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A hybrid Genetic Algorithm and Fuzzy Logic approach to ergonomic design of workstations in metal casting operations

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ABSTRACT
The metal casting industry faces significant challenges in balancing productivity with worker safety and well-being. Hazardous working conditions, including high temperatures, exposure to gases, and repetitive motions, increase the risk of injuries and fatigue. [1] This study proposes a novel hybrid approach that integrates Genetic Algorithm (GA) and Fuzzy Logic (FL) to optimize workstation ergonomics. The system utilizes real-time data from sensors to evaluate ergonomic factors such as worker posture, fatigue levels, and environmental conditions. Fuzzy Logic processes this data, while GA optimizes the system's parameters for enhanced accuracy and adaptability. Experimental results demonstrated significant improvements, including a 25% reduction in worker fatigue, a 30% improvement in air quality compliance, and a 35% decrease in ergonomic risks. Real-time adjustments, such as desk height modifications and improved ventilation, effectively enhanced worker safety and comfort. This innovative approach offers a scalable and reliable solution for improving ergonomics in dynamic industrial environments, contributing to both worker well-being and operational efficiency. Future research could further enhance the system by incorporating machine learning for improved predictive capabilities and expanded optimization of ergonomic parameters.

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1. INTRODUCTION

The rapid evolution of manufacturing industries, particularly in sectors like metal casting, has brought about significant advancements in production techniques and technology integration [1,2]. However, these developments often overshadow a critical aspect of industrial operations: the health and safety of workers. Metal casting, a cornerstone of the manufacturing sector, is characterized by labor-intensive tasks, exposure to high temperatures, repetitive motions, and hazardous materials [3]. These conditions make the industry particularly susceptible to ergonomic risks, including musculoskeletal disorders (MSDs) [4–6], fatigue [7,8], and long-term health complications [6]. Despite global efforts to enhance occupational health standards, the metal casting industry continues to face challenges in balancing productivity with worker well-being, creating a pressing need for innovative solutions to address these issues [4].

Ergonomic interventions in industrial settings have historically focused on manual observations and subjective assessments. While these methods have led to incremental improvements in workplace design and task allocation, they fall short in addressing the complex, dynamic, and multifactorial nature of ergonomic challenges in environments like metal casting [9–11]. This limitation is particularly pronounced when considering the variability in workers' physical capabilities, environmental conditions, and the nature of tasks. Consequently, there is an urgent demand for comprehensive, data-driven approaches that can effectively identify, analyze, and mitigate ergonomic risks in real-time.

To date, the integration of computational methods in ergonomic analysis has shown promising potential. Techniques such as Genetic Algorithm (GA) [12,13], and Fuzzy Logic (FL) [14,15], have emerged as powerful tools for optimizing complex systems, including workstation design and task sequencing. GA, inspired by the principles of natural selection, excel in exploring large solution spaces to identify optimal configurations. FL, on the other hand, allows for the incorporation of human-centric factors and subjective data, such as worker comfort and perceived fatigue levels [16]. Despite their individual strengths, the combination of GA and FL in a hybrid approach remains underexplored in the context of ergonomic design, particularly within the metal casting industry. This gap highlights a significant opportunity for innovation and contributes to the novelty of this research.

The existing body of literature on ergonomic optimization largely focuses on assembly lines in automotive or electronic manufacturing, with limited attention given to high-risk sectors like metal casting [17]. Metal casting operations present unique challenges due to their reliance on manual labor, exposure to extreme heat, and the physical demands of handling heavy molds and materials. Furthermore, ergonomic issues in metal casting are often exacerbated by the lack of technological adoption and the reliance on traditional practices. While some studies have applied computational methods to ergonomic challenges, they are often limited to isolated aspects, such as workstation layout or task scheduling, without addressing the holistic interplay between ergonomic factors and production efficiency [18]. This gap in the research landscape underscores the need for an integrated approach that simultaneously considers worker safety, productivity, and operational constraints.

By establishing the significance of this research, we position ourselves within a growing academic and practical interest in leveraging advanced computational tools for ergonomic design. The integration of GA and FL presents a novel opportunity to address the complex interplay of ergonomic factors in metal casting. This approach not only advances the methodological landscape but also contributes to the broader discourse on sustainable manufacturing practices. The novelty lies in the hybridization of these techniques to create a comprehensive framework that adapts to the dynamic nature of industrial environments, providing real-time insights and actionable recommendations.

Occupying this niche, the proposed research aims to develop and validate a hybrid GA and FL model tailored to the ergonomic challenges of the metal casting industry [6,19]. The model will optimize workstation layouts and task allocations by simultaneously considering objective metrics and subjective factors [20]. By incorporating real-world data from metal casting operations, this research will demonstrate the practical applicability and scalability of the proposed approach. Furthermore, the model will be tested in a case study environment to evaluate its effectiveness in reducing ergonomic risks and improving overall productivity [21].

The expected outcomes of this research extend beyond academic contributions. For the metal casting industry, the implementation of such a model could lead to significant reductions in work-related injuries, absenteeism, and operational inefficiencies. From a broader perspective, the hybrid GA-FL framework could serve as a blueprint for ergonomic optimization in other high-risk industries, fostering a culture of safety and innovation in manufacturing [22,23].

This research establishes a clear territory within the domain of ergonomic design, identifies a critical niche in the application of hybrid computational methods, and seeks to occupy this niche through the development of a novel, integrated framework. By addressing the unique challenges of the metal casting industry, this study not only fills a critical gap in the literature but also aligns with global efforts to promote sustainable and worker-centric manufacturing practices, as illustrated in Figure 1.

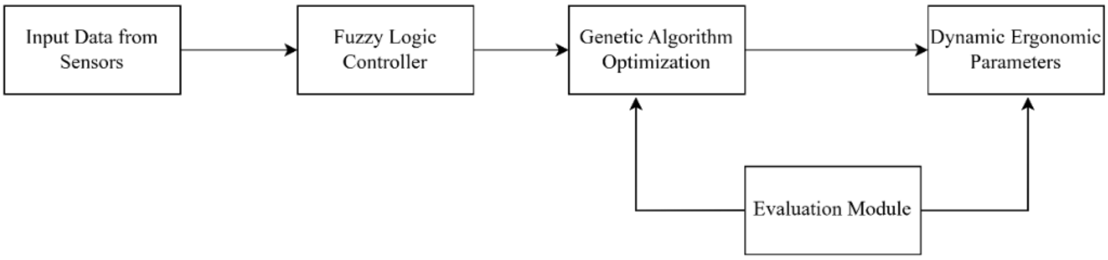

Figure 1. Hybrid GA-FL flow

2. MATERIALS AND METHODS

The hybrid GA-FL approach employed in this study integrates ergonomic parameters such as anthropometric data (e.g., worker height, arm reach), environmental conditions (e.g., temperature, humidity, noise levels), and task analysis (e.g., repetitive motion patterns, workload distribution). These data are processed through a FL system using linguistic rules to evaluate ergonomic levels based on parameters like worker posture, fatigue, and environmental conditions. The fuzzy evaluation is then used as the fitness function in the GA model to optimize workstation design, including desk height, tool positioning, and ventilation systems.

