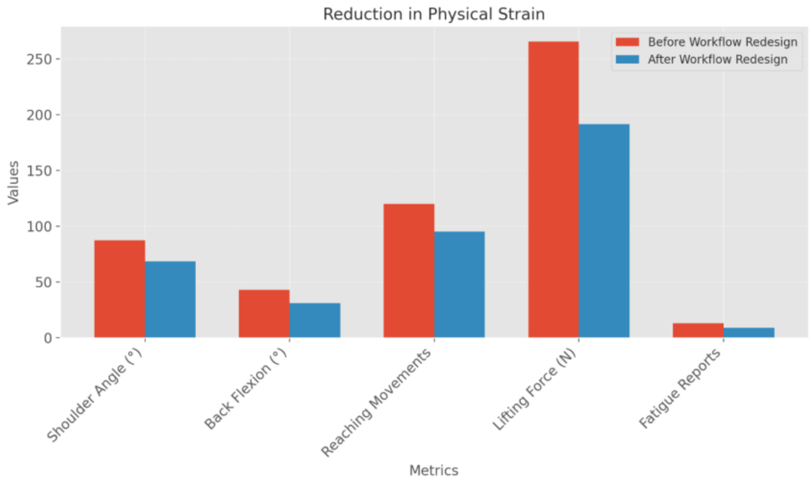

Figure 1. Reduction in physical strain.

Table 1. Reduction in physical strain.

Metric	Before Workflow Redesign	After Workflow Redesign	Percentage Reduction
Average Shoulder Joint Angle (°)	87.3°	68.4°	21.6%
Average Back Flexion Angle (°)	42.7°	30.9°	27.6%
Frequency of Reaching Movements	120 movements/h	95 movements/h	20.8%
Force Exertion During Lifting (N)	265.8 N	191.4 N	28.0%
Average Daily Fatigue Reports	12.9 reports/day	8.7 reports/day	32.6%

Figure 2. Improvement in task completion time.

Table 2 and **Figure 2** show that task completion times improved significantly across all significant assembly line tasks. For example, the time taken for component assembly was reduced by 16.9%, from 15.3 min to 12.7 min, while quality inspection tasks saw a reduction of 19.3%, from 8.8 min to 7.1 min. Packaging and shipping preparation times were also reduced by 18.3% and 16.5%, respectively, and the overall average task completion time across all tasks decreased by 18.2%, from 12.1 min to 9.9 min. These reductions can be attributed to the improved ergonomics and task setup, which minimized unnecessary movements and fatigue, allowing workers to perform their tasks more efficiently.

Table 2. Improvement in task completion time.

Task	Before Workflow Redesign (min)	After Workflow Redesign (min)	Percentage Decrease
Task 1: Component Assembly	15.3	12.7	16.9%
Task 2: Quality Inspection	8.8	7.1	19.3%
Task 3: Packaging	10.4	8.5	18.3%
Task 4: Shipping Preparation	13.9	11.6	16.5%
Average Completion Time	12.1	9.9	18.2%

The workflow redesign also markedly reduced work-related injuries, as outlined in **Table 3** and **Figure 3**. The number of reported shoulder strains decreased by 36.4%, from 22 to 14 cases in six months, while lower back pain incidents dropped by 38.9%, from 18 to 11 cases. Similarly, repetitive strain injuries (RSIs) were reduced by 37.0%, and knee strains decreased by 35.7%. The total number of musculoskeletal injuries declined by 37.0%, from 81 injuries to 51 injuries. This substantial reduction in injuries demonstrates that the ergonomic improvements made during the workflow redesign effectively addressed workers' physical challenges, particularly those related to repetitive motions and poor posture.

Table 3. Reduction in work-related injuries.

