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Improving Water-Efficient Irrigation in Terrain Durio Zibethinus Farming Using Hybrid Ant Colony Optimization-Based Soil Moisture Prediction Model

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Abstract: The vegetation stage of Durio Zibethinus trees is characterized by active root development, leaf expansion, and the initiation of reproductive structures. During this crucial phase, adequate irrigation is necessary to satisfy the trees' water requirements. A well-irrigated durian plantation encourages effective nutrient absorption, resulting in healthier trees with increased pest and disease resistance. Understanding the water needs of durian trees is essential for irrigation management to optimize water application and prevent water stress and waterlogging. Typically, sensors measure the soil moisture within the root zone. However, installing soil moisture sensors at each tree is laborious and prohibitively expensive. Using climatic data to forecast the value is a viable option in such a scenario. Climate data are used to create soil moisture predictions incorporated into the irrigation model. This research employs Ant Colony Optimization- Support Vector Regression (ACO-SVR) to predict soil moisture levels. The model is compared to other optimization methods, and its accuracy is assessed using statistical methods. Finally, the prediction models' findings determine the irrigation volume and schedule.

Keywords: Artificial Intelligence, Durio Zibethinus, Durian Farming, Irrigation System, Soil Moisture Prediction

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1. INTRODUCTION

Durio Zibethinus, also known as the Durian, is a king of fruits, is a tropical Southeast Asian fruit with a notable reputation for its strong odor and exceptional flavor richness. The fruit is harvested twice a year and is renowned for its economic significance and high demand both locally and internationally. Many Malaysian farmers, predominantly smallholders, cultivate durian due to its commercial importance. In Malaysia, durian boasts the largest planted area compared to other fruits [1]. Depending on their varieties, durian trees typically mature within three (3) to seven (7) years [2]. As depicted in Figure 1, the durian tree cultivation process comprises five significant stages: the planting stage, the vegetative stage, the blossoming stage, the harvesting stage, and the hibernation stage.

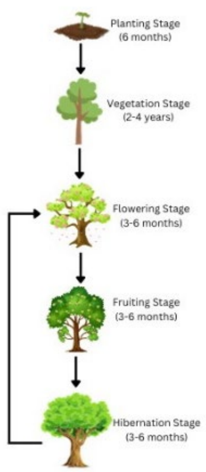

Figure 1. Durian Planting Stages

The vegetative stage, which is both the most prolonged and critical phase in durian tree cultivation, requires precise water management. This phase typically spans up to four (4) years for most durian varieties, during which tree growth is continuously monitored [3]. Farmers closely assess elements such as the colour and quality of the foliage, the trunk's diameter, and the tree's height, all of which significantly impact overall growth. As a result, regular irrigation and fertilization are indispensable. Notably, for durian trees, water takes precedence over fertilizer in terms of importance [4]. During this stage, ensuring the correct amount of water is applied to each tree is of utmost importance, and proper irrigation practices are essential to guarantee the optimal water supply.

2. LITERATURE REVIEW

2.1 Soil Moisture Prediction

Understanding soil moisture is essential in agriculture and environmental science, given the significant impact on plant growth, water resource management, and climate studies. Soil moisture refers to the quantity of water in the soil, and knowing the soil moisture value is essential. Knowing soil moisture levels is highly important to enhancing the efficiency of irrigation techniques. Soil moisture data is utilized by farmers to make decisions regarding irrigation practices, thereby guaranteeing that crops receive the precise amount of water necessary to maximize tree growth. This practice helps minimize water wastage and reduce crop damage caused by drought, hence enhancing agricultural efficiency [5].

Furthermore, soil moisture is crucial in hydrological models, especially in water resource management. Understanding the soil moisture content helps predict and manage water runoff, groundwater state, and the availability of water resources to manage water scarcity and maintain the water supply [6]. In addition, understanding soil moisture data is crucial for climate studies and weather forecasting. The heat impacts and ground moisture between the Earth's surface and the atmosphere influence local weather patterns and long-term climate trends [7]. The significance of soil moisture is absolute from both academic and practical perspectives. Various methodologies and technological advancements, such as utilizing soil moisture sensors and satellite-based remote sensing, have been developed to evaluate soil moisture levels effectively. These data offer significant information that can be utilized to enhance agricultural practices, manage water resources effectively, and give further understanding of climate change [8].

Soil moisture is a metric that quantifies the amount of remaining water in the soil. A soil moisture sensor is used to determine this value. However, having numerous soil moisture sensors on a farm is impractical and inefficient due to the expense and labor needs. In addition, the coverage area of a particular soil moisture sensor is unknown [9]. Forecasting soil moisture readings to depict the agricultural region is the solution. The moisture content of the soil is a crucial determinant when analyzing the soil's performance concerning irrigation application. It establishes the essential elements required for a logical application of irrigated agriculture, especially in arid or semiarid regions where water scarcity and poor water quality can hinder crop development and yield.

Numerous studies have used machine learning to predict soil moisture. The forecast depends on external factors such as meteorological information, electrical conductivity (EC), and soil salt [10]. Many machine learning techniques have been applied for prediction. For the prediction, numerous machine learning algorithms have been used employing regression techniques, including Support Vector Regression (SVR) and linear regression, to forecast soil moisture [11]. However, the paper did not provide specifics regarding the algorithm's input. Based on data from precipitation and evapotranspiration, SVR can forecast drought conditions for use in agriculture [12]. Using a multi-layer soil sensor, researchers used SVR to estimate soil moisture [13]. Artificial neural networks (ANN) have also been used to forecast soil moisture [14], [15]. However, pre-processing techniques were used on the raw data to remove partial data due to the unpredictably changing weather.

