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Technology-Assisted Decision Support System for Efficient Water Utilization: A Real-Time Testbed for Irrigation Using Wireless Sensor Networks

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ABSTRACT Scientific organizations and researchers are eager to apply recent technological advancements, such as sensors and actuators, in different application areas, including environmental monitoring, creation of intelligent buildings, and precision agriculture. Technology-assisted irrigation for agriculture is a major research innovation which eases the work of farmers and prevents water wastage. Wireless sensor networks (WSNs) are used as sensor nodes that directly interact with the physical environment and provide real-time data that are useful in identifying regions in need, particularly in agricultural fields. This paper presents an efficient methodology that employs WSN as a data collection tool and a decision support system (DSS). The proposed DSS can assist farmers in their manual irrigation procedures or automate irrigation activities. Water-deficient sites in both scenarios are identified by using soil moisture and environmental data sensors. However, the proposed system's accuracy is directly proportional to the accuracy of dynamic data generated by the deployed WSN. A simplified outlier-detection algorithm is thus presented and integrated with the proposed DSS to fine-tune the collected data prior to processing. The complexity of the algorithm is O(1) for dynamic datasets generated by sensor nodes and O(n) for static datasets. Different issues in technology-assisted irrigation management and their solutions are also addressed.

INDEX TERMS Crop irrigation, decision support system, outliers detection and correction, wireless sensor networks.

I. INTRODUCTION

Water is an important resource and must be used efficiently. The agriculture sector is the main water consumer; it uses approximately 70% of all available water resources worldwide [1]. This sector‘s consumption will be controlled if modern technology is adopted with traditional irrigation procedures, particularly flooding. However, in this sector, modern technologies are accepted only if they exhibit a sufficient potential to increase crop yield while preserving as many resources as possible [2]. At present, different activities, particularly irrigation, in agriculture are performed with traditional procedures that are time consuming, labor intensive, and wasteful [3]. The traditional agricultural paradigm was geared toward modern technology utilization in the last decade, and its acceptance ratio at the commercial level increased. Technology adaptation has led to the automation of different agriculture-related activities, and this automation is known as precision farming or precision agriculture in literature [4]. The main motivation is that crop quality and production rates will improve if the right resources are applied at the right time under suitable environmental conditions. Such mechanisms improve crop yield and conserve considerable resources, such as water, pesticide spray, and potassium. Different mechanisms are utilized to collect environmental parameters and soil features, such as moisture, salinity, pH, temperature, air humidity, and wind direction [5], [6].

Scientific and research organizations are eager to apply the potential of micro-electro-mechanical system (MEMS) technology and the overwhelming characteristics of wireless sensor networks (WSNs) in different application areas, including the military, intelligent buildings and bridges, medical field, industries, and precision agriculture [7]–[9]. In precision agriculture, WSNs are deployed in fields to sense and report various parameters that are vital to plant growth. Initial experiments with WSNs in the agriculture sector have been conducted in controlled environments, such as greenhouses, in which sensors/actuators are deployed to control the indoor environment automatically [10], [11]. WSNs have also been utilized in different projects, such as automating greenhouses, efficient water utilization, and identification of crop diseases. Most of these studies used WSNs as data collection tools, and decision support systems (DSS) were responsible for actual decisions. After the successful deployment of WSNs in controlled environments, researchers and scientists explored their applications in open field environments, but such an exploration was challenging. As part of a LOFAR project, Baggio [12] deployed a small network of wireless nodes in potato fields to detect a fungal disease known as Phytophthora. A similar experimental study was performed as a joint project of Switzerland and India in [13]. Mancuso and Bustaffa [14] explored the potential of WSNs to control various tomato diseases and described how this technology helps in controlling such diseases. Burrell *et al.* [15] deployed sensor nodes in a vineyard to assist managers in handling different scenarios, frost risk, and specific location by providing valuable information continuously. The FLOW-AID project used WSN to identify water deficit situations, scenarios where plants are in desperate need of water [16]. In 2011, Commonwealth Scientific and Industrial Research Organization Information and Communication Technology utilized WSNs to help recover the ecological integrity of Queensland‘s Spring Brook National Park and regenerate the rain forest from agricultural grassland [17]. Other experimental studies have been conducted recently, but their description is beyond the scope of this work.

The literature on WSNs in the agriculture sector is robust, but most of the studies neglected an important issue associated with data generated by sensor nodes, namely, outliers. Outliers are noisy data generated by sensor nodes when a sensor is malfunctioning or generated because of interference or colliding packets. These data must be detected and corrected prior to examination by DSS. Existing noise detection algorithms are highly complex, and their implementation in real-time DSS, a system that operates 24 hours a day and 7 days a week, is difficult. Therefore, a simple mechanism that does not degrade the overall performance of real-time DSS is needed to detect outliers. Most existing studies are designed for sprinkler systems and are inapplicable to real agriculture environments where flooding mechanisms are generally used to irrigate crops; such a practice is particularly common in Asia.

