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Original Article

Banana Irrigation System and Scheduling based on Reinforcement Learning

Angelin Blessy, Avneesh Kumar, Prashant Johri

Department of Computer Science and Application, School of Computing Science and Engineering, Galgotias University, Up, India.

johnmtech@gmail.com

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Abstract - *Water optimization and scheduling are essential for today's agriculture sector because water and energy usage are not adequately estimated. A tremendous amount of water is wasted in the irrigated fields. The combination of today's technologies provides the solution for managing water and providing the proper irrigation schedule. The Internet of Things and machine learning techniques are effectively used for smart agricultural fields. This paper proposes an effective water optimization and scheduling method that uses IoT components, the KNN algorithm, reinforcement learning, and person correlation techniques. The IoT components are used to collect the current requirements and predict the environmental status of the cultivation files. And is also used to transfer the information from the entire cultivation field to control fields. The KNN algorithm captures the nearest features from the cultivation fields. Environmental prediction, awards, or requirements of specific plants are performed using IoT and KNN capabilities. In this work, we applied a smart irrigation system used in banana cultivation. Based on the current prediction, the future requirements of water are calculated in a 12-hour time interval from 7 pm to 7 am, and it is calculated for up to 4 days. Compared to traditional cultivation, this proposed method reduces water usage by up to 24% of the water required.*

Keywords - *Smart Irrigation System, Scheduling, KNN, Reinforcement Learning, IoT, Banana Cultivation.*

1. Introduction

Globally, 85% of fresh water is being utilized for agriculture as food requirements gradually increase, thus increasing the production of the food chain. The traditional irrigation system has used much water but has given less productivity. So, an effective irrigation system is needed. Still, it is a challenging task in today’s environment because, when we plan for irrigation, we need to consider different scenarios, such as climatic changes, moisture of the plants, wind speed, etc. The water requirement for each plant changes according to the seasons, the growth of the plants, etc. Physically, pouring water for each plant is time-consuming. So, the equalized method of pouring water and irrigation system helps improve the water requirement for plants. Different irrigation methods were used to manage water, such as surface irrigation, micro-irrigation, drip irrigation, sprinkler irrigation, center pivot irrigation, irrigation by the lateral move, Lawn sprinkler, Hose-end sprinklers, sub-irrigation, subsurface textile, etc. [1]. Banana cultivation is the fourth most important crop after wheat, rice, and corn. Banana is the most cultivated, taking more fresh water throughout life. For example, the water requirement for banana cultivation per day in the litter is shown in Table 1[2]. In Table 1, cultivation starts in April and ends in December or January. Initially, the water requirement was low, but gradually, it increased. Morden technologies and techniques are used to manage the irrigation system. So, we can efficiently use the irrigation systems by using the Internet of Things (IoT), Artificial

Table 1. Month-wise Water Requirments for Banana Irrigation [2]

Month	Water Req. Lit/Day/Plant
April	5-6
May	4-5
June	5-6
July	6-8
August	10-12
September	8-10
October	6-8
November	10-12
December	12-14
January	16-18

Intelligence and its subsets, such as machine learning and deep learning, play an important role in managing irrigation systems. Various IoT devices and sensors connect and monitor the bottom to the top of the plant. Using IoT, we can easily monitor, control, trace and make a decision remotely without delay. Similarly, The Artificial Intelligence is used to take decisions automatically.

There are three processing layers of processing techniques, the combination of machine learning and IoT technique, which are used to minimize the energy and use the smart irrigation system. They are i. Data transferring and collection ii. Intelligence layer, and iii. End Application layers. These three layers consist of a different set of components and functionalities. The first stage is Data gathering and transmission. Data is collected from agricultural grounds and transmitted for further data processing, for which sensors are used. The components used for collecting data and transmissions are mobile data or Wi-Fi connections; for local data to be processed, the Zigbee Network is used, and for collecting data from the ground, the wireless Sensor Node is used. Raspberry Pi and other controlling components are used to control the motors. The intelligence and data processing is done in the second layer. To process the gathered data, intelligent techniques and machine learning is being used.

In the proposed technique based on the IoT, K-NN and Reinforcement learning method is introduced to manage the irrigation system and reduce water requirements [2]. The main contribution of the proposed hybrid is as follows.

- The proposed method schedules and optimizes the water using IoT and the Reinforcement learning method.
- In this proposed technique, IoT is used to collect the inputs, and KNN is used to find the nearest features to extract useful information such as moisture, water requirements, root moisture level, etc. Reinforcement learning is used to minimize the water requirements for the smart irrigation system.
- Compared to conventional irrigation systems, 10 to 24% of water requirement is optimized by this proposed system in terms of long-term irrigation system scheduling.

