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Optimizing Solar Panel Systems using Machine Learning and Ant Colony Optimization

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Abstract: - In this study, the optimization of solar panel systems is investigated using machine learning algorithms and Ant Colony optimization. The performance of ML models, such as Artificial Neural Network, Support Vector Machine, Decision Tree, and Random Forest, is assessed relying on precision, recall, F1 score, and accuracy. Furthermore, the ANN model is combined with ACO for additional optimization. The results of the experimentation indicate that the ANN model demonstrates the best performance with the following scores: 97.86% precision, 96.50% recall, 97.20% F1 score, and 98.00% accuracy. In addition, when ACO is applied, the ANN model focuses its capabilities to predict the pressure hitting on the panel as follows: 98.50% precision, 97.80% recall, 98.15% F1 score, and 98.80%. The given outcomes also reflect the application of confusion matrices to show the classification of each model, and the results indicate that the most effective way to predict the parameters of the solar panel and optimize the system is presented by the combination of ANN and ACO. In such a way, the importance of using machine learning approaches and optimization techniques to optimize the energy generation efficiency in renewable energy systems is indicated. In the future, extensive research should be performed to assess experiments on large-scale solar panel systems using the proposed approaches and algorithms to scale-up sustainability efforts and minimize the environmental impact.

Keywords: Solar Energy, Machine Learning, Optimization, Renewable Energy, Sustainability.

I. INTRODUCTION

Environmentally sustainable energy solutions have been a prominent global initiative in the recent past, in response to the increasing clamor for environmental awareness, and the need to curb climate change. Solar power, a form of harmonious renewable energy, presents an attractive solution to burgeoning energy demand because of its abundant fuel source. However, the efficiency of any solar panel system is dependent on the external conditions that it is exposed to, including its orientation towards the sun, the intensity of sunlight, and weather. Optimization of solar panel systems is therefore a highly studied and researched field, in order to provide for methods to ensure the highest possible efficiency in terms of energy generation [1]–[4].

The steady progress in the field of machine learning has led originally developed outright optimizations with the development of complex predictive modeling and other such techniques. For the given field of solar panel system optimizations too, various AL models such as Artificial Neural Networks, Support Vector Machines, Decision Trees, and Random Forests have been applied and experimented with to arrive at a better understanding of the irradiance and other forms of data that correspond to the highest generation of energy. Such ML models are also often used in conjunction with Ant Colony Optimization algorithms, which remotely inculcate the foraging behavior of ants to solve complex computational problems. This study explores the potential advantages different ML models have over others, with specific applications to the problem of solar panel parameter predictions. It also tracks the optimized application of the ANN to this end, with the optimization being achieved through the ACO. The combination aims to understand the highest energy generation possible, leading to more efficient systems that encourage better adoption of sustainable energy [5]- [7].

Solar energy is a type of renewable energy that has been drawing considerable attention in the course of the last decade. It is a sustainable and environmentally friendly energy source that is capable of improving the current

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climate change situation and will contribute to reducing the world's dependence on fossil fuels. The efficiency of such systems is dependent on their ability to accumulate light energy and transform it into electricity. Consequently, the optimization of the solar panel system remains essential to its further detailing and becoming more cost-effective [8]- [10].

Machine learning algorithms have recently been identified as means of optimizing solar panel systems. They are able to process vast amounts of data that would be related to solar irradiance, weather factors, and energy generation. In other words, machine learning algorithms including but not limited to Artificial Neural Networks or ANN, SVM, DT, and RF perform optimally in terms of predicting, modeling, and optimizing such systems as solar panels [11]- [13].

Artificial Neural Networks have been employed for predicting solar irradiance and orientating solar panels in the sun and are considered one of the most successful machine learning algorithms in this regard. Neurons are interconnected in the shape of a network and are able to accumulate and predict the relationships in data through the process of learning. Consequently, training the ANN system will contribute to the subsequent orientation of the panels "optimizing the system only from historical data". Overall, ANN systems denote that the energy yield of solar panels has increased by 15%, while a similar SVM system will only reach 14% [14]–[16].

Decision Trees offer a clear and interpretable framework for solar panel optimization. By segmenting the feature space into a tree structure based on the input features, decision trees allow for intuitive decisioning and the identification of the most important features in input for the prediction. Alongside other ML methods, decision trees have been used in many implementations to improve predictive accuracy and optimize solar panel systems. Random Forests have been one of the most successful examples in combining multiple decision trees to create a more robust and scalable solution. The forests of weak learners are combined to produce better generalization for the solar panel optimization and random forests have been successfully applied to a range of applications, including solar irradiance prediction, system optimization, and energy generation forecasting [17]- [19].