In this work, a WSN-based outlier detection and irrigation management system is developed to assist farmers in handling crop irrigation schedules. The proposed system collects environmental and soil-related data through sensor nodes that are examined by the outlier detection module. The proposed noise detection algorithm is implemented to improve the system‘s accuracy. Afterward, DSS further examines it to identify water deficient sites in agricultural fields. After identification, the alarming unit is activated, and text messages are sent over a local area network (LAN) to inform farmers.

The remainder of the paper is organized as follows. In Section II, a brief overview of WSNs, particularly in the agriculture sector, is presented, followed by the proposed system architecture in Section III. Section IV describes the proposed outlier detection algorithm and its working mechanism. The different issues identified and solved during this study are presented in Section V. In Section VI, the achievements of the proposed approach are described, and a comparison of the proposed algorithm with other algorithms is performed based on real-time and benchmark datasets. The last section provides the concluding remarks.

II. WSN IN AGRICULTURE SECTOR

The distinguishing characteristics of WSNs make this technology an ideal solution to various real-world problems. These problems arise in different domains, such as the military, medicine, telemetric, intelligent building, hazard environments, and agriculture [18]. In the agriculture sector, WSNs are used to assist farmers in different activities, such as irrigation (whether sprinkled or flooding), detection and prevention of crop diseases in early stages or preventing favorable occurrence conditions, water-deficient location identification, and duration of field monitoring and pesticide spraying [19]. Various experimental studies on WSNs in the agriculture sector have addressed particular problems. The studies that are relevant to our work are presented in this part.

WSNs have been deployed in greenhouses to control the dew condensation problem that arises due to temperature, air humidity, pressure, and other environmental factors [20]. Park et al used different sensor nodes to collect data and adjust greenhouse environments accordingly. To compute for dew condensation, they utilized a well-known Bahrenburg formula. In a joint project to determine the ratio of arsenic in underground water, a WSN was deployed in [21] to collect various soil parameters of a rice field, such as arsenic, soil moisture, temperature, calcium, carbonate, chloride, nitrate, and pH. The collected data were thoroughly examined in sophisticated laboratories to determine the required ratio. Similarly, sensor nodes were deployed in Malawi to collect pH, reduction/oxidation (redox), and turbidity values to determine the quality of water [22].

In Spain, WSN was deployed to monitor soil contents, such as moisture, salinity, pH, and temperature [23].

This system was successfully implemented in a real agriculture environment, but the decisions were not automated. To describe how few sensor nodes covered a particular area, the authors wrote an expression that describes the relationship between shower nozzle capacity and sensor node radius [24]. Konstantinos et al. presented a WSN-based architecture to control environmental conditions in a commercial greenhouse. The collected data were thoroughly examined to find their correlation with crop conditions [25]. Proper seedling of watermelon relies on environmental parameters, such as temperature, air humidity, and light values. Sensor nodes were deployed in greenhouses to collect and examine desired information and assist farmers in proper seedling of watermelon. A process control strategy management system was also designed in previous studies to determine proper and automatic seedling of watermelon; its various components were WSN, DSS, RFID-based method, and queuing theory-based algorithm [26], [27].

Phytophthora is a potato fungal disease that occurs due to certain environmental conditions, and if these conditions are prevented/avoided, then the possibility of the disease‘s existence will become negligible. Baggio [12] utilized a WSN to collect desired data and attempted to avoid conditions that are favorable for the disease. Similarly, WSNs were deployed in potato fields by Shinghal *et al.* [3] to improve productivity. Favorable conditions for tomato diseases were avoided by using WSNs inside greenhouses [14]. In vineyards, sensor nodes were deployed in different locations to collect valuable data that were used for predicting various diseases, pest control, and facilitating the handling of different activities [15]. Kotamäki *et al.* [28] deployed a WSN near a river basin to determine the quality of water and described its effects on soil content and crop yield. The Common Sense Net Project was designed for marginal farming in India, in which different sensor nodes were used to identify areas whose water, rain, reservation capacities were high. Additionally, the project can identify various crop diseases [13]. The Flow AID Project was designed to utilize the WSN‘s potentials in determining water-deficient sites in agriculture fields [16]. Dursun and Ozden [29] presented an automatic drip irrigation management system for cherry trees. Pardossi *et al.* [30] described a mechanism to integrate rote zone sensors with WSN and used it in the identification of water deficit situations. Various investigations on automatic control of greenhouses were reported in [4], [31], and [32]. Different site-specific automatic irrigation management systems were presented in [33]–[36].

III. PROPOSED SYSTEM ARCHITECTURE AND DEPLOYMENT

A. ARCHITECTURE

Fig. 1 depicts the architecture of the proposed DSS. In the proposed architecture, an application layer is designed to provide services to farmers through a user-friendly graphical user interface (GUI). These services include interaction with the real-time system, identification of water-deficient locations, vulnerable situation alarms, and environmental monitoring. The middle layer describes how various components of the proposed system interact with one another, physically or logically, to provide the desired services precisely. The sensor manager unit collects data from sensors and forwards these to a microprocessor that conducts aggregation for further processing. The gateway module receives packets from sensor nodes, and is attached to a computer that runs the proposed DSS. DSS collects the newly arrived packets from the gateway module, checks their accuracy through a noise detection module, decides the current situation, and stores it. The physical layer directly interacts with the environment. Sensor nodes that use various sensing capabilities collect soil moisture, air humidity, temperature, and leaf wetness data and send the data to the sensor manager. These parameters are vital in the development of a precise DSS for irrigation.

