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A Metaheuristic Optimization of Harvested Energy Consumption in Smart Farming Using Weather Forecasting

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ABSTRACT

This study proposes an Improved Particle Swarm Optimization (PSO) algorithm based on weather forecasting to minimize data transfer time in wireless sensor networks and maximize network lifetime. In addition, the research used a combination of an Improved Particle Swarm Optimization algorithm, improved Ant Colony Optimization (ACO), machine learning analysis and weather forecasting to further improve results. Sensor nodes have limited energy, using renewable energy to power sensor nodes provides a sustainable solution that ensures long-term reliable operation and avoids the need for battery replacement, especially for sensors located in remote locations, such as underground in agriculture. Since these sensors are likely to be operated day and night, the energy consumption needs to be optimized to extend the network lifetime. In this study, we used an optimized version of a metaheuristic algorithm called Particle Swarm Optimization to optimize the energy consumption of sensor nodes through optimal data transfer using weather forecast data (Temperature). In our work, we considered an optimal scheduling where data is represented by a directed acyclic graph (DAG). The results demonstrate the effectiveness of our proposed method in minimizing the data transfer time and thereby extending the sensor lifetime. Then, applying the combination improves the findings. Our method, based on weather forecasting, will make a significant contribution to improving the energy consumption of sensors, particularly in precision agriculture, which requires efficient use of sensor energy and maximizing network lifetime more than other fields due to its continuous monitoring and the need for continuous data collection over large areas, which requires a high level of sustainability.

1. INTRODUCTION

A wireless sensor network is a deployment of multiple devices equipped with sensors that interact with each other to perform a collaborative measurement process, as illustrated in Figure 1.

The Internet of things (IoT) is leading to major changes in agriculture by gathering real-time information such as soil, moisture, temperature and weather information, allowing farmers to react at the right time, optimizing irrigation, fertilizer, pesticide delivery, and helping to make the farm and its components easier to manage. Improving energy consumption in the Internet of Things (IoT) is critical, especially for smart agriculture, where IoT devices are used to continuously monitor crops and soil. Efficient energy use allows sensors and devices to operate for longer periods of time without frequent recharging or battery replacement, which is critical for managing extensive agricultural operations. By minimizing energy consumption, smart agriculture systems can improve sustainability, reduce costs and make better decisions.

A functional structure of a wireless sensor network platform composed of sensor nodes, gateway nodes and deployment devices can be used for multiple IoT applications and ensures high quality performance which, including early deployment and high quality service [1]. The primary components of WSN are sensors that communicate and share information over the internet. Several routing algorithms are designed to optimize power dissipation in WSNs [2]. The IoT is a giant network that provides a common platform and common language for all connected devices to communicate with each other. There are many classes of IoT applications like big data, business analytics, monitoring and control [3].

Radio Frequency Identification (RFID) and Wireless Sensor Networks (WSN) are the main technologies that ensure the proper functioning of IoT paradigm. Agriculture based on IoT allows automated control and energy efficiency on the farm [4]. Many energy harvesting techniques such as solar, thermal and vibration are used by WSN to solve the problem of limited energy of batteries instead of replacing them [5].

A Whale Optimization Algorithm with Simulated Annealing (WOA-SA) is used to choose the optimal cluster head of an IoT network in order to optimize the energy consumption of sensor nodes.

The hybrid algorithm proved its supremacy on artificial bee colony algorithm, genetic algorithm, WOA and adaptive gravitational search algorithm [6]. The NSGA II (Non-Dominated Sorting Genetic Algorithm) is used to optimize the battery control signal in photovoltaic system with grid connection [7]. Particle Swarm Optimization algorithm (PSO) is a non-deterministic method that can be used to solve difficult optimization problems, it was proposed by Kennedy and Eberhart [8]. This method is inspired by the social behavior of animals that evolve in swarms [9] and schools of fish [10].