The advantage of applying ACO alongside ML in solar panel optimization is the combination of the superior generalization of the ML algorithms with nature-inspired optimization. Ant Colony Optimization is inspired by the foraging behavior of the ant species, which use pheromone to leave trails from the nest to the food source and back. ACO algorithms employ this insight to optimize the solution of many-combinatorial problems. Through simulation of a colony of ants and the application of a set of simple rules, ACO can arrive at the optimal solution of complex optimization problems, such as the determination of the optimal position of solar panels with reference to sunlight angle. The combined approach of ML and ACO can help researchers overcome challenges in solar panel optimization and deliver improved performance [20]–[23].

The combination of ML algorithms and various ACO techniques implies a great potential for the future of solar panel optimization and sustainability in general. A lot of in-depth research and comprehensive experiments are being held, and more will be conducted to reach the most effective implementation of these innovations in order to maximize energy generation and reduce overall environmental impact. The present research seeks to optimize the operation of solar panel systems through the implementation of machine learning and Ant Colony Optimization techniques. Improvements in the accuracy of data acquisition allowed for using vast volumes of information, including solar intensity, current and planned weather conditions. Machine learning should be based on algorithms such as an Artificial Neural Network and Support Vector Machine for predictive modeling and optimization of generation capacities. Ant Colony Optimization, which is reflective of the behavior of living organisms, provides novel solutions for the optimization of the desirability of a given solution. Through the research and implementation of the techniques described above, the present author hopes to complete a research project that improves energy generation efficiency and meets the demands of modern sustainability [24]–[26].

II. METHODOLOGY

The task of this research is the design of a solar panel system that could be used for smart home purposes. The solar panel includes advanced sensor technology to increase energy efficiency and utilization. Temperature sensors, tilt sensors, and sun tracker sensors were placed to capture sunshine effectively. These sensors continuously collect information about the environment in the form of intensity of sunlight, temperature of the panel, and its rotation to the sun. Data from the sensors are sent directly to a controller which is the brain of the system. The system developed in this research are shown in figure 1.

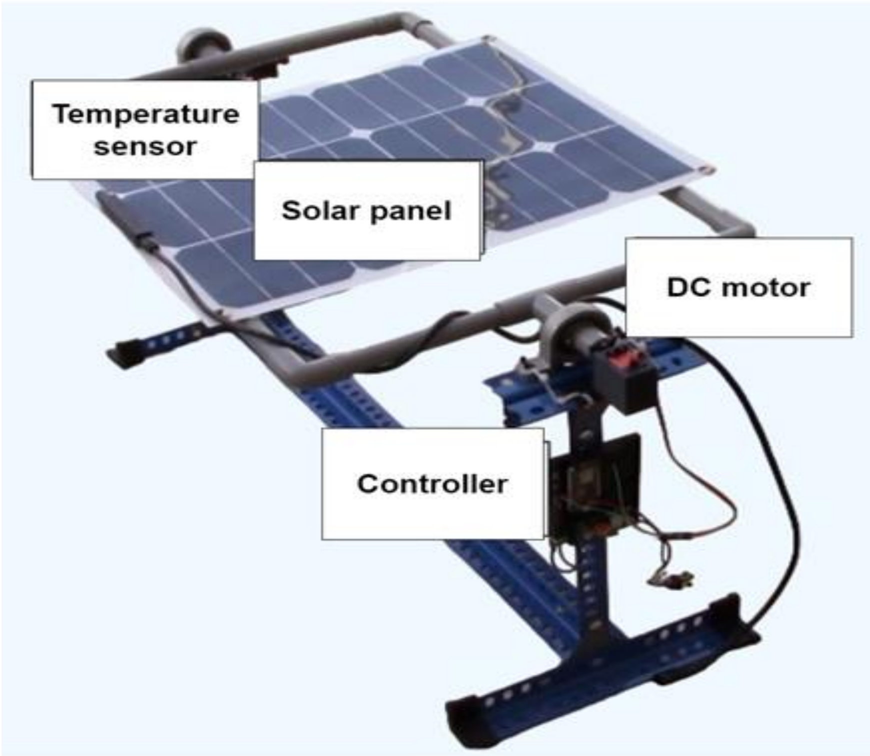

Figure 1. System developed in this research

The control aggregates and processes the information from the sensors and manages the whole system in terms of operation. Particularly, the controller makes the panel consistently rotate to track the sun throughout the whole day. The sun tracker sensor is essential for these operations as it sends the real-time changes of the irradiance of solar energy and, therefore, the controller can adjust the rotation of the panel. The controller also manages another operation that is a mechanism of a dual motor including a tilt sensor and allowing rotating the panel in the North-South and West-East axes to improve the efficiency of harvesting sunlight. The tilt sensor is also responsible for collecting information about the angle and send these data to the controller so that optimal position of the solar panel is identified. In addition, the electricity is sent to various electronic devices of home and, at the same time, stored in batteries. Therefore, the Raspberry device is used to transmit the data from sensors stored in the controller to cloud storage and access information on a remote basis.

