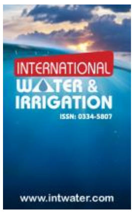

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Analysis Of Agricultural Electrical Automation Mapping Using XGS Decision Model

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Abstract: Energy conservation is crucial for intelligent agricultural decision-making, including plant development, automation of equipment, and cultivation. Industrial 4.0 technologies include the Internet of Things (IoT), artificial intelligence (AI), and big data. We use these technologies to control energy consumption and enhance the environment. This study proposes to apply an extended galactic swarm (XGS) decision model for agricultural electrical automation mapping by optimizing the effectiveness of the energy consumption forecasting process. We collect energy-related data from a range of environmental and agricultural production sensors to assess and train the XGS model. We normalize the raw data samples by eliminating the noisy data using the min-max normalization strategy. We then predict the energy usage amount using the random forest (RF) technique. Using the XGS model to modify the hyper-parameters can enhance the performance of the RF approach. We implement the proposed model on the Python platform and assess its success using several metrics. When compared to other existing models, the suggested XGS-based prediction framework provides the best efficiency in the energy consumption forecasting process. This article provides a practical agricultural electrical automation mapping solution for astute agricultural managers or farmers who wish to solve agricultural energy concerns more affordably and sustainably. When compared to current techniques, our proposed XGS-RF produced the lowest results in terms of RMSE (1998.12), RMPSE (6.53), and MAE (1384.15).

Keywords: Agriculture, Automation, Energy Consumption, XGS Decision Model, Random Forest (RF)

1. Introduction

A green farming method known as green agriculture lowers greenhouse gas emissions that supports farmers and their resources,it encourages the resilience and sustainability of food grains. Crop rotation, nitrogen management, pest control, recycling, and water harvesting are important accomplishments [1]. These procedures shield living beings from dangerous elements and help create a safer environment [2]. It is imperative to implement digital communication with farmers using wireless technology to connect agricultural landscapes as the globe undergoes a digital revolution. Not all ofEarth's entire surface is suitable for agriculture due to factors such as soil quality, geography, temperature, climate and non-homogeneous cultivable zones [3]. Several variables related to urbanization, politics and the economy constantly put pressure on the availability of arable land.There is a decline in the amount of land utilized for agriculture in food production and every field has different characteristics such as soil type, irrigation flow, availability of nutrients, and resistance to insects. Farmers using traditional farming methods must visit their fields during crop life to assess the conditions. Farmers could recognize current activities without physically being in the field because of the precise field image provided by modern sensor and communication technologies [4]. Deploying smart equipment from planting to harvest is made easier by wireless sensors, which allow for more precise agricultural monitoring and early problem diagnosis. With sensors installed on robotic weed killers, drones and autonomous harvesters, agriculture as a whole is a cost-effective and intelligent operation. However, to guarantee sustainability and reduce adverse ecological consequences, technological breakthroughs are required [5].

1.1 Smart Agriculture Using Iot Applications

Due to the IoT, farmers and researchers have access to effective technologies that are transforming the agricultural crop-producing industry. By making information regarding soil, water, pesticides, fertilizers and manures easily accessible, it facilitates decision-making. The IoT tackles global warming and climate change by emphasizing resource sustainability and environmental preservation. It also helps with post-harvest, end-user transactions and intelligent crop development [6]. Drones, remote sensing, computer imaging, smart greenhouses, intelligent livestock management and effective climate monitoring are few of the technologies that the IoT makes possible for precision farming as shown in Figure 1.