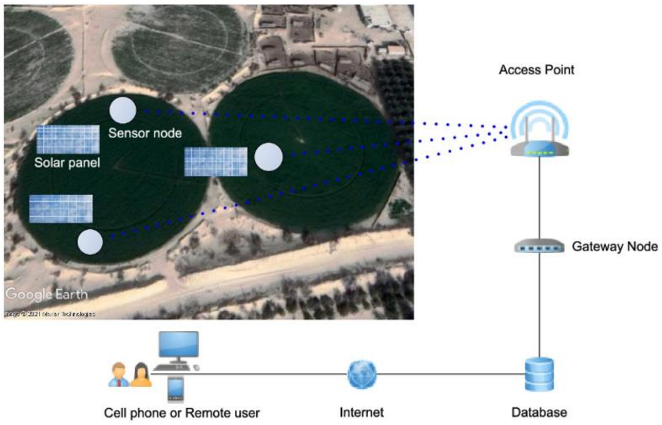

Figure 1. Internet of things devices in agricultural field

The equipment scheduling modeling method allows an energy consumption optimization in the IoT environment by using the multi-objective fuzzy algorithm [11]. Based on the Hybrid Energy Efficient and QoS Aware (HEEQA) algorithm, the energy consumption in the Internet of Things (IoT) was minimized and the network lifetime was maximized without affecting quality of service [12]. The use of cooperative nodes and relay deployment extends the lifetime of the wireless network by 12 times compared to the non-cooperative network [13]. LEACH (Low-Energy Adaptive Clustering Hierarchy) decreases the energy dissipation of sensor nodes by 8 times compared to conventional routing protocols [14]. A comparison between an existing exhaustive grid search algorithm and Particle Swarm Optimization-Multiple-Sink Placement Algorithm (PSO-MSPA) proved that the latter prolonged the lifetime of wireless sensor network from 3050 to 3450 [15].

The hybrid optimization algorithm named, Multi-Objective Fractional Artificial Bee Colony (MFABC), extends the wireless sensor network lifetime compared to LEACH, PSO and ABC by developing a new fitness function, which considers energy consumption, distance and delay [16].

Particle Swarm Optimization Algorithm is used to choose the best base station locations with the objective of reducing energy consumption [17]. Particle Swarm Optimization Algorithm can prolong the lifetime of the network and save 40% of energy by finding the optimal sink position to the relay nodes [18].

Adaptive signal processing and distributed source coding principles save the sensor node energy (from 10% - 65%) [19]. The Sensor Protocols for Information via Negotiation (SPIN) is used for information dissemination in wireless sensor networks and can transmit 60% more data than conventional approaches for a given amount of energy [20].

To develop a low cost solar powered soil and weather monitoring system, a system comprised of IoT, data mining and an android mobile application was created. This system helps to optimize irrigation, enhance accuracy and promote conservation efforts. It also invites low-income households to adopt advanced climate-smart farming practices [21]. The model of two-level weather forecast based on solar radiation prediction outperforms the Exponentially Weighted Moving Average (EWMA) in terms of simulated wireless sensor performance [22]. The use of the weather-dependent fuzzy logic model in generating irrigation valve control commands guarantees an optimal level of irrigation, enhancing the overall efficiency of the irrigation system [23].

The significance of incorporating weather forecasts into energy management systems is established by emphasizing the dependencies of various building components on weather conditions [24]. A real-time system implemented on a TI CC2530 platform using advanced clustering and routing methods showcases improved energy efficiency and extended lifetime for a Wireless Sensor Network (WSN) [25].

Multi Agent Architecture (MAS) implemented in a cloud environment with a WSN attains an average energy savings of 41% in the offices of the experimental group [26]. An automated solar-powered weather station reduces the cost of obtaining scientific weather information in local communities in Africa by using meteorological sensors, a liquid crystal display (LCD), a microcontroller and a GSM modem [27].

Renewable energy reduces the cost of electricity and the pollution of the environment that has been caused by the excessive use of fuel. The agriculture has been elevated to an entirely new level using renewable energy harvesting and IoT [28].

2. PROBLEM STATEMENT

Today, Algeria's agricultural sector is growing at a very fast rate, and needs to be improved with the development of Internet of Things (IoT) and solar energy harvesting technologies especially in desert regions where the annual sunshine is more than 3000 hours/year.

A better example is the city of El Oued, located in the northeastern Algerian Sahara. This city transforms the dry lands into agricultural lands by fighting the sand and its drift; it leads the agricultural production in Algeria with 60%.