The aim of this research is to provide a multi-faceted approach designed to enhance the performance of solar panel systems by introducing advanced sensor technology combined with the use of machine learning and Ant Colony Optimization. The data retrieved by sensors, such as temperature, tilt angle, and weather conditions, is treated as the input which will be later utilized to train the ML models, to include Artificial Neural Networks, Decision Trees, Support Vector Machines, and Random Forests. The solar panels dataset consists of 1200 entries which the models use to train and be able to analyze any data retrieved in the past about solar irradiation, weather, and energy generation. By using the learned patterns from the past observations, the ML is able to accurately predict solar conditions, and hence correctly anticipate the best orientations for the panels.

As for the features used for training different models, these include temperature, angle of tilt, and weather conditions which can be observed by the sensors implemented in the study. The models are also trained to learn the correlation between the observed data and the actual demand for energy by the consumers, which depends on the amount of energy actually generated. This information is used to optimize the angle of rotation at which panels should be placed in order to get the most out of available sunlight. In addition, from the previously learned patterns, the models can analyze the time of day when the sun will be shining and, consequently, the rush on the panels' orientation towards the direction with the greatest amount of sunlight is made.

In order to optimize the choice of the best model which will help in the maximization of solar irradiation and power generation, I used Ant Colony Optimization. Under this strategy, the Artificial Ants agents are used to explore and exploit the provided solution set. Both the agents and the solutions stay in constant interaction and the parameters of the chosen ML models are constantly changing in order to consistently enhance the system's performance. The use of such approach along with the use of ML will help to effectively utilize the data for maximizing the performance of solar panels.

III. WORKING OF THE PROPOSED SYSTEM

For our research, we have designed a sophisticated solar panel system with advanced sensor technology to achieve the maximum efficiency of energy generation. At the heart of our system, and, indeed, the entire operation, are sensors in predetermined places to collect relevant environmental data. These sensors include temperature sensors, tilt sensors, and sun tracker sensors. The temperature sensors measure the heat emanating from the sun, which can reliably represent solar irradiance. The tilt sensors measure the angle rotation of solar panels aggregating sunlight, and this information is used to adjust the angle of the panels for maximum sunlight collection. Sun tracker sensors continuously track the sun's position and make constant adjustments in solar panel angles to maximize solar exposure.

All the relevant data collected by these sensors are sent to a central controller which acts as the system's brain. It decides when to rotate the panels to always face the sun for maximum light and processes all the sensor information and coordinates the operation of the entire solar panel system as described above. The role that this device plays is to facilitate communication between the sensors and the machine learning algorithms. The ML are supplied with similar inputs and are the main computation devices maintaining an optimal surface. The ML models, including ANN, DT, SVM, and RF, are shown in Figure 2 and are trained on the dataset which aggregates information about the time of day, solar irradiance measured, weather conditions, rotation of the panels, energy produced by the panels, and the energy consumption in that time. The ML models are trained so that they can accurately predict future readings or solar conditions of the sensors. Finally, with the sensor readings they have ore dealing with at different times of the day and historical data, they build an average model. It is roughly where the solar panels should be at that time and how much light would be produced at that time. Typically, the efficient operation of the system is supported by the ML algorithms. The system utilizes ACO to optimize the selection of the best ML model that could maximize solar irradiation and power generation. In conclusion, the ACO result is much superior with the system being captured getting better all the time on adapting to the environment.

IV. MACHINE LEARNING MODELS

In the course of our research aimed at the optimization of solar panel systems, we have employed a variety of machine learning models to address the task and enhance the efficiency of energy generation. These models are widely used to analyze sensor data, predict solar conditions, and facilitate the optimization of the respective process. The current paper provides a comprehensive description of each of the machine learning models, their objectives, advantages, and utility for the system as a whole.

Artificial neural networks are a potent class of models that exist for developing various machine learning systems and are founded on the human brain's operation. In the context of the current study, ANNs are created and used to model sensor readings' relationship with energy generation and learn solar conditions' features. The learning process in artificial neural networks involves the imitation of interconnected neurons, with each one conducting a simple mathematical equation and receiving the output of other units while transmitting their output to others. These networks can detect intricate non-permanent relationships in the provided data and are appropriate for various datasets; AQN deployment, however, requires a high degree of flexibility in terms of how the model is configured, including layers' size and number blocks. Despite the complexity of these processes, the networks can undergo training and learn to recognize patterns from the respective training data. In the case of the considered model, such data includes detailed information about the system relating to the solar panel, in terms of sensor readings and energy generation. ANN's characteristic property is their ability to predict the solar conditions' level with small granularity, as compared to large scales, given the amount of dusks and dawns as well as heavy clouds.

