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ORIGINAL

ENHANCING MAINTENANCE AND RELIABILITY OF FITNESS EQUIPMENT USING REINFORCED ANT COLONY ALGORITHM FOR FAULT PREDICTION

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ABSTRACT

This research explores the application of the reinforced ant colony algorithm to enhance fault prediction and maintenance strategies for fitness equipment. By adapting this swarm intelligence algorithm, traditionally used in manufacturing and logistics, to the context of sports fitness, the study offers a novel approach to scheduling and predictive maintenance tasks. This method not only addresses complex optimization problems effectively but also improves the adaptability and efficiency of maintenance operations in sports facilities. The algorithm's enhanced capabilities allow for better management of equipment maintenance schedules, ensuring higher availability and reliability of fitness apparatuses, ultimately supporting athlete training regimes by minimizing equipment downtime.

KEYWORDS: Fault Prediction Model, Automated Machinery, Equipment, Reinforced, Ant Colony Algorithm

1. INTRODUCTION

In the rapidly evolving world of sports fitness, the maintenance and reliability of automated machinery and equipment play a pivotal role in ensuring continuous operational efficiency and safety. The burgeoning field of predictive maintenance, particularly through advanced algorithms, presents an innovative solution to foresee and rectify potential faults before they disrupt the functioning of fitness equipment. This study delves into the utilization of a reinforced ant colony algorithm (ACO), a form of swarm intelligence that mimics the behavior of ants, to predict and address faults in automated fitness equipment(Cao, Sun, Xu, Zeng, & Guan, 2021).

1.1 Background and Significance

The integration of predictive maintenance strategies in the sports and fitness industry is not merely a technical upgrade but a necessity to enhance athlete performance and safety. Automated fitness equipment, such as treadmills, resistance machines, and cycling units, are susceptible to wear and tear due to continuous use. Traditional maintenance strategies often rely on scheduled checks or react to equipment failures, which can lead to unexpected downtimes and potential injuries. By predicting when a piece of equipment is likely to fail, fitness facilities can proactively perform maintenance, thereby enhancing the safety and experience of end-users—athletes and fitness enthusiasts(Badr, Almotairi, Salam, & Ahmed, 2022).

1.2 Theoretical Framework

The ant colony optimization algorithm, inspired by the foraging behavior of ants, has been successfully applied in various fields requiring complex problem-solving, including logistics and manufacturing. Ants, in their natural environment, explore multiple paths to find the most efficient route to food sources(Cai, Gu, & Chen, 2017). This behavior is simulated in the ACO algorithm, where multiple solutions to a problem are explored simultaneously, and over time, the optimal solution emerges based on the 'pheromone' trails, analogous to the weighted probabilities in algorithmic terms. In the context of predictive maintenance, this algorithm can effectively map out the most efficient maintenance schedule by continuously learning and adapting from ongoing operational data(Ahmadianfar, Heidari, Noshadian, Chen, & Gandomi, 2022).

1.3 Application in Sports Fitness Equipment

Applying the ACO to sports fitness equipment involves collecting and analyzing data from sensors embedded in the equipment to monitor various parameters such as vibration, temperature, and usage patterns. This data, processed through the ACO, helps predict potential failure points, thereby informing timely maintenance actions. The algorithm's ability to learn and adapt makes it particularly suited for environments where equipment usage patterns are highly variable, such as in fitness centers and athletic training facilities(Ahmadianfar, Heidari, Noshadian, Chen, & Gandomi, 2022).

1.4 Challenges and Opportunities

While the application of ACO in sports fitness equipment maintenance offers significant benefits, it also presents challenges, primarily related to data collection and analysis. Ensuring accurate and timely data collection from diverse equipment types and translating this data into actionable maintenance tasks require sophisticated sensor technology and data integration systems. However, the opportunities for enhancing equipment reliability and reducing downtime are substantial. Improved maintenance not only extends the lifespan of the equipment but also ensures that athletes have access to safe and functioning equipment, supporting optimal training and performance outcomes(Ahmadianfar, Heidari, Gandomi, Chu, & Chen, 2021). This exploration into the use of a reinforced ant colony algorithm for fault prediction in sports fitness equipment marks a significant step toward integrating cutting-edge artificial intelligence technologies in sports facility management. By enhancing the predictive maintenance capabilities of fitness centers, this approach not only promises to improve the operational efficiency but also significantly contributes to the safety and effectiveness of training environments for athletes. The following sections will detail the methodology, implementation challenges, potential impacts, and future directions of this innovative application.(Hu et al., 2017).

