Parameter Adaptation of Enhanced Ant Colony System for Water Quality Rules Classification

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***Abstract*—Water quality monitoring in aquaculture involves classifying and analyzing the collected data to assess the water quality that is appropriate for breeding, rearing and harvesting aquatic organisms. Systematic data classification is essential when it comes to managing large amounts of data that are continuously sensed in real time and have various attributes in each instance of a sequence. Ant Colony System (ACS) has been employed in optimizing the data classification in smart aquaculture, where the majority of the research focuses on enhancing the classification procedure using predetermined parameters within a specified range. Nevertheless, this approach does not guarantee ideal performance. This paper enhances the ACS algorithm by introducing the Enhanced Ant Colony System-Rule Classification (EACS-RC) algorithm, which improves rule construction by integrating pheromone and heuristic values while incorporating advanced pheromone update techniques. The optimal parameter values to be used by the proposed algorithm are obtained from parameter adaptation experiments in which different values within the defined range were applied to obtain the optimal value for each parameter. Experiments were performed on the Kiribati water quality dataset and the results of the EACS-RC algorithm were evaluated against the AntMiner and AGI-AntMiner algorithms. Based on the results, the proposed algorithm outperforms the benchmark algorithms in classification accuracy and processing time. The output of this study can be adopted by the other ACS variants to achieve optimal performance for data classification in smart aquaculture.**

Keywords—Parameter adaptation; rules classification; water quality monitoring; ant colony system; pheromone update techniques

I. Introduction

Smart aquaculture refers to the implementation of intelligent aquaculture management systems, in which smart devices are utilized within a carefully designed ecosystem to continuously monitor environmental parameters in real-time. These devices collect data, which is then used to assist with decision-making processes. The automation and centralized management of smart aquaculture are made possible by big data, artificial intelligence (AI), the Internet of Things (IoT), and robotics [1]. These technologies work together to minimize human intervention in the operation of complete production systems through the control of facilities, machinery, and other devices. Sensor data is gathered by smart aquaculture, transmitted in real time to a database, and processed into useful information. All of these challenges can be resolved with a smart aquaculture system that can be remotely controlled and requires less labor [2]. Thus, smart aquaculture aims to develop the aquaculture industry in a manner that is both environmentally and economically sustainable.

Traditional aquaculture involves the selection of seeds, the preparation of water, nourishment, and maintenance [3]. Aquaculture workers often struggle to maintain water quality because frequent water sample collection is required. Ponds and tanks must be kept clean, and any changes in the water quality that take place outside of the regular cleaning schedule can have several negative consequences. In some cases, diagnosis and treatment cannot be administered while the fish that live in ponds are still alive, presenting an additional challenge. Ultimately, these factors impact productivity and quality. Incorporating sophisticated technology including automation, data analytics, real-time monitoring, and many more, smart aquaculture solves traditional aquaculture issues with innovative production techniques [4, 5].

Dissolved Oxygen (DO), temperature, and pH (hydrogen potential) are key parameters in smart aquaculture water quality monitoring to determine whether the water is suitable for breeding, rearing, and harvesting aquatic animals [6,7]. Managing massive real-time data with varying properties for each sequence requires systematic data classification. Data classification is considered a Nondeterministic Polynomial (NP)-complete problem, meaning it cannot be solved in polynomial time by an exact algorithm. One of the most effective approaches to solving NP-complete problems is using metaheuristic algorithms, which explore various optimization options to identify the best-performing solution.

Ant Colony Optimization (ACO), a metaheuristic algorithm, has successfully improved classification performance in terms of execution time, model size, and accuracy [8, 9]. ACO is inspired by the foraging behavior of real ants, which find the shortest route from their nest to a food source during foraging is the basis for ACO. To communicate, ants use chemical substances known as pheromones. As they traverse a path, they deposit pheromones, which may encourage more ants to follow the same path. Paths with higher pheromone concentrations are more likely to be reinforced, while paths with lower pheromone levels fade more quickly due to evaporation [10]. Consequently, ants must continuously deposit pheromones to guide others toward the optimal path. Several ACO variations have been applied to NP-complete problems, including the Max-Min Ant System (MMAS), Ant System (AS), and Ant Colony System (ACS) [11].