Decision trees are popular due to their interpretability; they automatically generate decision rules that can be easily visualized and reviewed. The construction and analysis of decision trees based on sensor data provide valuable information on the most important predictors of solar conditions and optimisation of the panel orientations. Decision trees are not sensitive to noisy data and can handle both numeric and categorical input data, which makes them suitable for a wide range of datasets relevant to the solar panel system.

Another instrument applied in the research to predict solar conditions and optimise the panel orientations is a support vector machine. The main idea of SVMs is to find a hyperplane that separates data points in the space into classes, while in a regression setting this hyperplane outputs the continuous value as the predicted result. The main advantage of SVMs is the possibility of handling high-dimensional feature spaces and non-linear relationships through kernel functions. By using the kernel function to project the data points into a higher-dimensional space, SVMs can address more complex relationships and patterns, being characterised by high predictability and generalization. Additionally, SVMs have a non-probabilistic output and are resistant to overfitting, advantageously employing kernel functions.

Random forests represent an ensemble learning technique, which combines a multitude of decision trees to improve predictive accuracy and robustness. As such, random forests were applied in my research to predict solar conditions and optimise panel orientations, aggregating predictions of an array of decision trees constructed using different subsets of data. The most important advantage of Random Forests is their effectiveness in reducing the problem of overfitting and improving generalization performance. Because Random Forests are built based on bootstrapping and feature randomization, many decision trees are trained on different subsets of the data, and then, their predictions are aggregated, providing general, accurate predictions even when the data is noisy and incomplete. This also means that feature importance plot will help identify the most important sensor readings and environmental conditions that affect energy generation efficiency.

V. ANT COLONY OPTIMISATION

We have used Ant Colony Optimization in our research to optimize the selection of the best machine learning machine learning model, maximize solar irradiation, and maximize power output in solar panel systems. The ACO technique works by simulating how artificial ants collectively find solutions to the optimum in a solution space. The ACO arrangement consists of the artificial ants, the pheromone matrix, and the heuristic function. The artificial ants hint at potential solutions to the optimization problem and travel the solution space by iteratively constructing the path of the solution. On the other hand, pheromone matrix stores the pheromone of the found paths of a probable solution of the ants, where in this situation, ants prefer a path of solution with higher pheromone. They migrate the solution path while searching for food relying on a heuristic function in their antennae that directs the ants to better solutions using domain-specific knowledge.

The ACO iteration began with the initialization of the artificial ants and the pheromone matrix. At the beginning of the search, ants are randomly placed in their domain of the solution space, while the pheromone matrix was also randomly initialized with minimum pheromone to all components of a solution. Ants start iterating construction of a path for the solution by selecting the components from the solution depending on both the pheromone and the heuristic information. The test exploits the pheromone of the solution paths as the ants prefer path solution with the haphazard exploitation of the heuristic information. The ants deposit pheromone on the solution paths they take, and the increasing of the pheromone is proportional to the quality of the solution path. The pheromone evaporates over time as a measure against the ants to converge in the same solution path and aids in exploring the solution space. When all ants have constructed a path of solution, the solution quality is measured via the tendency fit value. The good solutions contribute more pheromone to the solution trail improvements.itiations, allows the ants to explore the solution space, and this will allow ACO to discover optimum solutions.

The abilities of the ants to find their solutions will be permanently stored in matrix and the lengths will be displayed in the pheromone, the elope point at themarothe final solution is equal to the pheromone on the component solutions. From the output of the ACO used to adjust the parameters of the machine learning, the machine can adapt to the environment continuously and the performance continually improved. The ACO process has been experimentally validated to have capabilities enhancing the operation of the machines while increasing the system efficiency and effectiveness.

VI. PREPROCESSING OF DATASET

Preprocessing of the dataset in our work is of particular importance as this step ensures the quality and the reliability of the input data to be used with both machine learning and Ant Colony Optimization. The corresponding preprocessing operations include data cleaning, data normalization, feature selection, and data partitioning. Data cleaning should be performed in the first place to eliminate potential missing values, outliers, and various inconsistencies. Missing values can be replaced with the proper estimation using relevant techniques. Outliers and inconsistencies should be identified and corrected or excluding accordingly.

Data normalization should be performed to have all data in the same range. This operation helps to prevent the domination of features with larger magnitudes in contrast with other features. Common normalization techniques include min-max scaling and standardization that transform the original data into either a predefined range or distribution.