The harvest season in this region is always early and has a high quality compared to the other cities due to the climate.

This city has a huge reserve of groundwater that goes deep to approximately 2000 meters, and with this El Oued gathered between the soil fertility, climate and water availability, but it had a lot of problems and challenges such as wind, storms; the appearance of some dangerous insects because of the free fall of temperature especially in May and October.

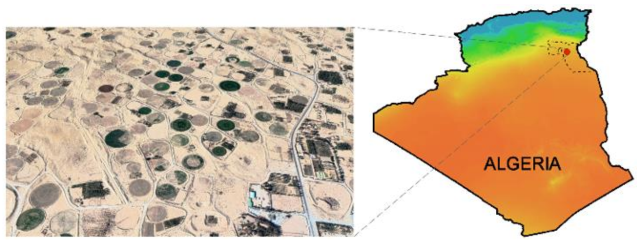

Figure 2. Agricultural area in El Oued City

In addition, the main problem is the lack of electricity, which leads to a constant search for fuel to power engines especially for irrigation. El Oued's geographical location has several advantages for a large use of solar energy to provide a strategic position to play an important role in the electricity energy generation. We captured a satellite image of a small Agricultural area in El Oued City-Algeria from Google Earth Pro that rises to 799 meters as shown in Figure 2.

In addition to energy harvesting, precision agriculture, which consists of IoT, cloud computing, and big data, can address the previous problems, reduce farmers' efforts, lower costs, and increase yields. Even though the southern region of Algeria has a high number of hours of sunshine per year, which is very efficient for solar energy harvesting, the farms are very large and their management is quite complex, so the sensors are very busy day and night and the energy consumption needs to be optimized.

We see that the solar energy harvested must be used in a rational way in order to preserve the electricity during the night or on cloudy days. Optimizing the use of solar energy in precision agriculture is an interesting concept that we have studied in our paper, all with the aim of exploiting the wealth of our country and the world and promoting its economy.

3. PROPOSED WORK

3.1 Fitness function

To find an optimal scheduler that correctly transfers all data with the replicated and unallocated backup copies, we minimize the scheduling length.

Based on the assumption that at most one node (sensor) can experience a permanent failure, we propose some new static techniques that minimize the scheduling length in the worst-case scenario.

The advantage of static scheduling is that it can take dependencies and data transfer costs into account when making scheduling decisions. To achieve this, we use our Improved Particle Swarm Optimization algorithm (PSO) since the problem under study is an optimization problem.

It is assumed that there are n_{node} nodes in the system named n_1, n_2, n_3…, n_{node}. The problem's inputs are defined by the direct acyclic graph (DAG), G= (D, E, Exe (D)), where D= d_1, d_2…, d_n represents the data set. E present data dependency, from the node of data d_i to the node of data d_j, Exe(d) is a function representing the cost of transmission, which is the time required to compute and transmit the data d ∈ D.

Any node may fail due to battery discharge caused by successive transmit and receive operations, especially in the absence of solar energy (at night or on cloudy days). It is assumed that at most one node will be unable to transmit the data properly in our proposed algorithm.

A replicated backup copy of the primary copy is transferred independently of whether the primary copy (Pri) is successfully transferred or not. An unallocated backup copy of the primary copy is transferred if the primary copy (Pri) fails. D_{msg} is a message from a primary copy Pri to its unallocated backup copy, indicating whether Pri was successfully transferred or not.

D_{msg} is used to indicate message time cost. Since our solution is based on a hybrid approach that combines both passive and active redundancy, we use two types of backup copies, replicated and unallocated. The order of data dependencies is modeled by binary variables that allow the order of the data to be determined. x (i, j, k) is a binary variable, such that x (i, j, k) = 1 if and only if the primary copy x_i^P of the data x_i is correctly transmitted by the node N_k at step j. Similarly, the binary variables x^{Repli} (i, j, k), x^{Desal} (i, j, k) are used for replicated x_i^R and unallocated x_i^D backup copies.

$$\forall i \in \{1,\ldots,n\},\ \forall j \in \{1,\ldots,\lambda\},\ \forall k \in \{1,\ldots, n_{node}\}.$$
$$x(i,j,k), x^{Repli}(i,j,k), x^{Desal}(i,j,k) \in \{0,1\}$$

λ is an upper limit on the scheduling length, n_{node} is the number of nodes.