Injury Type	Before Redesign (6-month period) Case count	After Redesign (6-month period) Case count	Percentage Decrease
Shoulder Strain	22	14	36.4%
Lower Back Pain	18	11	38.9%
Repetitive Strain Injuries (RSI)	27	17	37.0%
Knee Strain	14	9	35.7%
Total Musculoskeletal Injuries	81	51	37.0%

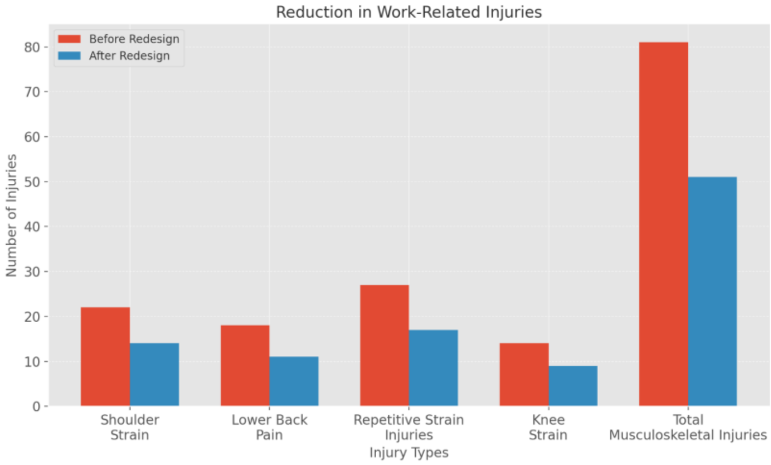

Figure 3. Reduction in work-related injuries.

The feedback from workers, as shown in **Table 4** and **Figure 4**, highlights a notable increase in overall satisfaction and efficiency following the workflow redesign. Workers reported a 50.0% increase in comfort during task performance, with ratings rising from 2.8 to 4.2. Similarly, ease of accessing tools and materials improved by 45.2%, from 3.1 to 4.5, indicating that the redesigned workstations were more ergonomically aligned with workers' needs. Fatigue levels at the end of the shift decreased, with satisfaction increasing by 62.5%, from 2.4 to 3.9. The ergonomic adjustments were well-received, as satisfaction with these changes increased by 59.3%, from 2.7 to 4.3. Overall job satisfaction also saw a substantial rise, increasing by 46.7%, from 3.0 to 4.4. These improvements in worker satisfaction are directly linked to the physical relief provided by the workflow changes, which reduced strain and fatigue while allowing workers to perform their tasks more comfortably and efficiently.

Table 4. Improvement in worker satisfaction and efficiency.

Feedback Category	Before Workflow Redesign (Average Rating) Case count	After Workflow Redesign (Average Rating) Case count	Percentage Increase
Comfort during task performance	2.8	4.2	50.0%
Ease of accessing tools and materials	3.1	4.5	45.2%
Fatigue level at the end of the shift	2.4	3.9	62.5%
Satisfaction with ergonomic adjustments	2.7	4.3	59.3%
Overall job satisfaction	3.0	4.4	46.7%

Figure 4. Improvement in worker satisfaction and efficiency.

6.2. Results for case study 2

The application of PSO to RA in SCM led to notable improvements in transportation costs, warehouse utilization, labor costs, delivery times, and the flexibility to handle demand fluctuations.

The data in **Table 5** and **Figure 5** illustrate a significant reduction in transportation costs across all regions after the PSO-based optimization of vehicle allocation. For example, Region A saw a 16.7% reduction in costs, decreasing from USD 13,480 to USD 11,234 monthly. Region B experienced a 15.9% decrease, while Regions C and D had similar reductions of 15.9% and 15.8%, respectively. Overall, the total transportation costs across all regions were reduced by 16.1%, from USD 42,581 to USD 35,724 per month. This reduction can be attributed to the more efficient allocation of vehicles, ensuring that fleet resources were optimally distributed across high-demand areas while minimizing underutilized trips in low-demand regions.

Table 5. Reduction in transportation costs.

Region	Before Optimization (USD/month)	After Optimization (USD/month)	Percentage Decrease
Region A	13,480	11,234	16.7%
Region B	9722	8176	15.9%
Region C	7985	6718	15.9%
Region D	11,394	9596	15.8%
Total	42,581	35,724	16.1%