Support Vector Regression (SVR) was employed by [11], [16], [17], [18], [19] the most frequently when modelling soil moisture. Using precipitation and evapotranspiration data, SVR can forecast drought conditions for agricultural applications [12]. Using a multi-layer soil sensor, researchers employed SVR to estimate soil moisture [13]. However, the performance of SVR models can be highly dependent on the selection of their hyperparameters and optimizing these hyperparameters is essential for increasing the precision of soil moisture predictions.

A method based on the Particle Swarm Optimization algorithm (PSO) has been proposed [20] for SVR-based soil moisture prediction using remote sensing data. The outcomes demonstrated that the proposed method could successfully optimize the SVR model and improve its prediction accuracy. Using a genetic algorithm to optimize the model parameters revealed that the model outperforms conventional SVR models [21]. The efficacy of an SVR-based model for estimating soil moisture using remote sensing data was compared to that of other machine learning algorithms [22]. Consequently, it was determined that the SVR model had the highest level of accuracy and that its performance could be improved by optimizing its hyperparameters. Using remotely sensed data, various machine learning algorithms, including SVR, were contrasted for estimating soil moisture [23].

Moreover, a Grid Search algorithm-based optimization method for SVR was proposed and found to enhance the efficacy of the SVR model significantly. SVR and multiple linear regression were evaluated for their ability to predict soil moisture, and a genetic algorithm-based optimization method for SVR was proposed [24]. It was discovered that the SVR model with optimized hyperparameters outperformed the multiple linear regression model in terms of accuracy.

The previous results highlight the necessity for additional studies to address limitations in previous research relevant to the improvement of SVR models for accurate soil moisture prediction. The potential to improve the performance of SVR models can be observed by utilizing several optimization techniques, such as particle swarm optimization, grid search, and genetic algorithms. Nevertheless, it is essential to understand that the most suitable methodology may differ based on the dataset and problem within the study. Hence, before selecting the most suited optimization approach, it is crucial to perform a comprehensive evaluation and comparison of different optimization methodologies.

2.2 Irrigation Management

The Soil-Plant-Atmosphere Continuum (SPAC) model, initially proposed by B.J. van den Honert in 1948, provides a fundamental framework for understanding the dynamics of water transport in the soil-plant-atmosphere system. The present model elucidates the complex interconnections among these constituents and carries significant ramifications for irrigation methodologies [25]. The concept of transpiration is considered a fundamental principle within the SPAC model. The process, which plays a vital role in the transportation of water throughout plants, has a strong correlation with the principles outlined in the model. Transpiration is a physiological process in plants whereby water vapor is emitted through microscopic apertures known as stomata, facilitated by the tension generated by evaporation occurring on the surfaces of leaves.

The SPAC model is an indispensable tool for farmers and agricultural practitioners to manage irrigation effectively. This model offers valuable insights for making informed decisions on irrigation timing, quantity, and methods. Among the crucial factors the model highlights, soil water potential takes center stage. This parameter is influenced by a range of factors, such as soil texture, organic matter concentration, and nutrient availability, and it plays a pivotal role in determining the rate at which plant roots absorb water. For this reason, soil water potential is a vital component for improving irrigation techniques [26]. In addition, the SPAC model places significant emphasis on maintaining an ideal soil moisture level. Ensuring adequate water for plants facilitates their optimal growth and developmental processes. Furthermore, the model emphasizes the significance of transpiration in the regulation of plant temperature and the absorption of nutrients. Implementing appropriate irrigation techniques is crucial in managing excessive transpiration in times of drought, hence guaranteeing a consistent water supply for plants [27].

The use of technology developments in irrigation management has proven advantageous for contemporary agriculture. Precision agricultural approaches leverage data from multiple sources, such as soil moisture sensors and weather forecasts, to optimize irrigation procedures. The utilization of data-driven methodologies facilitates the alignment of irrigation practices with the principles of the SPAC model, leading to a decrease in water wastage and an enhancement in crop yields. The field of precision agriculture has yielded findings that highlight the capacity to enhance irrigation and crop management practices, hence increasing the efficiency and sustainability of agricultural systems [28].

The weather, soil moisture readings, runoff, and infiltration all influence the quantity of water required [29]. Numerous studies and techniques have been conducted to correlate these factors with irrigation systems, with the Water Balance approach being the most widely used [30]. As shown in Figure 2, the Water Balance approach represents soil moisture as a function of water streaming into the soil through irrigation and precipitation and water flowing out through evapotranspiration (E_t), runoff, and deep percolation below the plant's root zone. In contrast, Water Balance reflects the soil moisture value, the quantity of water remaining in the soil at a given time. Consequently, it is essential to determine the soil moisture content (θ_s). Several soil parameters, such as the wilting point, field capacity, and saturated zone, must be determined to develop the optimal irrigation strategy based on the water-balanced model. Previous research has demonstrated that soil moisture content is one factor considered when administering irrigation systems [31], [32]. It can be used daily and annually to monitor crop response and water intake. The inventive irrigation system will also be designed to respond to varying soil moisture content levels, allowing for more tailored irrigation [33].