Real-time systems need to be continuously operational to assist farmers, but at the same time, the sensor node sampling rate must be adjusted accordingly to prolong the WSN‘s lifetime. In our testbed, wasp-mote agriculture sensor boards with desired functionality were programmed and deployed in a real agriculture environment, namely, an orange orchard. During the first phase of the experimental setup, the boards were placed in close proximity to reduce packet losses, thereby improving communication reliability. In the second phase, the boards were placed to cover as much area as possible, and each node can communicate with the gateway either directly or through multi-hop communication. Their transceivers use the Xbee protocol and can communicate within a 500 m range. $Node_3$ was deployed within the direct communication range of the gateway (460 m), and $Node_1$ and $Node_2$ were placed at a distance of 460 m from Node3. The distance between the nodes and gateway was kept small to maximize their throughput.

The proposed DSS performance is not affected by increasing or decreasing scalability of sensor nodes because these nodes act as data collection points. Dense deployment increases data packets, but this situation is not an issue, particularly in the agriculture sector, in which the sampling rate of the deployed sensor nodes must be very low, namely, two or three packets per 24 hours.

B. WASP-MOTE BOARDS DEPLOYMENT

The implementation of a precise real-time DSS in any application depends on the selection of appropriate technology, sensors, and parameters to be monitored. Sensor board selection is based on coverage area, battery lifetime, processing capability, transceiver, and integration of sensors. Parameter selection is application-specific. In our study, we considered soil and environmental parameters. Soil moisture is vital in the development of a precise irrigation schedule; that is, if the sensed value is below a threshold value, then this area needs water and must be irrigated. For this purpose, soil moisture sensors were deployed at three different levels

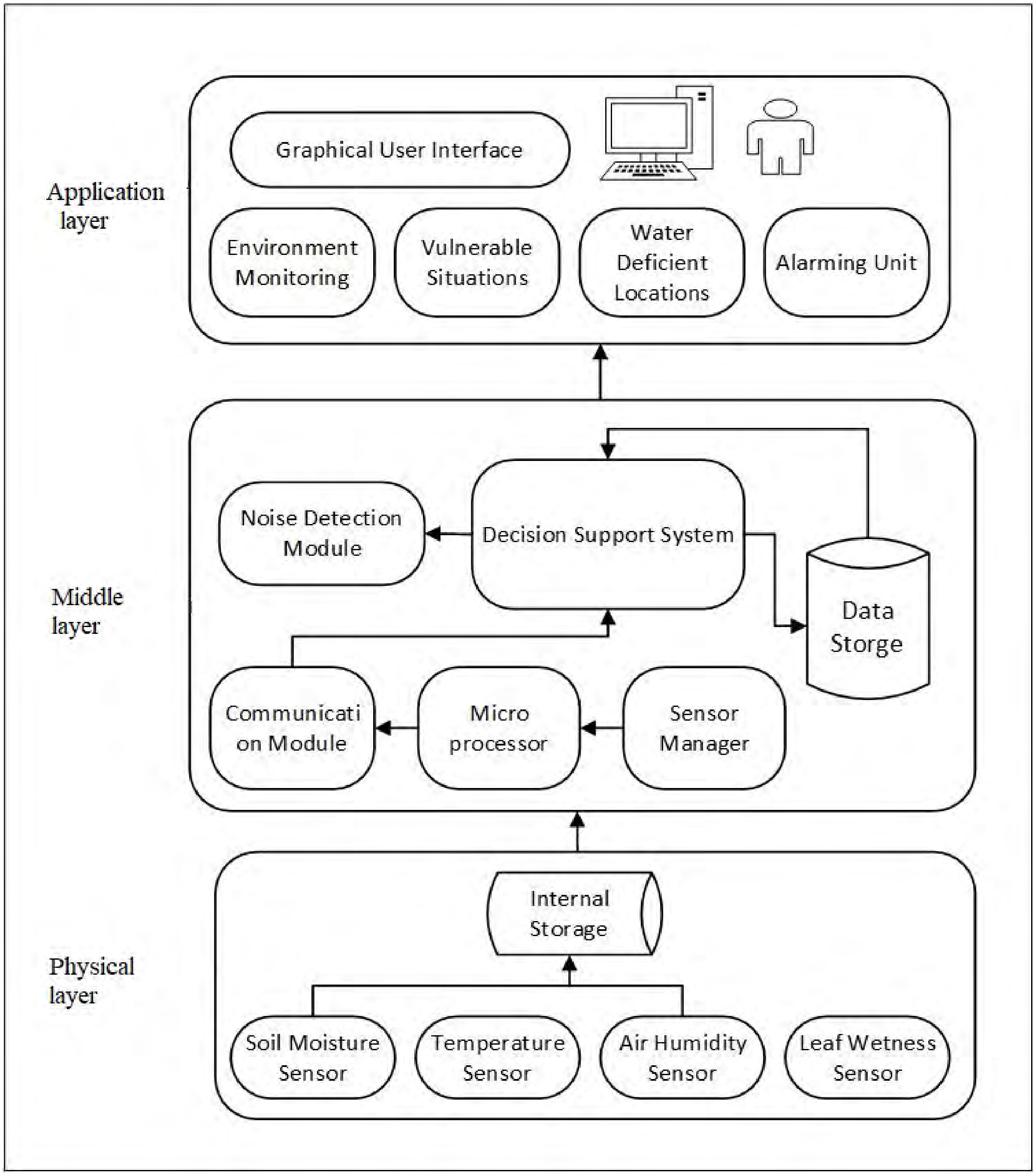

FIGURE 1. Architecture of the proposed DSS.