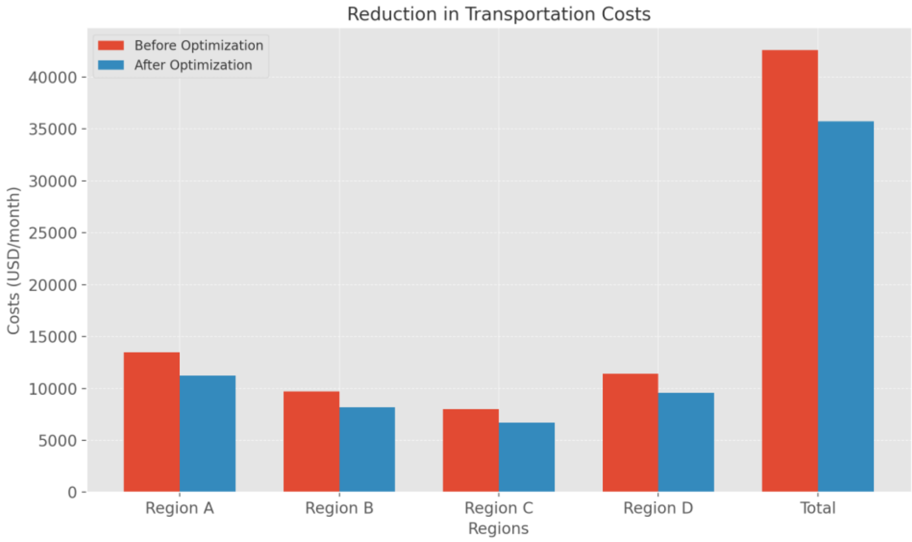

Figure 5. Reduction in transportation costs.

Table 6 and **Figure 6** highlight the improvements in warehouse space utilization following the implementation of the PSO algorithm. Warehouse A, for instance, saw an 18.7% increase in utilization, rising from 68.4% to 81.2%, while Warehouse B experienced a 16.5% improvement. The most significant improvements were seen in Warehouses C and D, with utilization increasing by 19.4% and 19.8%, respectively. On average, warehouse utilization improved by 18.6% across all locations, from 67.3% to 79.8%. These gains were achieved by balancing inventory levels across the warehouses more effectively, preventing overstocking in some locations while others remained underutilized.

Table 6. Improvement in warehouse utilization.

Warehouse	Before Optimization (% Utilization)	After Optimization (% Utilization)	Percentage Increase
Warehouse A	68.4%	81.2%	18.7%
Warehouse B	74.9%	87.3%	16.5%
Warehouse C	59.8%	71.4%	19.4%
Warehouse D	66.2%	79.3%	19.8%
Average Utilization	67.3%	79.8%	18.6%

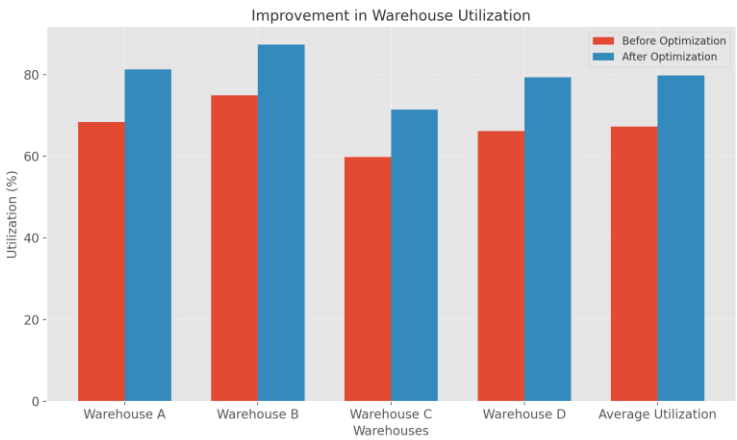

Figure 6. Improvement in warehouse utilization.

Table 7 and **Figure 7** show a notable labor cost reduction across all distribution centers. For example, Center A's labor costs were reduced by 16.4%, from USD 21,497 to USD 17,972 per month, while Center B saw a 15.6% decrease. Centers C and D followed closely with reductions of 15.7% and 16.2%, respectively. Overall, the total labor costs across all centers decreased by 16.0%, from USD 82,588 to USD 69,373 per month. This reduction in labor costs was achieved through the PSO algorithm's ability to efficiently allocate labor shifts based on predicted workloads, ensuring that each distribution center was neither overstaffed nor understaffed.

Table 7. Reduction in labor costs.