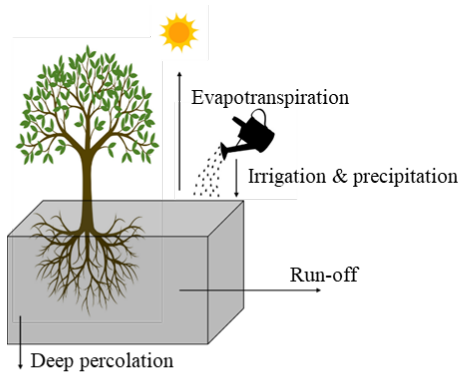

Figure 2. Water Balance Model

There are two irrigation strategies using Artificial Intelligence (AI): Open Loop Irrigation and Close Loop Irrigation. Open Loop AI Irrigation is relatively straightforward; the irrigation volume threshold is calculated using a specific AI soil moisture model, and irrigation is initiated and terminated based on the volume estimate. Close Loop AI Irrigation is considerably more advanced, involving intelligent processes before and during irrigation. In recent years, numerous studies have been conducted to determine the applicability of Artificial Neural Networks to irrigation scheduling. ANNs were used to develop and validate data-driven models for forecasting the reference canopy temperatures necessary to compute sugar beetroot and wine grape water stress [34]. The models could estimate reference temperatures and automate the generation of the crop-water-stress index for efficient crop-water stress evaluation. Following the implementation of ANN in irrigation scheduling, water and energy savings were demonstrated, with soil moisture and physical characteristics such as flow rate and weather data functioning as model inputs [35].

A system of expert-controlled irrigation equips farmers with the knowledge required to accurately anticipate the amount of crop water required at the optimal time, weather, and growing medium parameters, such as temperature, humidity, and soil type [36]. Numerous academicians have used expert systems to solve a wide range of agricultural issues, such as irrigation scheduling [37], irrigation in arid conditions [38], and drip irrigation system design [39]. The efficiency with which knowledge is acquired influences the performance of an expert system. Process errors pose a significant threat to the dependability and efficacy of expert systems.

Previous studies conducted on the development of an ideal irrigation model have identified some limitations. The existing knowledge gaps include the requirement for an in-depth understanding of the relationships among soil, plants, and the atmosphere, combined with the necessity for enhanced data-driven methodologies in irrigation management. Furthermore, it is vital to investigate the effects of climate change on irrigation methods and explore possibilities to include new technologies to maximize water utilization. In general, the deficiencies in prior research highlight the significance of constructing comprehensive and technologically sophisticated irrigation frameworks to address the escalating complexities in agricultural practices and water resource governance.

3. METHODOLOGY

3.1 Site Setup

The setup occurred at the MIE Agro Durian Farm in Selangor; Malaysia located at 3.38551/101.45574. In the farm, there are 5,000 durian trees planted in four blocks, with multiple sub-blocks in each of which the trees are planted at terraces. The number of terraces varies between subblocks, and each terrace's incline gradient depends on the subblock's characteristics. For irrigation purposes, each sub-block is equipped with a 2200-litre water reservoir. Each tank is additionally fitted with a pump for irrigation water discharge. As depicted in Figure 3, the test was conducted in a section of Sub-block B2 containing four terraces. Each terrace consists of four trees spaced 10 meters apart. On the same day, twelve six-month-old trees were planted in a one-meter-deep trench. Water was drizzled on each tree using a 180-microjet spray. For optimal root absorption, water was dispersed within the tree's canopy during irrigation [3]. Figures 4 and 5 depict the farm's terrace configuration and microjet irrigation.

Figure 3. Arial view for MIE Durian Farm and Sub-block B2 (highlighted)

Figure 4. Terrace setup for durian plantation

Figure 5. Microject Irrigation Spray

3.2 Soil Moisture and Weather Station

The soil moisture sensors were installed within sub-block B2's five (5) terraces, each containing four trees. Each tree was fitted with a sensor to verify the soil moisture data. As depicted in Figure 6, they were planted at a depth of 10 cm, corresponding to the tree's current root zone depth. Individual RS-485 connections were made between the sensors and the LoRa controller. Each hour, data was transmitted to the cloud system.

A UBIQ Davis Vantage Pro 2 weather station was installed at the highest point of the land to capture meteorological data by measuring the temperature, humidity, wind speed, wind direction, precipitation, and solar radiation. It is powered by a battery with a solar charging module to replenish the onboard supercapacitor; during the day, the weather station is powered by a capacitor and at night, by batteries [40]. The station is mounted on a 2-meter-tall pole that extends from the ground. Figure 7 illustrates the installation of the station. Weather station data is uploaded to the cloud via the 3G Network to a gateway every fifteen minutes. Figure 8 depicts the installation architecture for the soil moisture sensor and the weather station.

Figure 6. The installed soil moisture sensor

Figure 7. Weather Station install at the farm.

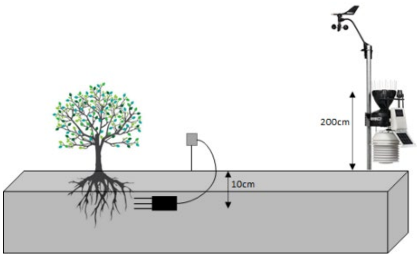

Figure 8. Sensor installation architecture.

3.3 Ant Colony Optimization- Support Vector Regression (ACO-SVR)

Support Vector Regression (SVR) requires tuning hyperparameters to ensure model precision. The procedure of the fine-tuning is known as Optimization. As this work implements the Gaussian Radial Basis Function (RBF) Kernel, three (3) hyperparameters, namely Constraints *(C)*, Boundary Line *(ε)* and *γ*, must be configured. The hyperparameter values selection reflects the error rate of the model. The lower the hyperparameter values will produce the less error and vice versa. However, this rule of thumb is not universal and only occasionally pertains to specific datasets. Figure 9 below shows the general graph for SVR model and its hyperparameters.