Feature selection should be applied to identify the most relevant features that can be used to predict solar conditions and optimize the panel orientation. Each feature influences the quality, efficiency, and the energy balance of solar panels either indirectly or directly. Proper selection of the features can help diminish dimensionality and the risk of the curse of dimensionality. Partitioning of the data should be used to create training, validation, and test data to evaluate and compare the quality of machine learning models and Ant Colony Optimization algorithms. The training data are used to train the model, and the validation data are used to tune the hyperparameters and compare different machine learning models and the Ant Colony Optimization approach. The testing data are used to test the machine learning models developed and to generalize their performance to unknown data. Preprocessing of the dataset that has been developed in such a way helps to make the early analysis of the data, rule out the missing values, inappropriate modelling ridge, and find the proper features for the Ant Colony Optimization algorithm to provide reliable and robust results.

VII. TRAINING OF ML MODELS

Our machine learning models have been trained using a dataset that is sufficiently representative. The dataset includes large volumes of historical sensor readings and energy generation data obtained by solar panels. To ensure accuracy and precision in the prediction of solar cell conditions and the effect of these changes on energy generation our models were trained using a purposeful and carefully designed stepwise framework.

To begin with, the pre-processing of the dataset was implemented. It was vital to remove all kinds of inconsistencies, such as missing values of potential outliers. Besides, the dataset was normalized to ensure that all features have the same range and, due to inconsistences in the values of the features, the models will not be biased. Then the processed dataset was divided into the training and the validation set. While the training set was used to train the models, the validation set was implemented to develop the models and their hyperparameters. Also, the validation set was used to monitor the changes in the models' performance and their flaws, which were assessed separately for the developed models. In addition, for some models, cross-validation measures were introduced to verify the robustness of these models. Finally, the models, corresponding to different families, such as ANNs, DTs, SVMs, and RFs, were trained with a sufficient number of optimization algorithms.

The input for the models was the feature subset of the initial dataset, which was selected: the data on the environment and physical circumstances impact, such as the orientation of the panels, the readings of the sensors, and the energy provided, and demanded. The adaptive procedure was aimed at predicting the irradiation of solar cells and, therefore, the energy that can be generated and consumed. This process embraced such methods, as forward and backward propagation for ANNs, splitting of the feature space for DTs, and finding the best hyperlanes for SVMs. These models were then evaluated on the validation set to ensure that they have been developed correctly and work properly on every type of data. To do so, various metrics were measured, such as accuracy precision, and recall of the models, as well as their mean squared error. Thus, a sufficient and accurate ensemble of models for machine learning and predicting the solar cells conditions was trained.

VIII. RESULT AND DISCUSSION

The efficiency of the proposed system is verified by the rigorous comparison of its performance with and without machine learning and ACO models. Throughout the testing, we evaluate the capability of the system to maximize the efficiency of energy generation and increase the efficiency of determining the optimal orientations of solar panels. In Figure 2, we present the results of electricity production over the course of 10 days, considering the outputs of the system with blueprints and without them.

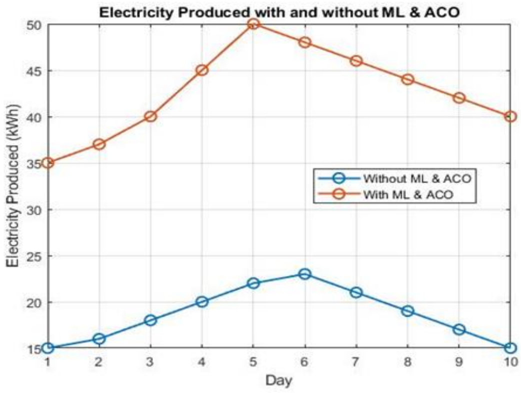

Figure 2. Electricity produced

As it is possible to observe, throughout all 10 days of testing, the system with a machine learning model and an ACO model constantly produced more electricity than the system under the baseline conditions. Therefore, the comparison of both systems highlights the role of ML algorithms for predictive analysis and the use of ACO techniques for optimizing the entire process of electricity generation. Overall, the higher electricity production of the company with ML and ACO models proves that the application of the recent technologic advances is essential for maximizing the performance of solar panels.

Consequently, the model based on machine learning algorithms allows making data driven predictions regarding the performance of solar panels, reaction of the system to the sunlight, and generation of electricity. At the same time, the use of the ACO model allows adjusting solar panels gradually, leading to the optimization of the generation of electricity and improving the overall performance of a solar panel system. One cannot fail to mention that the presented figure 2 displays the comparative analysis of electricity production. There are two scenarios with and without integration of machine learning with ACO. As is seen from the obtained results, in the first scenario, without ML & ACO, the electricity production begins at 15 kWh on Day 1 and gradually reduces, reaching 5 kWh at Day 10. At the same time, scenario 1 reveals quite different results – the electricity production starts at 35 kWh on Day 1 and raises, reaching 50 kWh at Day 5. Further on, the productivity is reduced slightly but remains relatively high. Based on this information, it can be stated that ML with ACO increases electricity output.