ACO can be used for rule development in data classification to accurately classify dataset instances. Each rule is represented by an ant that follows pheromone trails. Rules with higher levels of pheromone concentration are more likely to be selected by ants. The ACO algorithm begins with a collection of randomly generated rules, each of which specifies the attributes and values that an instance must have to be classified into a particular class. Ants are distributed across the feature space. Next, each ant then selects a feature based on pheromone concentration and a heuristic function that evaluates the feature's relevance to the classification task [12]. Fig. 1 shows the development of classification rules by ants where each term is represented as a node and possible paths connect the nodes. Consequently, each ant develops its own path, representing a classification rule.

- IF attribute 1 = A1, 3 AND attribute 2 = A2, 1 AND attribute N = An, 2 THEN class = Class1.
- IF attribute 1 = A1, 1 AND attribute 2 = A2, 2 AND attribute N = An, 1 THEN class = Class2.

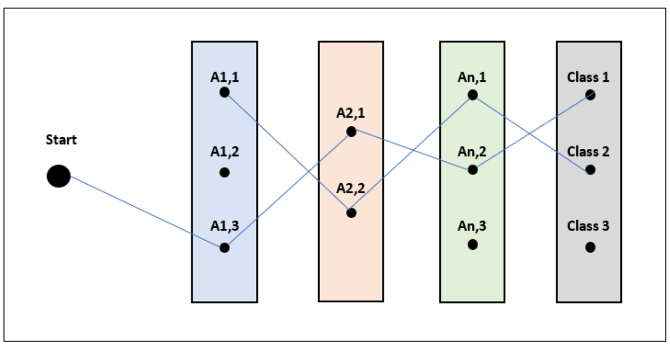

Fig. 1. Development of ant-based classification rules.

A fitness function evaluates the current set of rules to determine the reliability of each rule in the classification model. Ants adjust their pheromone trace according to the strength of a feature. The potency of a pheromone trail is determined by how effectively the features contribute to classification accuracy. By encouraging ants to select the same features in subsequent iterations, the algorithm gradually converges on a refined subset of attributes. To prevent the algorithm from settling on a suboptimal solution, it is possible to eliminate weak features with low pheromone intensity from the subset [13, 14]. Once the most relevant features have been selected, a classification model can be developed.

This paper analyzes parameter adaptation by the proposed algorithm to enhance the data classification process in smart aquaculture. The impact of each parameter is assessed by applying different values within a defined range to measure classification accuracy. The results demonstrate the effectiveness of the optimal parameter values, which can be applied to the proposed algorithm specifically and to other ACS variants more broadly, in the context of smart aquaculture. A final comparison is conducted by applying the optimal parameter values and evaluating them against other ACO-based classification algorithms. Section II discusses data classification in real-world applications, while Section III reviews recent ACO approaches in data classification. The proposed data classification algorithm is detailed in Section IV followed by experimental results and discussion in Section V and Section VI respectively. Lastly, Section VII provides concluding remarks.

II. Real-Life Applications Using Ant-Based Data Classification

Classifying data involves organizing information based on a set of policies and standards. Data classification is typically based on three criteria which are risk levels, sensitivity, and importance [15]. In general, data classification enables organizations to store, access, and retrieve data safely, efficiently, and effectively. ACO can be applied to rule construction in data classification, where it searches for a set of rules that accurately classify instances within a dataset [16]. An ant constructs a rule by following a pheromone trail, moving from one term to another. The pheromone trail represents the attractiveness of a term to ants, with more attractive terms having higher pheromone concentrations. The algorithm begins with a randomly generated set of basic rules. Each rule consists of a set of conditions that describe terms composed of attributes and values, determining classification into a specific class. The ants are initially dispersed randomly throughout the terms. Then, each ant selects a term based on a heuristic function and the pheromone concentration.