in the agricultural field, as shown in Figs. 2 and Fig. 3. In addition to the soil moisture parameter, an atmospheric moister exerts drastic effects on the watering schedules of various crops and must be monitored regularly. These sensors are deployed in close proximity to plant leaves, as shown in Fig. 4. Additionally, temperature and humidity parameters are significant in the design of a precise DSS because the soil moisture threshold value is directly proportional to the environmental temperature. Therefore, these sensors are integrated with wasp-mote boards to collect their full potential, as shown in Fig. 5. The gateway module is connected to a computer to receive data and process them.

IV. PROPOSED DECISION SUPPORT SYSTEM

The proposed system collects soil and environmental parameters through its deployed WSN in the orange orchard. Initially, the collected data are examined by the concerned board to minimize redundant packets via aggregation, and the

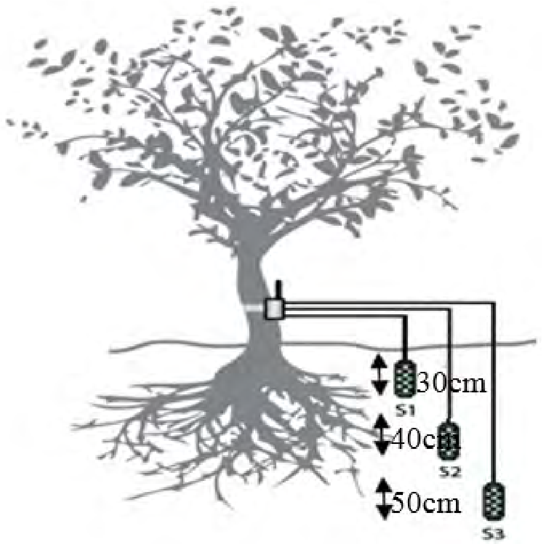

FIGURE 2. Deployment of soil moisture sensors in orange orchard.

FIGURE 3. Deployment soil moisture sensor in real agricultural environment.

FIGURE 4. Leaf wetness sensor deployment near plant leaves.

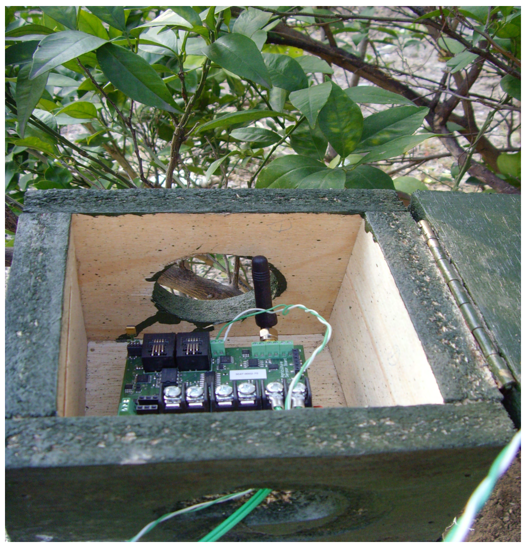

FIGURE 5. Air temperature and humidity sensors deployment.

data are transferred to the destination via a gateway. The data sensed by four different sensors are merged into one packet to increase the efficiency of the proposed system in terms of energy consumption. These packets are forwarded to the outlier detection module where their accuracy is checked and sent to DSS for onward processing if found correct. DSS thoroughly examines these packets by comparing different parameters with their defined threshold values, particularly soil moisture (250 Hz).The threshold values such as soil moisture (250Hz), are determined through deploying the sensors (3) in dry soil; and collecting their readings over a period of three days. If the data are in the defined range, then they are stored in a database; otherwise, the alarm unit is activated, and alert messages are forwarded to the LAN or mobile phone. The GUI of the proposed system shows collected data in graphical and textual formats. The operation of the proposed system is summarized in Fig. 6.

A. PROPOSED OUTLIERS DETECTION ALGORITHM

Outliers are data packets generated by a malfunctioning sensor or via interference and collision. WSNs are highly susceptible to outliers due to various restrictions on their size, processing, and transceivers. The literature on outlier/noise detection is bulky, but most of the approaches were presented and validated based on static datasets, and their implementation in a real-time system is difficult or impractical. These algorithms improve dataset accuracy but equally degrade the overall performance of a real-time system because for every packet, the mechanism repeatedly searches the entire dataset [37], [38]. Moreover, the accuracy of these algorithms is directly proportional to dataset size and computation time.