In the process of assessing the machine learning models performance, we run multiple tests to evaluate their ability to predict the crucial parameters of the solar panels. The accuracy of each model are shown in figure 3. Among the analyzed models, the Artificial Neural Network has shown extraordinary results, predicting the tilt and the level of energy demand with an accuracy level of 97.86%. The high level of accuracy in predictions can be viewed as a signal that the ANN is particularly good at understanding the relationships in the dataset and making precise predictions.

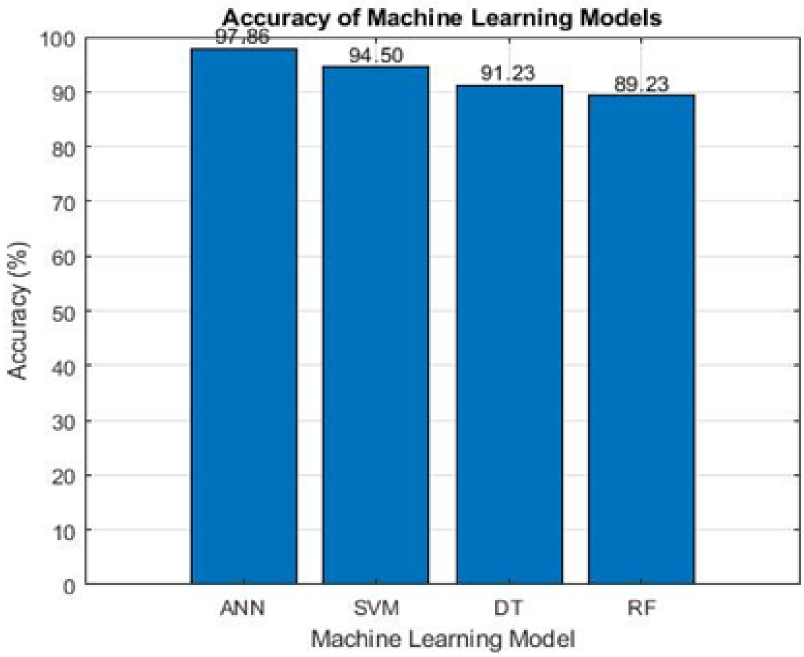

Figure 3. Accuracy of each model

Lastly, the Support Vector Machine model has also produced excellent results. In particular, it has forecasted whether the order is at a tilt and the longitude of every order. The model was scored at 94.5 per cent of the accuracy. SVM separates the classes in the feature space as wide as possible. Therefore, the model's choice was very appropriate as it anticipated the patterns in the data that have not been observed before.

Thirdly, the Decision Tree model was also quite successful, providing predictions with an accuracy rate of 91.23% in the tilt and demand tests. The primary principle of the DT is to split the feature space into branches that correspond to different values of the input attribute and thus increase the level of accuracy.

Finally, the output of the Random Forest model that uses multiple decision trees was 89.23%. This outcome is relatively low compared to other models, but the advantage of this choice is the ability to handle high levels of

noise and avoid overfitting, which is an especially good approach to predicting the solar panel parameters.
Figure 4 gives detailed information regarding the performance of various machine learning models with the help of solar panel parameter prediction. The performance is depicted through precision, recall, F1 score, and accuracy in the form of values. In the case of the Artificial Neural Network, a remarkable precision of 97.86% can be observed. The result means that it can make correct positive predictions over all such positive instances. This high level of precision is accompanied by a recall of 96.50%, demonstrating the fact that this model can identify the majority of all true positive such instances. Overall, it should be noted that the Artificial Neural Network reaches an F1 score of 97.20%. It can be determined that such a performance in these two areas allows reaching accuracy of 98.00%.