The accuracy of the classification model is determined by evaluating the existing set of rules using a fitness function. Over time, ants modify their pheromone trails based on the quality of the selected terms. The effectiveness of these terms is directly correlated with pheromone concentration [17]. Ants are encouraged to select the same terms in subsequent iterations, leading the algorithm to converge on a specific set of attributes. Weak terms with low pheromone intensity can be eliminated to prevent the algorithm from selecting an unsuitable solution. Table I presents a list of ant-based data classification applications in real-world scenarios, categorized into five main domains which are agriculture, aquaculture, health and medicine, autonomous vehicles, and finance.

Based on Table I, data classification plays a crucial role in various Real-world applications across multiple domains, including aquaculture systems. The classification challenge was successfully addressed in real-life scenarios using an ACO-based classification technique.

TABLE I. DATA CLASSIFICATION IN REAL-LIFE APPLICATION

Domain	Author(s)	Application
Agriculture	[18]	Reducing operational and seepage losses in agricultural water distribution systems by using ACO algorithm
	[19]	Utilizing a hybrid of Hopfield Neural Networks and ACO for agricultural soil fertility analysis
	[20]	Identifying cotton leaf diseases and forecasting yield with the use of support vector machines (SVM) and ACO algorithm
	[21]	IACO refines the variables of the disease detection model by choosing features from the leaf images
Aquaculture	[22]	ACO improves the feature selection procedure for classifying water quality
	[23]	Improving the accuracy of models that predict groundwater nitrate concentrations by using ACO algorithm
	[24]	ACO improves the fish disease identification system by optimizing feature selection.
	[25]	Optimizing rule-based data classification technique to improve data classification in smart aquaculture
Health and Medicine	[26]	Optimizing breast cancer classification by using hybrid ACO and Fisher's method
	[27]	Classifying depressive disorders by using an improved ACO algorithm
	[28]	Integrating ACO and XGBoost for early diabetes detection
	[29]	ACO improves the knee osteoarthritis severity classification framework
Autonomous Vehicle	[30]	Enhanced ACO technique for autonomous surface vehicle local path planning
	[31]	Improving lane detection with an adaptive ACO algortihm
	[32]	Dynamic obstacle avoidance through the application of the Quantum Ant Colony Algorithm
Financial	[33]	Utilizing ACO to develop a model for financial crisis prediction
	[34]	Employing ACO to maximize high-frequency and dynamic pair trading in financial markets
	[35]	Optimizing the classification of credit data by combining Random Forest and hybrid ACO algorithm

III. RELATED WORK

ACO has demonstrated promising results in optimizing data classification, where its effectiveness heavily depends on the accuracy of the features used for classification and the size of the dataset. Applying ACO to feature selection has enhanced classification performance and efficiency by reducing complexity, minimizing overfitting, and improving accuracy. A multi-label feature selection approach based on ACO (MLACO) was proposed by study [36] to identify the most relevant features with minimal redundancy. This approach combines supervised and unsupervised heuristic functions to refine feature selection over multiple iterations. According to experimental results, MLACO, which employs a global pheromone update to detect and eliminate redundant features, performed more efficiently and accurately than other algorithms.

To optimize the process of rule generation and selection, [37] proposed a self-training utilizing associative classification using ant colony optimization (ST-AC-ACO). This method integrates a semi-supervised associative classification technique with ACO to enhance classification performance by leveraging both labeled and unlabeled data. The method incorporates unlabeled cases into the learning process, addressing the problem of limited labeled data. This enables the system to identify valuable patterns and rules that may not be apparent from labeled data alone. ACO is employed to optimize the rule generation and selection steps within the associative classification process. Using pheromone-based techniques, the system guides the search for high-quality classification rules. The proposed method was compared with existing supervised and semi-supervised classification algorithms. Experimental results demonstrated the advantages of integrating associative classification with ACO, showing improved classification robustness and accuracy, particularly when working with unlabeled data.