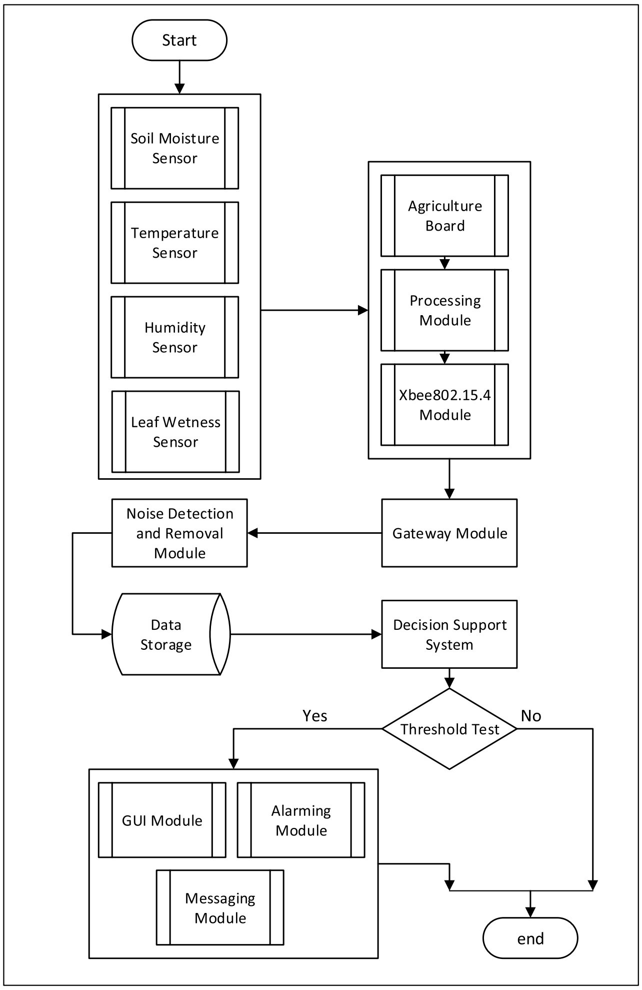

FIGURE 6. **Working of the proposed system.**

Their accuracy for large datasets is extremely high, but the computation time is also high and results in low performance of DSS, particularly in a real-time system. Therefore, a simplified outlier detection algorithm was developed to overcome these issues and improve the performance of real-time DSS and dataset accuracy. The performance of a real-time system based on the proposed outlier detection algorithm is unaffected by dataset size because the algorithm does not scan the overall dataset and considers the most recent packets only. Its computation time and performance are exceptionally good in real-time datasets, and it is equally applicable to static datasets.

Algorithm 1 starts by matching the currently received packet with the previously stored one, which is the last accurate packet, that is, the packet received at time T_i and T_{i-1}. If their difference is less than the defined threshold value (10 Hz for the soil moisture sensor), then it is forwarded to the DSS for further analysis. However, if their difference crosses the defined limit, then it is either an outlier or an abrupt change scenario that occurs because of direct connection of water with soil moisture sensors. In this case, data are stored temporarily, and further processing is delayed until the next packet from that particular node arrives. Then, the recently received packet is compared with two packets, namely, the one that is temporarily stored and the last packet stored in the database. For example, data collected at time T_3 are matched with data received at time T_2 and stored temporarily, and data gathered at time T_1 is successfully stored. If the difference between packets received at T_3 and T_1 is less than the defined threshold value, then the data packet received at T_2 is an outlier and replaced with the average value of data packets T_1 and T_3. However, if the difference between data packets T_2 and T_3 is less than the threshold value, then it is an abrupt change scenario, and both values are stored in the database.

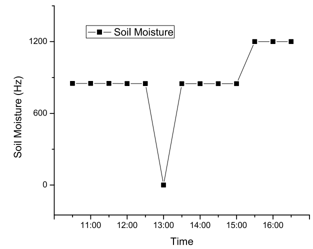

FIGURE 7. **A scenario of both outliers and abrupt change.**

We consider Fig. 7 in which the soil moisture value received at time 13:00 is 0 Hz, representing the most recent packet. The packet collected at time 12:30, 850 Hz, is the last accurate value stored in the database. These two values are matched, and their difference is much larger than the threshold value, which is 10 Hz in our case. Therefore, this packet is temporarily stored, and the decision is delayed until the next packet from the same node, $Node_1$, arrives. When the next packet at time 13:30 is received, it is matched with the packet collected at time 12:30 or with most recently stored packet. The difference between these packets is below the threshold value, 1 Hz, indicating that the temporarily stored packet is an outlier and must be replaced with the average value of data packets that arrived at times 12:30 and 13:30 (840 Hz). Then, both values are stored in the database, and the data are as shown in Fig. 8. In this scenario, a real-time DSS that does not use the outlier detection mechanism activates the alarm unit for the water deficit condition and sends a text message over LAN because the soil moisture value is less than the threshold value. However,