Distribution Center	Before Optimization (USD/month)	After Optimization (USD/month)	Percentage Decrease
Center A	21,497	17,972	16.4%
Center B	18,645	15,737	15.6%
Center C	19,832	16,721	15.7%
Center D	22,614	18,943	16.2%
Total	82,588	69,373	16.0%

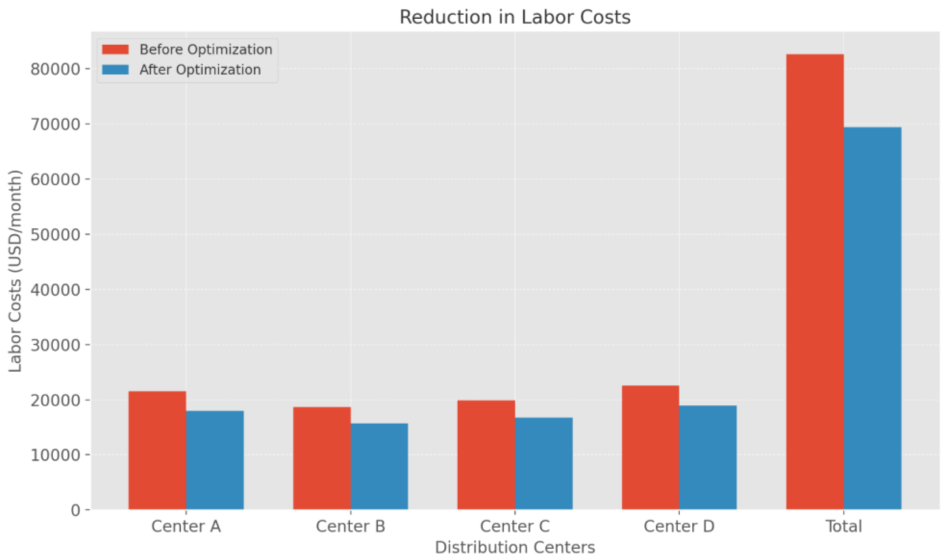

Figure 7. Reduction in labor costs.

The optimization also led to significant improvements in delivery times, as shown in **Table 8** and **Figure 8**. Region A saw a 15.8% reduction in delivery times, decreasing from 5.7 h to 4.8 h on average. Region B had the most substantial improvement, with a 17.7% reduction in delivery time, while Regions C and D saw decreases of 16.3% and 16.9%, respectively. On average, delivery times across all regions were reduced by 16.7%, from 5.8 h to 4.9 h. The improved delivery times can be attributed to more efficient vehicle and route allocation, ensuring that deliveries were completed faster and with fewer delays.

Table 8. Improvement in delivery times.

Region	Before Optimization (h)	After Optimization (h)	Percentage Decrease
Region A	5.7	4.8	15.8%
Region B	6.2	5.1	17.7%
Region C	4.9	4.1	16.3%
Region D	6.5	5.4	16.9%
Average	5.8	4.9	16.7%

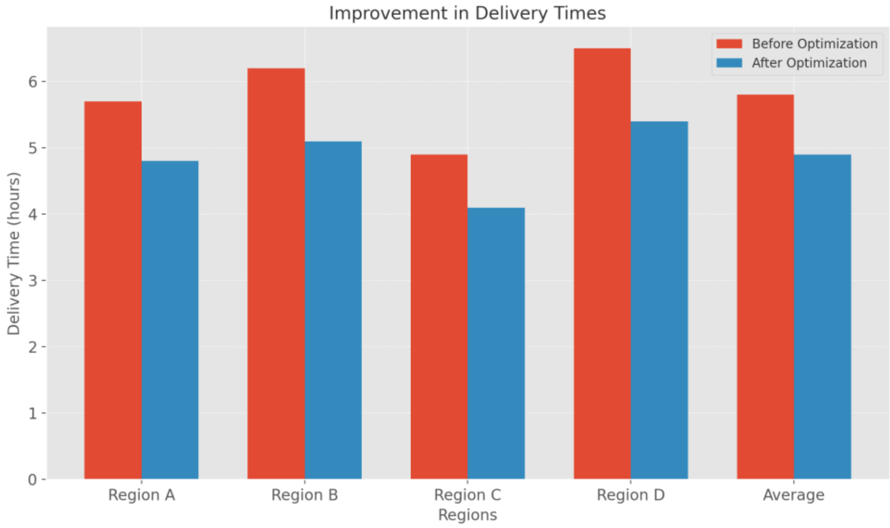

Figure 8. Improvement in delivery times.