Applying ACO algorithms for data classification in smart aquaculture presents an innovative approach to organizing and analyzing large and complex datasets. In this context, data classification refers to the process of structuring and analyzing data collected through advanced technologies to enhance the sustainability, efficiency, and management of aquaculture systems. Smart aquaculture optimizes various aspects of aquaculture operations by integrating technologies such as sensors, data analytics, machine learning, and automation.

By integrating the ACO technique into a boosting framework, the study by [22] aims to develop an optimization-based feature selection method to enhance the accuracy of water quality classification models. The proposed algorithm identifies key features within the dataset while eliminating irrelevant and redundant ones to optimize the classification process. ACO utilizes pheromone trails to select features during each iteration of the boosting process. Ants use heuristic information and updated pheromone levels to construct a new feature subset. To achieve optimal performance, ants identify the subsets with higher pheromone values. Additionally, pheromone updates are applied to balance the exploration and exploitation of potential feature subsets. Experimental results demonstrate that the proposed approach effectively improves accuracy, sensitivity, and precision compared to other classification algorithms.

The integration of the ACO algorithm with the random forest algorithm was proposed by study [23] to enhance the accuracy of nitrate concentration mapping in groundwater within the multi-layer coastal aquifer system of the Mekong Delta. ACO is responsible for the feature selection process, identifying the most significant features that contribute to accurate groundwater nitrate concentration predictions. Ants utilize heuristic information and pheromone levels to make probabilistic feature selections, facilitating the convergence of feature subsets that improve the prediction model's performance over multiple iterations. At the end of each iteration, pheromone levels are adjusted to reinforce effective feature subsets and suppress ineffective ones. This iterative process continues until an optimal feature subset is identified. By assisting in the selection of the most relevant features from a potentially large dataset, ACO enhances both the accuracy and efficiency of the random forest model.

The study by [24] aims to optimize fish disease identification by integrating a Deep Convolutional Neural Network (DCNN) for feature extraction, ACO for feature selection, and a hybrid random forest for classification. ACO is employed to select a subset of relevant features based on pheromone concentrations, with the number of ants determining the extent of feature space exploration. Features with high pheromone values are selected, while an evaporation procedure is simultaneously applied to prevent convergence on a locally optimal solution. Experimental results demonstrated that the proposed algorithm achieved the highest accuracy compared to other classification algorithms.

Based on the reviewed literature, ACO demonstrates significant potential in addressing classification challenges within the aquaculture domain. However, none of the prior studies explicitly highlight the significance of individual parameter values. The objective of this study is to identify the optimal parameter values that can be utilized by ACO for data classification in smart aquaculture.

IV. Enhanced Ant Colony System For Data Classification In Smart Aquaculture

The proposed Enhanced Ant Colony System for Rules Classification (EACS-RC) algorithm is an adaptation of ACS, consisting of three main phases which are rule construction, pheromone update, and evaluation, as illustrated in Fig. 2. The new algorithm variant is revolutionized from the ACS [38] as an improvement to the AS for enhancing the classification performance. While both ACS and AS are based on foraging behavior, they differ in three key aspects which are rule construction, local pheromone update, and global pheromone update. ACS employs a more aggressive action-selection rule, where pheromone is partially removed from each visited path, and additional pheromone is only applied to the global best solution.

The rule construction phase focuses on using ants to iteratively develop the model by constructing classification rules. These rules are formulated based on heuristic information and pheromone values obtained from previous iterations. The pheromone update phase consists of two key steps which are local pheromone update and global pheromone update. The local pheromone update acts as a control mechanism to prevent excessive accumulation of specific parameters and minimize the overfitting of noisy data, thereby reducing the runtime of the classification process. Conversely, the global pheromone update is applied to the most optimal rule identified by the ant during each iteration. This step ensures that the algorithm progressively converges toward a more accurate and effective model by selectively reinforcing high-quality rules. As a result, the overall classification solution is improved by the end of the process. In the final stage, the most optimal rule from each iteration is selected to form the classification model. The performance evaluation phase then assesses the effectiveness of the proposed classification algorithm by measuring the model's accuracy.