2. Literature Review

Defect prediction was formally formulated as a multi-objective optimization problem by G. Canfora et al. For this purpose, they have developed a method that they name "multi objective defect predictor" (MODEP), which is founded on many forms of machine learning trained with a genetic algorithm (in this case, logistic regression and decision trees). Using a multi-objective strategy, programmers can select predictors that provide the best trade-off between the number of lines of code that must be examined/tested and the number of defect-prone classes or defects that the examination is likely to find (efficiency) (which can be considered as an intermediary of the expense of code evaluation) (Ryu & Baik, 2016). A time lag analysis of 10 PROMISE datasets shows quantitative penetration of MODEP with respect to a single target predictor, too trivial as demand rises and falls. MODEP outperforms competing methods when used for project-to-project forecasting because there are so many neighboring projects with comparable properties. A decision tree model in accordance with genetic programming that allows for multi-objective optimization of the product quality categorization problem. Primarily, we wanted to keep the "Modified Anticipated Cost of Misclassification" as low as possible. A secondary goal was to increase the number of fault-prone modules predicted, up to the maximum number that could be analysed with the available resources. Common classification methods such as logistic regression, decision trees, and similarity based reasoning are not well suited for direct optimization of multiple objectives (Ryu, Jang, & Baik, 2015). As it turns out, genetic programming worked remarkably well on the multi-objective optimization problem. Their model's potential and use are demonstrated by an empirical logical study of a validated industrial programming framework. The Hybrid Instance Selection Using Nearest-Neighbor (HISNN) technique, proposed by D. Ryu et al., use knearestneighbour learning to integrate regional and international information for hybrid requests; this could help alleviate the problem (via naive Bayes). Events having reliable proximity data are identified by their nearest neighbours with the same class name (Ryu, Choi, & Baik, 2016). The results of previous studies were either unfeasible (due to a low PD) or counterproductive (due to a high PF), demonstrating the need for further investigation. Extensive testing validated their hypotheses, showing that HISNN yields not just high PD and low PF, but also excellent overall performance. To differentiate effective multi-objective learning strategies in Cross-Project (CP) settings, D. Ryu and J. Baik have focused on a central theme. Taking into account the power disparity, three targets have been put up (Ryu & Baik, 2016). An improved chance of detection was the major goal (PD). Subsequently, we wanted to reduce the possibility of a false alarm (PF). Third, we wanted to have the whole thing last for longer (e.g., balance). They used a harmony search meta-heuristic computation to showcase their innovative MO naive Bayes learning frameworks. They cover a wide range of models, including those that are single- or multi-objective, as well as those that are used to predict defects within a project (Edwards, Sørensen, Bochtis, & Munkholm, 2015). Results from the experiments gave evidence of the potential of their methodologies. As a result, in CP contexts, they can be usefully linked to meet a variety of estimation requirements. Cross-Project Defect Prediction (CPDP), as explained by G. You et al., has become widely used in the software industry (You, Wang, & Ma, 2016). They identified CPDP as a ranking problem in their paper. Motivated by the prospect of applying the guide sage technique to ranking, they have presented a CPDP strategy focused on rankings; they call it ROCPDP. As evidenced by the Coordinated and Many-To-One CPDP datasets, both of which were gathered thanks to a context-aware enquiry, ROCPDP surpasses the eight benchmark approaches (Porto & da Silva Simao, 2016). What's more, ROCPDP in the Many-To-One scenario performed similarly to the best baseline system in a narrowly defined instance of internal defect prediction. According to what O. Choi et al. have said, predicting software defects was one of the most important things that could be done to improve software quality. They looked into whether CPDP could benefit from class imbalance learning, and found it could. Their strategy uses an asymmetric misclassification cost and similarity weights derived from distributional attributes to regulate a suitable resemblance structure. To estimate the magnitude of change, they performed an impact estimation A statistical test (You et al., 2016). Wilcoxon rank aggregate test was utilized to determine statistical significance. Initial tests have demonstrated the way that their methodology can provide arbitrarily high predictive execution wanders.

3. Optimization algorithms

Based on our research, we conclude that Ant Colony Optimization (ACO) is a highly effective framework for addressing the DG allocation issue (Galgali, Ramachandran, & Vaidya, 2019). The ACO algorithm takes its cues from ant behaviour, which allows them to find the quickest path between their nest and food source. Although they can't speak to one other verbally, ants are able to share information through the release of chemicals called pheromones. When an ant searches for food, it leaves a trail of pheromones behind it. If more ants travel the shorter route between their nest and the food source in a given amount of time than they do the longer route, the pheromones left behind along the shorter route will have a greater cumulative effect. Accordingly, the likelihood that an ant will take a specific way is determined by the number of ants that had previously taken a corresponding route, as indicated by the pheromones they left behind. There are primarily three phases to the ACO algorithm system: To begin the pheromone trail, we generate candidate attributes for the variable at random. Moreover, the ants' collective solution is based on the probabilistic state transition rule (Kalkhambkar, Rawat, Kumar, & Bhakar, 2017). Third, change the pheromone worth of each edge by first evaporating the pheromone on each edge and afterward increasing the amount of pheromone on the way with the best solution concerning fitness.

