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Research Article

Construction site safety and quality analysis utilizing KHNN Model

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Abstract

Improving construction site safety through effective hazard identification and mitigation is critical. This study aims to predict rework, defects, and associated costs using artificial neural networks and optimization algorithms. Traditional safety planning approaches lack pre-construction hazard analysis. To examine deficiencies, various metrics were analyzed, including rework costs per $1M scope and injury rates. Ineffective safety practices like inadequate training and protection have led to accidents. This work identifies approaches to enhance worker safety performance through hazard identification. Inputs to a neural network model predict rework workers, defects, and costs. Safety execution aims to systematically identify hazards before construction. Model performance using actual data was evaluated. Two soft computing methods - artificial neural network and optimization algorithms - were implemented in MATLAB. Krill herd and grey wolf optimization techniques optimized hidden neuron weights in the neural network structure. Predictions from these algorithms outperformed other existing methods like particle swarm and genetic algorithms. This study provides a framework to quantitatively forecast rework, defects, and associated costs through systematic pre-construction hazard analysis and modeling. The proposed optimization-enhanced neural network models can help construction managers implement targeted safety improvements.

Keywords: *Krill Herd Neural Network, Particle Swarm Optimization, Grey Wolf Optimization, Work Health and Safety, Artificial Neural Network*

Introduction

The construction industry plays a vital role in the economic and safety development of any country. However, it is also known to have high rates of accidents, injuries, and fatalities which rank it as one of the most dangerous industries (Zhou et al., 2015). Ensuring safety and quality as well as understanding the causes and types of accidents on construction sites is important. Additionally, soft computing approaches can help in predicting performance parameters. Safety and quality management are two important aspects of the construction industry. Safety management aims to identify risks and reduce accidents to improve site efficiency (Wu et al., 2015).

This research aims to understand safety and quality issues in construction and how to mitigate accidents and enhance productivity. Traditional safety management involves a top-down approach with minimal worker involvement and focuses on technical compliance (Todd et al., 2006).

Soft computing techniques like artificial neural networks (ANN), genetic algorithms, fuzzy logic, and support vector machines can help predict performance parameters like injury rates, rework, and defects (Zhang et al., 2014; Vu et al., 2016). Optimization algorithms can then find optimal neuron weights for improved prediction (Xinning et al., 2010).

The objectives of this research are to (1) identify causes of construction accidents and assess worker safety, (2) understand factors influencing quality and recommend approaches to improve worker quality, and (3) use optimization techniques to predict safety parameters like rework workers and defects. A literature review is conducted to understand existing methodologies. Survey data is collected and ANN with optimization algorithms like krill herd and grey wolf is proposed for prediction. The results are analyzed and compared with existing models.

In summary, this research aims to analyze safety and quality issues in construction and propose a soft computing approach integrated with optimization techniques to predict key performance parameters for improved safety and quality management. A literature review, problem definition, research methodology, results and analysis, and conclusion are presented.

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Construction is considered as one of the most hazardous industries globally, with high rates of accidents and injuries (Haslam et al., 2005). Fall from heights, being struck by moving objects, collapse of structures, and trench failures are common types of accidents on construction sites (Hinze et al., 2013). Zhou et al. (2015) analyzed accident reports from 250 construction sites in China over 5 years and found fall accidents accounted for 35% of total accidents, followed by being struck at 24%.

Traditional safety management practices focus on compliance through inspections, safety training, and the use of personal protective equipment (Teo et al., 2005). However, Hinze et al. (2013) argued a top-down approach alone is insufficient and worker involvement is critical. Researchers have suggested integrating safety into design to reduce risks during construction (Teo and Ling, 2006). Safety culture, leadership commitment, and communication are other aspects emphasized for effective safety management (Tam et al., 2004; Wu et al., 2008).

Issues affecting quality in construction include design changes, inadequate planning, lack of skilled workforce, and ineffective communication (Love et al., 1998). Rework due to defects and errors increases project time and cost significantly (Love, 2002). Akintoye (2000) identified factors influencing rework as incomplete design, insufficient supervision, and lack of coordination between trades. Makul et al. (2014) found quality problems are interrelated with safety issues on sites.