Based on Fig. 2, each ant begins selecting terms to add to the rule during the rule construction phase. Two key factors considered when choosing terms are the pheromone value and heuristic information. The state transition rule is applied to balance the exploitation of prior terms and the exploration of new terms, as represented by the following equation.

$$S = \begin{cases} argmax \in U, & \text{if} \quad q \leq q_0 \text{ (exploitation)} \\ P, & otherwise \text{(exploration)} \end{cases} \qquad (1)$$

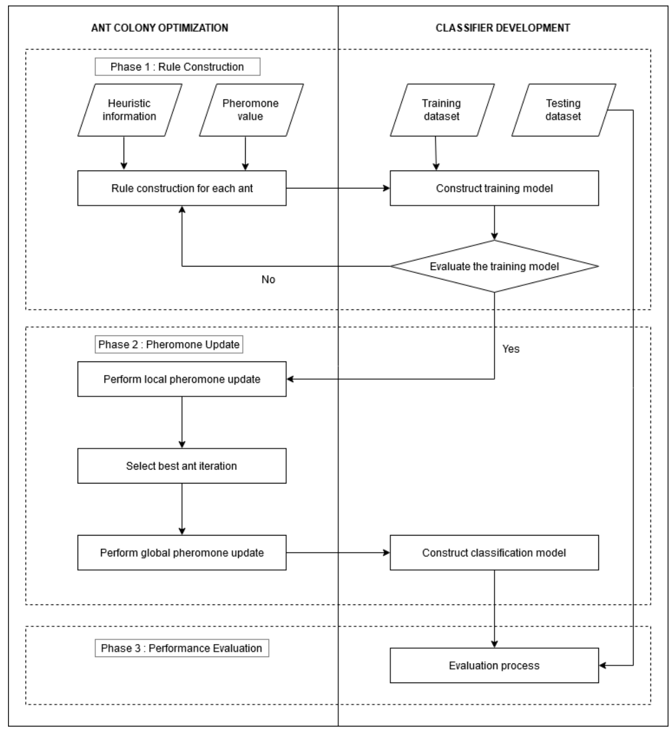

Fig. 2. Framework of the proposed EACS-RC classification algorithm.

where q is a random number uniformly distributed between 0 and 1 and q_0 is a parameter value ($0 \leq q_0 \leq 1$). When q is less than or equal to q_0, the ant makes a deterministic (greedy) choice by selecting the condition with the highest pheromone level or heuristic information. In this case, the probability is set to 1 for the selected variable and 0 for all other variables. Otherwise, when q is greater than q_0, the ant follows a probabilistic path selection process, using pheromone and heuristic information to calculate the probability of selecting each rule.

U represents the probability of selecting a specific value from available options and P is the proposed equation to calculate the probability of term selection to be added to the current rule which is calculated using the following equation:

$$P = \frac{\left[\left(\tau_{rs(t)}\right)^{\alpha}.(\eta_{rs})^{\beta}\right]}{\sum\left(x \cdot \sum\left[\left(\tau_{rs(t)}\right)^{\alpha}.(\eta_{rs})^{\beta}\right]\right)} \qquad (2)$$

where the concentration of pheromones at any given time (t) for each term is represented as $[\tau_{rs(t)}]$ while the heuristic information or desirability is represented as $[\eta_{rs}]$ which considers the pH, temperature and DO value of water. The variable $[x]$ represents the number of iterations. The outer summation $(\sum)$ iterates over the number of ants or iterations.

Each rule created by an ant undergoes pruning by eliminating unnecessary terms during the rule pruning process. The proposed algorithm determines the predictive class of the pruned rules by assigning them to the majority of the cases they cover. This process is repeated iteratively to enhance the quality of the rules. To refine the discovered rules, a local pheromone update is applied using the following equation:

$$\tau_{n(t+1)} = (1-\rho).\tau_{n(t)} + \rho.S(t) \tag{3}$$

In the given context, ρ represents the evaporation rate, which controls the accumulation of a specific parameter to prevent unlimited accumulation. For each threshold value, $\tau_{n(t)}$ denotes the quality level that determines the most probable selection. Meanwhile, $S(t)$ represents the quality of the discovered rule, which is defined as follows:

$$S_t = \frac{[N_T][P_T]}{(P_T+N_F)(N_T+P_F)} \tag{4}$$

where N_T represents the total number of instances that do not belong to the expected class and are not covered by the discovered rule, while P_T indicates the total number of instances that belong to the expected class and are covered by the discovered rule. On the other hand, N_F signifies the Total number of instances covered by the discovered rule but classified incorrectly. Finally, P_F indicates the total number of instances that are classified correctly by the rule but are not covered by the discovered rule.