The rest of the paper is as follows: Section 2 presents the related and current works on smart irrigation techniques. Section 3 presents feature selection and water requirement prediction using IoT and reinforcement learning. Section 4 delves into implementation details and results in a discussion of proposed work with previous dominating methods.

2. Related Work

The researchers have proposed different methods for requirement calculation of smart irrigation systems. This section presented related works that support reinforcement models, and the corresponding advantages and limitations are summarized. The authors of [3] summarized different devices, edge technologies, and software for the smart irrigation system. And also authors summarized different challenges and opportunities for the irrigation system. The authors of [4] proposed deep reinforcement learning for irrigation systems, and solutions are deployed on cloud infrastructure. The main advantages of the proposed work are scalable and practical oriented, but this method does not consider the surrounding features of prediction and forecasting of requirements. The authors of [5] proposed a hybrid method for prediction and requirement forecasting using IoT and machine learning techniques. The authors found the requirements within the short term and not supported for long-term predictions. The implementation was performed using banana tree cultivation and different dynamic parameters. The authors of [6] proposed a DRL-based architecture for scheduling the irrigation system. The experiments were conducted for 12 days, and the water requirement was reduced to 7.5%. The authors of [7] proposed an edge computing device and deep reinforcement learning for the irrigation system. In this work, different challenges and applications are discussed. The authors of [8] proposed a model based on Markov Decision and reinforcement learning for energy optimization and water reduction. This work considered only threshold values for prediction and did not use real-time data to estimate requirements. The authors of [9] proposed an irrigation model for rice cultivation, found the weather's uncertainties, and produced the best irrigation model. The authors of [10] proposed a model using Q-learning and reinforcement learning for an effective irrigation system. But the prediction accuracy is very low compared to the other methods. The authors of [11] proposed energy consumption and reduced the water requirement using the Marko process and reinforcement learning. The requirement is estimated based on the threshold values and does not consider the real scenarios. The authors of [12] proposed deep reinforcement learning for smart irrigation systems using real-time environment features. In this work, the authors are not considered dynamic and uncertain parameters for irrigation. But the main advantage of this work is that it does not consider the threshold values for estimating requirements and the real-time partial values. The authors of [13] proposed [13] that an RL-ABM framework with Q-learning is used for water usage prediction. This proposed framework is applied to the case study (CRSS) for a long time water management, and this work is simulated using seven intelligent agents. The simulated agents are aggregative, forward-looking, and myopic conservative for learning and action making. But this work is not effective for real-time prediction and analysis. The authors of [14] proposed a model called DRLIC and a neural network model for optimal learning, current soil requirement calculations and future requirements prediction. The authors of [15] proposed optimized machine learning for smart irrigation using types of plants, different parameters, controlling environments, and sensory feedback such as humidity, moisture measurement and camera images. The authors of [16] proposed a model to implement an openAI environment to manage policy, growth, and fertility policy to reduce the environmental impacts. This work is not considered the real issue for implementation. The authors of [17] investigated the irrigation control system's reinforcement learning and temporal features. In this investigation, researchers considered offline data, online data, and sensors to handle different possibilities of data. The simulation calculates crop yields and water expenses based on spatial locations. But in this work, temporal features are not considered for the implementations. The authors of [18] proposed a case study in Portugal using deep reinforcement learning and short-term memory for next-day requirement prediction of the crop to reduce the water shortage. In this work, artificial intelligence, conventional neural networks and LSTM are used to train the requirement table of a smart irrigation system. The authors of [19] proposed a CNN and DDQL with the help of an agent to find the immediate requirement of crops and soil moisture. This work reward-wise immediately responded to different regions and other temporal data requirements. The authors of [20] proposed a model based on the behavior theory and reinforcement learning spatial-temporal behavior of pooled resources are managed. This work supports and finds the different possible activities in dynamic changing environments using deep multi-agent reinforcement learning. The authors of [21] proposed a model for predicting and scheduling irrigation systems using dynamic parameters. Using this work evapotranspiration rate is calculated using the kernel canonical and SVM techniques. Most researchers considered different parameters, threshold values, and dynamic parameters for the irrigation system. The reinforcement learning also helped to improve the predictions and considered different parameters for predictions. But dynamic parameters and longtime predictions are not considered in the irrigation system. This work considers the spatial and temporal parameters in different time intervals and longtime water requirements for the smart irrigation system.