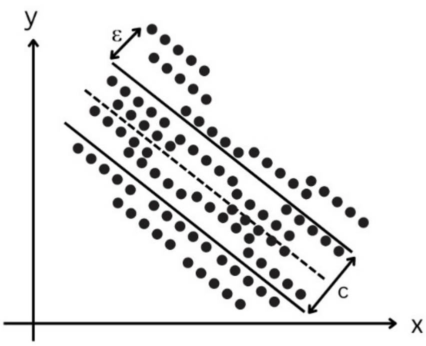

Figure 9. SVR general model and hyperparameters

The *C*, *ε* and *γ* parameters are pivotal in determining the behavior and performance of the SVR model. The *C* parameter balances the trade-off between a smooth decision boundary and accurately classifying training points. A lower *C* value results in a smoother, more straightforward decision surface. In contrast, a higher *C* value aims for the correct classification of all training data by allowing the model to choose more complex boundaries. Nevertheless, a high *C* value can cause overfitting due to the model's excessive proximity to the training data, while a low value can result in underfitting. The *ε* parameter governs the epsilon-tube's width, penalizing points outside the tube. A larger *ε* value incorporates more points into the tube, making the model less sensitive to errors and thus less precise with training data. Conversely, a higher *ε* value makes the model overly sensitive to training data noise. Given the RBF kernel's usage in the model, fine-tuning the Gamma value is crucial for achieving optimal SVR performance. A higher *γ* value increases the decision boundary's sensitivity to nearby data points, leading to a more complex boundary that aims for correct classification, potentially causing overfitting. Conversely, a low *γ* value yields a smoother decision boundary with less influence from individual data points, risking underfitting.

Ant Colony Optimization (ACO) depicts the behavior of ant colonies, in which ants exist collectively instead of independently. Their behavior is determined by the goal of colony survival rather than individual survival. When searching for food, ants randomly investigate the area encircling their nest. As they travel, ants leave behind a chemical trail of pheromones. Ants can detect the pheromones of others. Probabilistically, they tend to choose paths with high pheromone concentrations. When an ant discovers a food source, it evaluates its abundance and quality before transporting a portion back to its habitat. On the return journey, the quantity of pheromones may depend on the quantity and quality of food ingested. The pheromone trails will lead other ants to the food source [41]. As many ants use the same path, more pheromones will be updated on the path. If the food source is far away, the quantity of pheromones will decrease due to evaporation. The movement cycle of ants from their colony to their food source and back is shown in Figures 10 (a) to (f) below.

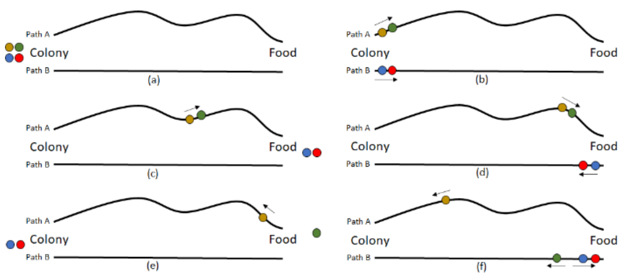

Figure 10. Ants' movement from the colony to the food source and return

The analysis of ant movement architecture reveals that pheromone plays a crucial role in the ants' ability to effectively choose the most efficient path. The Mean Squared Error (MSE) is employed in this study to establish the quantity of pheromone. Additionally, in this work the pheromone level was set to reduce over-time if the trail was no longer in used. The input variables utilized in the model for predicting soil moisture are temperature, humidity, solar radiation, evapotranspiration, and terrace height. The site consists of a total of five terraces. For training, data from the first three terraces (Terrace 1 to Terrace 3) is utilized, while data from the last two terraces (Terrace 4 and Terrace 5) is employed for testing. The following pseudo-code demonstrates the application of ACO-SVR in this study for determining the optimal hyperparameter values.

```
1. Initialize the ants with hyperparameters.
2. Start Iteration:
3.   Repeat until termination criteria is met:
4.   For each ant:
5.     Apply SVR to the data to predict the Soil Moisture.
6.     Calculate MSE of the model.
7.     Get pheromone deposit level.
8.     Update pheromone level with vaporization.
9.     Calculate the probability of the path.
10.    Move the end based on the probability.
11.    Update the best solution.
12. End of iteration
13. Return the best solution found.
```

Each pheromone's deposit level, total pheromone update and path probability are stored in a table, and the content of the table will be updated accordingly as per ant movement. During ants' initialization at the start, to ease the computability process, pheromones deposit level, total pheromone update and path probability are set to one (1), and the values will decrease until the process terminates. The pheromone vaporization rate in ACO is critical, preventing the algorithm from becoming entrenched in suboptimal solutions as the artificial pheromone trails naturally diminish over time. A higher evaporation rate fosters algorithmic exploration, while a lower rate enhances exploitation. Determining the ideal pheromone vaporization rate hinges on the specific problem and may necessitate experimentation. Although values typically range between 0.1 and 0.5, these are not rigid guidelines. Investigating the problem domain's characteristics, scale, and the desired balance between exploration and exploitation is crucial. Fine-tuning an ACO algorithm for a specific application involves adjusting the pheromone evaporation rate. Researchers and practitioners typically conduct experiments to identify the values that yield optimal results for their problem instances.