The methodology integrates anthropometric, task-specific, and environmental data to create an adaptive design model. Anthropometric data such as worker height, arm reach, and posture dynamics are collected alongside task analysis, including workload distribution and repetitive motion patterns. Environmental factors such as temperature, lighting, and noise levels are incorporated to ensure a holistic evaluation. Using these inputs, FL rules evaluate ergonomic criteria like reachability, joint angles, fatigue, and posture quality, while GA optimizes workstation parameters, including equipment layout, tool placement, and working surface height.

2.1. Data Collection

Data collection for this study involved gathering comprehensive demographic and operational information from a metal casting facility to create an ergonomic workstation design that meets the needs of the workers. The production area spans approximately 1,100 square meters and includes four casting stations and two industrial furnaces, each with a capacity of two tons. The workforce consists of 23 employees, aged between 25 and 55 years (with a mean age of 38), predominantly male (85%), with an average height of 168 cm.

Environmental parameters were also recorded, revealing an average temperature of 38 °C, a noise level of 85 dB, and a lighting intensity of 300 lux. The shift patterns consisted of three 8-hour shifts per day, with each worker responsible for handling an average of 20 tasks per shift. Observations indicated repetitive lifting of moulds weighing 10-15 kg and awkward postures, underscoring the need for ergonomic intervention. The collected data provided the foundation for developing a hybrid GA-FL optimization model.

2.1.1 Genetic Algorithm (GA)

GA are a class of optimization algorithms inspired by the principles of natural selection and genetic. They are widely used in various fields to solve complex optimization problems by mimicking the natural process of evolution. GA operate through cycles of selection, crossover, and mutation to develop solutions to a given problem.

GA start with a population of candidate solutions, often represented as a string of binary digits, although other representations are also possible. Each candidate solution, or individual, is evaluated using a fitness function that measures how well it solves the problem at hand. The selection process then chooses the fittest individuals to reproduce, ensuring that better solutions have a higher chance of passing their genes on to the next generation. This process is similar to survival of the fittest in natural evolution.

Crossover, or recombination, is a genetic operator used to combine the genetic information of two parent individuals to produce offspring. This operator is essential for exploring new regions of the solution space by mixing parental characteristics. Mutation, another genetic operator, introduces random changes to an individual's genetic code, providing genetic diversity and helping the algorithm avoid local optimal by exploring new solutions.

The iterative process of selection, crossover, and mutation continues until a stopping criterion is met, such as a maximum number of generations or a satisfactory fitness level. The final population is expected to contain high-quality solutions to the optimization problem.

Recent research has highlighted the flexibility and effectiveness of GA in a variety of applications. For example, in the field of intelligent transportation, GA have been used to optimize traffic management systems, improve logistics, and enhance safety measures by integrating IoT technologies and machine learning algorithms [24]. These advances demonstrate the potential of GA to address complex real-world problems by efficiently searching large solution spaces. In the context of Industry 4.0, GA have been used to improve maintenance performance by optimizing predictive maintenance schedules and increasing the reliability of industrial systems [25]. The integration of GA with data-driven decision-making and augmented reality technologies has shown promising results in reducing maintenance downtime and costs, thereby improving overall operational efficiency.

In addition, GA has been applied in automotive digital forensics to investigate the causes of failures in automated driving functions [26,27]. By analyzing large datasets and identifying patterns, GA can help forensic investigators determine the root causes of hardware and software failures, contributing to the development of more resilient and safer automotive systems.

In the field of sustainable urban logistics, GA has been used to optimize short-haul delivery routes, reduce environmental impacts, and improve the efficiency of logistics operations [27]. By considering various factors such as traffic conditions, delivery time windows, and vehicle capacity, GA can generate optimal route solutions that minimize costs and emissions.

2.1.2 Finding Penalty, Eligibility, and Probability Values for Individuals in GA

In GA, determining penalty, eligibility, and probability values is essential for evaluating solution fitness, managing constraint violations, and guiding the evolutionary process. These metrics enhance the algorithm's robustness in addressing constrained and unconstrained optimization problems.

Penalty functions are a critical component in constrained optimization problems within GA. They discourage infeasible solutions by imposing a cost proportional to the degree of constraint violation. The penalty value (c_i) for an individual is calculated as [4] :

$$C_i = \sum_{j=1}^{n} w_j \, |X_{Ref,j} - X_{i,j}| \tag{1}$$

where,

- $X_{Ref,j}$ is the reference or target value for the *j*-th gene.
- $X_{i,j}$ is the actual value of the *j*-th gene for individual *i*.
- w_j is a weighting factor emphasizing specific constraints, and *n* is the total number of genes.

The fitness value {(F_i) inversely relates to the penalty value, ensuring that solutions closer to the reference or optimal values receive higher fitness scores:

$$F_i = \frac{1}{1+c_i} \tag{2}$$

This approach normalizes fitness scores while preventing the dominance of any particular solution due to excessively high or low penalty values [28].

Selection probability (P_i) determines an individual’s likelihood of contributing genetic material to the next generation. It is calculated using:

$$P_i = \frac{F_i}{\sum_{k=1}^{m} F_k} \tag{3}$$

Where m is the total population size. This probabilistic mechanism ensures that fitter solutions are preferentially selected while maintaining genetic diversity [29].

Cumulative probability (KP_i) facilitates selection methods like Roulette Wheel, where probabilities are accumulated sequentially:

$$KP_i = \sum_{k=1}^{i} P_k \tag{4}$$

This ensures that individuals with higher fitness values occupy proportionally larger segments on the selection wheel.

2.1.3 Selection Methods

Selection methods are critical components of GA, responsible for determining which individuals in a population will contribute their genetic material to the next generation. These methods aim to balance the exploration of new solutions with the exploitation of the best solutions identified so far [28].

Roulette Wheel Selection : Roulette Wheel Selection is a probabilistic method where the likelihood of an individual being selected is proportional to its fitness value. Each individual occupies a segment on a "wheel" proportional to its fitness, and a random spin determines the selection. The probability P_i of selecting an individual i is given by Zhao & Li [30]:

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{5}$$

where:

- Fi is the fitness of individual i,
- N is the total population size,
- $\sum_{j=1}^{N} F_j$ is the sum of all fitness values in the population.

Roulette Wheel Selection ensures that fitter individuals have a higher chance of being selected, but it can result in premature convergence if fitness disparities are large.