The objective function of our problem is linear and the minimization of the scheduling length can be mathematically formulated as follows:

$$min \sum_{j=1}^{\lambda} \sum_{k=1}^{n_{node}} j * x(d_0, j, k) \tag{1}$$

where, d_0 is a fictional node added to the DAG data model in order to calculate the total scheduling length. The minimisation of the total scheduling length is done under the following constraints:

(a) The primary copy of each data is scheduled only once, $\forall i \in \{1, \ldots, n\}$,

$$\sum_{j=1}^{\lambda} \sum_{k=1}^{n_{node}} x(i,j,k) = 1 \tag{2}$$

(b) Only one backup copy of each data is scheduled, $\forall i \in \{1, \ldots, n\}$,

$$\sum_{j=1}^{\lambda} \sum_{k=1}^{n_{node}} x^{Repli}(i,j,k) + x^{Desal}(i,j,k) = 1 \tag{3}$$

At any given time, an Nx node is being used to transfer either a primary copy of a data or its replicated backup copy. $\forall j \in \{1, \ldots, \lambda\}$, $\forall k \in \{1, \ldots, n_{node}\}$.

$$\sum_{i=1}^{n} x(i,j,k) + x^{Repli}(i,j,k) \leq 1 \tag{4}$$

(c) Backup copies must respect the same priority as their primary copies, $\forall i \in \{1, l\ldots, n\}$, and $k \neq I$,

$$\sum_{j=1}^{\lambda} \sum_{k=1}^{n_{node}} j * x^{Repli}(i,j,k) + Extc(m_i) \leq \sum_{j=1}^{\lambda} \sum_{k=1}^{n_{node}} j * x^{Repli}(l,j,k) \tag{5}$$

(d) The primary copy and its backup should not, under any circumstances, be assigned to the same node. $\forall i \in \{1, \ldots, n\}$, $\forall k \in \{1, \ldots, n_{node}\}$,

$$\sum_{j=1}^{\lambda} x(i,j,k) + x^{Repli}(i,j,k) + x^{Desal}(i,j,k) \leq 1 \tag{6}$$

We used our fitness function and the constraints in the

Improved Particle Swarm Optimization Algorithm in Section 3.4 to achieve improved results.

3.2 High performance computing

The University of Batna 2 in Algeria has a high performance computing (HPC) cluster composed of a master node, twelve computing nodes and a storage node with a capacity of 20 TB.

These nodes are connected by two networks, a Giga Ethernet management network and a 100 Gbps InfiniBand computing network, see Figures 3 and 4.

The HPC cluster was deployed and commissioned in February 2020.