This process will continue until all the ants have learned the complete set of rules. The most effective rules discovered in each cycle will be added to the final list of classification rules. The best rule from each iteration is selected using the global pheromone update, calculated as follows:

$$\tau_{n(t_{best})} = (1-\rho).\tau_{n(t_{best})} + \rho.S(t_{best}) \tag{5}$$

where ρ represents the parameter responsible for the quality decay, while $S(t_{best})$ denotes the quality of the best discovered rule at a given iteration. Once all steps completed, a new iteration will begin, following the same process.

V. Experimental Results

The ideal parameters for EACS-RC in classifying data in smart aquaculture were determined through experiment. The α value controls the influence of pheromone information on the ant's decision-making process, while β value determines the importance of heuristic information or domain-specific knowledge used by the ants to make decisions. Additionally, pheromone trails evaporate over time at a rate determined by the evaporation rate (ρ).The q_0 value regulates the balance between exploration and exploitation, helping ants effectively navigate the search space.

The optimal value for α, β, ρ and q_0 as well as their effects on the system were determined through experiments using Kiribati water quality monitoring data [39]. Classification accuracy was used as the evaluation metric for parameter adaptation. The EACS-RC algorithm was assessed using standard ACS parameters, including the number of ants, rule discovery criteria, number of iterations, and the experiment parameters. Table II presents the simulation parameters used in the experiment.

TABLE II. SIMULATION PARAMETERS

Parameter	α, β, ρ and q_0
Performance metric	Classification accuracy
Number of Ants	10
Minimum number of cases that each rule must cover	5
Maximum of uncovered cases by the discovered rule	10
Number of iterations	100

The optimal value of α, which determines the impact of pheromone value on the ant's decision-making process, was evaluated in the first set of experiments. A range of values from 1 to 10 was tested to assess the classification performance of EACS-RC. As shown in Fig. 3, the optimal α value is 3 (highlighted in red) as it yields the highest classification accuracy. Selecting the optimal α value is crucial, as it directly influences the convergence speed of the algorithm.

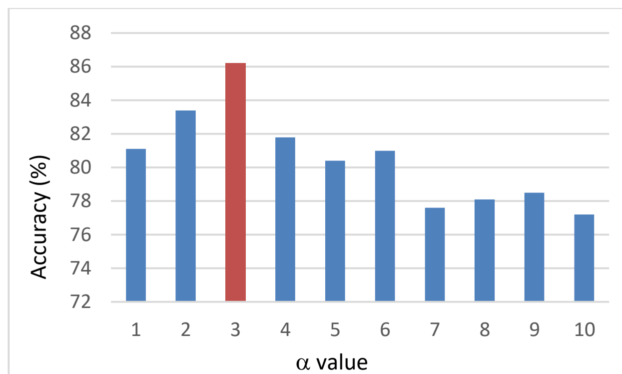

Fig. 3. Effect of α value on accuracy of EACS-RC.

The second set of experiments aimed to determine the optimal value of β for EACS-RC, where $0 < \beta < 10$. Fig. 4 illustrates that the ideal value of β is 4 (highlighted in red), as it results in the highest classification accuracy based on the experimental results. The β parameter plays a crucial role in balancing the exploitation of pheromone trails and the use of problem-specific knowledge, ensuring an effective classification process.