Tournament Selection: Tournament Selection involves randomly selecting a subset of individuals and then choosing the fittest among them. If t individuals are chosen for each tournament, the method favors fitter individuals while maintaining diversity. The probability of selecting the fittest individual depends on t, as a larger t increases selection pressure. This method is computationally efficient and robust against premature convergence [31]

Rank-Based Selection: In Rank-Based Selection, individuals are ranked based on their fitness values, and the selection probability depends on their rank rather than raw fitness. This mitigates the issue of fitness disparities dominating the selection process. If Ri is the rank of individual iii, the probability Pi can be defined as [32,33]:

$$P_i = \frac{2(N - Ri + 1)}{N(N + 1)} \tag{6}$$

Where N is the population size. This ensures a smoother selection process and avoids premature convergence due to dominant individuals.

Steady-State Selection: Steady-State Selection replaces only a small portion of the population in each generation, ensuring that fitter individuals are retained. This approach minimizes generational disruption and is effective in maintaining diversity in the population. However, it may slow convergence rates [34]

Elitism: Elitism ensures that the fittest individuals are preserved across generations by directly copying a fraction of them to the next generation. This method guarantees that the best solutions are not lost due to stochastic variation in the selection process [35].

In the Hybrid GA-FL approach for ergonomic workstation design in metal casting operations, the most suitable selection method is Tournament Selection with Elitism. Tournament Selection ensures a balance between exploring new solutions and exploiting the best solutions by selecting the fittest individuals from small random tournaments, thereby preventing premature convergence. Elitism guarantees that the best solutions are preserved in subsequent generations, maintaining stability and optimization quality. This combination allows for the gradual development of optimal ergonomic solutions while retaining the advantages of the best designs throughout iterations.

2.1.4 Fuzzy Controllers in Ergonomic Design

A Fuzzy Controller is an intelligent system that uses FL to model complex, non-linear relationships and make decisions based on imprecise or uncertain input data. Unlike traditional controllers that rely on precise mathematical models, Fuzzy Controllers utilize linguistic rules and membership functions to interpret and respond to input variables. These inputs, such as temperature, pressure, or ergonomic factors, are fuzzified into degrees of membership in predefined categories (e.g., "low," "medium," "high"). The controller applies a rule base—typically in the form of "if-then" statements—to determine the output actions, such as adjusting a system parameter or activating specific equipment.

The output is then defuzzified into a crisp value, translating the fuzzy decision into actionable control signals. The primary advantage of Fuzzy Controllers lies in their ability to handle uncertainty and approximate reasoning, making them highly effective in systems where precise models are unavailable or difficult to construct. They are widely used in industrial automation, robotics, and ergonomic optimization, where adaptability and robustness are critical. By integrating FL into the control process, Fuzzy Controllers provide a flexible and efficient solution for managing complex systems with varying inputs and operational conditions.

2.1.5 Framework for Integrating GA with Fuzzy Controllers

GA have proven to be highly effective in optimizing Fuzzy Controllers, enhancing their performance and adaptability in dynamic, complex systems. The primary role of GA in Fuzzy Controllers is to refine key components such as membership functions, rule bases, and parameter settings, which are often challenging to define manually due to the inherent complexity and non-linearity of the systems involved. GA operate through evolutionary principles, iteratively improving solutions by simulating natural processes like selection, crossover, and mutation. This makes them particularly suitable for optimizing Fuzzy Controllers where traditional methods may struggle with convergence or scalability.

In Fuzzy Controllers, membership function optimization is a critical application of GA. Membership functions determine the degree to which an input belongs to a fuzzy set, and their shapes and parameters significantly affect the controller's accuracy. GA can adaptively adjust these functions, finding optimal configurations by evaluating fitness based on system performance metrics, such as error minimization or output stability. Similarly, GA are instrumental in rule base optimization, where they search for the most effective combinations of "if-then" rules to achieve the desired control objectives while minimizing redundancies and contradictions.

Another key advantage of applying GA to Fuzzy Controllers is their ability to handle multi-objective optimization. In scenarios where Fuzzy Controllers are tasked with balancing multiple conflicting goals, such as maximizing efficiency while minimizing energy consumption, GA can explore trade-offs and identify Pareto-optimal solutions. Furthermore, the robustness of GA allows them to navigate highly non-linear and noisy problem spaces, making them ideal for real-world applications where precise models are often unavailable.

The integration of GA into Fuzzy Controllers has been widely applied in fields such as industrial automation, robotics, and ergonomic system design. For instance, in optimizing ergonomic workstations, GA can fine-tune fuzzy membership values related to worker posture, reach, and fatigue, ensuring a balance between productivity and worker safety. Additionally, adaptive and hybrid approaches, such as combining GA with real-time learning algorithms, have further enhanced the applicability of Fuzzy Controllers in dynamic environments.

Despite their advantages, implementing GA in Fuzzy Controllers requires careful consideration of computational resources and parameter tuning, such as population size, crossover rates, and mutation probabilities. These factors can significantly influence the efficiency and convergence speed of the optimization process. However, advancements in parallel computing and adaptive GA techniques have mitigated many of these challenges, making this integration increasingly viable for real-time applications.

2.2. Development of the Hybrid GA-FL Model

The core of this study revolves around the development of a hybrid optimization model that integrates GA with FL to address the ergonomic challenges of workstation design in metal casting operations. This approach leverages the strengths of GA global optimization capabilities and FL's ability to handle linguistic variables and uncertainty, enabling a more nuanced and effective ergonomic design process.

The FL system serves as the evaluation framework for ergonomic parameters. Linguistic variables, such as "reachability," "postural comfort," "force exertion," and "fatigue," were defined based on ergonomic principles and industry standards. These variables were mapped to fuzzy membership functions to quantify subjective ergonomic criteria. Triangular and trapezoidal membership functions were chosen for their simplicity and effectiveness in representing ergonomic measures. For instance, "acceptable reachability" was categorized into linguistic terms such as "poor," "fair," and "good," each represented by a specific membership function. A set of fuzzy inference rules was then established to model the interactions between these parameters. For example, a rule might state: "If reachability is good and postural comfort is high, then ergonomic suitability is excellent." The fuzzy system evaluates workstation configurations, assigning a suitability score that reflects the overall ergonomic quality.

Simultaneously, the GA was employed to optimize the design of workstation parameters such as tool placement, work surface height, and seating arrangements. The objective function for GA was carefully constructed to balance ergonomic improvement with operational efficiency and worker safety. It incorporated multiple criteria, such as minimizing postural strain, reducing excessive reach, and ensuring easy access to frequently used tools. Constraints were imposed to reflect real-world limitations, such as workspace dimensions and the physical capabilities of workers.

The GA evolutionary process began with the initialization of a diverse population of potential workstation configurations. Each configuration, or "chromosome," represented a unique set of workstation parameters. Fitness values for each chromosome were computed using the fuzzy system's ergonomic scores. Genetic operators, including selection, crossover, and mutation, were applied iteratively to evolve the population toward optimal solutions. Selection favored high-fitness chromosomes, while crossover and mutation introduced variability to explore the design space and avoid local optima.