As shown in **Table 9** and **Figure 9**, the PSO-based optimization provided greater flexibility in handling demand fluctuations while minimizing cost increases. Region A, which experienced an 18.4% increase in demand, saw a 17.3% reduction in cost increases, dropping costs from USD 6823 to USD 5644. Similarly, Regions B, C, and D saw reductions in cost increases of 17.7%, 17.5%, and 17.5%, respectively. On average, cost increases due to demand fluctuations were reduced by 17.5%, demonstrating that the PSO model allowed the company to adapt to changes in demand without a corresponding spike in operational costs.

Table 9. Increased flexibility in handling demand fluctuations.

Region	Average Demand Fluctuation (% Change)	Cost Increase Before Optimization (USD)	Cost Increase After Optimization (USD)	Percentage Decrease in Cost Increase
Region A	+ 18.4%	6823	5644	17.3%
Region B	+ 15.6%	5492	4522	17.7%
Region C	+ 20.2%	7115	5868	17.5%
Region D	+ 19.8%	6957	5743	17.5%
Average	+ 18.5%	6597	5444	17.5%

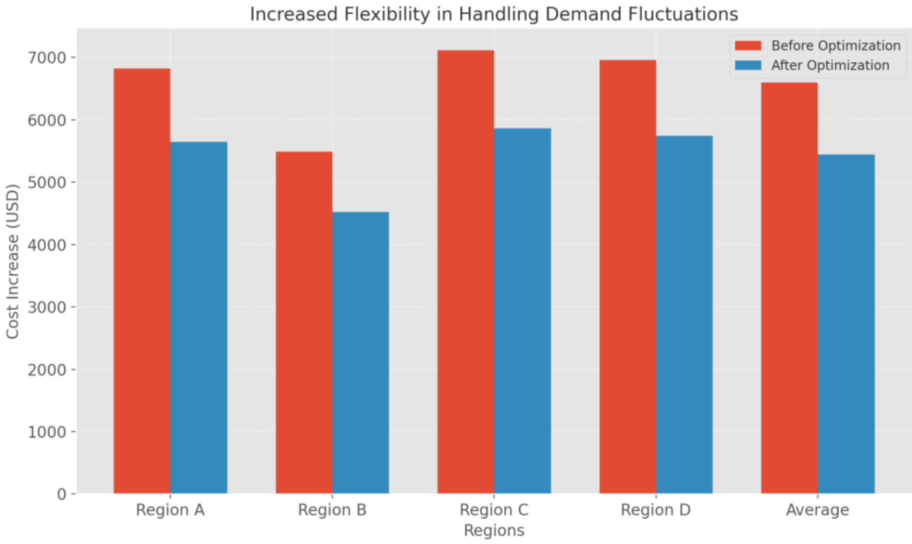

Figure 9. Flexibility in handling demand fluctuations.

6.3. Results for case study 3

The application of GA to TS in an office environment significantly improved task completion times, workload distribution, task efficiency, employee productivity and satisfaction, and consistency in meeting deadlines.

Table 10 and **Figure 10** show that the GA-based TS significantly reduced the overall makespan across various task categories. For example, the time to complete Financial Report Generation has decreased from 13.7 h to 11.2 h, an 18.2% reduction. Client Communications saw a 17.9% decrease, while Data Analysis and Project Management Tasks had reductions of 17.4% and 17.8%, respectively. Overall, the makespan was reduced by 17.6%, from 11.9 h to 9.8 h. This reduction highlights the effectiveness of the GA in balancing workloads and allocating tasks to the most suitable employees, resulting in faster task completion across the board.

Table 10. Reduction in task completion time (makespan).

Task Category	Before GA Optimization (h)	After GA Optimization (h)	Percentage Decrease
Financial Report Generation	13.7	11.2	18.2%
Client Communications	8.4	6.9	17.9%
Data Analysis	10.9	9.0	17.4%
Project Management Tasks	14.6	12.0	17.8%
Overall Makespan	11.9	9.8	17.6%