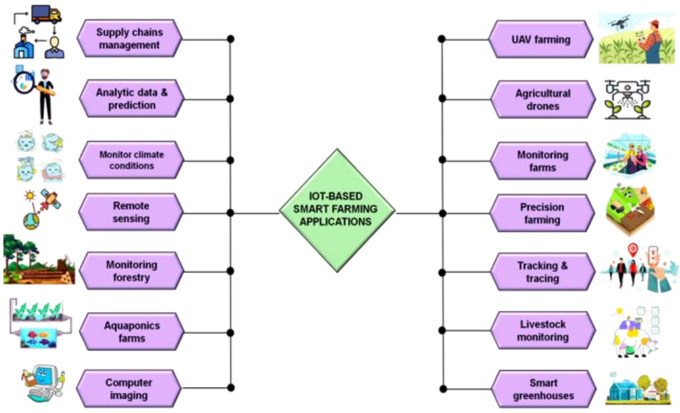

Figure 1: Overview Of Smart Agriculture Based Iot

There is a continuing need for innovative ideas and technology to suit the demands of mankind on a global scale [7]. For agricultural electrical automation mapping, this study proposes to apply an XGS-RF decision model by optimizing the effectiveness of the energy consumption forecasting process.

2. Related works

The research aims to increase network performance and reliability in agriculture applications by presenting an adaptive network mechanism for a smart farm system employing IEEE 802.11ac and LoRaWAN protocols [8]. Reliable monitoring duties are ensured by the process that modifies protocols in response to network circumstances. According to the author of [9] an interactive online application, FastMapping produces field maps of geographic variability, and multivariate management zones and automatically cleans agronomic data collected on farms. In contrast to Management Zone Analyst software, it integrates data layers, employs an R language interface and generates data reports. Site-specific agriculture management is supported by FastMapping.To create 3D farm maps, the author [10] suggested a ground-level mapping and navigation system that makes use of computer vision and IoT. Robotic cars, edge nodes and a cloud layer for deep computing and administration are all part of the system. Because of its superior scalability and precision, the Mesh Simultaneous Localization and Mapping algorithm, or Mesh-SLAM (Mesh-SLAM) method, can be used in farms.The study [11] suggested data that has been collected over the last 20 years from a farmer's case study in North Italy is assessed and quantified. Soil analysis, drone photos and on-site weather stations were among the data sources. The report emphasizes better data storage options are required in the agriculture industry.The author [12] investigated the use of traditional and contemporary prediction techniques in precision fertilization, combining machine learning (ML) and spatial interpolation with agronomic elements. It assesses both traditional and contemporary approaches and emphasizes the value of remote sensing techniques and data in advancing precision agriculture, even in the face of difficulties handling complicated data. The use of IoT technology to create a smart farm for resource and crop management that is more affordable is covered in the article [13]. The system provides farmers with a dependable and adaptable smart idea by collecting and analyzing data from several sensors via wireless sensor networks. According to the author of [14] examined with an emphasis on six prerequisites for the smooth integration, processing and use of farm data, the article presents the platform method for smart farming. It draws attention to the difficulties in handling enormous volumes of data and the requirement for standardized procedures for integrating data and technology, which will boost output and profitability. The study [15] created a Smart Farm Watering System for remote agricultural monitoring utilizing the IoT, information and communication technology (ICT). The system lowers labor costs and enhances agricultural output by monitoring soil moisture, irrigation and safety using sensors, control panels, and software. The LoRaFarM IoT platform, which is flexible and low-cost, is based on the Long-Range Wide-Area Network (LoRaWAN) [16] and intended to improve and optimize farm management. The platform uses sensor data collection and use to work toward more ecologically friendly agriculture. The work of [17] suggested automating and instantly gathering and analyzing environmental data, the platform improves agricultural yield and management while conserving natural resources.

Contribution of the study

- To optimise the efficiency of the energy consumption forecasting technique, this research recommends using an extended galactic swarm (XGS) decision model for mapping agricultural electrical automation.

- In order to train and assess the XGS model, data regarding energy is collected from a number of environmental and agricultural production sensors. We use the min-max normalisation method to standardise the raw data samples after we remove the noisy data. Next, the energy consumption forecast is made using the random forest (RF) method.

- To enhance the performance of the RF approach, the XGS model is employed by modifying the hyperparameters. We put the suggested model into action on the Python platform and evaluate it using various metrics to see how well it performs.

- When compared to other models in use today, the proposed XGS-based prediction framework provides the most accurate predictions of future energy use. If you are a farmer or smart agricultural management looking for a way to map out agricultural electrical automation that's both cost-effective and environmentally friendly, this article will assist you.