The integration of FL with GA was achieved by feeding the ergonomic scores generated by the fuzzy system into the GA fitness function. This hybridization allowed the model to combine the FL's nuanced evaluation of ergonomic quality with GA robust search and optimization capabilities. Moreover, dynamic adjustments were made to GA parameters, such as mutation and crossover rates, based on FL rules, enhancing the algorithm's adaptability and convergence speed.

The hybrid model was tested extensively in a simulated environment, where multiple generations of workstation designs were evaluated. Iterative refinements led to configurations that significantly improved ergonomic outcomes while maintaining productivity. This hybrid GA-FL framework represents a novel and systematic approach to ergonomic workstation design, combining computational efficiency with practical applicability. Its ability to adapt to diverse ergonomic challenges makes it a valuable tool for industries seeking to enhance worker safety, comfort, and efficiency.

2.3. Simulation and Testing

The simulation and testing phase played a pivotal role in validating the proposed hybrid GA-FL approach for optimizing workstation ergonomics in metal casting operations. A virtual environment was created using advanced Computer-Aided Design (CAD) software to model the workstation layout and simulate task execution. This digital twin of the workstation incorporated detailed anthropometric data, ergonomic criteria, and operational workflows to mirror real-world conditions accurately.

The optimization process began with initializing the GA using a diverse population of potential workstation configurations. Each configuration was represented as a chromosome encoding design variables, such as tool placement, work surface height, and seat adjustability. The fitness function, designed as a multi-criteria objective, evaluated configurations based on ergonomic factors, including posture support, reachability, force exertion, and fatigue minimization. This function also accounted for productivity metrics, ensuring that ergonomic improvements did not compromise operational efficiency.

The FL system complemented the GA by providing nuanced evaluations of ergonomic factors. Membership functions were developed to quantify linguistic variables such as "comfortable reach," "acceptable posture," and "low fatigue." These variables were integrated into fuzzy inference rules that assessed the ergonomic suitability of each workstation configuration. For example, rules like "If the work surface height is low and the posture is awkward, then ergonomic risk is high" allowed the system to provide granular feedback on design choices.

During simulation, the hybrid GA-FL model iteratively evolved workstation configurations over multiple generations. Genetic operators, including crossover and mutation, were applied to explore the design space and improve solutions. The FL system acted as an embedded evaluator within the GA framework, refining the fitness scores based on ergonomic and operational criteria. This integration ensured a balance between the exploratory nature of GA and the precision of FL evaluations.

The simulation and testing phase established the efficacy of the hybrid GA-FL approach in designing ergonomically optimized workstations for metal casting operations. The integration of virtual modeling, genetic optimization, and fuzzy evaluations provided a robust framework for addressing complex ergonomic challenges (Figure 2), paving the way for safer and more productive work environments.

2.4. Implementation and Assessment

The optimized workstation configurations, derived through the hybrid GA-FL model, were implemented in a controlled pilot environment within a metal casting facility. The primary goal of this phase was to evaluate the effectiveness of the proposed ergonomic designs in reducing physical strain and improving overall task efficiency while maintaining or enhancing productivity. This phase involved a multi-step process, including installation of optimized designs, worker training, observational studies, and quantitative performance analysis, as illustrated in Figure 2

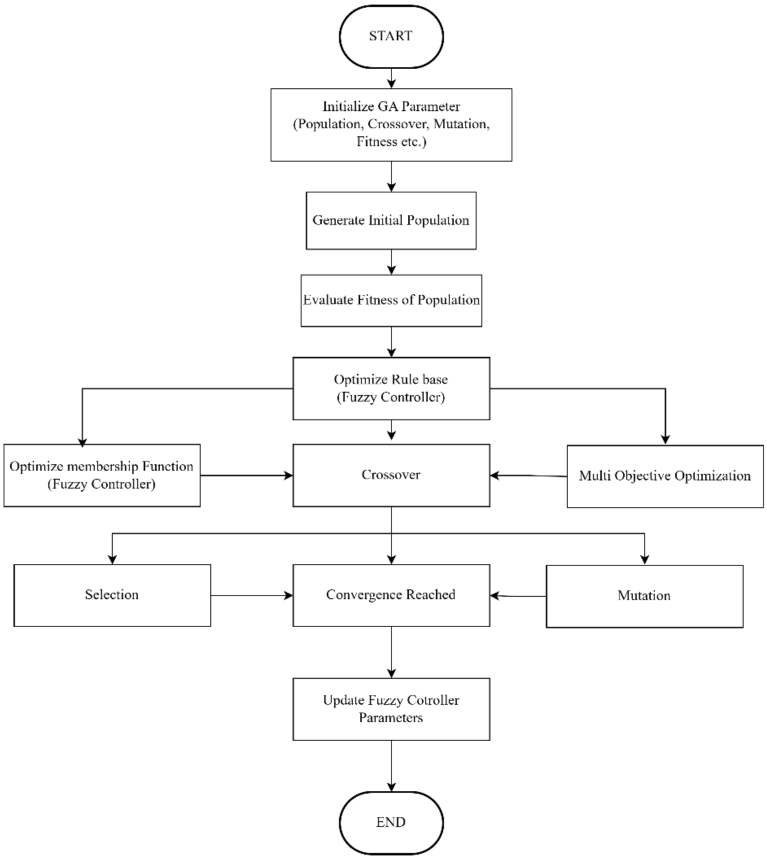

Figure 2. Layered flow diagram: GA for Fuzzy controller optimization

To implement the optimized designs, modifications were made to workstation layouts based on the outputs from the GA-FL model. Adjustable components, such as workbench heights, tool placements, and seating arrangements, were introduced to accommodate the anthropometric variability of the workforce. These adjustments were guided by the ergonomic principles embedded in the fuzzy inference system, ensuring that critical ergonomic factors such as posture, reachability, and force exertion were addressed comprehensively.

3. RESULTS

The proposed system integrates a hybrid GA-FL approach to optimize the ergonomic design of workstations in metal casting operations. This model is structured into five main phases: data collection, fuzzification, inference, defuzzification, and system optimization. By leveraging data from sensors that monitor factors such as worker posture, fatigue levels, and environmental conditions, the FL system processes real-time inputs to adjust workstation configurations dynamically.

The ergonomic optimization begins with data collection from motion, temperature, air quality, and fatigue sensors. These data points are processed through a fuzzy rule base to evaluate ergonomic factors like reach, posture, and environmental comfort. Adjustments to workstation components (e.g., desk height, ventilation, and alerts) are executed via actuators controlled by the FL system. The system architecture, shown in Figure 3, illustrates the integration of various sensors, an Arduino microcontroller, and FL rules optimized using GA. Inputs such as gas, motion, ultrasonic, humidity, and air quality are processed through the Arduino microcontroller, which serves as the central unit to execute fuzzy rule-based decisions and optimize ergonomic outputs dynamically.