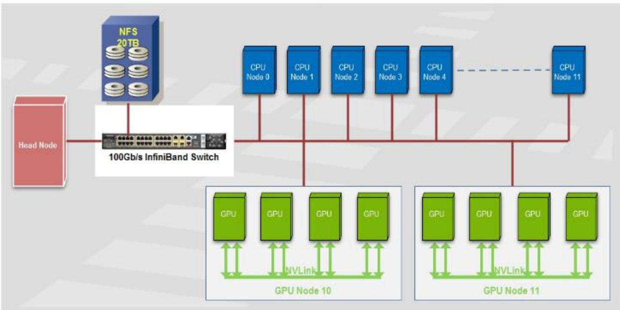

Figure 3. HPC architecture

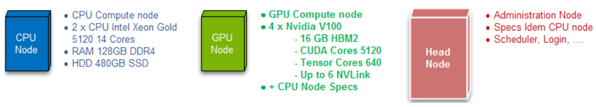

Figure 4. HPC components

3.3 Weather prediction data

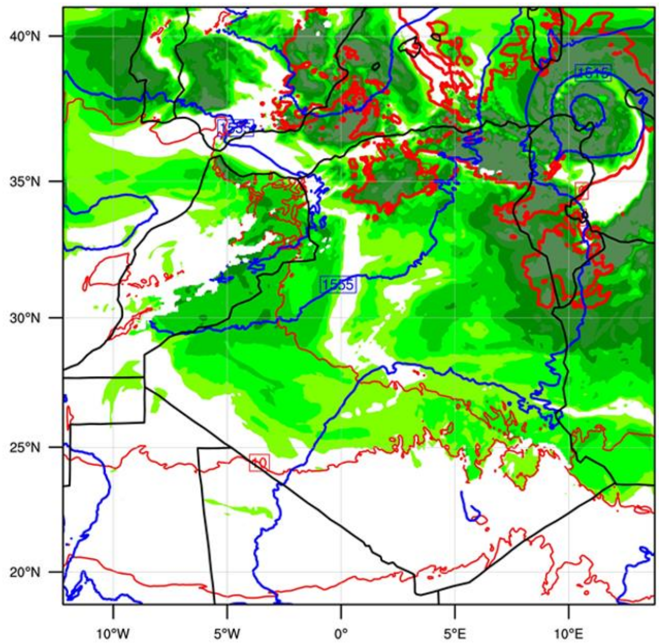

Figure 5. Height contours in Algeria at 850 hpa

Weather data plays an important role in agriculture by providing information that helps farmers organize activities such as planting, fertilizing, irrigating and harvesting and take the necessary measures to protect crops from storms, droughts and other ecological events that could harm them.

Precipitation meteorological data helps reduce water waste and optimize irrigation. Meteorological frost forecasts allow the protection of sensitive crops and ensure that the necessary measures are taken. Temperature and humidity information is critical in preventing plant fungal diseases. Weather forecasting helps improve agricultural productivity and sustainability.

Weather data plays an important role in optimizing renewable energy harvesting, especially solar and wind energies. Knowing when the sun shines most intensely enable us to maximize energy harvesting, which can be stored for later use during low production periods.

Algeria is characterized by climatic diversity due to its vast geographical area. The weather data we collected clearly illustrated this diversity clearly, allowing the simultaneous harvesting of many types of renewable energy, especially wind and solar energy since we focused on El Oued city, which will have a positive impact on its agricultural region by maximizing network lifetime.