3. Methods

Determining seasonally peak demand is the primary goal of the time series forecasting of loads in agriculture, since this forecast can be used to construct a demand response scheme. IoT devices help with data collection, which is the first step in this process. Real-time data from the ground is gathered by sensors in open agriculture, smart farms, sun radiation, soil, and plants. It is possible to create precise estimates for one or more future periods using previous consumption data. In Figure 2 the suggested workflow is shown.

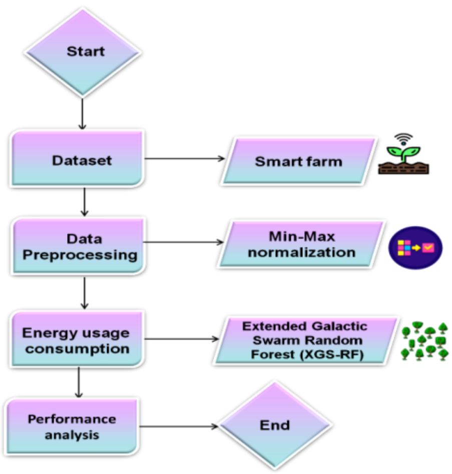

Figure 2: Proposed Workflow

3.1 Dataset

The study looked at data on smart farm agricultural energy for a period of eighteen months, from (October 2020 to April 2022). The study examined several variables, including hourly solar radiation (HSR), internal temperatures (IT), internal humidity (IH) levels, ventilation temperature (VT), heating temperatures (HT), crop output production (COP), outside temperature (OT)andtemperature differential (TD). There is also information on Agricultural Electrical Automation Mapping in the dataset. This extensive collection covers a wide range of factors that are essential to comprehending and improving agricultural operations. Informed decision-making for effective farming techniques was aided by the alternate months' insights on seasonal changes and trends influencing crop energy dynamics.

3.2 Data Preprocessing Using Min-Max Normalization

The most basic approach, referred as normalization of min-max values or expansion, entails adjusting the feature variables' range to either $[0, 1]$ or $[-1, 1]$. The type of data determine which target range is chosen. The following is the general Equation (1) for a min-max of$[0, 1]$:

$$Y' = \frac{Y - Min\,(Y)}{Max(Y) - Min\,(Y)'} \quad (1)$$

When the normalized value is denoted by $Y'$and the original value by Y. The Equation (2) can be expressed as follows a range between an arbitrary set of values $[c, d]$:

$$Y' = c + \frac{Y - Min(Y)(c-d)}{Max(Y) - Min\,(Y)'} \quad (2)$$

The min and max values are represented in c, d.

3.3 Energy Usage Consumption Of Agricultural Using Extended Galactic Swarm Random Forest (XGS-RF)

The mapping automation system in agriculture for increased energy efficiency is the process of classification in the smart agricultural electrical automation employed in XGS-RF. To optimize the energy employed in automated smart agricultural operations XGS-RF combined the optimization power of the XGS with the reliable classification capabilities of RF.

3.3.1 *Random forest*

The random forest (RF) approach uses a cluster of classification trees to vote on which class receives input data the most frequently. Applications of RF include feature selection (FS), regression, and classification. The methodological approach analyzes each variable's significance utilizing depth analysis. When it comes to huge smart farm datasets with plenty of features, supervised learning techniques like RF perform better than many ML methods. It is trained using the bagging technique, in which each tree is built by a random selection from training data. The architecture of the RF is shown in Figure 3.