3. Materials and Methods

This section presented the required materials and proposed methods for predicting and forecasting smart irrigation systems. The proposed irrigation system consists of IoT devices, KNN and deep reinforcement learning. IoT devices and sensors are used to collect current dynamic information. The KNN collect the nearest features information, and deep reinforcement learning uses current and future requirement of irrigation system. Using this proposed method, current and future requirements of water are managed.

3.1. Materials

The proposed method consists of two parts: requirement collection and intelligence. Data collection is performed using different components such as sensors, IoT, and transmission devices. Requirement collections are performed using table 2 components [3]. The sample components for data collection are shown in figure 2.

Table 2. Components and their usage

S. No	Components	Usages
1	F-28	A soil Sensor and used to manage the moisture of the soil
2	RS485, HPT675	water level measurement
3	THERM200	The temperature of the soil
4	HTM2500LF	Measure water vapour and humidity
5	SHT11	Root Moisture
6	WSN	Surveillance, Monitoring and transmission
7	M2M (ZigBee)	Personal communication network
8	Digital Inclinometer	Gradient and slope of land measured.

Table 2 components are interconnected, and data is collected from each source of the location and roots. The collected data is stored in the cloud and processed using computational intelligence. The sample data, soil moisture, and surrounding information are collected from the Kanyakumari district, India. The sample collected location, and experimental location is shown in figure 3.

8°14'50.5"N 77°16'27.7"E

Fig. 1 Sample collected location

The longitude and latitude of the experimental performed location are 8.2473502, 77.2743729,345. Early paddy cultivation was being done in this location, but currently, banana cultivation is done here. Especially, these two species of banana cultivation are being done in these areas:Ethapazham/NendramPazham/Nendrapazham/ Changalikodan is Plantain Banana and in English as Red Dacca (Australia), Red banana, 'Red' banana (USA) Claret banana. Apart from banana species, Tapioca or Maravalli Kizhangu or cassava plant cultivation is also done in some locations. This location has two ponds on either side. So, apart from April, May and half of June, we always have water facilities in this location. So, this location is chosen for this cultivation, and one more reason is that it always has water facilities required for proper banana cultivation.

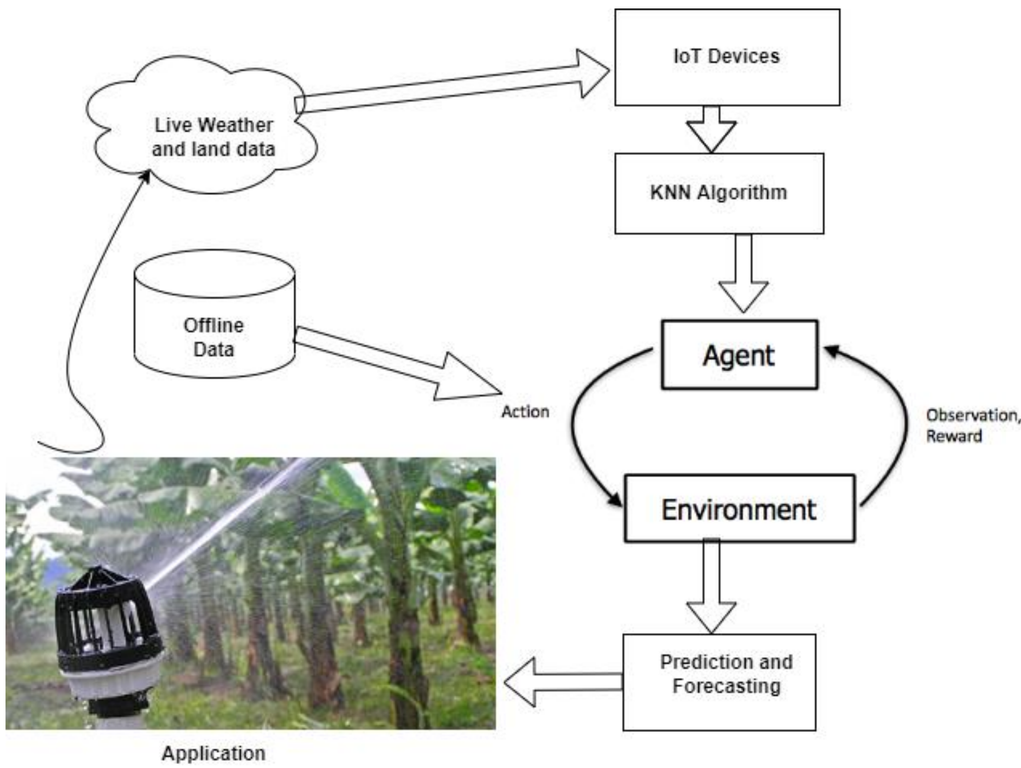

Fig. 2 Block Diagram Using IoT and Reinforcement Learning

3.1. Method

The proposed method used IoT devices, the KNN algorithm and Deep Reinforcement Learning. The IoT devices connect all the devices since all the requirements and communication between the devices. The nearest required features are managed and collected using the KNN algorithm. Reinforcement learning is used to find the behavior of the online and offline data. Based on the behavior and rewards from the data, new predictions and decisions are performed. The proposed block diagram is shown in Figure 2.