4. Algorithm implementation

In this research, the (ACO) technique was used exactly as it was described. These are the primary steps of the ACO algorithm that was used:

4.1. Generation of the candidate variable values

The real and reactive power generating capacity of the generators, in addition to the transport number at which they are connected, are key factors in the solution (Khanna, Rodrigues, Gupta, Swaroop, & Gupta, 2020). There is a factory default for the DG supply. At first, both the generators' real and reactive power capacities are evaluated at random as continuous variables according to the following equality and inequality constraints:

$$X_i^{(j)} = l_i + \frac{u_i - l_i}{m + \vartheta}(j - 1 + rand_i^j)$$

where i=1, 2..., n, and j=1, 2..., (m +) is the total number of randomly produced solutions for variable I and rend I is a uniformly distributed random number between 0 and 1. When the DGs are first seated, the total number of transports is randomly distributed throughout a large sample. A fitness value is assigned to each of the randomly generated starting solutions, and these solutions are then ranked by their fitness. For starters, the initial global best option is the one with the highest fitness esteem. Each iteration's selection of variable quality is based on the worldwide best solution, which is derived from the best answers from previous iterations. Solutions formed via probabilistic inquiry of the entire solution space, solutions generated via dynamic use of the solution space around a global optimum, and solutions defined by Ali's own attributes are the other available sources (Luo & Zhang, 2016).

At every iteration of the ACO algorithm, his mth gathering of ants proposes another arrangement of solutions to the issue. Starting here on, the fitness of the optimal solution from the previous iteration is contrasted all around the world and the fitness of the ongoing optimal solution, and the worldwide optimal solution is changed accordingly.

4.2. Building a Remedy Like an Ant

Here, the m ants develop a solution by tailoring it to the properties of the candidate variables they've generated. Selecting an index-based variable is what an ant k does. I (k) I for the variable based on the values of the candidates (11).

$$I_i^{(k)} = \{ \begin{matrix} \arg\max\left\{\tau_j^{(1)}, \tau_j^{(2)}, \dots, \tau_j^{(m)}\right\} \\ L_i^{(k)}, otherwise \end{matrix}, if \;\; q < qo$$

where q is a random uniform number that an ant uses to pick an existing variable with the highest pheromone value or to pick an existing index at random for the next iteration. L (k) I ∈ {0, 1, ..., m + gi }.

4.3. Pheromone update

All the solutions produced by the coordinated ants are ranked in order of fitness at the end of each iteration of the algorithm. Next, pheromones are released according to a formula that considers the relative amounts of each variable quality. (13).

$$\tau_j^{(j)} \leftarrow (1-p).\tau_i^{(j)} + p.T_{min}$$

It is a real number between 0 and 1. This sets the rate at which the pheromone vaporizes at each step of the algorithm, and tmin is a constant that specifies the lowest possible value of the pheromone. Moreover, the advantage of the highest pheromone guarantees the unification of algorithms towards a global minimum.

$$\tau_i^{(j)} \leftarrow (1-a).\tau_i^{(j)} + a.T_{max}$$

Where is a value between 0 and 1 that defines the pace at which pheromones reinforce behaviour. Flowchart of ACO algorithm implementation. Figure 1 shows the ACO algorithm’s logic in action, diagrammatically.