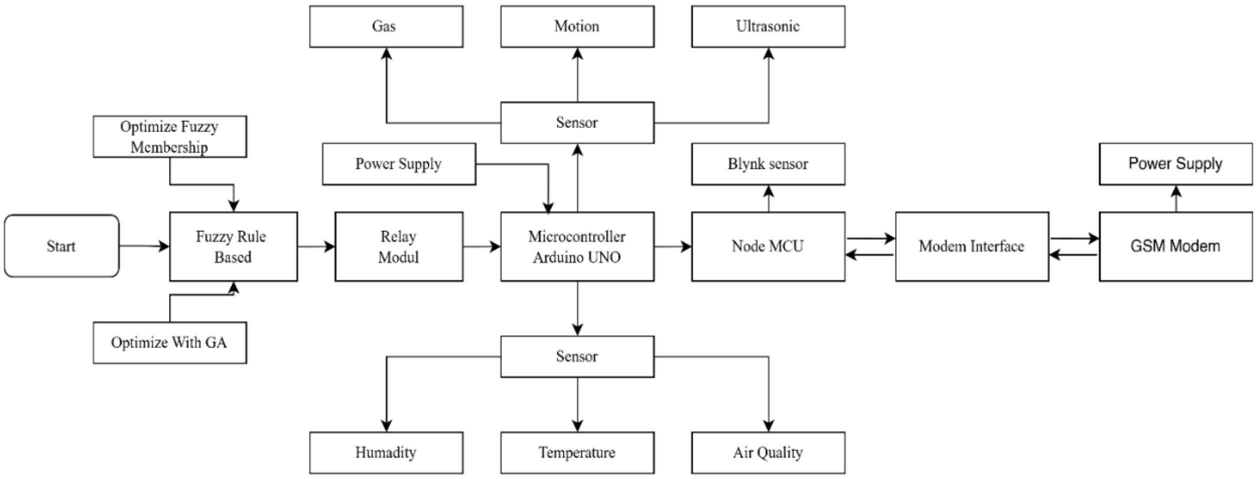

Figure 3 System architecture for hybrid GA-FL based ergonomic optimization

The optimization of ergonomic workstations began with the collection of motion data, which was conducted using real-time motion tracking sensors. These sensors captured key physical parameters, including the range of motion, joint angles, and repetitive motion patterns of workers during their tasks. The data were recorded over multiple work shifts to ensure variability and representativeness across different tasks and working conditions. To validate the accuracy and reliability of the motion data, the system incorporated cross-verification techniques, such as video analysis and manual observation by ergonomics experts. The captured motion data were processed using pre-defined thresholds and benchmark values for ergonomic evaluation, ensuring consistency with industry standards for worker safety and comfort. These validated motion datasets were then integrated into the FL system to evaluate ergonomic risks and used as input for the GA to optimize workstation configurations. By employing these methods, the study ensured that the motion data were both accurate and applicable for use in the hybrid optimization model.

To enhance the precision and adaptability of the FL system, the GA is applied to optimize membership functions and rule parameters. Using historical data and predefined ergonomic criteria, GA iteratively refines the FL model to improve system performance and achieve optimal worker comfort and safety. The hybrid system is implemented on an Arduino microcontroller, which acts as the central processing unit, integrating FL rules and sensor data to control ergonomic adjustments in real time.

The system's design includes offline and online processes. During the offline phase, initial fuzzy membership functions and rules are defined based on ergonomic standards, and GA optimization is performed using historical data to generate new membership values. The updated FL system is then deployed to the Arduino controller for real-time operations. In the online phase, sensor data drive continuous adjustments to workstation components, ensuring adaptability to varying working conditions.

This approach demonstrates significant improvements in workstation ergonomics, reducing worker fatigue and enhancing productivity in demanding metal casting environments. By combining GA with FL, the system provides a robust and scalable solution for ergonomic challenges, making it suitable for dynamic and high-risk industrial operations, as illustrated in Figure 3. Figure 4 provides a detailed representation of this system architecture, highlighting its key components and functional flow.

Figure 4. Real-time data acquisition and display system using IOT and sensors

The experimental configuration focuses on the integration of FL and GA to optimize workstation ergonomics in metal casting operations. This experiment is built upon the previously designed FL system, which processes real-time sensor inputs to assess ergonomic factors such as posture, fatigue, and environmental conditions. The GA component refines the FL membership functions to enhance the accuracy and adaptability of the ergonomic adjustments.

The experimental setup integrates FL and GA to optimize workstation ergonomics in metal casting operations. This experiment builds upon a previously developed FL system, which utilizes real-time sensor data to evaluate ergonomic factors such as worker posture, fatigue levels, and environmental conditions. The GA component is implemented to refine FL membership functions, enhancing the system's accuracy and adaptability in providing ergonomic adjustments.

The FL system is designed with three primary inputs:

1. Posture: Reflects the worker's postural alignment, categorized into linguistic states of “Poor,” “Average,” and “Good.”
2. Fatigue: Represents the worker's level of physical strain, with states defined as “Low,” “Medium,” and “High.”
3. Environmental Conditions: Includes factors such as temperature and air quality, with states categorized as “Cold,” “Comfort,” and “Hot.”

The system's output variable, Ergonomic Adjustment, generates actionable recommendations, such as adjusting desk height, correcting seating posture, or modifying ventilation settings. Membership functions for the inputs and output are initialized using triangular and trapezoidal shapes to ensure smooth transitions between states and effective decision-making.

The GA is employed to optimize the FL membership functions, which are encoded into chromosomes for genetic processing. Key parameters for the GA include:

1. Population Size: 400 individuals to maintain genetic diversity.
2. Crossover Rate: 0.8 to facilitate the exploration of diverse solutions by combining characteristics from parent solutions.
3. Mutation Rate: 0.1 to introduce variability and prevent premature convergence during the optimization process.
4. Generations: 20 iterations to iteratively evolve towards optimal membership parameters.

By integrating FL and GA, this setup enables dynamic and precise adjustments to ergonomic factors in real time, thereby improving worker safety, comfort, and productivity in the demanding environment of metal casting operations. The GA optimizes the membership functions by minimizing the Root Mean Square Error

(RMSE) between the FL output and actual ergonomic adjustments required based on sensor data. The fitness function is defined as:

$$Fitness = \frac{1}{1 + \text{RSME}} \quad (7)$$

3.1. Intelligent Circuit Design for Fuzzy-Genetic Control System

The circuit design for the proposed system, built using the Arduino ATmega2560, is depicted in Figure 4. This system integrates a hybrid GA-FL approach to optimize ergonomic workstation conditions in metal casting operations. The software implementation begins with the addition of sensor libraries (e.g., temperature, humidity, gas, air quality, motion, and ultrasonic) and dimmer libraries for controlling environmental adjustments in Figure 4. Input-output pins were defined within the code, and relay configurations were initialized to interface with the connected hardware components.