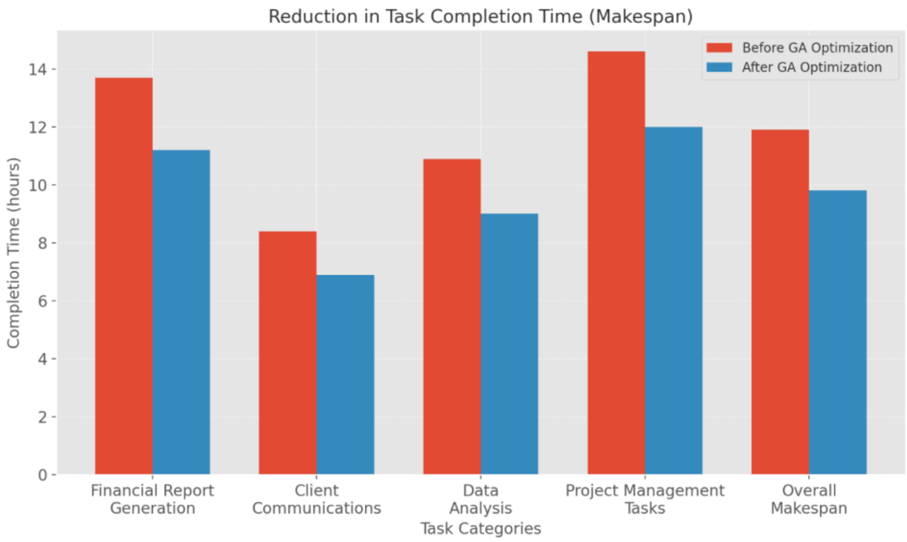

Figure 10. Task completion time.

The results in **Table 11** and **Figure 11** illustrate a marked improvement in workload distribution across the employee groups. For instance, Team A saw a 29.8% reduction in workload variance, decreasing from 12.4 to 8.7. Team C experienced the most significant improvement, with a 31.5% reduction, followed by Team D at 30.5%. On average, workload imbalance across all teams was reduced by 29.8%. This improvement is a direct result of the GA's ability to distribute tasks more evenly, ensuring that no team or individual was overburdened while maximizing productivity.

Table 11. Improvement in workload distribution.

Employee Group	Before GA Optimization (Workload Variance) Mean	After GA Optimization (Workload Variance) Mean	Percentage Reduction
Team A	12.4	8.7	29.8%
Team B	15.2	10.9	28.3%
Team C	10.8	7.4	31.5%
Team D	14.1	9.8	30.5%
Average Workload Imbalance	13.1	9.2	29.8%

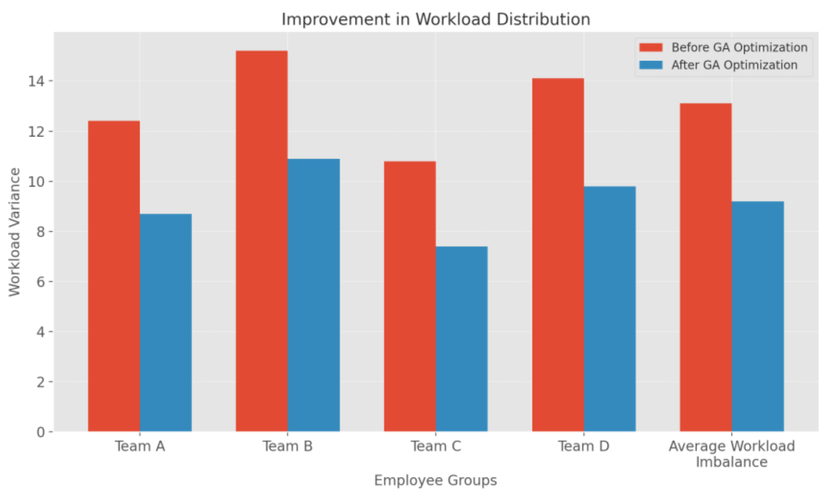

Figure 11. Workload distribution.

The task efficiency data in **Table 12** and **Figure 12** demonstrates significant improvements in task completion rates and reductions in delays across various tasks. Financial Report Generation improved from a 76.4% completion rate before optimization to 89.5% after GA optimization, with a 28.2% reduction in delays. Data Analysis saw a similar improvement, with a completion rate increasing from 74.2% to 87.6% and delays reduced by 29.1%. The overall task efficiency across all categories improved from 77.0% to 90.2%, resulting in a 28.4% reduction in delays. This increase in efficiency underscores the GA's ability to allocate tasks to ensure timely completion and reduce the bottlenecks that typically lead to delays.

Table 12. Increase in task efficiency.