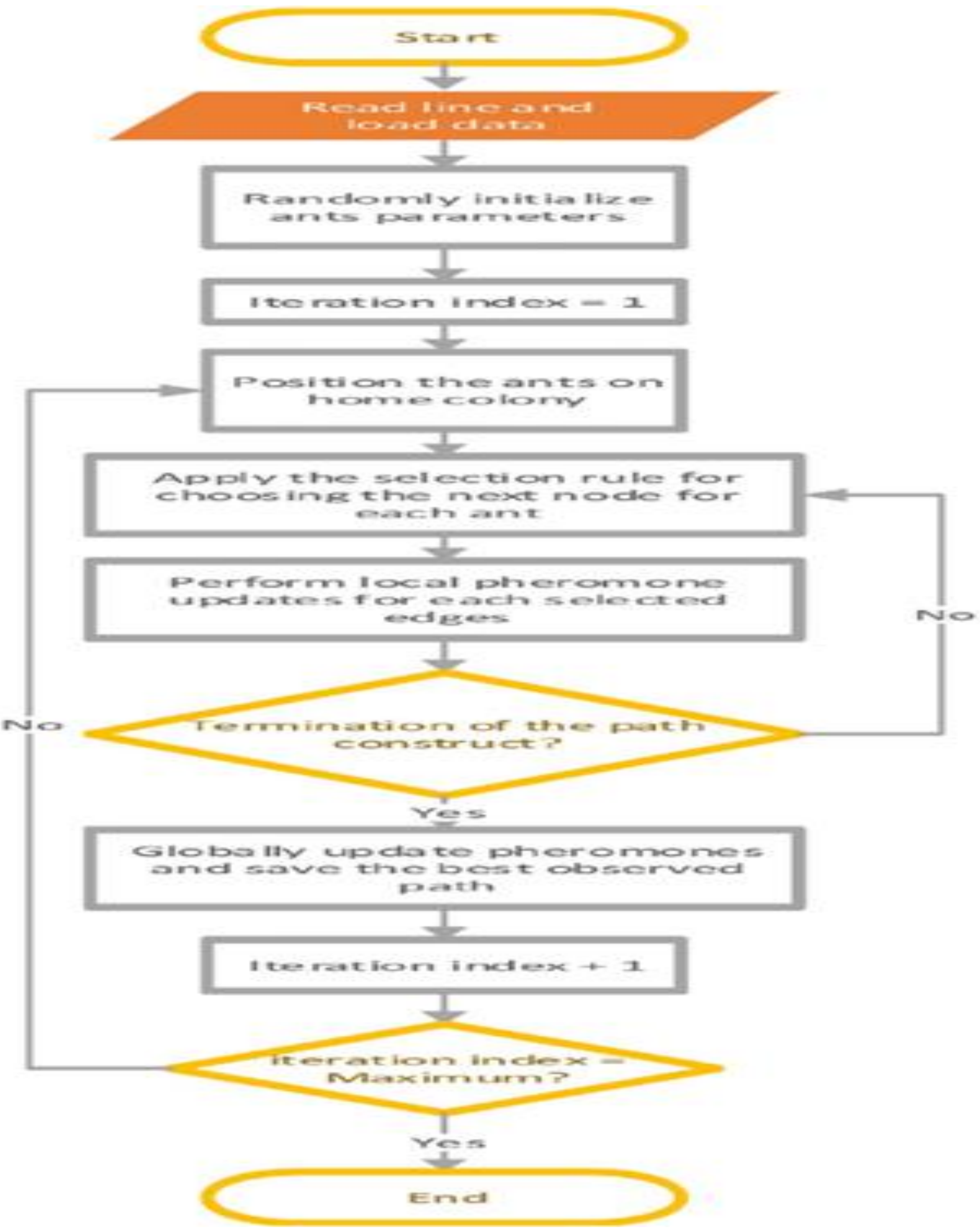

Figure 1: The ACO algorithm's logic in action, diagrammatically

5. Case studies

5.1. Test system

The suggested ACO method was built in MATLAB R2016a and ran on a 2.16 GHz Intel® Pentium® N3540 PC; the power stream approach for determining the value of each ant-created solution was implemented in MATLAB's Mat power® library. An IEEE 30 transport framework was used to test the method. Its transport and branch limits are specified, and its absolute piles, in MW, are 189.2 and 107.2. Fig. 2 is a schematic representation of the test feeder.