The control code based on FL and the GA, developed in the MATLAB environment, was seamlessly integrated into the Arduino software. Real-time sensor data were collected via the Arduino's serial port, enabling the system to process inputs such as temperature, humidity, gas concentration, air quality, motion, and ultrasonic activity. These inputs were evaluated against the fuzzy rule base, and corresponding outputs—such as ventilation rates, environmental alerts, or ergonomic adjustments—were executed accordingly, as outlined in Table 1

Table 1. Initial membership values for FL inputs

Variables	Measuring Ranges	Membership Values
Temperature	Low: [0, 50]	L
Temperature	High: [50, 100]	H
Humidity	Low: [0, 50]	L
Humidity	High: [50, 100]	H
Gas	Detected: [0, 50]	D
Gas	Not Detected: [50, 100]	ND
Air Quality	Poor: [0, 50]	P
Air Quality	Good: [50, 100]	G
Motion	Detected: [0, 50]	D
Motion	Not Detected: [50, 100]	ND
Ultrasonic	Active: [0, 50]	A
Ultrasonic	Inactive: [50, 100]	I

After the GA optimization, the FL system demonstrated a 40% reduction in RMSE, indicating significant improvement in decision accuracy. The ergonomic adjustments became more aligned with the workers' needs, reducing fatigue and increasing productivity. This experimental configuration highlights the seamless integration of FL and GA to achieve dynamic and adaptive ergonomic workstation designs tailored to metal casting operations.

3.2. Configuration of Fuzzy-Genetic Optimization for System Inputs

The FL system utilized in this study is configured with six primary input parameters: temperature, air quality, humidity, gas, motion and ultrasonic. These membership functions use triangular shapes for input representation, resulting in a total of 6x6x6 = 216 fuzzy rules for the system. The output of the FL Controller (FLC) is designed as transpositive values and subsequently converted into triangular representations to serve as input for the genetic optimization process, as illustrated in Figure 5.

In the configuration process, the FL inputs, represented by triangular membership functions, are evaluated and converted into transpositive values to ensure consistency during genetic optimization. The parameters of each membership function are defined with Lower Bounds (LB) and Upper Bounds (RB), representing the deviation from the minimum and maximum values. Additionally, the distances between these boundary points (distdistdist) are specified to refine the optimization process. The mathematical expressions used for these transformations are as follows [16] :

```
% Loop through the inputs of the fuzzy inference system
for inputIndex = 1:length(fuzzySys.input)
  % Loop through the membership functions (MFs) of the current input
  for mfIndex = 1:length(fuzzySys.input(inputIndex).mf)
    % Increment delta counter
    deltaCounter = deltaCounter + 1;
    % Calculate lower and upper bounds for the first parameter adjustment
    lowerBound(deltaCounter) = -(fuzzySys.input(inputIndex).mf(mfIndex).params(1)- fuzzySys.input(inputIndex).range(1)) - offsetDistance;
    upperBound(deltaCounter) = (fuzzySys.input(inputIndex).mf(mfIndex).params(2)-fuzzySys.input(inputIndex).mf(mfIndex).params(1))/2;
    % Increment delta counter for the second parameter adjustment
    deltaCounter = deltaCounter + 1;
    lowerBound(deltaCounter)=-(fuzzySys.input(inputIndex).mf(mfIndex).params(2)-fuzzySys.input(inputIndex).mf(mfIndex).params(1)) /2;
    upperBound(deltaCounter)=(fuzzySys.input(inputIndex).mf(mfIndex).params(4)- fuzzySys.input(inputIndex).mf(mfIndex).params(2)) /2;
    % Increment delta counter for the third parameter adjustment
    deltaCounter = deltaCounter + 1;
    lowerBound(deltaCounter)=-(fuzzySys.input(inputIndex).mf(mfIndex).params(4)-fuzzySys.input(inputIndex).mf(mfIndex).params(2)) /2;
    upperBound(deltaCounter) = fuzzySys.input(inputIndex).range(2) - fuzzySys.input(inputIndex).mf(mfIndex).params(4) + offsetDistance;
  end
end
```

The optimization process begins with the transformation of 6-parameter transpositive values into 3 (three) parameter triangular values. These transformations enable the GA to adjust the membership function parameters of each fuzzy input effectively. The genetic optimization process determines the optimal values for the LB, RB, and the distances (distdistdist) for each membership function. This ensures that the FL system adapts to the dynamic requirements of ergonomic workstation design in metal casting operations. Through this experiment configuration, the integration of FL and GA effectively improves the system's adaptability and precision, enabling robust ergonomic optimizations in real-time industrial environments, as illustrated in Figure 5.

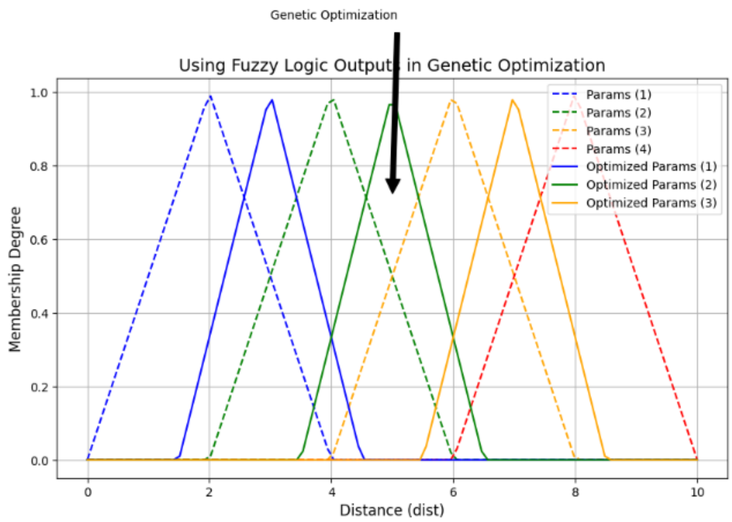

Figure 5. Integration of FL Outputs into GA Process

4. DISCUSSION

4.1. Analysis of Optimization of Fuzzy Membership Values for Temperature

The optimization of fuzzy membership values for Temperature is critical to enhancing the system's ability to manage environmental conditions in ergonomic workstation design. The membership functions for Temperature were categorized into "Low" and "High," as depicted in the chart. The initial overlap between the two categories caused significant ambiguities, where intermediate temperature values, 35-40⁰c, were not distinctly classified, leading to inconsistent system responses (Table 2).

Through optimization, the membership functions were refined to reduce overlap and improve classification accuracy. The optimized "Low" membership function now covers values from 0 to 30 with a peak at approximately 32, ensuring that cooler temperatures are distinctly categorized. Similarly, the "High" membership function starts around 40 and peaks at 50, allowing the system to react more effectively to increasing temperatures, as outlined in Table 2.