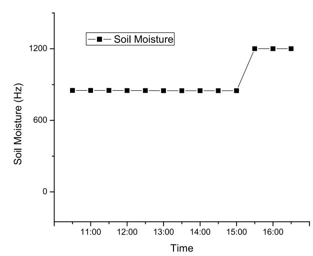

FIGURE 8. **Outliers free scenario.**

Algorithm 1 Proposed Outliers Detection and Correction Algorithm

Require: Received Data Packets
Ensure: Return Accurate Data
Pre-Pkt $\leftarrow$ Latest Stored Packet in DB
Cur-Pkt $\leftarrow$ Recently Collected data from WSN
$Temp - Location_i \leftarrow 0$
Outliers-ID $\leftarrow$ 0
DB $\leftarrow$ Existing Data
if Distance(Cur-Pkt,Pre-Pkt) $\geq$ Threshold value and Outliers-ID = 0 **then**
    $Temp - Location_i \leftarrow$ Cur-Pkt
    Outliers-ID $\leftarrow$ 1
else if Distance (Cur-Pkt, Pre-Pkt) $\leq$ Threshold value and Outliers-ID = 1 **then**
  If Distance (Cur-Pkt, Temp-location) $\leq$ Threshold value **then**
    Value at $Temp - location_i$ is an Outlier
    $Temp - Location_i \leftarrow$ Avg(Cur-Pkt, Pre-Pkt)
    DB $\leftarrow Temp - Location_i$
    DB $\leftarrow$ Cur-Pkt
    Outliers-ID $\leftarrow$ 0
  else
    $Temp - Location_i \leftarrow$ Cur-Pkt
    Outliers-ID $\leftarrow$ 1
else if Distance (Cur-Pkt, Pre-Pkt) $\leq$ Threshold value and Outliers-ID = 0 **then**
    DB $\leftarrow$ Cur-Pkt
else
    $Temp - Location_i \leftarrow$ Cur-Pkt
    Outliers-ID $\leftarrow$ 1
end if

smart DSS, which possesses outlier detection facility, easily handles this situation. Another debatable scenario for real-time DSS in the agricultural environment is the separation of the abrupt change that occurs because of the direct connection of water with a soil moisture sensor, as shown in Fig. 8 at time 15:30. The proposed algorithm handles this situation through a similar mechanism described for the detection of outliers. However, in this case, the temporarily stored value and the currently received value are identical or approximate each other. Both values are stored in the database without modification.

V. ISSUES RESOLVED DURING PROPOSED EXPERIMENTAL SETUP

During the deployment phase of the proposed testbed, various issues were identified and resolved.

A. PACKETS COLLISION AND NODES OVERHEARING

A sensor node uses a broadcasting mechanism to communicate with the gateway and other nodes in the network, thereby resulting in the collision of packets or reduction of throughput. Collision usually occurs due to the concurrent communication of sensor nodes deployed in close proximity or within the communication range of one another. In the proposed testbed, a simplified mechanism, namely, delay timers in wasp-mote boards, is used to avoid concurrent communication of sensor nodes and collision. Every experimental setup uses a sampling rate or a sensor node rate of transmission, which is 30 minutes in our case. The criteria for packet transmission of every node are adjusted according to the neighbor node communication schedules. For example, if $node_1$ begins communication with other nodes or the gateway at time 10:00:00, then its neighbor nodes must wait for the maximum propagation delay; that is, the time required for successful communication between the most widely separated nodes (approximately 5 seconds in the proposed experimental setup). Therefore, $node_2$, a neighboring node of $node_1$, must delay its communication for 3 seconds and start around 10:00:04 if its neighbors are not interested in transmission. However, this mechanism works only for a testbed in which a limited number of sensor nodes are used. For dense WSNs, other mechanisms, such as channelization, are utilized.

Overhearing of a sensor node in WSNs exerts drastic effects on node lifetime and needs to be handled efficiently, particularly in highly dense networks. To avoid this problem, sensor nodes are placed in such a manner that each node has at most one path for communication with the gateway and does not hear other neighboring nodes where feasible. In our case, the problem was successfully solved through manual adjustment of the distance between sensor nodes. However, this method is useful only in the engineered setup of WSN only and is not feasible for random deployment. This technique introduces the path loss problem in large networks, but it is efficient for small networks.

B. CROPS CANOPY

Crop canopy is another important problem associated with the deployment of WSNs in agricultural fields, particularly orchards. Crop canopy affects the communication range of sensor nodes in a network and environmental parameters. During the initial phase of our project, the problem was not considered, and nodes were deployed randomly at different locations but within the direct communication range of the gateway module. However, only $node_3$ packets were received successfully, and the remaining node packets were lost due to crop canopy. Further analysis of the experimental setup and field was performed, and different alternatives were applied to resolve this issue. This thorough investigation led us to the problem of crop canopy and its effects on the communication range of sensor nodes because $node_1$ was in the direct line of sight with the sink node, whereas the other nodes were not. Obstacles or orange trees were also present. Therefore, nodes were deployed in the orange orchard in such a manner that each node was in the direct line of sight with its intended receiver node. Node deployment in direct line of sight does not necessarily mean that nodes are unable to communicate when obstacles exist between transmitting and receiving nodes. Nodes placed in the crop canopy can communicate, but their coverage area and transmission range are much smaller than those in the direct line of sight communication. Another issue caused by crop canopy was the effects on sensor node readings, particularly sensors that collect environmental data (e.g., temperature and humidity). In summer, nodes deployed in a shady region generate temperature readings of 40 °C – 44 °C, whereas sensors exposed to sunlight sense temperatures in a range of 44 °C – 49 °C. To overcome this problem, 50% of the sensor nodes were deployed in direct sunlight, and the remaining nodes were placed in shady areas.