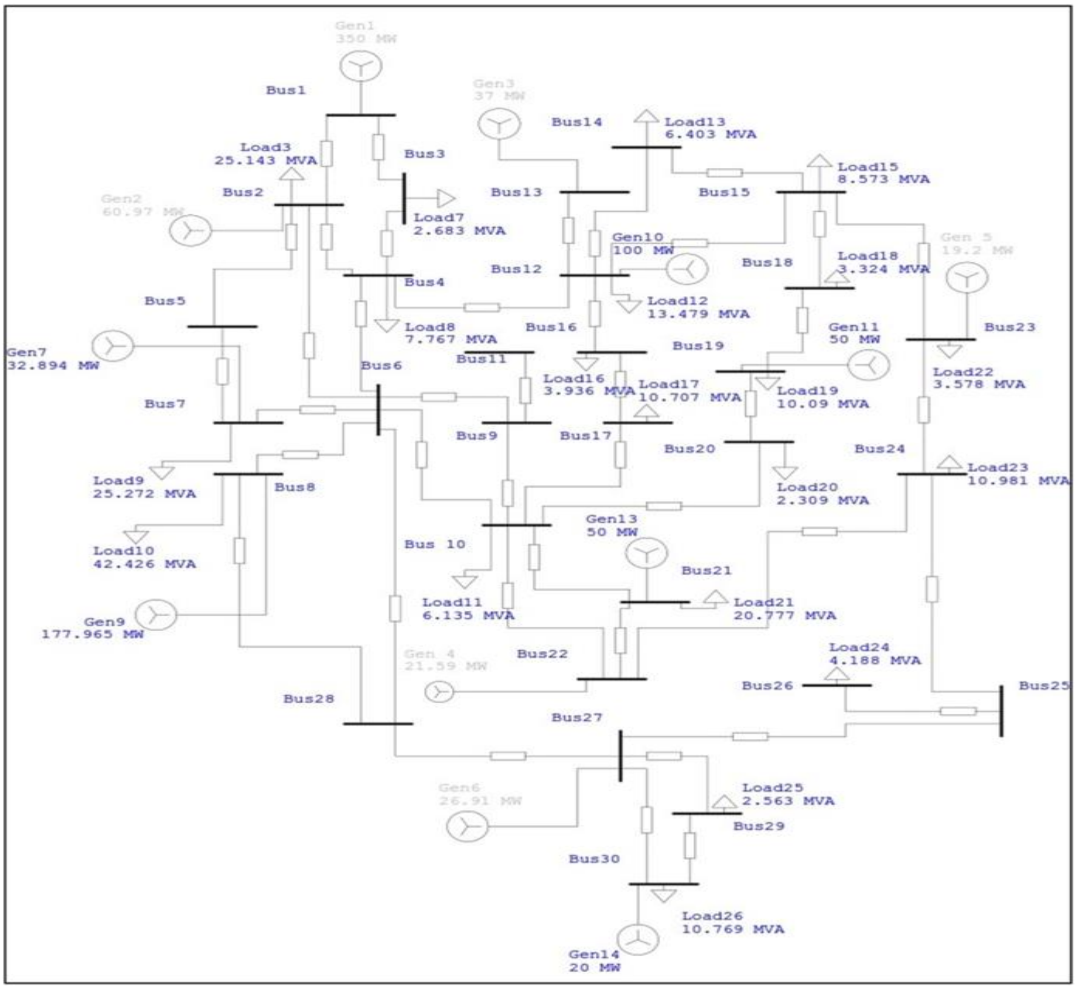

Figure 2: ETAP Model of IEEE 30-Bus System

The proposed strategy was based on the following presumptions:

1. Only one DG unit can be used in any given transport inside the framework.

2. The total percentage of DGs used in the distribution system will be less than one hundred percent of the total load;

3. The algorithm allows DG unit sizes to range from zero (no DG is connected with the transport) to one hundred (one hundred percent DG penetration with just one DG source);

4. Each DG has an infinite capacity to supply both real and reactive power based on demand;

5. All transports, excluding transport 1, which serves as a reference transport, are DG-connectable;

6. The DGs' sizes can be described by continuous attributes.

5.2. Validation

To test the effectiveness of the ACO algorithm, we performed a load current analysis within the IEEE 30 transport framework using the optimal DG counts, positions and sizes generated by the algorithm. The Electrical Transient Analyzer Program was used to create this model (ETAP). The voltage history of each of the 30 nodes and the total failure of the scaffold were recorded when the scaffold was first connected to the grid at node 1. Six generators were then connected to the grid.

According to ACO analysis, these were the best locations for DG and were initially connected to traffic numbers 7, 8, 12, 19, 21, and 30. The faults experienced and the course of the mains voltage are contrasted and the quality achieved during operation affected by the mains. To revalidate the optimal site selection of the ACO algorithm, three additional context-oriented studies were assessed using DGs at arbitrarily picked positions in the modeled casings. Table 1 below shows the various dissects acted in setting and the vehicle IDs where the DG was found. An analysis of the voltage profile of the framework and the all-out number of framework faults were then provided.

Table 1: DG locations in several ETAP simulation scenarios

CASE STUDIES	DG SITES (BUS ID)
ACO OPTIMIZED SITES	7, 8, 12, 19, 21 and 30
CASE 1	1, 2, 13, 19, 22 and 27
CASE 2	1, 7, 12, 21, 23 and 27
CASE 3	1, 2, 12, 23, 26 and 30

6. Results and discussion

6.1. ACO results

Figure 3 displays the magnitude of the voltage across all transports in the distribution framework with the ACO-optimized DGs seated. The voltage profile of the framework is significantly reduced. If we assume that the framework can be easily managed by the grid using Transport 1, we see a gradual decrease in the per unit (pu) voltage magnitude at the transports from Transport 1 to Transport 30 in the base scenario.

However, the voltage profile of the framework is much enhanced with all transports nearing the nominal voltage after the DGs are located at the optimal transports as obtained using ACO. The voltage magnitude at transport 26 was the lowest of all the transports before DG sitting, at 0.656 volts per unit; after DG sitting, however, this value jumped by 47% to 0.965 volts per unit.