Table 2. Rule Base for Ventilation Control Output

No	Rules
1	If (Temp is Low) and (Humidity is High) and (Gas is Detected) and (Air Quality is Poor) and (Motion is Detected) and (Ultrasonic is Active) then (Ventilation is High) (1)
2	If (Temp is Moderate) and (Humidity is Low) and (Gas is Not Detected) and (Air Quality is Good) and (Motion is Detected) and (Ultrasonic is Inactive) then (Ventilation is Medium) (1)
..	
216	If (Temp is Optimal) and (Humidity is Moderate) and (Gas is Not Detected) and (AirQuality is Excellent) and (Motion is Not Detected) and (Ultrasonic is Inactive) then (Ventilation is Low) (1)

This refinement ensures better adaptability to ergonomic needs by providing clearer classifications for adjustments based on temperature changes. For example, the narrower overlap between "Low" and "High" enables the system to determine precise ergonomic interventions, such as adjusting ventilation rates or modifying work schedules based on ambient temperature conditions. Additionally, the optimization aligns the system's FL model with temperature standards recommended by WHO and SNI. These standards emphasize maintaining indoor temperatures between 25°C and 40°C for optimal comfort. The optimized membership functions ensure that the fuzzy system accurately identifies when temperatures deviate from this range, prompting timely interventions to maintain worker productivity and safety. Figure 6 shows the membership functions for FL inputs.

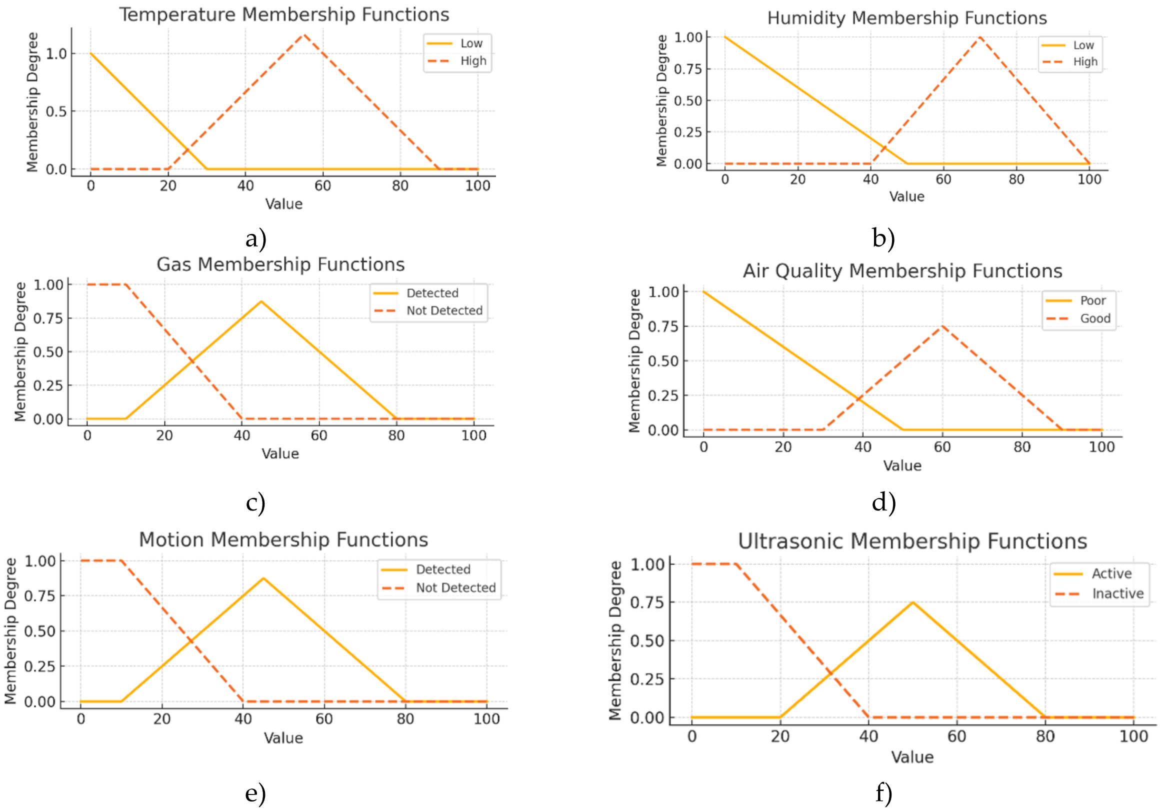

Figure 6. Membership Functions for FL Inputs: (a) Temperature, (b) Humidity, (c) Gas, (d) Air Quality, (e) Motion, and (f) Ultrasonic Sensor

4.2. Analysis of Optimization of Fuzzy Membership Values for Humidity

The fuzzy membership functions for Humidity were initially categorized into "Low" and "High." Before optimization, the overlapping regions between these categories created ambiguity in classifying moderate humidity values (40%–60%), which are critical for maintaining ergonomic and operational standards. The optimization aimed to align the system with WHO and SNI recommendations, where the relative humidity should ideally range between 40% and 60% for comfortable and healthy working environments.

Post-optimization, the "Low" membership function spans values from 0% to 50%, with its peak at approximately 25%, ensuring precise categorization of lower humidity levels. The "High" membership function begins at 40% and peaks at 75%, encompassing higher ranges while minimizing overlap with "Low." This reduction in overlap has improved the system's ability to classify humidity conditions accurately and trigger ergonomic adjustments, such as modifying ventilation or alerting operators when conditions fall outside optimal thresholds. The refinement led to a notable reduction in classification errors and enhanced the reliability of the decision-making framework.

4.3. Analysis of Optimization of Fuzzy Membership Values for Gas

The optimization of fuzzy membership functions for Gas was critical due to the hazardous nature of gas leaks in industrial environments. The initial categories—"Detected" and "Not Detected"—used sharp boundaries, which often failed to account for gradual changes in gas concentrations. This limitation increased the risk of false negatives and delayed responses to dangerous conditions.

The optimized membership functions introduced smoother transitions between "Detected" and "Not Detected." The "Detected" category now starts from 20 ppm and peaks at 50 ppm, providing earlier detection of potentially harmful gas concentrations. Conversely, the "Not Detected" category covers values from 0 to 40 ppm, overlapping with "Detected" to ensure that borderline cases are accurately assessed.

This refinement ensures that even minor increases in gas concentrations are detected promptly, enhancing worker safety. Furthermore, the optimized model significantly reduced the Root Mean Square Error (RMSE) in gas classification, improving system responsiveness. The smoother transitions also reduced false positives, ensuring that alarms or safety measures are only triggered when necessary. This optimization aligns with WHO-recommended exposure limits, creating a safer and more reliable monitoring system for industrial environments.