3.1.1. K-Nearest Neighbours Algorithm

To determine the closest values from the anticipated sensors, the KNN algorithm is used. It is a non-parametric algorithm that generates real numbers devoid of any presumptions. The dataset or data from the sources' K closest values make up the input. The distance or prediction of the closest neighbor affects the prediction's outcome. The vote of the closest forecast is used to predict the output class. Multiple features and spaces are present in the KNN training set. The prediction values depend on whether the distance between the features is continuous or discontinuous. Euclidean Distance affects how far apart the feature's predictions are. Equation 1 displays the representation of the prediction made by the nearest neighbours using different x parameters.

$$Y = C_n^w \left(x_1, x_2, \dots, x_n\right) \quad (1)$$

Y - denotes predicted features, *C* - denotes nearest required features, *n* denotes features, *w* denotes the weight of different, $\{x_1,\dots,x_n\}$ denotes different weight. The variations of the features are calculated using Euclidean distance as represented in equation 2.

$$D = \sqrt{\sum_{i=0}^{n} (x_i - x_j} \quad (2)$$

D – denotes distance, *n*- denotes the number of features *x*, j - and i - various features variations.

3.1.2. Reinforcement Learning

Machine learning agents interact with their environment through reinforcement learning with observations, actions, and rewards. The agent seeks to identify the best possible course of action or optimal policy that maximizes the total amount of future benefits. The representation of the reinforcement learning and agent with different parameters are shown in equation 3.

E={S,A,P,R}

In the equation, S denotes state space, A denotes action, P denotes transition, and R denotes reward function. The state space *S* consists of environmental parameters for the irrigation system, and it is represented as

$S_t = (W_t, p_t, W_{min}, W_{max}, X_p)$

S_t –It denotes state with time, W_t is the water depth on a particular time, W_{min},- Minimum Water depth, W_{max}- Maximum Water depth, X_p- Future rainfall prediction.

3.1.3. Working Process

The proposed work process has represented in Algorithm 1. Initially, IoT devices collect the required information from the bottom of the layers. Initially, all the parameters are considered zero. After that, in the particular interval, initial predictions are performed, initial calculations are performed, and required water is pumped using pumping motors. The KNN algorithm collected the nearest features and transferred them to reinforcement learning. The required parameters are collected continuously and transferred to the processing unit. The entire values are collated using Pearson correlations (PC). The entire step-by-step process has shown in algorithm 1.

Table 4. Training and Testing Ratio

Hours	Zone	Min and Max Water Requirments	Training Ratio (70%)	Testing Ratio (15%)	Validation Ratio(15%)	Total
12	1	Min	4900	1050	1050	7000
		Max	3500	750	750	5000
24	1	Min	3150	675	675	4500
		Max	2800	600	600	4000

Algorithm 1:
Input: KNN, E, S, A, P, R, Required parameters
Output: Estimated values

1. Initialization
2. Criteria ⟵ 1
3. For (Criteria ≤ 12), do
4. KNN ⟵ PC(Initial Prediction)
5. E ⟵ (RL parameters)
6. RL ⟵ (Rewards and Actions)
7. Action ⟵ { KNN, Rl_{Para}, E}
8. $Best^h_{SR}$ ⟵ PC { KNN^n_{SR} , Rl_{Para} }
9. R (hr) ⟵ { rewards of Actions }
10. hr ⟵ hr +1
11. While (hr≤ 12) do
12. Final Action $^{hr}_{n}$ ⟵ R(hr)* $Best^h_{SR}$
13. End

4. Results and Discussion

The basic experimental setup and material requirements are described in section 3.1. The basic experimental measurement, number of nodes, and other information are mentioned in table 3, and training and testing ratios of water requirement are shown in table 4.