Many researchers have suggested incorporating quality checks, increasing supervision, strict material quality control, worker training, and integrating quality into a design for improved management (Love et al., 2002; Abd Rahim et al., 2016). Quality function deployment is one approach used for linking design quality to construction quality (Akintoye, 2000). Statistical process control techniques have also been applied for quality control and assurance (Kaming et al., 1997).

Data-driven soft computing techniques can help address complex, non-linear relationships involved in construction performance prediction (Zhang et al., 2016). Artificial neural networks (ANN) have been widely used for modeling construction productivity, project duration, defects, and safety performance (Moselhi et al., 1991; Vinesh and Udayakumar, 2014). Genetic algorithms are effective optimization techniques employed with ANN for parameter optimization (Zayed and Halpin, 2001).

Fuzzy logic has found applications in decision-making, risk assessment, and construction management (Zheng et al., 2004). Research has also explored integrating ANN with fuzzy logic to improve prediction accuracy (Tah and Carr, 2000). Support vector machines (SVM) have emerged as a powerful tool and have been adopted in areas such as cost estimation, crane operation, and structural health monitoring (Son and Kim, 2009; Kim et al., 2007).

While safety and quality management practices have improved traditionally, soft computing and data-driven techniques provide new opportunities for predictive modeling to enhance performance in the construction industry. This research aims to apply such approaches for predicting key safety and quality parameters.

Methodology in construction site

Health and safety are critical in construction due to high occupational risks. Addressing safety issues through various means can enhance protection. This research examined injury rates and prevention by investigating the relationship between safety and quality performance using predictive modeling. An ANN-optimization approach accurately predicted key metrics. Results demonstrated integrating soft computing with algorithms like krill herd optimization to assess construction processes and impacts, as represented in Fig. 1. This provides insights for effectively managing risks and improving construction safety.

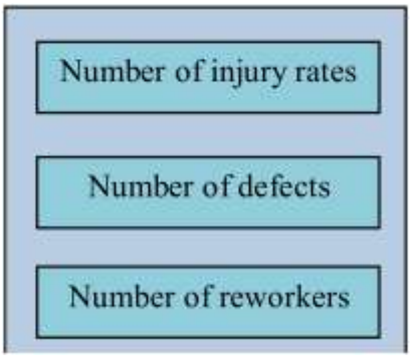

Fig. 1 Analyzed parameter

Quality performance in construction site

Quality and safety management are important concerns in construction. The integration of these systems can reduce variability and costs by limiting component failures, rework, and injuries. Previous research shows such an integrated approach can improve productivity, health, and safety while limiting overruns. This study assessed the relationship between quality and safety performance through predictive modeling, demonstrating opportunities to optimize project outcomes by effectively combining these critical management functions.

Safety management

Safety management is crucial to prevent injuries, reduce costs, and improve the quality of construction projects. Most accidents are preventable through effective safety programs. However, not all firms implement safety due to misconceptions about productivity versus safety. In reality, research shows good safety performance is compatible with high efficiency. Furthermore, management style and pressure on workers can impact safety and productivity. While injuries temporarily reduce crew performance, integrated safety systems ultimately benefit projects by limiting disruptions from accidents. This study analyzed relationships between key safety and quality metrics to provide insights for optimal construction management.

Safety methods

Improving construction safety is a complex task that requires a holistic safety approach. This requires employers to use the following methods:

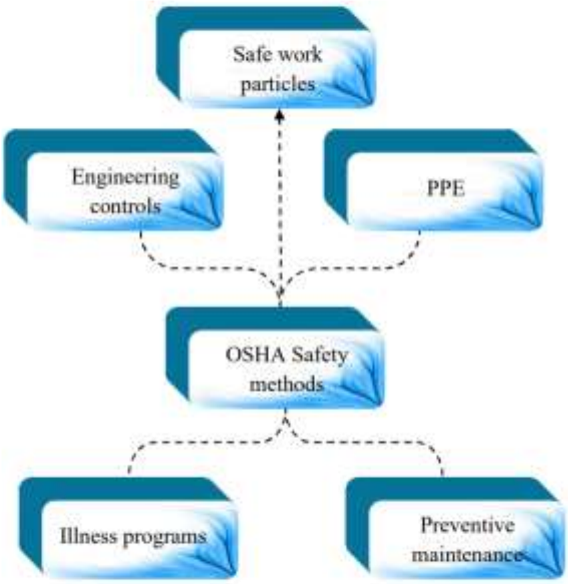

Fig. 2 OSHA

Prevention of accidents in construction Sites

According to the Occupational Safety and Health Administration (OSHA), construction work fatalities account for one in five occupational deaths, highlighting the need for thorough safety and health programs. This research developed predictive models integrating soft computing techniques to examine relationships between various safety and quality metrics. Findings confirm a link between these performance indicators and demonstrate how such integrated approaches can optimize construction management outcomes. By accurately predicting key parameters, organizations can proactively implement mitigation measures to reduce risks. Presenting data-driven insights in this manner provides value for project managers seeking to fulfill their duty of ensuring worker well-being according to regulatory standards. With a continued focus on safety system improvements through technologies like those explored here, the construction industry can make progress toward OSHA's goal of lessening the unacceptable risk faced by workers daily.

Fig. 3 prevention of hazards

This study developed an ANN approach optimized through various techniques to predict injury rates, quality, and other metrics, as represented in Fig. 4. The aim was to distinguish and control hazards to achieve safe construction sites. Optimization assisted in obtaining optimal weights and minimizing error in the ANN model. This research demonstrates the potential of data-driven techniques integrated with soft computing for construction safety management and performance improvement through more accurate predictive capabilities.

Fig. 4 A proposed methodology for construction site safety

Sample size and sampling technique

A questionnaire survey was conducted among 30 engineering professionals from construction organizations in India. Respondents included safety engineers, planning engineers, project managers, and consultants. Questions were explained to ensure accurate responses. Data were collected on 30 construction projects located in India through questionnaires to assess relationships between safety and quality metrics. Project stakeholders provided opinions on performance and management strategies. A variety of project types with scopes from $1-10 million were represented. Data gathering provided insights into predictive modeling approaches for optimizing safety and quality outcomes.

Injury rate

- INJ1—OSHA recordable injury rate (OSHA recordable injuries per 200,000 worker-hours); (Results in death, days away from work, restricted work or transfer to another job, medical treatment beyond first aid, or loss of consciousness) and

- INJ2—First-aid injury rate (First-aid injuries per 200,000 workers) one-time treatment and subsequent observation of minor injuries such as cleaning wounds on the skin surface; applying bandages; flushing an eye; or drinking fluids to relieve heat stress

Level of Quality

- Q1—Number of defects per $1 million project scope completed;
- Q2—Number of defects per 200,000 worker hours;
- Q3—Cost of rework per $1 million project scope completed;
- Q4—Cost of rework per 200,000 worker hours;
- Q5—Number of worker hours spent on rework per $1 million project scope completed;
- Q6—Number of worker hours related to rework per 200,000 worker hours

Artificial Neural Network (ANN)

An ANN in Fig. 5, comprises an input layer, an output layer, and one or more hidden layers. Data flows through the network from input to output nodes via connections weighted to identify patterns. During training, backpropagation optimizes weights between layers to minimize error. ANNs are well-suited for nonlinear applications like estimation, optimization, and recognition. The multilayer structure allows self-organized learning from both unlabeled and labeled datasets according to input similarities and classifications. This research leverages ANN capabilities for predictive modeling and insights into construction safety and quality management.

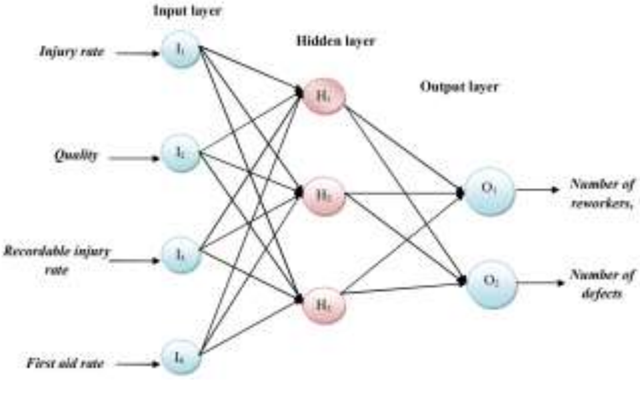

Fig. 5 ANN structure

There are two main types of ANNs - feedforward and feedback networks. Feedforward networks transmit information in one direction from input to output nodes via hidden layers. They are commonly used for supervised learning of non-time series data. Feedback networks also allow bidirectional information flow to enable optimization problems.