C. EFFECTS OF HEAVY RAIN

Heavy rain is vital to plant growth rate, particularly in summer when watering requirements are high. In traditional approaches, flooding/watering schedules are postponed due to heavy rain and particularly based on farmers‘ experience. Therefore, the proposed DSS must handle this scenario in a manner similar to traditional approaches but without requiring an experienced farmer to monitor the system and judge its decisions. In the proposed DSS, the decision whether to irrigate or not is primarily based on soil moisture content and other supplementary parameters. In the case of heavy rain, soil moisture sensor readings exceed the threshold value, clearly indicating that the irrigation schedule must be deferred. Similarly, conducting specific case studies for every season is not needed because if soil moisture content values are above the threshold value, then irrigation is unnecessary. Additionally, the proposed system possesses the flexibility to adjust threshold values whenever required and can be used in different agricultural scenarios.

D. WSNS LIFETIME

An important aspect of the applicability of WSNs in different application areas is their lifetime, which mostly relies on the onboard batteries of sensor nodes. Efficient utilization of available power resources increases WSN lifetime. In the proposed testbed, sensor nodes actively probe the environment for the shortest duration of 1 minute and then switch to sleep mode for approximately 29 minutes. Every board conducts aggregation of the data collected by its sensors and merges the data into a single packet. The aggregation approach combines the data gathered through temperature, air humidity, soil moisture and leaf wetness sensors into a single data packet. The aggregation mechanism reduces the number of transmitted packets from 4 to 1, and individual packets for every sensor are attached to a wasp-mote board, thereby improving the lifetime of WSNs. Additionally, in the agriculture sector, particularly in the watering schedules of open field crops, collection of data once or even twice a day is appropriate or needed. Therefore, the sampling rate of deployed nodes must be decreased to 12 hours or more to further increase WSN lifetime.

VI. RESULTS AND DISCUSSION

In the case of real-time data, the worst case complexity of the proposed outlier detection algorithm is O(1), whereas pattern anomaly value (PAV), MPAV, and rare pattern drift detector (RPDD) algorithms [37], [38] have complexities of $O(n^2)$, $O(n)$ and $O(n^2 + n)$ respectively. Hence, the proposed algorithm is the best solution among these algorithms for real-time DSS because it does not affect the functionality of DSS. Similarly, the proposed algorithm‘s worst case complexity for a static dataset is $O(n)$, where n represents size of the dataset.

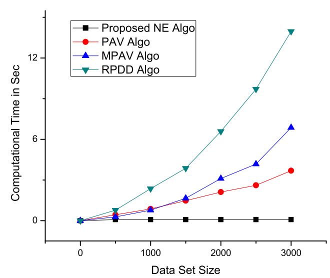

FIGURE 9. Computational time comparison on real time data set.

These algorithms were tested on real-time data obtained via our testbed deployed in an orange orchard. The performance of the algorithms in terms of computational time is presented in Fig. 9, which shows that the proposed algorithm outperformed contemporary schemes. Moreover, the performance of these algorithms was examined thoroughly by continuously increasing the dataset size. Unlike the proposed algorithm, the other schemes were inconsistent with the dynamically changing dataset. In the case of the real-time

TABLE 1. Comparative computation time of the proposed algorithm on benchmark data sets.

Data Set	Proposed Algorithm Real Time Data	Proposed Algorithm Static Data	PAV Algorithm	MPAV Algorithm	RPDD Algorithm
50words	0.1080	2.3280	3.6090	2.8590	3.0780
B-Cancer	0.1080	2.4220	3.0780	2.7800	2.9060
Two Pattern	0.1080	2.1700	3.1880	2.7130	2.2960
Yoga	0.1080	2.1250	2.8750	2.3900	2.7030
Fish	0.1080	2.0775	2.5630	2.4850	2.5620
Mote Strain	0.1080	2.7340	3.7350	2.9370	3.0160
Diatom-Size-Red	0.1080	2.0180	2.8600	2.0938	2.6980
Amex	0.1080	2.1090	3.4840	2.2500	3.000
Hobo Link	0.1080	2.3120	3.3590	2.4380	2.9530
Face UCR	0.1080	2.0158	3.7340	2.6400	3.4840

TABLE 2. Comparative accuracy of the proposed algorithm on benchmark data sets.