The third set of experiments aimed to determine the optimal value of q_0 which serves as a threshold in the state transition rule to balance the exploration of new terms and the exploitation of previously selected terms. The impact of q_0 on the classification performance of EACS-RC for the water quality index was evaluated using values ranging from 0.1 to 1. As shown in Fig. 5 (highlighted in red), the optimal value of q_0 is 0.5, yielding the highest classification accuracy. Identifying the optimal q_0 value is crucial as it directly influences how the ACO algorithm balances exploration (random selection) and exploitation (pheromone-based selection), thereby affecting the overall performance of the classification process.

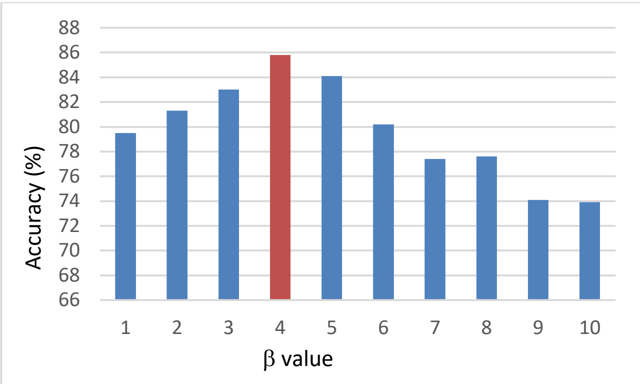

Fig. 4. Effect of β value on accuracy of EACS-RC.

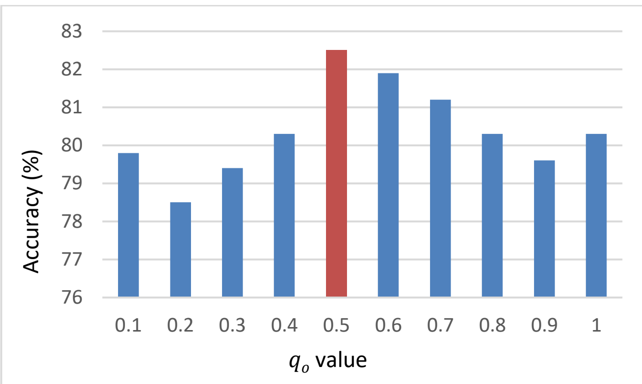

Fig. 5. Effect of $\boldsymbol{q_0}$ value on accuracy of EACS-RC.

In the next set of experiments, the optimal evaporation rate (ρ) value for pheromone decay was investigated. Pheromone decay is essential to prevent the excessive accumulation of pheromones, which could lead to stagnation or convergence toward suboptimal solutions. The experimental results, as shown in Fig. 6, indicate that the optimal (ρ) value is 0.5 (highlighted in red), yielding the highest classification accuracy. These findings emphasize the crucial role of (ρ) in the algorithm, as it ensures that ants continue exploring different terms while preventing them from being overly influenced by outdated information.

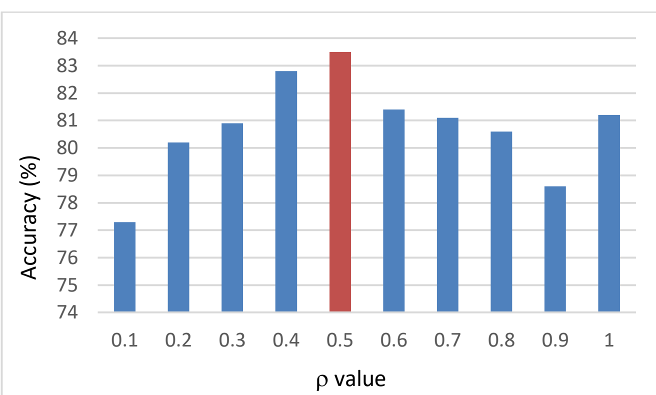

Fig. 6. Effect of ρ value on accuracy of EACS-RC.