Table 1.0 below shows the equation proposed in this work to calculate pheromone deposit level, total pheromone update and path probability in applying ACO-SVR to predict the soil moisture with vaporization rate is set to 0.5.

Table 1. Formula for ACO-SVR applied to predict the soil moisture.

Pheromone deposit level	$\frac{1}{MSE}$
Total Pheromone update	$[(1 - evaporation\ rate) \times current\ total\ pheromone] + pheromone\ deposit\ level)]$
Path probability	$\frac{pheromone\ deposit\ level}{\sum pheromone\ values}$

3.4 Soil Moisture Balance Irrigation System

Ensuring the survival and health of trees is contingent upon providing appropriate water levels. Inadequate or excessive irrigation can harm the growth and vitality of trees. Understanding the Chequebook Deficit is crucial to determining the precise irrigation needs. This metric represents the percentage difference between the soil moisture content at field capacity and the current soil moisture content in the root zone. It quantifies the amount of water required to reach field capacity in the root zone. Therefore, the first step necessary for adequate irrigation is determining the area's soil water. This can be accomplished using either manual or scientific techniques [42].

As the objective of this study is to provide a precise irrigation system for durian farming, the soil sample was sent to a laboratory for analysis. This examination was conducted to discover the components and characteristics of the soil. The actual soil type is defined based on the percentage of each soil component in the soil which are Clay, Sand, and Silt. Figure 11 shows a soil triangle used to select the final type of soil based on these components.

Saturation *(θ_s)*, Field Capacity *(θ_{fc})* and Wilting Point *(θ_{wp})* are the aspects of soil moisture content that are crucial for irrigation systems. In saturation state, the soil is filled with water and no air is available. Thus, significant surface runoff will occur at this stage. At field capacity, the amount of water and air in the soil is balanced. Therefore, the soil is in a stable state and the plant roots manage to expend and absorb water from the soil freely. At Wilting Point state, the soil is filled with air with zero amount of water. The soil is extremely dry, and it is insufficient for plant roots to extract water from it [43]. The values of the three variables are soil dependent and can be observed from specific soil standard, such as Malaysia Soil Standard [44] and USDA Soil Standard [45]

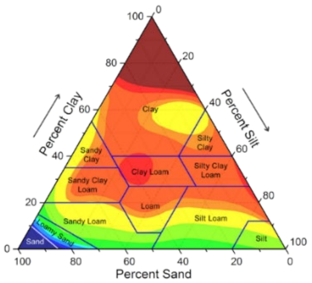

Figure 11. Soil Triangle (source: “Soil Types – RainMachine,” n.d.)

In this work, the irrigation proposed is based on Field Capacity and Wilting Point value. The amount of irrigation volume required is calculated as in the steps below:

- Step 1: Calculate the soil threshold value, θ_x by using the Eq. 1 below.

$$\theta_x = \theta_{fc} - (ASMD\ x\ (\theta_{fc} - \theta_{wp}\ ) \qquad (1)$$

where ASMD is Available Soil Moisture Deficit which the allowance allowed for the trees before they are in deficit state. Assuming ASMD durian tree is 0.2 which is 20%.

- Step 2: Calculate weighted average soil moisture, θ_a at root zone level by using Eq. 2.

$$\theta_a = (\theta_{SM}\ x\ D_s)/RZD \qquad (2)$$

Where θ_{SM} is the predicted soil moisture value from the sensor, D_s is Sensor Depth and RZD is the Root Zone Depth, where RZD for less than 1-year durian tree is 0.1-meter depth.

- Step 3: Compare θ_x and θ_a values. If θ_a is lower than θ_x, calculate the irrigation volume as in Step 4. If higher, no irrigation is required.

- Step 4: Calculate the irrigation volume, V_{irr} by using Eq. 3 below.

$$V_{irr} = (\theta_{fc} - \theta_a) * RZD * 1000 \qquad (3)$$

where the V_{irr} is in liter.

4. RESULTS AND DISCUSSION

This section presents the results obtained using the Ant Colony Optimization-Support Vector Regression (ACO-SVR) method, along with a comparison to other optimization techniques. In addition, the irrigation volume determined using the proposed approach is also provided.

4.1 Collected Data

This section provides an overview of the on-site data, encompassing weather data such as temperature, humidity, solar radiation, and rainfall. Additionally, soil moisture sensor data for Terrace 1 to Terrace 5 is included. It is essential to highlight that soil moisture information for Terrace 1 to Terrace 3 serves as training data, while Terrace 4 and Terrace 5 are designated for testing purposes. The data collection period spans from 3 November 2020 to 30 August 2023, and all values are based on average daily data. Figure 12 and Figure 13 show weather data collected at site which consist of Daily Average Temperature, Daily Average Humidity, Daily Total *ET*, and Daily Total Rain.