The basic ANN structure consists of input, hidden, and output layers connected by weighted links. The input layer receives data and transmits it to the hidden layer. Hidden layers apply activation functions like sigmoid to introduce nonlinearity. The output layer provides predictions.

$$B_f = \sum_{j=1}^{N} W_i * \beta_{ij} \quad (1)$$

$$A_f = \sum_{j=1}^{h} \delta_j * \left\{\frac{1}{1+exp(-\sum_{i=1}^{N} M_i \gamma_{ij})}\right\} \quad (2)$$

Training algorithms aim to minimize errors between actual and predicted outputs by adjusting weights according to a fitness function, such as the mean squared error. Basis functions define hidden neuron activation based on input-weight combinations. Sigmoid functions are widely used as the S-shaped curve allows complex decision boundaries to emerge from simple building blocks.

Training Algorithm

The training phase adjusts connection weights iteratively to minimize error between actual and predicted outputs.

The Levenberg-Marquardt (LM) algorithm approximates the Hessian matrix as shown in Equation 3:

$$N = J^t J \quad (3)$$

Where J is the Jacobian matrix of the first derivatives of network errors with respect to weights and biases.

The gradient can be computed as shown in Equation (4):

$$g = J^t e \quad (4)$$

The LM update takes the form, as shown in Equation (5):

$$Y_{k+1} = Y_k - [J^t J + UI]^{-1} J^t e \quad (5)$$

Where k is a scalar. For k = 0, it is Newton's method using the estimated Hessian. LM interpolates between Newton's method and gradient descent to rapidly minimize error during training, as demonstrated by Equations (3) and (5). This research applied the LM algorithm to train the ANN model.

Optimization techniques for the proposed method

The weights from ANN training are optimized using optimization algorithms to retrieve optimal neurons and minimum error for each parameter. Weight and structure are optimized by

- Weight optimization
- Structure optimization

Fitness is calculated using the MSE function shown in Equation (6):

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (A_i - P_i) \quad (6)$$

Weight optimization algorithms include GWO, PSO, and GA to find optimal weights. GWO mimics grey wolves' social hierarchy with alphas, betas, deltas and omegas to guide optimization. This approach was evaluated to train the ANN model.

Fig. 6 Grey Wolf Algorithm

Flowchart of GWO

GWO mimics the hunting behavior of grey wolves to guide the optimization process. As shown in Fig. 6, the general hunting procedure of GWO involves a number of grey wolves randomly searching for prey in a multidimensional space. By imitating this natural hunting mechanism, the Grey Wolf Optimization (GWO) algorithm was developed. GWO was evaluated as part of this research to optimize weights for training the ANN model, as depicted in the behavioral steps outlined in Fig. 6.