The optimal value of α, β, ρ and q_0 from the previous experiments were applied in next set of experiments to evaluate the performance of the proposed EACS-RC algorithm. The Kiribati Water Quality Monitoring dataset was used to assess its accuracy and processing time with two other classification algorithms, AntMiner [40] and AGI-AntMiner [41]. Fig. 7 illustrates that the EACS-RC algorithm achieved an accuracy of 83% with a processing time of 598 seconds. In comparison, the AGI-AntMiner algorithm attained a slightly lower accuracy of 82%, with a processing time of 649 seconds. Meanwhile, the AntMiner algorithm recorded an accuracy of 77% and required 700 seconds to complete the process. These findings highlight the efficiency and accuracy of the EACS-RC algorithm in analyzing the Kiribati Water Quality Monitoring dataset.

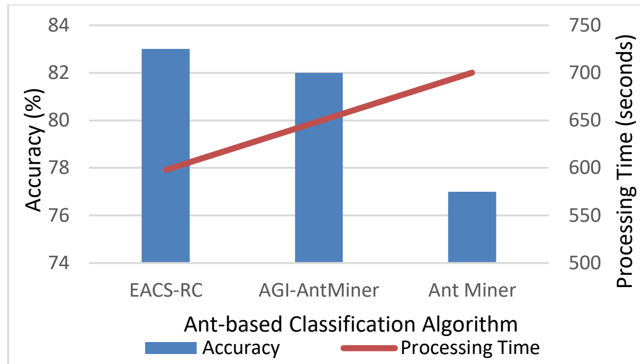

Fig. 7. Comparison of accuracy results between EACS-RC, AGI-AntMiner and AntMiner.

VI. Discussion

Four sets of experiments were conducted to determine the optimal parameter values for EACS-RC, and the results are summarized in Table III.

- The optimal α value is 3, as it influences the convergence speed of the algorithm. A higher α may cause premature convergence to suboptimal solutions, while a lower α can slow down the optimization process.
- The optimal β value is 4, balancing the use of heuristic information and pheromone influence. A higher β gives more weight to problem-specific knowledge, while a lower β prioritizes pheromone trails.
- The optimal q_0 value is 0.5, ensuring a balanced exploration-exploitation trade-off during the local pheromone update phase.
- The optimal ρ value is 0.5, allowing pheromone trails to dissipate optimally. This prevents ants from being overly influenced by outdated information and encourages better exploration of feature subsets.

These values are considered optimal for the EACS-RC algorithm in smart aquaculture systems for water quality classification. However, factors such as simulation settings, topology, environmental conditions, and dataset size may affect the need for further parameter tuning to achieve optimal performance.

TABLE III. THE OPTIMAL VALUE FOR THE PARAMETERS TO GAIN BEST ACCURACY

α	3
β	4
q_0	0.5
ρ	0.5

VII. CONCLUSION

While optimizing the efficiency of the ACS algorithm in smart aquaculture for water quality classification, it is undeniable that selecting the most suitable parameter values is essential. An algorithm functioning at peak efficiency ensures optimal performance. By fine-tuning the parameters, the proposed EACS-RC algorithm can effectively leverage available data, such as pheromone trails and heuristic information, to enhance classification accuracy. Compared to previous studies that overlooked parameter adaptation, refining these values can significantly improve the precision of water quality classification, which is vital for smart aquaculture management. This efficiency is particularly important in smart aquaculture, where timely and accurate water quality classification is crucial for effective decision-making and ensuring the well-being of aquatic organisms. The process of parameter adaptation plays a crucial role in improving algorithm performance and its applicability in real-world aquaculture scenarios.

Future research could focus on fine-tuning parameters for other ACO algorithm variants across diverse application domains, topologies, and environments. Beyond parameter optimization, future research could explore the integration of adaptive and self-learning mechanisms into the EACS-RC algorithm. Incorporating machine learning techniques, such as reinforcement learning or metaheuristic-based adaptation, could enable the algorithm to dynamically adjust its parameters based on real-time environmental conditions. This adaptability would enhance its robustness and responsiveness to changing water quality factors in smart aquaculture systems.

ACKNOWLEDGMENT

The authors acknowledge the financial support provided by the Ministry of Higher Education through the Fundamental Research Grant Scheme (FRGS) under a grant number of FRGS/1/2021/ICT02/UNIMAP/02/5.

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