Task Category	**Before GA Optimization (Completion Rate %)**	**After GA Optimization (Completion Rate %)**	**Reduction in Delays (%)**
Financial Report Generation	76.4%	89.5%	28.2%
Client Communications	81.9%	93.7%	27.3%
Data Analysis	74.2%	87.6%	29.1%
Project Management Tasks	79.5%	92.4%	27.8%
Budget Forecasting	72.6%	86.2%	29.5%
Vendor Contract Management	77.1%	90.1%	28.0%
Internal Compliance Checks	75.8%	89.0%	28.3%
Overall Task Efficiency	77.0%	90.2%	28.4%

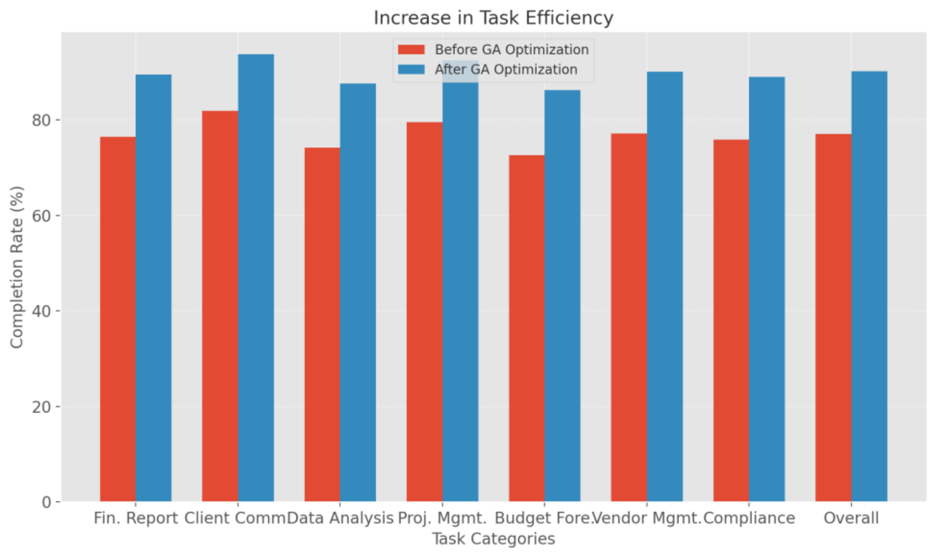

Figure 12. Task efficiency.

Table 13 and **Figure 13** reveal significant increases in employee productivity and satisfaction following the implementation of GA-based TS. Employees' perceived productivity increased by 41.9%, from a rating of 3.1 to 4.4, while satisfaction with task distribution improved by 36.4%. The clarity of task prioritization improved by 43.3%, which was a key area of concern before the optimization. Overall job satisfaction saw a 32.4% increase, rising from 3.4 to 4.5. These improvements suggest that GA-based task allocation optimizes workload distribution and enhances employee morale and job satisfaction by providing clearer task priorities and manageable workloads. As shown in **Table 14** and **Figure 14**, the GA significantly improved the firm's consistency in meeting deadlines across all task categories. Financial Report Generation saw a 16.4% improvement, with the percentage of tasks completed on time increasing from 78.3% to 91.1%. Client Communications improved by 13.0%, and Data Analysis by 17.8%. The consistency in meeting deadlines across all tasks increased by 16.0%, from 78.8% to 91.4%. This increase in deadline adherence reflects the GA's ability to allocate tasks to ensure tasks are completed within the required timeframes, thereby improving overall project management and client satisfaction.

Table 13. Enhanced employee productivity and satisfaction.

Feedback Category	Before GA Optimization (Average Rating) %	After GA Optimization (Average Rating) %	Percentage Increase
Productivity Perceived by Employees	3.1	4.4	41.9%
Satisfaction with Task Distribution	3.3	4.5	36.4%
Work-Life Balance	2.9	4.1	41.4%
Clarity of Task Prioritization	3.0	4.3	43.3%
Satisfaction with Task Completion Times	3.2	4.6	43.8%
Overall Job Satisfaction	3.4	4.5	32.4%