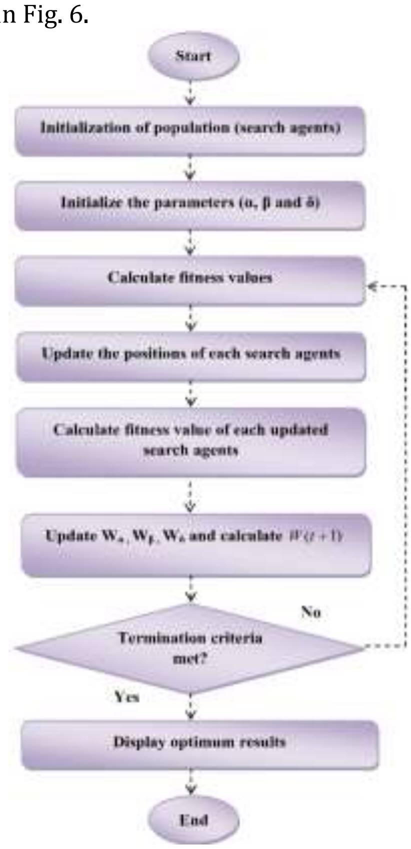

Fig. 7 Flow chart of Grey Wolf Algorithm

The GWO algorithm initializes a grey wolf population and calculates fitness according to the optimization equation. As shown in Fig. 7, the flowchart of the GWO algorithm involves ranking the population based on fitness and imitation of the alpha, beta, delta, and omega wolves to guide exploration. This flow, depicted in Fig. 7, provides an efficient optimization technique for applications such as training the ANN model in this research. By mimicking grey wolves' hunting hierarchy and behaviors as represented in Fig. 6, and 7, the GWO algorithm was evaluated for optimizing ANN weights.

Prey behaviour of GWO

In GWO, alpha, beta, and delta are assumed to have better knowledge of prey position Equation 7-9. Their positions guide other search agents including omegas. Encircling behavior is modeled using Equations 10-11.

$$D^{\alpha} = |C_1.W_\alpha - W|, D^{\beta} = \left|C_1.W_\beta - W\right|, D^{\delta} = |C_1.W_\delta - W| \qquad (7)$$

$$W_1 = W_\alpha - A_1.(D_\alpha), W_2 = W_\beta - A_2.\left(D_\beta\right), W_3 = W_\delta - A_3.(D_\delta) \qquad (8)$$

$$W(t+1) = \frac{W_1+W_2+W_3}{3} \qquad (9)$$

Components A and C in Equations 7-11 are random vectors [0,1] that decrease linearly from 2 to 0 over iterations to transition between exploration and exploitation.

$$D = \left|C.W_p(t)\right| - W(t) \qquad (10)$$

$$A = 2a.r_1 - a,\ C = 2.r_2 \qquad (11)$$

Hunting ends when the prey stops moving. Search agents attack prey based on alpha, beta, and delta positions from the hunting stage.

The key steps of GWO are outlined, initializing population and parameters a, A, and C. Fitness is calculated for alpha, beta, and delta positions using Equation 7-11 to guide search agents toward optimal solutions over iterations. This approach optimized ANN weights.

Particle Swarm Optimization (PSO)

PSO initially randomly selects candidate solutions within the search space. Fig. 8, depicts the particle selection process. Each particle maintains its position, fitness, individual best fitness/position, and awareness of global best fitness/position.

The updating procedure for PSO is:

Initialize population randomly and assess fitness of each particle

Update position and speed using equations 12 and 13:

$$V_k^{y+1} = c.V_k^y + h_1 r_1 (Pbest_k - p_k^y) + h_2 r_2 (Gbest_k - P_k^y) \quad (12)$$

$$V_k^{y+1} = W_k^y + V_k^{y+1} \quad (13)$$

Where h_k is velocity, h_1-h_2 are learning factors, r_1-r_2 are random values in [0,1].

Reassess fitness using new speeds and positions. Update best solutions found. Repeat until optimal solution is obtained.

This PSO approach was evaluated for optimizing weights in training the ANN model.

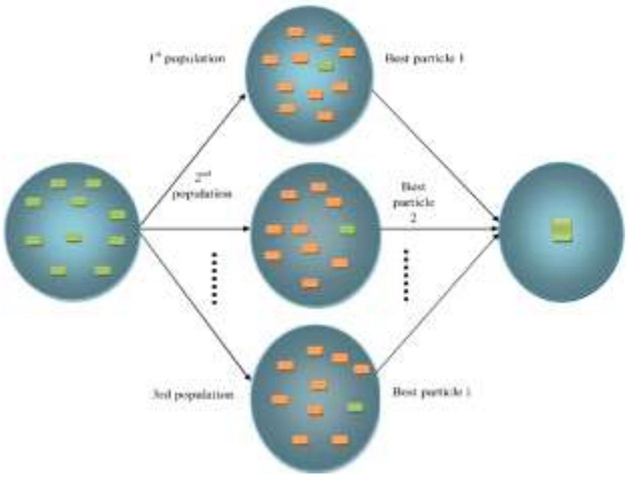

Fig. 8 Particle Swarm Optimization

Genetic Algorithm (GA)

Genetic algorithms are inspired by natural evolution to evolve solutions over generations. Each candidate solution has genetic properties (chromosomes) that can be mutated.