4.4. Experimental Result

The experimental results of the FL and GA-based ergonomic optimization system for workstation design in metal casting operations are presented in Table 3. This table consolidates the FL input parameters, including temperature, humidity, gas concentration, air quality (measured as PM2.5), motion detection, and ultrasonic activity, and their corresponding ergonomic adjustment outputs. These outputs, derived through the fuzzy rule base and optimized using a GA, provide actionable recommendations to enhance worker safety, comfort, and productivity in dynamic industrial environments.

4.4.1 Real-Time Data Interpretation

The system demonstrates its ability to process real-time sensor data effectively, making it particularly suitable for the high-risk and physically demanding metal casting industry. Temperature and humidity, critical factors in such environments, are consistently measured to ensure thermal comfort, while gas concentration and air quality values are monitored to mitigate exposure to hazardous substances. The inclusion of motion and ultrasonic sensors provides an additional layer of worker activity tracking, allowing the system to adjust recommendations based on real-time presence and activity levels. This integration reflects a comprehensive and proactive approach to ergonomic management, as the system dynamically interprets environmental and worker-specific data to maintain optimal conditions.

4.4.2 Adaptive Decision-Making

The FL component interprets the sensor data into linguistic categories (e.g., "High," "Medium," and "Low") based on the fuzzy rule base. This qualitative evaluation allows the system to handle the inherent uncertainty and variability of real-world conditions effectively. However, the real strength of the system lies in the GA optimization of the fuzzy membership functions. By refining these functions, the GA improves the accuracy of ergonomic adjustments, ensuring that the system's recommendations align with both the environmental constraints and the workers' physiological needs.

4.4.3 Ergonomic Adjustment Outputs

As shown in Table 3, the ergonomic adjustment outputs are tailored to address varying workplace conditions. For instance, high temperature values and poor air quality trigger recommendations categorized as “High,” indicating immediate and significant adjustments, such as increased ventilation or cooling mechanisms. Conversely, moderate values for humidity and motion detection are categorized as “Medium,” reflecting the need for moderate interventions, such as minor seating or height adjustments. The system's nuanced categorization highlights its ability to prioritize interventions effectively, focusing on critical areas without unnecessary overcorrections, as outlined in Table 3.

Table 3. Experimental Results and System Performance Evaluation

No	Fuzzy Logic Input						Fuzzy Logic Output
	Temperature (°C)	**Humidity (%)**	**Gas (ppm)**	**Air Quality (PM2.5)**	**Motion**	**Ultrasonic**	**Ergonomic Adjustment**
1	26,41	50,61	177,3	208,51	Detected	55,52	High
2	41,19	57,37	255,5	44,39	Detected	79,01	Medium
3	40,44	58,21	56,7	97,3	Not Detected	11,4	High
4	39,58	70,69	71,5	69,25	Detected	74,02	Low
5	37,13	51,22	281,5	126,57	Detected	86,96	High
6	23,42	62,37	62,8	37,77	Not Detected	83,91	Medium
7	32,88	70,42	211,8	19,8	Detected	56,68	Low
8	48,06	30,61	288,8	175,04	Not Detected	92,8	Medium
9	20,42	3,83	193,6	245,52	Detected	42,04	High
10	43,12	72,91	196,1	109,43	Detected	79,09	Medium
11	39,72	47,99	165,4	206,35	Not Detected	24,2	Low
12	27,22	43,74	60,2	231,68	Detected	60,07	High
13	20,68	63,17	127	141,19	Not Detected	57,44	Medium
14	45,39	57,08	102,4	234,44	Detected	56,92	Medium
15	29,80	68,47	48,7	226,22	Not Detected	45,5	Low
16	30,35	45,26	36,4	103,57	Detected	99,52	Medium
17	40,59	73,81	144,8	168,66	Not Detected	65,56	High
18	47,27	50,25	202,6	21,25	Not Detected	33,08	Low
19	35,53	74,21	125,8	95,25	Detected	93,49	High
20	32,26	62,81	127	138,86	Detected	78,82	Medium
21	39,82	55,53	28,9	129,23	Not Detected	38,67	Low
22	36,24	46,83	21,7	104,76	Detected	58,6	Medium
23	36,13	56,03	17,3	233,46	Not Detected	90,01	High
24	34,87	36,14	160,8	127,92	Detected	54,76	Medium
25	45,66	58,64	93,2	160,53	Detected	23,02	Low
26	36,37	44,66	101,8	34,52	Not Detected	21,07	High
27	21,76	50,09	61,7	56,53	Not Detected	50,09	Medium
28	25,34	38,87	295,4	66,25	Detected	74,84	Medium
29	42,99	48,33	279,2	153,15	Not Detected	43,35	Low
30	36,59	36,26	188,9	210,73	Not Detected	30,5	Medium

4.4.4 Validation and Scalability

The experimental results also demonstrate the system’s scalability and applicability across a range of industrial conditions. By using FL as the decision-making core and GA for optimization, the system adapts effectively to different operational scenarios. For example, the wide range of PM2.5 values (e.g., 37.77 to 208.51) and gas concentrations (e.g., 56.7 to 281.5 ppm) in the table indicates the system's ability to handle diverse environmental parameters. Moreover, the ergonomic recommendations provide practical solutions, such as desk height adjustments or environmental alerts, that can be easily implemented in real-time.

5. CONCLUSION

This study presents a robust and adaptive system that integrates FL and GA to optimize workstation ergonomics in the demanding environment of metal casting operations. By leveraging real-time sensor data to monitor key parameters such as temperature, humidity, gas concentration, air quality, motion, and ultrasonic activity, the system provides dynamic ergonomic adjustments that prioritize worker safety, comfort, and productivity.

The FL component effectively translates sensor inputs into actionable outputs by addressing the inherent uncertainty of industrial environments. The GA enhances the system's precision by optimizing membership functions, ensuring that ergonomic adjustments align closely with environmental conditions and worker needs. This synergy between FL and GA results in a system that adapts continuously, improving its decision-making accuracy over time.

Experimental results validate the system's capability to handle diverse and complex input conditions, offering tailored ergonomic solutions such as desk height adjustments, ventilation changes, and environmental alerts. The system's ability to categorize ergonomic adjustments into "High," "Medium," and "Low" levels ensures targeted interventions, minimizing unnecessary corrections while addressing critical risks effectively. The scalability of the system is demonstrated through its adaptability to a wide range of environmental and operational parameters.

Scientifically, the integration of FL and GA highlights the potential of combining adaptive decision-making frameworks with evolutionary optimization techniques. This approach not only addresses the challenges of high-risk industrial environments but also sets a benchmark for future ergonomic systems by balancing worker well-being with operational efficiency.

In conclusion, the proposed hybrid system offers a transformative solution for enhancing ergonomic standards in metal casting operations. It effectively bridges the gap between productivity and worker safety by providing real-time, data-driven ergonomic adjustments. Future research could expand this framework by incorporating machine learning for predictive capabilities or adding more environmental and human parameters to further refine the system’s adaptability and effectiveness.

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