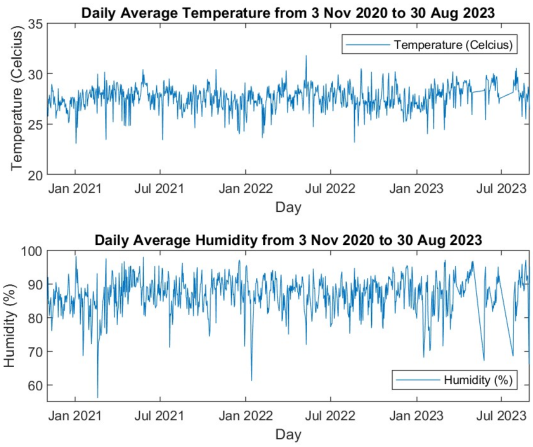

Figure 12. Average Daily Temperature and Humidity from 3 Nov 2020 to 30 Aug 2023

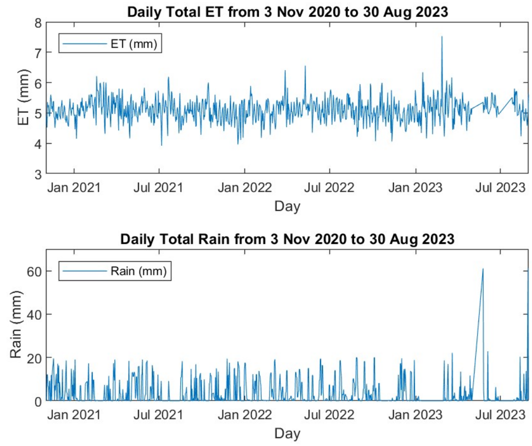

Figure 13. Total Daily ET and Rain from 3 Nov 2020 to 30 Aug 2023

The data collected for this study reveals consistent daily average temperatures and humidity levels, ranging from 23℃ to 30℃ and 55% to 95%, respectively. Noteworthy is the absence of significant fluctuations in temperature and humidity throughout the data collection period. Evapotranspiration (*ET*) readings remained within the average daily range of 4 mm to 6 mm, aligning with Malaysia's established average daily *ET* [46]. However, a deviation occurred in February 2023, with a recorded value exceeding 7 mm/day. Rainfall quantities at the research site exhibited regularity, with a consistent daily average of 20 mm on certain days. Monthly observations indicated precipitation every month, although 2023 experienced reduced rainfall compared to the preceding year. Notably, there was a less absence of rain between February and March 2023, constituting a departure from the typical weather patterns. A singular instance of heavy rainfall (60 mm) was observed in June 2023.

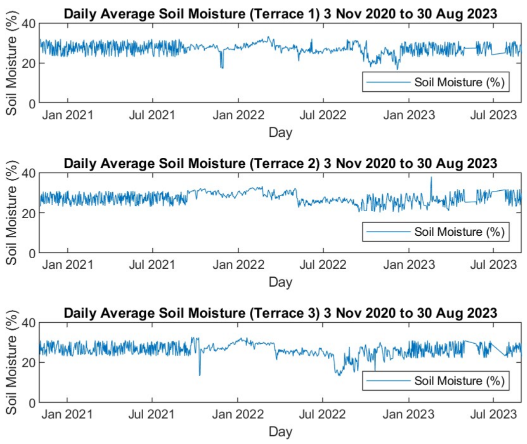

Figure 14. Daily Average Soil Moisture for Terrace 1 to Terrace 3 from 3 Nov 2020 to 30 Aug 2023

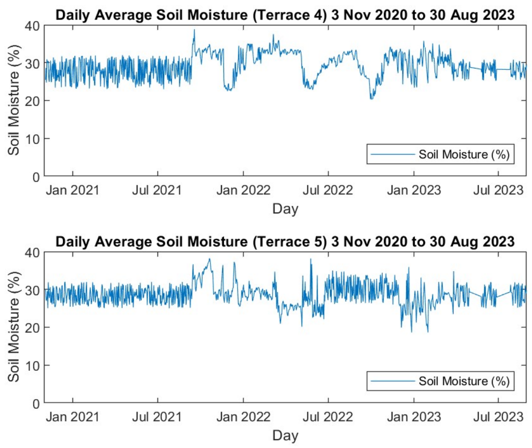

Figure 15. Daily Average Soil Moisture for Terrace 4 and Terrace 5 from 3 Nov 2020 to 30 Aug 2023.

Figure 14 and Figure 15 above show the average soil moisture values collected from site at Terrace 1 to Terrace 5 in sub-block B2. The data was gathered between 3 November 2020 and 31 August 2023. Each tree in each row was equipped with four (4) sensors, and the average soil moisture was calculated daily to represent the average soil moisture in that row. According to the data, all terraces' maximum soil moisture content is less than 40%, and the minimum is less than 20%. There is inconsistency in the data, with some rows displaying greater values than others. This is because the height of the rows differs, with Terrace 1 being the highest and Terrace 5 being the lowest. This is because the irrigation reservoir was located at Terrace 1, so water flowed from the high (Terrace 1) to the low (Terrace 5) during irrigation. Considering water runoff and flow, the soil moisture reading for the lower row will be greater than the upper row.

4.2 ACO-SVR Soil Moisture

ACO-SVR is a memory- hungry algorithm that requires a lot of memory resources to complete the process. The total cycle duration in the algorithm exhibits a strong dependency on the configuration of both the total number of ants and the number of iterations as mentioned in Section 3.3 with minimum two (2) ants per process. For instance, an ACO-SVR configuration employing 10 ants with five (5) iterations results in 50 cycles, demonstrating a comparable total cycle duration to that of five (5) ants with 10 iterations. Notably, ACO-SVR operates as a multi-processing algorithm, necessitating the simultaneous execution of all ants. Consequently, an increased number of ants imposes greater demands on processing resources, highlighting the resource-intensive nature of the algorithm. A bigger quantity of ants with a smaller number of iterations requires higher computational resources, while a smaller quantity of ants with more iterations results in a longer processing time with less resources. Figure 15 below shows the different amount of time required to run ACO-SVR for 120 cycles with different total ants and iteration setup as shown in Table 2.0. Noted that the model ran in Python and the process was executed using Intel Processor i9-13900H with GPU NVIDIA GForce RTX 4050 with 40GB RAM on-board memory.