The GA procedure involves:

- Initializing a random population of individuals
- Assessing the fitness of each individual
- Selection of parents based on fitness
- Crossover of parent chromosomes to produce offspring
- Mutation of child chromosomes, introducing diversity
- New generation replace sold to evolve toward optimal solutions

The key steps are selection, crossover and mutation to combine traits and introduce variation, simulating the natural process of evolution. The population iteratively evolves toward better solutions through genetic operations on the binary string representations of candidates.

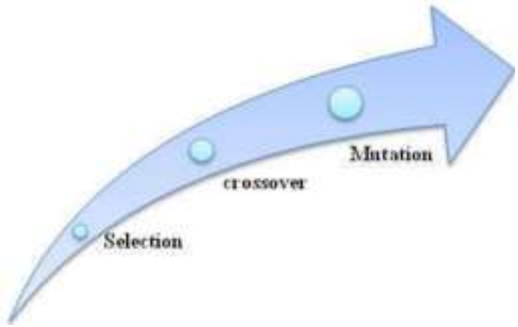

Fig. 9 GA operators

Parent Selection

- Keys parents are selected for mating based on fitness, with fitter solutions more likely to be chosen
- Selection pressure guides evolution toward optimal solutions over generations

Crossover

- Parent chromosomes are combined (e.g, single-point crossover) to form offspring solutions
- Fig. 10 illustrates crossover combining parts of two parent strings

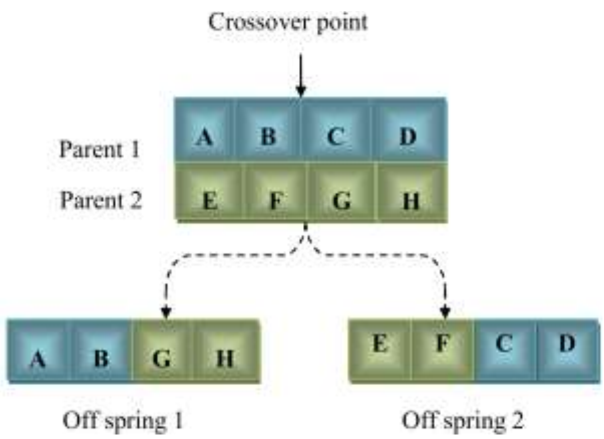

Fig. 10 Crossover Operation

Mutation

- Randomly alters chromosomes of offspring solutions
- Maintains genetic diversity and prevents premature convergence
- Fig. 11 shows mutation changing a value within an offspring chromosome string

Together, selection, crossover and mutation operators simulate the natural genetic processes of mating, recombination and random mutation to evolve higher-fitness solution populations in GA. Selection guides evolution while crossover and mutation combine/explore traits and maintain diversity.

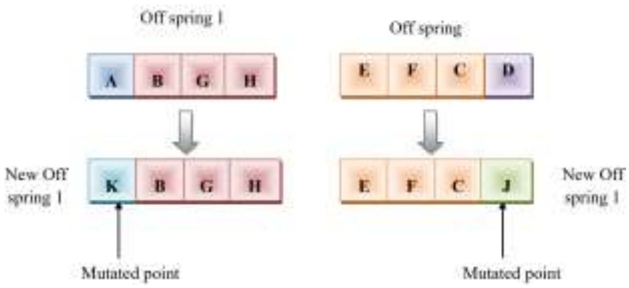

Fig. 11 Mutation Operation

Structure Optimization

Hidden layers and hidden neurons from the ANN structure using fish-based optimization demonstrate that is Krill herd optimization (KHO). From that system get the output layers and neurons to look at the construction health parameters

Krill Herd Optimization (KHO)

Krill herds exhibit natural grouping behavior without centralized control.

Fig. 12 represents krill herd optimization which mimics the swarming of Antarctic krill.