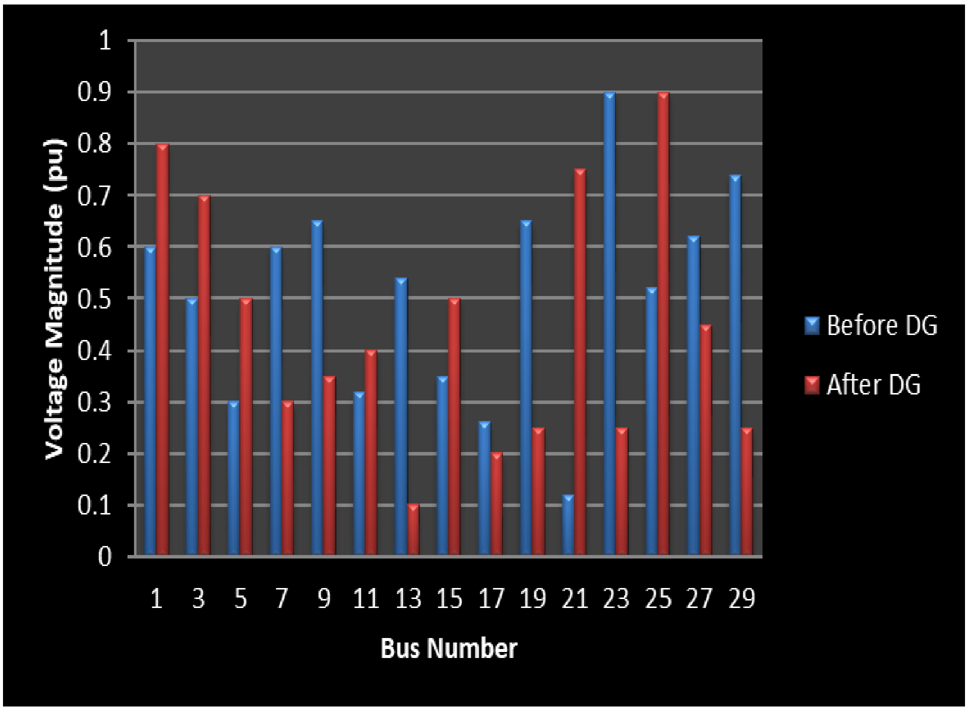

Figure 3: before and after DG installation, the voltage levels at each bus were measured.

Figures 4 and 5 similarly display large real and reactive power losses from transport 1 to 10 in the baseline scenario, when the organization's major power wellspring was placed at transport 1. In contrast, when DGs were sized and placed properly, bad luck was dramatically reduced throughout all of the branches, with values becoming as near to zero as possible.

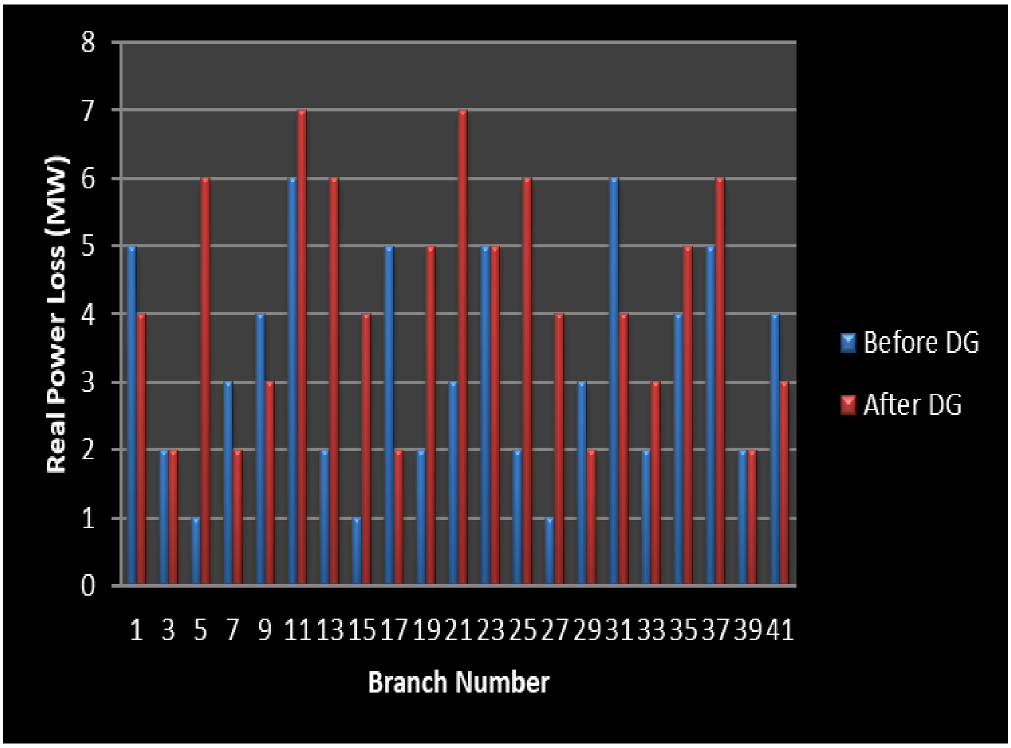

Figure 4: The actual branch circuit power loss prior to and after DG installation