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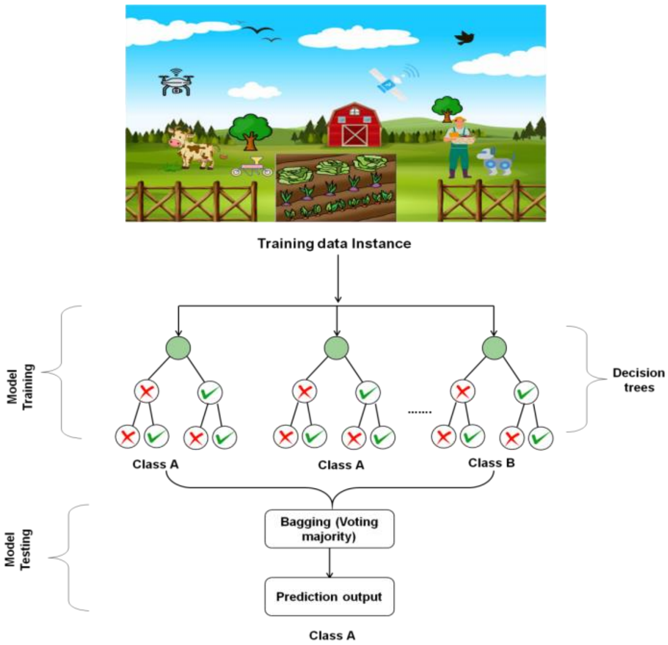

Figure 3: RF Structure

The model uses decision tree predictions to aggregate its output. Because bagging models reduce variation and over fitting of data, RFhas become more important in decision tree analysis. It is frequently applied to address missing data as well. Sensitivity to sample size, amount of variables, responsiveness to various technique parameters and sensitivity to the existence of correlated variables are the characteristics that define the RF architecture. The number of classification trees is merged with the RF classifier. The outcome of the categorization is computed by using Equation (3).

$$D(s) = \max_{O} F_s \sum_{j=1}^{L} \left(d_j(S) = O\right) \quad (3)$$

For each subset S of the original dataset with the desired category O, the method creates decision trees using a random vector. Hyper-parameters for random forests are used to speed up the process or increase the accuracy of the model's predictions.

$$j(s) = 1 - e_1^2 - e_0^2 \quad (4)$$

Gini impurity is measured using Equation (4). In this case, every node is denoted by s, which might be any RF decision tree node. In addition, $i = 0, 1$ denotes the class in Equation (5) and $e_i$is the proportion of m_i samples.

$$e_i = \frac{m_i}{m} \quad (5)$$

By dividing and distributing items to two distinct sub-notes s_o&$s_r$by a variable's criterion r, accomplish diminishing δj. The process is reflected in Equation (6).

$$\delta j(s) = j(s) - e_o j(s_o) - e_r j(s_r) \quad (6)$$

Subsequently, an all-inclusive search is conducted using Θ values that are obtained from the node's overall thresholds. Taking into account all nodes, Equation (7) maintains declines in Gini impurity levels for each variable separately.

$$J_H(\Theta) = \sum_q \sum_r \delta j_\Theta (s, S) \quad (7)$$

3.3.2 *Extended galactic swarm (XGS) decision model*

The XGS is an optimization algorithm that simulates the motion of stars, galaxies, and superclusters throughout the cosmos. Galaxies are collections of stars that are not evenly spaced. The finest solutions within each subpopulation serve as an inspiration for all the individuals or solutions from that subpopulation. Superswarm treatment is given to the subpopulation that is thought to offer the optimum answer. A swarm resides in every subpopulation's optimal solution. In XGS, the swarm is represented as a B set that consists of $B_i^{(j)}$ components. With many swarms working together to achieve better exploration, it is possible to achieve better exploration while investigating in a certain direction as opposed to using only one swarm. The corresponding sub-swarm has examined the search space independently. Particle velocity calculations are used to start this process, and the results are updated as equations (8 & 9):

$$U_i^{(j)} \leftarrow \omega_1 U^j + F_1 q_1 \left(O_i^{(j)} - B_i^{(j)}\right) + F_2 q_2 \left(h^{(j)} - B_i^{(j)}\right) \tag{8}$$

$$B_i^{(j)} \leftarrow B_i^{(j)} + U_i^{(j)} \tag{9}$$

The particle's velocity is $U_i^{(j)}$ the optimal solution found is $O_i^{(j)}$, the global best solution is denoted by $g(i)$, and the particle's current location is $B_i^{(j)}$, where F_1 and F_2 represent the acceleration coefficients that offer the direction to optimal local and global solutions, ω1 denotes the inertial weight, and q_1 and q_2 denote random values between $0\ and\ 1$. To sustain an ever-expanding global search capability and a heterogeneous sub-swarm, the feedback avoidance mechanism supports the XGS metaheuristic. The following Equations (10 & 11) are used to update the super swarm's location and velocity in the subsequent clustering level:

$$U^{(j)} \leftarrow \omega_1 U^j + F_3 q_3 \left(O^{(j)} - A^{(j)}\right) + F_4 q_4 \left(h - A^{(j)}\right) \tag{10}$$

$$A^{(j)} \leftarrow A^{(j)} + U^{(j)} \tag{11}$$

If the best personal answer is $O^{(j)}$, the weight of inertia is ω_1, the velocity $U^{(j)}$ is related to $A^{(j)}$, and the random numbers (q_3 and q_4) are similar to those shown in the first level. The best global at this stage is g, and it is left unchanged once the best solution has been found. The super swarm focuses on the subswarms' optimal global solutions, improving exploitation in the process. Combining XGS optimization with RF improves mapping precision and efficiency for agricultural electrical automation. Using a range of agricultural datasets, XGS is an advanced optimization strategy that increases classification accuracy by accurately selecting RF parameters. Galactic movements serve as its source of inspiration. This hybrid method solves energy-related problems while enhancing the categorization method by identifying and ranking energy-efficient techniques. This technique ensures accurate and energy-efficient mechanization in agriculture, leading to more efficient and sustainable farming operations. It does this by using XGS for parameter adjusting and RF for robust labeling. Thus, XGS and RF integration offers an important step in smart agriculture innovation.

4. Result and discussion

8GB of RAM, a C-drive with 100 GB of storage, and a 64-bit version of Windows 10 were used in the experiment. For each testing process, Python was utilized. The study's findings showed a strong relationship correlation study between maximum energy usage and the simulations that were chosen. The primary findings from many models were used to determine the months and seasons of peak demand.

Correlation Analysis: Eight distinct energy datasets were used in this study to evaluate the ML model: IT, IH, VT, HT, OT, HSR, TD, and COP. This has made it more difficult to record each energy parameter since sensor readings are either unavailable or ambiguous. The most used technique for analyzing the connections between the qualities is the correlation coefficient approach, which is used. The strength of the relationship between the independent and dependent variables can be ascertained using this kind of correlation test is shown in Table 1.

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Table 1: Correlation Test Analysis

Energy Data	IT	IH	VT	HT	OT	HSR	TD	COP
IT	1	-	-	-	-	-	-	-
IH	0.092	1	-	-	-	-	-	
VT	0.44	-0.077	1	-	-	-	-	-
HT	0.6	-0.037	0.72	1	-	-	-	-
OT	0.77	0.4	0.15	0.33	1	-	-	-
HSR	0.49	-0.091	0.52	0.58	0.27	1	-	-
TD	0.33	-0.32	0.085	-0.071	-0.5	-0.021	1	-
COP	-0.035	-0.01	-0.011	-0.016	-0.037	-0.01	0.034	1

Seasonal Energy Usage by Months: Greenhouse holders can provide real-time environmental energy usage statistics by deploying sensors on the demand side of the smart farm. In the temporal dimension, the energy consumption patterns of smart farms might last for a day, an hour, a month, or even a year. As a consequence, in a range of periods, from an hour to a year, greenhouses can be used to describe the power action of the surroundings. The hourly average of a smart farm's environmental energy use is very variable. The greenhouse's application of the maximum ambient temperature during the day varies at various periods. The monthly peak energy fluctuations are influenced by a wide range of external circumstances. The annual environmental peak energy variance of a smart farm's use is depicted in Figure 4.