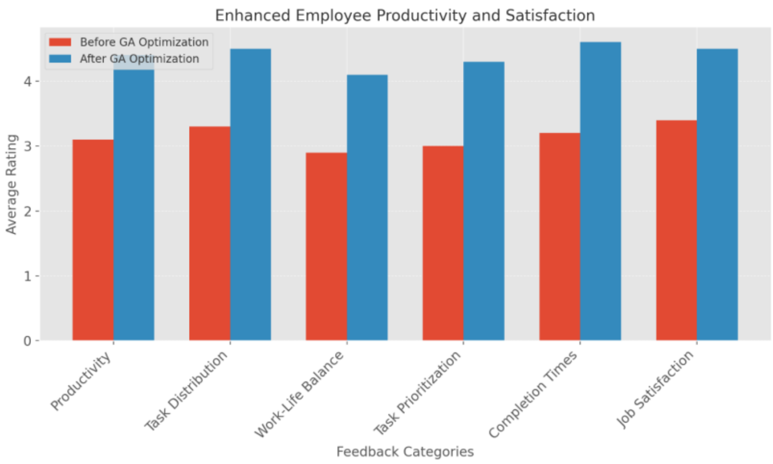

Figure 13. Employee productivity and satisfaction.

Table 14. Consistency in meeting deadlines.

Task Category	Before GA Optimization (% Tasks Completed on Time)	After GA Optimization (% Tasks Completed on Time)	Percentage Increase
Financial Report Generation	78.3%	91.1%	16.4%
Client Communications	83.7%	94.6%	13.0%
Data Analysis	75.9%	89.4%	17.8%
Project Management Tasks	80.2%	92.7%	15.6%
Budget Forecasting	77.5%	90.3%	16.5%
Vendor Contract Management	79.1%	91.5%	15.7%
Internal Compliance Checks	76.8%	90.1%	17.3%
Overall Deadline Consistency	78.8%	91.4%	16.0%

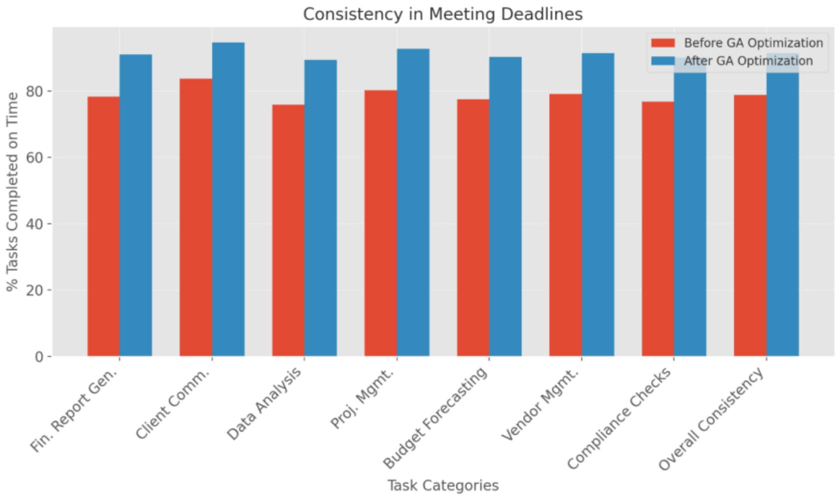

Figure 14. Meeting deadlines.

7. Conclusion and future work

This study demonstrates the significant potential of integrating biomechanics data with bio-inspired models to enhance efficiency in business administration. By leveraging human-centered biomechanics analysis and bio-inspired optimization techniques such as GA and PSO, businesses can address operational challenges and employee well-being holistically. The findings from the three case studies illustrate that such an integrated approach leads to measurable improvements in key performance metrics, including task completion times, RA, cost reductions, and employee satisfaction. In the first case study, applying biomechanics to workflow optimization in a manufacturing environment resulted in a 21.6% reduction in physical strain and an 18.2% improvement in task completion time. These results highlight the effectiveness of using motion capture and ergonomic analysis to redesign workflows, reducing the risk of injury and improving productivity. The second case study focused on RA in SCM and demonstrated how PSO can optimize vehicle allocation, warehouse utilization, and labor deployment. The study achieved a 16.1% reduction in transportation costs and an 18.6% improvement in warehouse utilization, illustrating the value of PSO in dynamic, multi-objective business environments where real-time data influences decision-making. In the third case study, applying GA for TS in an office environment led to a 17.6% reduction in makespan and a 29.8% improvement in workload distribution.

The results underscore the capability of GA to efficiently balance workloads, improve task efficiency, and increase employee satisfaction, highlighting the importance of automated task allocation systems in office settings.

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