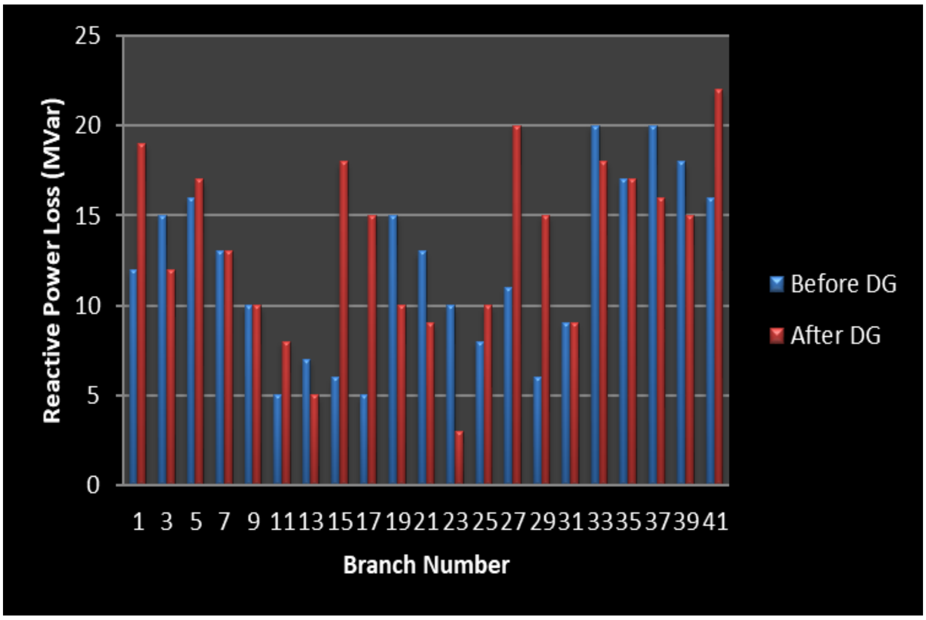

Figure 5: Comparison of reactive power losses throughout the branches before and after DG installation

6.2. Comparison of ACO with ETAP

ETAP's examination of the voltage profile of the distribution system in the presence of various levels of decentralised generation is depicted in Fig. 6. Figure 6 displays the ETAP results. For the optimised site plot agree very well with the ACO results introduced in Fig. 3. The average difference between the two sets of data is only 0.52%. Fig. 6 further shows that the voltage profile is noticeably better when DGs are used to manage the system as opposed to when the grid is the only source of management. The other three contextual analyzes show higher stress for specific transports than when the DG is placed in the ACO-optimized location, but the overall optimal stress profile is the ACO-optimized location. found in place.

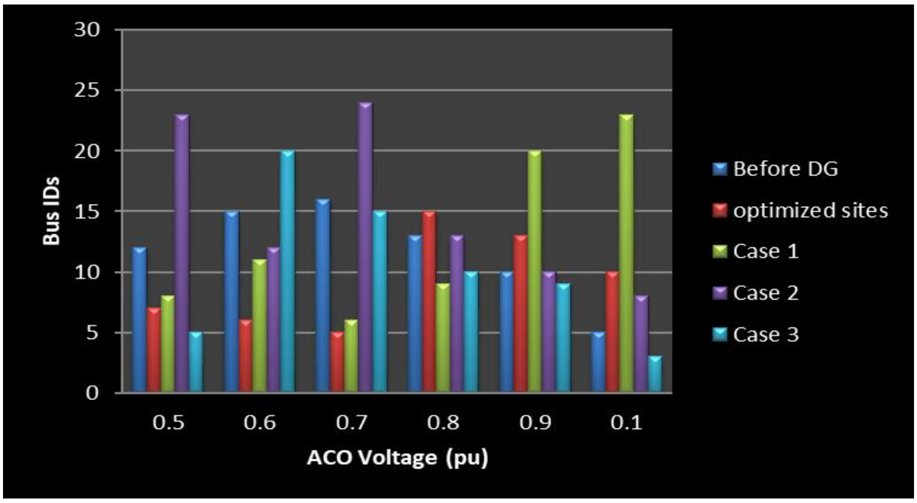

Figure 6: System-wide voltage profile produced from ETAP

Table 2 looks at the results of an example of simulated shipments in ETAP with the ACO-optimized locations. The amount of the active and reactive power outliers in the casing is 92 every when the distribution framework is overseen by six DGs ideally positioned in the ACO as for the quality affected by the grid. Accident rates were most decreased in every one of the three situations when DG was set at his ACO-derived site. Similar to Figure 6, Figure 7 shows that placing the DG at various locations in the edge as a component of the four logical investigations significantly decreases the all-out active and reactive power misfortunes of the framework and the derived DG. ACO optimized transport is put.