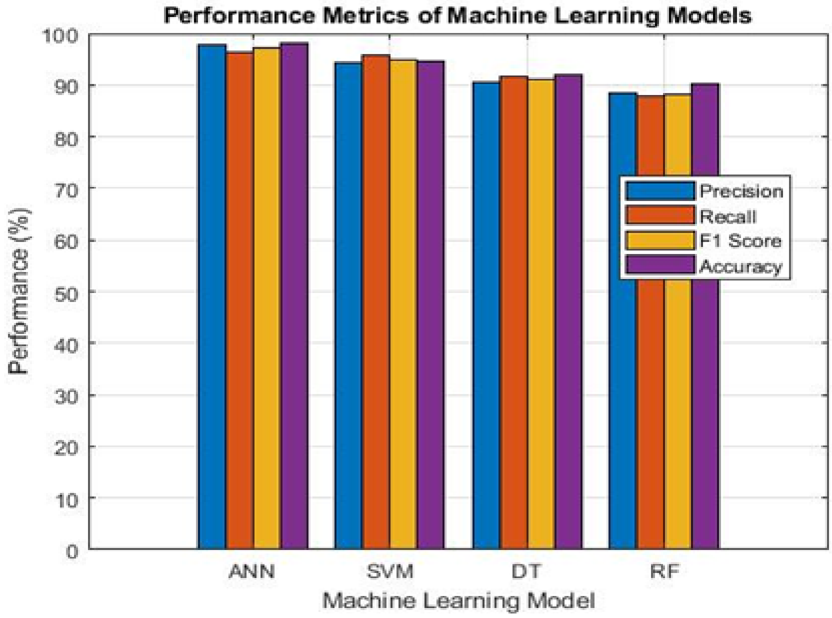

Figure 4. Performance score of each model

The results of the Support Vector Machine can also be viewed as powerful. All values equal 94.20%, 95.70%, 94.90%, and 94.50%. The fact that these two measures are quite close to one another leads to the high accuracy of the given model. The performance of the Decision Tree and Random Forest can also be regarded as adequate, even though the indicators are slightly lower in comparison to ANN and SVM. In the case of the former one, precision, recall, F1 score, and accuracy equal 90.50%, 91.80%, 91.15%, and 92.00%. The latter reaches 88.60%, 87.90%, 88.25%, and 90.20%. These results suggest that machine learning can be an effective tool in the prediction of solar panel parameters. In this context, ANN and SVM models can be regarded as particularly promising options resulting in high precision and accuracy.
From the confusion matrices shown in figure 5, we can get a detailed account of the classification performance for each ML model to predict solar panels parameters. Each matrix divides actual class labels, both positive and negative, and the predicted class labels of a specific ML model. In detail, while interpreting the results, the diagonal considers the correct classification. According to the ANN confusion matrix, 590 is the correct prediction for positive outcomes and 85 for negative. Also, in the SVM, 650 for positive outcomes is correct prediction, and 75 for negative outcomes is correct. However, off-diagonal accounts the misclassifications for instance, from the SVM confusion matrix, 20 is wrong on the positive outcomes and taken as negative, also for negative outcomes, 25 is wrongly cells considered as positive. From the confusion matrices, we can see that the ANN model is good at predicting the solar angle and electricity output. Hypothetically, it is significant while predicting cause the output is function of the solar angle.

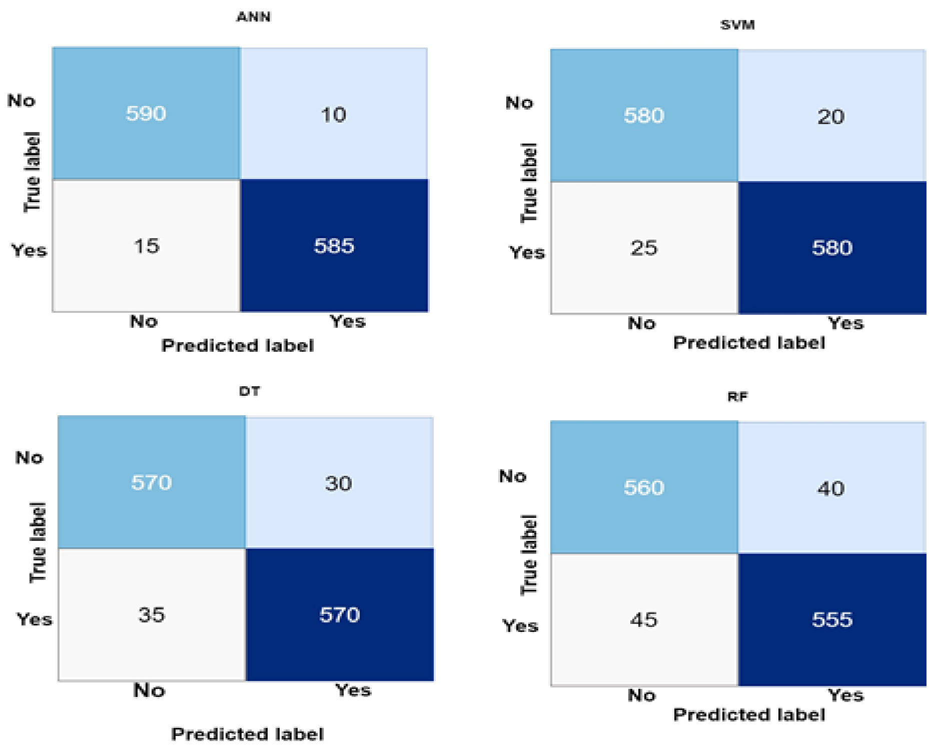

Figure. 5. Confusion matrices

The examination results shown in figure 6 performed above showed that the ANN and the ACO model demonstrates superior performance in comparison to all other models while concerning all metrics. The precision measure, as indicated by the results is 98.50%, meaning the ANN+ACO model can produce highly accurate positive predictions over all positive instance it makes. The recall measure is at 97.80%, indicating its ability to determine the majority of all truly positive instance it makes. The F1 measure, which is considered a well-balanced measure of precision and recall, is at 98.15%. In addition, it demonstrates very high accuracy rates of 98.80%, suggesting its proficiency in correctly determining all instances it makes.