Table 2. Ants and Iteration combination for 120 cycles

Total Ants	Total Iterations	Total cycle
2	60	120
3	40	120
4	30	120
5	24	120
6	20	120
8	15	120
10	12	120

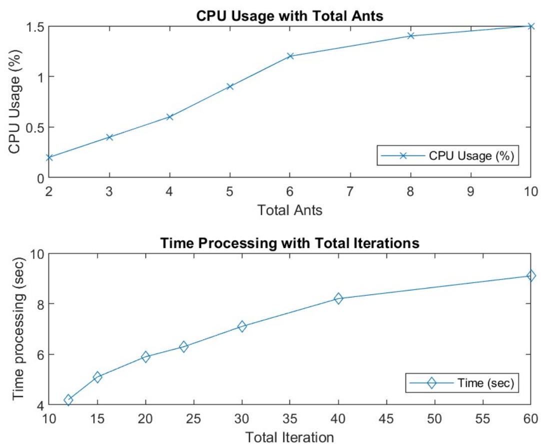

Figure 16. CPU Usage and Time Processing reflecting total ants and iterations for 120 cycles.

Figure 16 illustrates the correlation between total ants, CPU usage, total iterations, and processing time. Combining two ants with 60 iterations requires 0.2% CPU and 9.1 seconds to complete the process while using 10 ants with 12 iterations demands 1.5% CPU and 4.2 seconds. The disparity indicates that a higher number of ants will increase CPU usage due to multi-processing, as all ants are seeking better Mean Squared Error (MSE) based on previous pheromone values left by their predecessors. However, if fewer ants are set with higher iterations, each ant will execute more episodes in path searching, consequently taking much longer to meet the termination criteria. Since this research employs the latest processor and GPU versions, memory usage and processing time are less significant concerns. Nevertheless, achieving the correct combination of ants and iterations is imperative to ensure a smooth process.

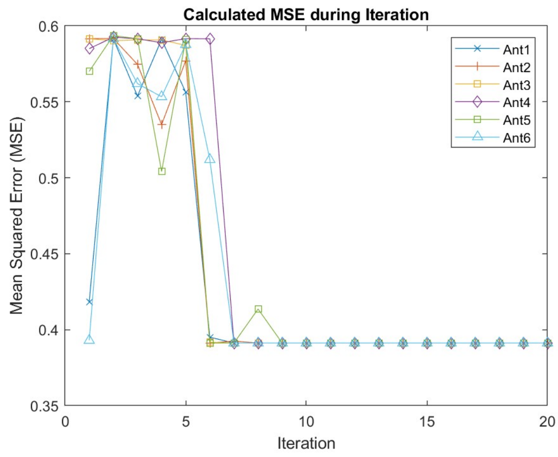

Figure 17. Calculated MSE for six (6) ants with 20 iterations

Figure 17 illustrates the Mean Squared Error (MSE) computed for six (6) ants across 20 iterations in this study. The MSE values represent the accuracy between the actual and predicted data for the test dataset. Initially, as hyperparameters are randomly assigned, the MSE values differ among ants during the first iteration. However, by the fifth iteration, the calculated MSE starts decreasing, with Ant 3 and Ant 5 achieving the lowest MSE, leading to updates in total pheromone values and path probability values. Eventually, by the 9th iteration, all ants converge at the lowest MSE values. At this point, ants cease searching for new hyperparameters, having identified the optimal MSE values for the training dataset. Despite reaching the lowest MSE, the process continues without updating the best hyperparameters until it reaches the termination state at the 20^{th} iteration.

The optimization of Support Vector Regression (SVR) parameters is a topic addressed in the literature, with four typically employed strategies. GridSearch Support Vector Regression (SVR), Genetic Algorithm (GA-SVR), and Particle Swarm Optimization (PSO-SVR) are among the most recognized optimization approaches employed by researchers. The primary aim of the optimization technique is to ascertain the best value for the Regularization Value *(C)*, as well as the distances between the hyperplane and vectors *(ε)*, and the impacts of the hyperplane and vectors *(γ)*, all of which are dependent on the training dataset. The experimental data was subjected to using the Radial Basis Function (RBF) as the kernel.

In Table 3.0, a comparison is shown between the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) as evaluation metrics for the optimization process. Furthermore, the Random (Unoptimized) SVR was subjected to random assignment of hyper-parameter values to evaluate its performance compared to the Optimized SVR, employing the previously mentioned evaluation metrics.

Table 3. Result comparison among all tested optimization

	ACO-SVR	Random SVR	GridSearch SVR	GA-SVR	PSO-SVR
C	7.7	10	0.1	1	14.495
ε	0.16	15	0.003	1.988	1.0
γ	1.0	5	0.1	1.435	2.796
MSE	0.391	7.639	3.054	3.055	2.282
MAE	0.567	2.477	1.474	1.587	1.210
$MAPE$ (%)	0.02	9.2	5.3	5.8	4.4

Theoretically, a Mean Squared Error (MSE) score of 0 indicates an entirely accurate model. Therefore, as the model demonstrates enhancement, the related value exhibits a drop. The analysis of the MSE reveals that the ACO-SVR model demonstrates the lowest MSE values, signifying its greater precision in forecasting absolute soil moisture levels. The PSO-SVR and GridSearch-SVR models subsequently follow this. However, the difference in MSE between GridSearch-SVR and GA-SVR is substantial, which means that both are comparable in performance. In contrast to the approach mentioned above, it is seen that the MAE for ACO-SVR exhibits the lowest value, followed by PSO-SVR and GridSearch-SVR. Of all five models examined, all demonstrated MAPE values that were below 10%. The models exhibit a notable degree of precision in the predictions they produce. Hence, by the integration of these data, it can be inferred that ACO-SVR exhibits the highest level of performance, followed by PSO-SVR, GridSearch SVR, PSO-SVR, and Random SVR, in terms of their prediction capacities for soil moisture.