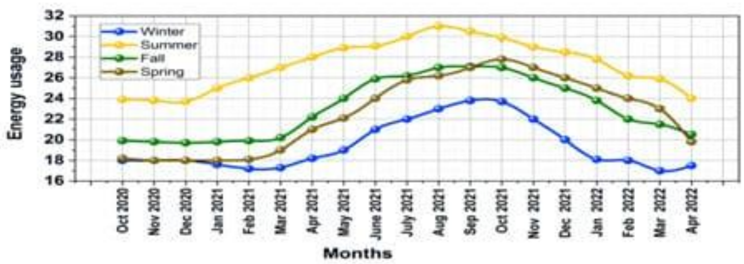

Figure 4: Temperature values acrossOctober 2020 to April 2022

Comparison Analysis: In this study, our proposed XGS-RF approach is to build a system that can autonomously monitor energy consumption in smart agriculture. The effectiveness of load forecasting has been evaluated using the Mean Absolute Error (MAE), Root Mean Square Percentage Error (RMSPE), and Root Mean Square Error (RMSE). The suggested method's effectiveness is contrasted with current methods, such as (long short-term memory (LSTM) [18], Random Forest (RF) [18], and SARIMA [18]). Table 2 represents the outcome of the existing and proposed methodologies.

Table 2: Outcome Of Existing and Proposed Methods

Methods	MAE	RMSE	RMPSE
SARIMA	1532.63	2018.28	8.69
Random forest	1652.13	2353.76	7.98
LSTM	3229.02	3463.04	13.5
XGS-RF [Proposed]	**1384.15**	**1998.12**	**6.53**

RMSE: When evaluating the effectiveness and precision of prediction models, the RMSE is an essential statistic. It acts as a measure for the difference between values that a model predicts and the actual observations are made from the environment that is being studied. The quadratic evaluation method known as RMSE measures the mean size of errors. When compared to other existing methods, our proposed achieve the lowest RMSE value of 6.53.

RMSPE: The average of the squared percentage errors squared root is determined by RMSPE, nonetheless. Except for the findings being reported in percentages, it is identical to RMSE in terms of characteristics. Squared error represents the measure's loss function. Our suggested XGS-RF approach produced the lowest RMSPE values of 1998.12 when compared with other current techniques.

MAE: The model's generic and bounded performance metric given by MAE matches an approximation of the absolute error. The real and anticipated values' average magnitude is shown by this level. The model's accuracy increases as the MAE gets closer to zero. Figure 5 shows the comparison of Metrics. In comparison to other existing approaches, our suggested XGS-RF approach produced the lowest MAE values, at 1384.15.

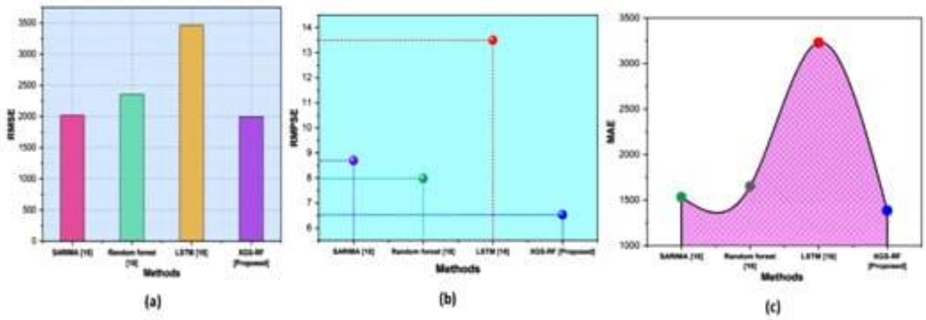

Figure 5: (a) RMSE, (b) RMSPE, (c) MAE Comparison

5. Conclusion

The agricultural industry is one of the most energy-dependent industries, it is important to estimate power consumption according to the monsoon or season. This article examined the agricultural sector's seasonal peak demand for electricity usage. The proposed study uses XGS-RF methods to compare and forecast trends in power use. Among these models, this method finds peak demand and performs better. The outcome indicates that the season from months when demand peaks. Based on the link in smart agricultural systems between energy and climate modifications, the results demonstrate that XGS-RF models are useful in identifying important inputs connected to agricultural production's energy consumption. In terms of our proposed XGS-RF achieved the lowest values RMSE (1998.12), RMPSE (6.53), and MAE (1384.15) in the result simulation of current approaches. Using variable-temperature data from the smart farm, future studies will concentrate on identifying the worst and best projected days. Use deep learning with big data and ML algorithm model analysis to determine the optimal crop growth day by adjusting the parameters of different data measurement techniques.

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