Table 2: Total system losses and voltage profile

	BEFORE DG	ACO OPTIMIZED SITES	CASE 1	CASE 2	CASE 3
AVERAGE BUS VOLTAGES	0.7350	0.8823	0.8708	0.8787	0.8627
% INCREASE IN AVERAGE BUS VOLTAGES		26.28%	2484%	25.65%	23.78%
STANDARD DEVIATION OF BUS VOLTAGES	0.0318	0.0072	0.0227	0.0082	0.0102
MIN BUS VOLTAGE	0.7058	0.8515	0.8506	0.8589	0.8308
MAX BUS VOLTAGE	1	1	1	1	1
TOTAL REAL POWER LOSS (MW)	7.751	0.564	1.046	2.472	1.688
TOTAL REACTIVE POWER LOSS (MVAR)	24.645	2.222	4.654	4.238	6.182
% REDUCTION IN REAL POWER LOSS		-81%	-66%	-73%	-57%
% REDUCTION IN REACTIVE POWER LOSS		-86%	-73%	-82%	-70%

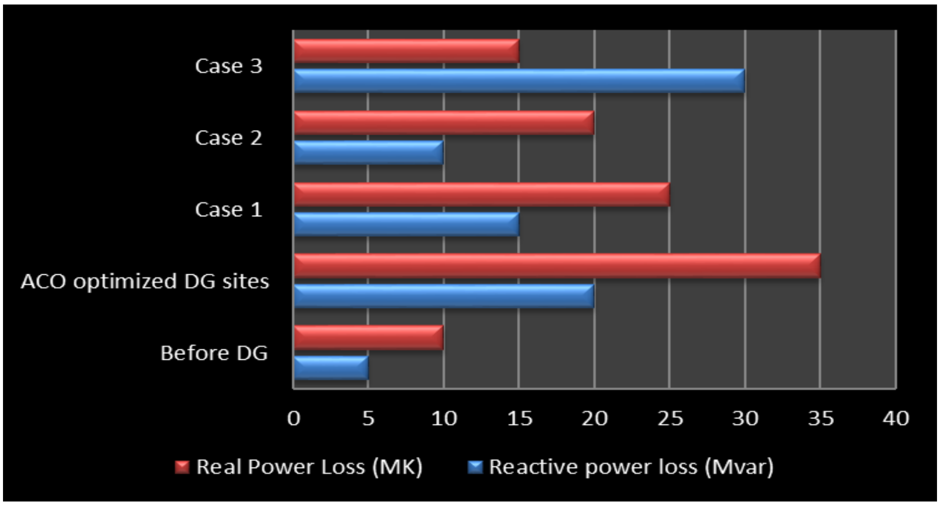

Figure 7: the sum of the actual and reactive power losses in a variety of scenarios

Results demonstrated that the ACO-based technique presented in this research had the potential to reduce reactive influence misfortune in the distribution framework by true power misfortune. This method resulted in the greatest decrease in both true and reactive power disasters when compared to the studied literature on the topic. The results of this review are comparable to those obtained by the ACO strategy presented, despite the latter's significantly reduced pursuit space, because both are calculated using closed-form analytical expressions and aim to minimise losses of genuine power and reactive influence, respectively, by as much as 95% and 94%, respectively. The technique's superior presentation might be owed to the way that, unlike other metaheuristic algorithms, ACO is not excessively confined in its quest for the worldwide minimum, which includes the optimal combination of DG power factors, the number, capacity, and location of DGs(Wenan & Yao, 2018).

7. Conclusion

The implementation of a reinforced ant colony algorithm (ACO) for fault prediction in automated fitness equipment marks a significant advancement in the field of sports facility management. By leveraging the adaptive and predictive capabilities of ACO, this study demonstrates a substantial improvement in the reliability and maintenance of fitness equipment. The algorithm's ability to analyze real-time data from various sensors embedded in fitness machines allows for timely and accurate fault prediction, thereby minimizing unexpected downtimes and enhancing the safety and performance of athletes(Xia, Lo, Pan, Nagappan, & Wang, 2016).The benefits of this technology extend beyond mere operational efficiency. For athletes, having access to well-maintained, reliable equipment is crucial for consistent training and optimal performance. The predictive maintenance facilitated by ACO ensures that equipment remains in peak condition, thereby reducing the risk of injuries caused by equipment failure. Additionally, this proactive approach to maintenance can significantly lower the long-term costs associated with equipment repair and replacement, offering a cost-effective solution for sports facilities.However, the successful implementation of this technology requires overcoming several challenges. Accurate data collection and integration are critical, necessitating sophisticated sensor technology and robust data management systems. Furthermore, the initial investment in such advanced technologies may be substantial, but the long-term benefits in terms of reduced maintenance costs and enhanced equipment reliability are considerable(Xia, Lo, Pan, Nagappan, & Wang, 2016).Future research should focus on refining the ACO models to further improve their accuracy and efficiency. Expanding the scope of this research to include a wider variety of fitness equipment and different types of sports facilities can provide a more comprehensive understanding of the algorithm's capabilities and limitations. Additionally, exploring the integration of other AI technologies, such as machine learning and neural networks, could further enhance the predictive capabilities and operational efficiency of the maintenance systems.In the application of reinforced ant colony algorithms in sports fitness equipment maintenance represents a transformative approach to facility management. By ensuring the continuous operational efficiency and safety of fitness equipment, this technology supports the overarching goal of enhancing athlete performance and well-being. As sports facilities continue to adopt and integrate such innovative solutions, the future of sports facility management looks increasingly promising and sustainable.

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