4.3 Irrigation Volume

The calculation of irrigation volume is determined by the soil moisture levels and the soil characteristics, which vary depending on the kind of soil. The present study utilized Sandy Clay Loam soil, with a field capacity (θ_{fc}) value of 0.36 and a wilting point (θ_{wp}) value of 0.16. The durian tree's age at the time of the experiment was six months. The trees' Root Zone Depth (RZD) was measured to be 0.1 meters in depth. The sensors were positioned at a depth of 0.1 meters, equivalent to the level of the RZD. The water pressure generated by the microjet irrigation system was quantified at a rate of 0.5 liters per minute.

The ACO-SVR algorithm has superior accuracy in predicting results. Therefore, using ACO-SVR is deemed appropriate for devising the irrigation schedule. Figures 18 and 19 compare the difference irrigation volume between the Actual Soil Moisture and the Predicted Soil Moisture obtained by implementing the ACO-SVR technique for Terrace 4 and Terrace 5. The maximum difference between the irrigation calculated using ACO-SVR and actual soil moisture reading is 4.5 liters for Terrace 4 and 3.8 liters for Terrace 5. The average difference for Terrace 4 and Terrace 5 is 0.94 liters and 0.72 liters accordingly. The difference between the anticipated and actual values is minimal and acceptable, as depicted in the figures. Therefore, the relevance of utilizing ACO-SVR to forecast data to plan the irrigation schedule is evident.

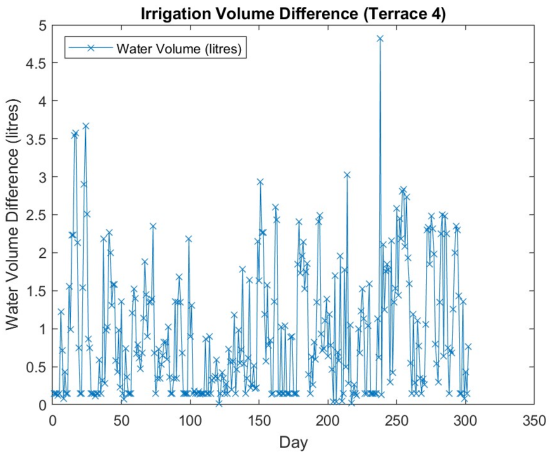

Figure 18. Irrigation volume difference for Terrace 4

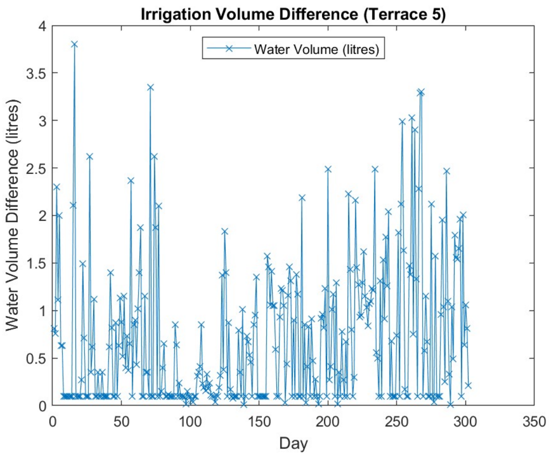

Figure 19. Irrigation volume difference for Terrace 5

5. CONCLUSION

The study utilized climate data from an on-site weather station to predict the soil moisture content. The prediction was made using climate data obtained from the weather station in conjunction with the height of the terrace. The methodology involved utilizing Ant Colony Optimization to optimize Support Vector Regression in defining best hyperparameter values, evaluated using Mean Squared Error (MSE). The prediction accuracy generated by ACO-SVR was compared with other optimization techniques which are Random SVR, GridSearch SVR, GA-SVR and PSO-SVR, and the irrigation volume was calculated based on the predicted soil moisture data. The performance of the proposed ACO-SVR is evaluated using statistical methods. The study demonstrates that the proposed ACO-SVR model with pheromone evaporation achieves highest accuracy among other optimization techniques in predicting soil moisture. Apart from that, including terrace height as part of the input variable is highly relevant to predict different soil moisture levels at various heights. It is particularly significant in precision agriculture, where accurate soil moisture data is crucial for efficient water management. Additionally, the irrigation volume using Checkbook method calculated using the soil moisture ACO-SVR model closely aligns with the irrigation volume calculated using actual soil moisture. This alignment emphasizes the model's accuracy and dependability in measuring soil moisture levels at different terrace heights. Thus, the ACO-SVR model proposed in this work is highly relevant for large-scale agricultural operations, where installing many soil moisture sensors is impractical. Its ability to predict soil moisture accurately with minimal physical sensor deployment makes it a valuable tool for optimizing irrigation practices and enhancing water resource management in precision agriculture.

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