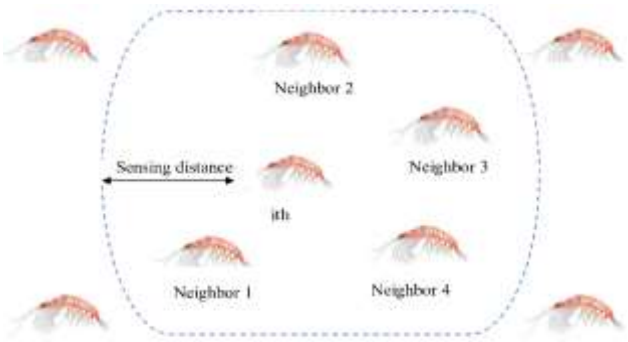

Fig. 12 Krill Herd Algorithm

Krill herding balances multiple objectives:

- Increasing density
- Reaching food areas
- Searching for high food concentration

Individual krill move toward solutions of higher density and food proximity, minimizing the objective function.

Predation decreases density and separates krill from food, initializing the KHO algorithm.

Krill fitness evaluates distance from food and highest swarm density.

Krill position is influenced by:

- Movement of neighboring krill
- Foraging activity
- Random diffusion

This krill swarm behavior is modeled to optimize parameters of the ANN model in following sections.

Figure 5.10 shows the krill herd optimization flowchart.

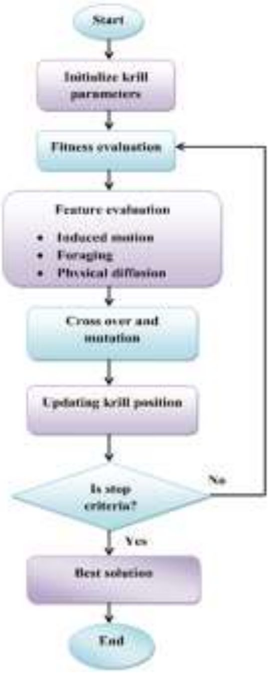

Fig. 13 flow chart of KHO

Key variables in equations:

- Kmax = maximum induced rate
- w = inertia weight
- Xn = last induced movement
- fj = neighborhood influence
- fg = objective direction influence
- NN = number of individuals

Position updating balances exploration of neighboring krill movement and exploitation of food sources.

Optimal Solution

Based on the above-mentioned process attain the optimal weights and also find the optimal fitness which is defined as in this optimal fitness-based output. The optimal values based predict the output which is the performance of defects, rework workers per million scopes and re worker per 20000 workers.

$$F_{i(optimal)} = \sum_{j=1}^{h} \alpha_{j(optimal)} * \left\{ \frac{1}{1+exp\left(-\sum_{i=1}^{N} W_i \beta_{ij(optimal)}\right)} \right\} \tag{14}$$

Where; → Target output and → obtained output and m number of data

Testing Phase

In the testing stage, select the best arrangement (ideal hidden layers and neurons) from the preparation stage, which we have given to the input of the ideal NN. In this manner, we acquire the rework workers and defects of the construction safety site system

Conclusion

This research aimed to analyze the relationship between construction safety and quality performance through predictive modeling using soft computing techniques. A literature review was conducted to understand key factors influencing safety and quality in construction. Primary survey data on safety parameters like recordable injury rates and rework was collected from construction sites.

An artificial neural network model was developed and optimized using algorithms like krill herd, grey wolf optimization, genetic algorithm, and particle swarm optimization. The ANN model with krill herd optimization achieved the lowest error and best predicted the number of rework workers and defects, demonstrating its efficacy.

The results show that recordable injury rates have a positive correlation with rework, while first aid rates positively correlate with defects. This confirms the interrelationship between safety and quality issues as suggested in previous studies. Furthermore, the proposed hybrid ANN-optimization approaches more accurately predicted performance parameters compared to traditional models.

Among the optimization algorithms tested, krill herd achieved the lowest MSE and highest accuracy for defect analysis, indicating its superiority over other techniques for this application. This research thus demonstrated how soft computing models integrated with nature-inspired optimization can enhance predictive capabilities for complex, non-linear construction management problems.

The findings provide insights into effectively managing both safety and quality simultaneously. Future work can expand the research to include additional factors and larger datasets. Overall, the study highlighted the utility of soft computing approaches for construction performance improvement.

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