Table 3. Experimental Basic Requirements

Parameters	Crop details (Banana)
No of Tree	1000/ Per Acre
Duration	April- Jan
Maximum water requirements of a single node in each month	50 Liters
Starting of Agriculture	April 2020
Max Requirements of Water per node	360/400 Liters
Interval of smart irrigation	7 Days

The cultivation starts from April 2020 to End Jan 2020. The cultivation started due to environmental rewards; the first two months required more water. But after two months, due to the environmental changes, the requirement of the prediction is changed immediately. The experiment values are predicted using the following metrics as spearman correlation (S.C,) Coefficient of Determination (R^2), and Root-Mean-Square Error (RSTM). The predicted values are shown in Table 4.

Table 4. The predicted values of R^2 and RSTM using KNN and RL

Zone				
KNN +RL				
epochs	S.C	R2	RSTM	PT(s)
12	0.72	0.95	0.41	16
24	0.61	0.92	0.63	22
36	0.63	0.93	0.43	21
48	0.69	0.94	0.54	35
60	0.96	0.96	0.71	36
72	0.68	0.92	0.45	34

Table 4 predicted the different values in different time intervals such as 12, 24, etc. The processing timing entire structure also has shown in table 4. The number of hours is increased, automatically the processing time also increased differently. Figure 3 shows the water requirement for the month of the middle; as shown, the initial requirement prediction is low, and the water requirement gradually increases at different intervals.

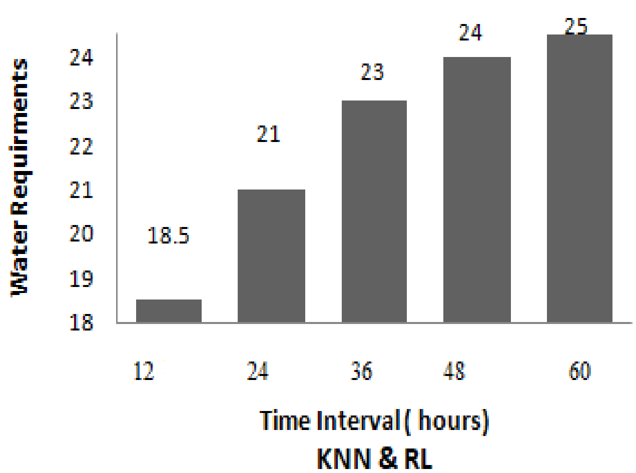

Fig. 4 Water Requirements of different time intervals

Similarly, the every month water requirement of prediction has shown in figure 4 and water overall water optimization per month wise as shown in table 5.

The month-wise water requirement is shown in figure 4. In this graph, in April, cultivation is started, and initial time the water requirement is very low. After that, the requirement for water gradually increased in the next two months. But in July and Aug, water requirement is reduced due to rain in the cultivation location. Again at the end of the cultivation, the water requirement is reduced

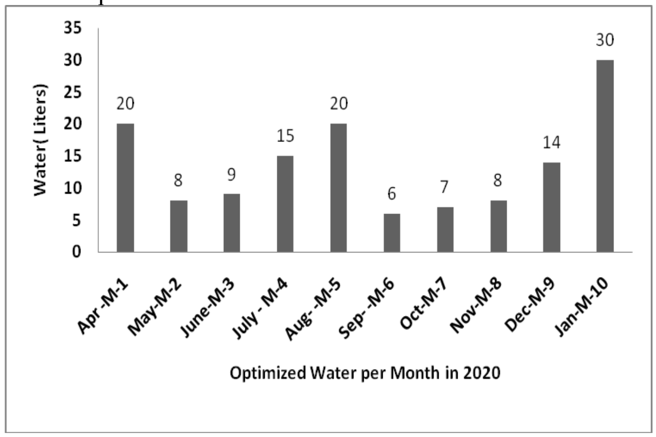

Fig. 5 Month-wise water Optimization of Entire cultivation for one Tree

5. Conclusion

In the proposed technique based on the IoT, K-NN and Reinforcement learning method is introduced to manage the irrigation system and reduce water requirements. The main contribution of the proposed hybrid is as follows. The proposed method schedules and optimizes the water using IoT and the Reinforcement learning method. In this proposed technique, IoT is used to collect the inputs, and KNN is used to find the nearest features to extract useful information such as moisture, water requirements, root moisture level, etc. Reinforcement learning is used to minimize the water requirements for the smart irrigation system. Compared to the conventional irrigation system, 10 to 24% of water requirement is optimized by this proposed system in terms of long-term scheduling. This work is extended in three ways: effective knowledge sharing, appending different techniques, and collaborations of predicted parameters. The continual learning technique is used to recommend better predictions. The ensemble learning algorithms are recommended for better appending different prediction techniques. Federated learning is recommended for collaborating in different cultivation fields and sharing the best effective model using the best effective prediction models.

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