Data Set	Proposed Algorithm %	RPDD Algorithm %	PAV Algorithm %
50words	90.40	94.66	96.59
B-Cancer	89.29	93.48	96.30
Two Pattern	89.95	93.12	95.83
Yoga	90.62	94.50	96.74
Fish	90.18	94.31	95.69
Mote Strain	89.63	93.85	95.35
Diatom-Size-Red	90.06	94.19	96.56
Amex	87.54	93.65	95.91
Hobo Link	91.05	94.76	96.82
Face UCR	91.98	94.38	96.98

dataset, the computational time of the other algorithms was directly proportional to the size of the dataset, whereas the proposed algorithm was not affected. Moreover, the proposed algorithm‘s memory requirements were fewer than those of the other algorithms. The implementation of these complex algorithms in real-time DSS required highly sophisticated and demanding technology, which is expensive, whereas the proposed algorithm worked well with existing technology. The algorithms were also tested on a static dataset, and their computation time is depicted in Fig. 10. Our algorithm‘s performance was better than that of the other algorithms, particularly in terms of execution time.

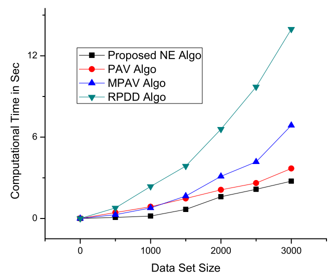

FIGURE 10. Computational time comparison on static data set.

The complexity of an algorithm is vital to its development, implementation, and execution in real-time systems. Complexity is directly proportional to algorithm accuracy and computation time. In real-time DSS specifically for the agriculture sector, an algorithm must be as accurate and simple as possible so the overall performance of DSS is unaffected. If the algorithm is accurate and precise but degrades the overall performance of the system, then it is useless. An accuracy comparison is presented in Fig. 11. Although the proposed algorithm‘s accuracy is lower than that of the other algorithms, its effect on the overall performance of real-time DSS was smaller, and the algorithm works on a personal computer. Improving the accuracy and precision of an algorithm results in increased complexity, degradation of the overall performance of the real-time system, and inability to run efficiently on personal computers.

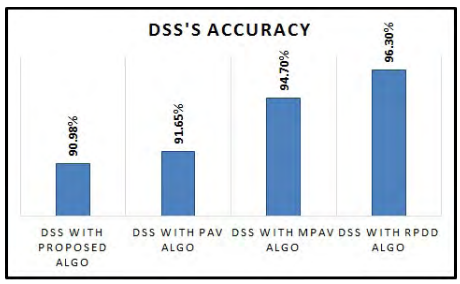

FIGURE 11. DSS's accuracy.

In addition to the real-time dataset, the algorithms were examined thoroughly by using benchmark datasets, as shown in Table 1. The execution time of the proposed algorithm was less than that of the other algorithms specifically for dynamic datasets. The proposed algorithm is an ideal candidate for an efficient real-time DSS. The precision and accuracy of these algorithms on the benchmark datasets are presented in Table 2. Accuracy is described in terms of accurate decisions taken by DSS when these algorithms were implemented as a separate module to fine tune data before processing. The proposed algorithm is not precise for datasets that possess multi-valued noise, such as the FacesUCR dataset.

However, when datasets have single-valued outliers only, the proposed algorithm is ideal.

A real-time decision support system was designed in this study to facilitate farmers in various agriculture-related activities. Farmers will adopt a technology-assisted system if it has a simplified interaction paradigm, possesses a simple GUI, and provides the desired services. The proposed DSS possesses a user-friendly interface that is can be easily understood by inexperienced users and provides different services simultaneously, as shown in Fig. 12.

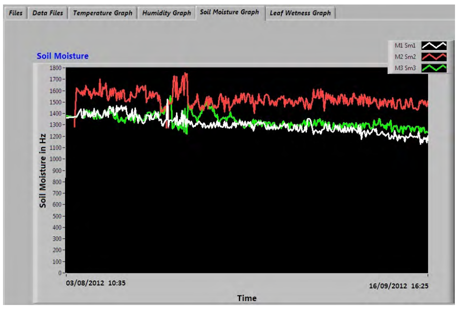

FIGURE 12. A sample screen shot of the proposed system showing data of soil moisture sensor.

VII. CONCLUSION AND FUTURE WORK

The demand for efficient utilization of available water resources, specifically in the agriculture sector, is increasing daily due to water scarcity and global climate change. Therefore, technology-assisted irrigation mechanisms, sensors, and actuators must be realized in real agriculture environments. These approaches provide water upon demand and control water wastage. They are helpful in controlling water resources but exert drastic effects on plant growth rate and yield. In this work, we developed a technology-assisted outlier detection and decision support system (DSS) to facilitate irrigation, particularly flooding. The proposed system is highly precise because it uses an embedded outlier detection module that thoroughly examines the correctness of the collected data and forwards the data to DSS for further processing. DSS analyzes different parameters to identify water-deficient sites and reports them to farmers or generates an alarm. This system possesses a user-friendly interaction environment that makes it easy to use.

In the future, we will further improve the accuracy of the proposed DSS by examining additional parameters and will enhance it to assist farmers in other agriculture-related activities, such as pesticide and fertilizer use and determination of soil properties. Furthermore, due to nodes un-availability and their security issues, the proposed scheme was evaluated only on three sensor nodes. As a future work, we will investigate the proposed algorithm on a large-scale.

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