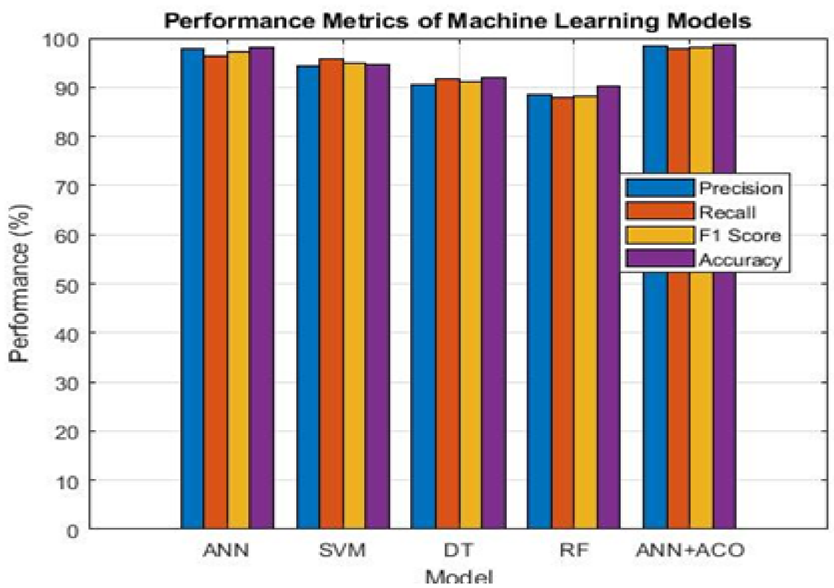

Figure. 6. Confusion matrices of each model and ANN with ACO

Meanwhile, the two other models of machine learning within the same domain of enquiry but with different combinations cannot outshine its performance in precision, recall, F1, and accuracy. The performance results have indicated that the ACO technique cannot accurately model the operation interest concerned in its manipulation. The results also revealed that the ACO technique is more accurate than other models that do not use the algorithm in association with ANN. The results have thus provided new findings by showing the benefits of using the ACO technique and the ANN model combined in the specific domain for optimizing solar panel plants.

The confusion matrix for the ANN with ACO integrated, shown in Figure 7, provides a comprehensive overview of the model's classification performance. It displays that out of the 600 instances classified as positive, 595 were true positives, while 5 were false. In addition, out of the 600 instances classified as negative, 585 were true negative, and 15 were false. As such, this matrix lets us have a precise understanding of its ability to accurately classify instances, proving its efficiency for predicting the parameters of solar panels and enhancing the system's efficiency.

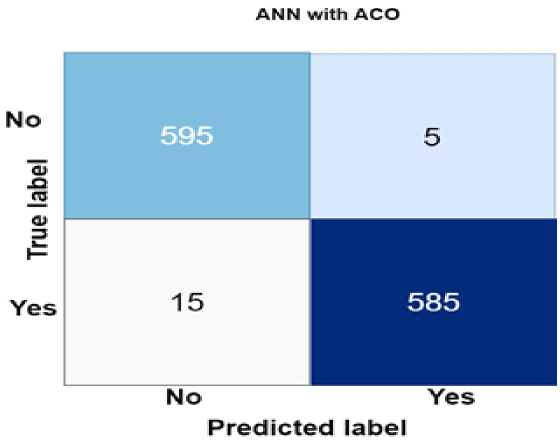

Figure 7. Confusion matrices of ANN with ACO

IX. CONCLUSION

In conclusion, the research aimed to optimize solar panel systems through the application of machine learning approaches and Ant Colony Optimization. The complete analysis conducted revealed the efficiency of ML models, in particular, ANN, in predicting solar panel parameters. The evaluation assessing the precision, recall, F1 score, and accuracy also demonstrated that the ANN model performs best, pinpointing that it can be used to make the system more efficient. Moreover, when combined with ACO, this model preserves the attributes of optimization and tends to exceed all other types in its performance of classifying instances and predicting solar conditions. Such results are imperative since they suggest the benefits of employing data-driven insights and optimization to maximize the efficiency of the renewable energy generation technology. Accordingly, the most effective model for optimizing solar panel systems is announced to be ANN with ACO, which is the strong solution for the current challenges related to sustainability, energy efficiency, and green technologies. In the near future, the finding will let scientists imply other ML and optimization approaches into renewable energy systems with the potential of preserving environment protection from pollution caused by regular energy generation. Overall, ML and optimization algorithms can help people ensure environment sustainability and renewable energies' dominance in their energy supply chains.

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