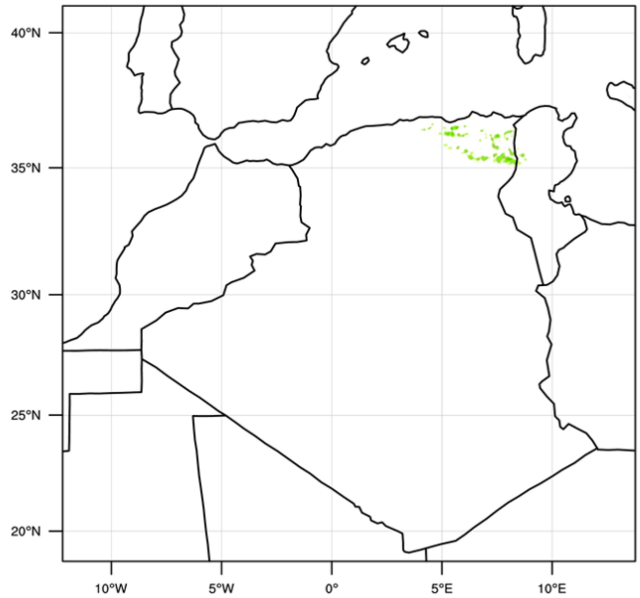

Figure 6. Accumulated total grid scale graupel

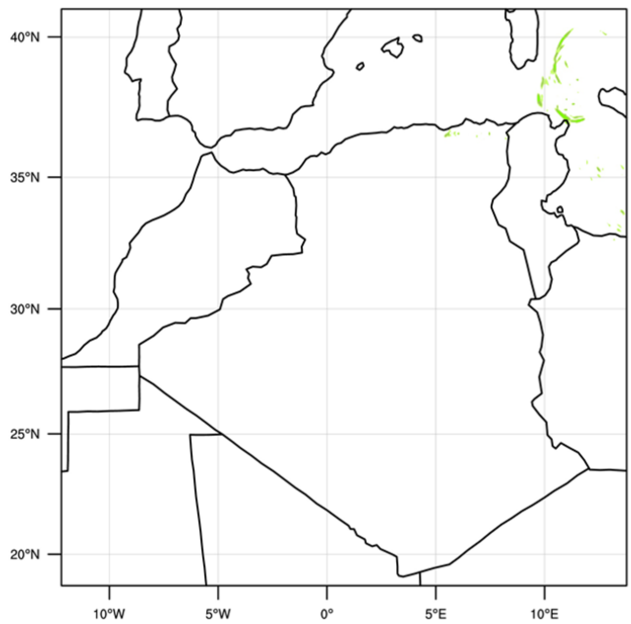

Figure 7. Accumulated total grid scale hail

The meteorological data shown in the Figures 5-13 are detected by weather research and forecasting V4.2.1 model at the High Performance Computing (HPC) center of University of Batna 2.

The figures show the importance of solar energy in El Oued city that can be used to power sensors.

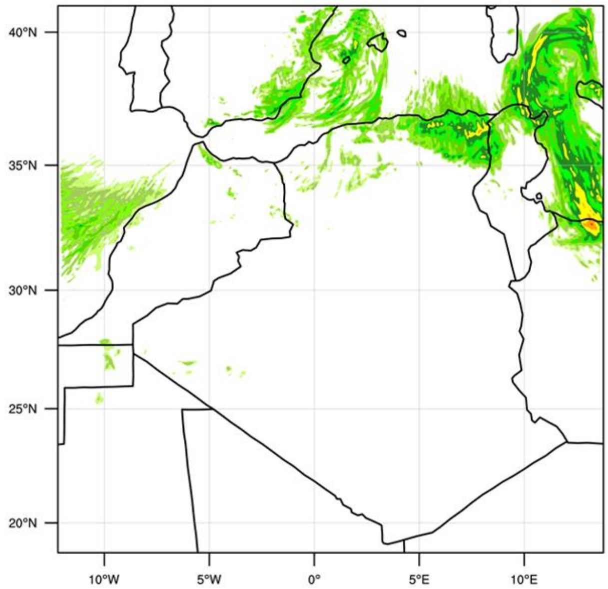

Figure 8. Total precipitation

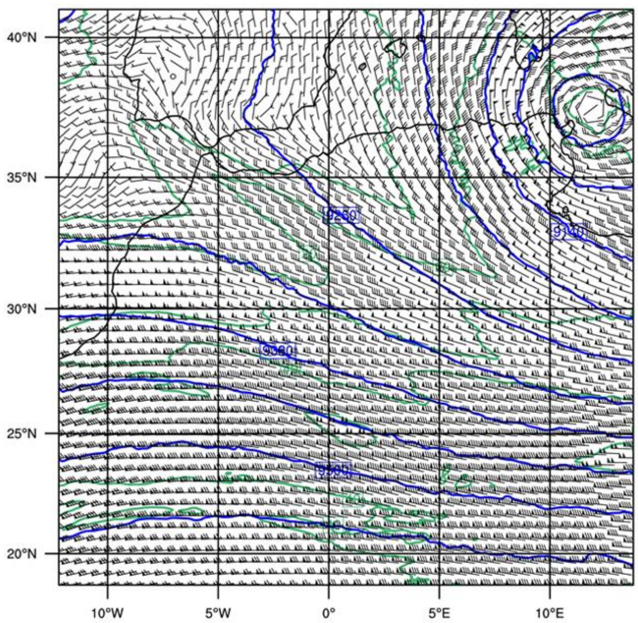

Figure 9. Wind speed contours

Table 1. Weather forecasting data in El Oued City

Data	Value
Height Contours	From 1475 to 1615 by 20 at 850 hpa
Graupel	From 1,6 to 12,8
Hail	From 1,6 to 12,8
Total Precipitation	From 1,6 to 51,2
Wind Speed Contours	From 0 to 70 by 10 at 300 hpa
Snow	From 0,4 to 25,6
Sea Level Pressure Contours	From 900 to 1100 by 4
Relative humidity at 2 m above ground	From 50 to 80
Surface Temperature	From 4 to 16

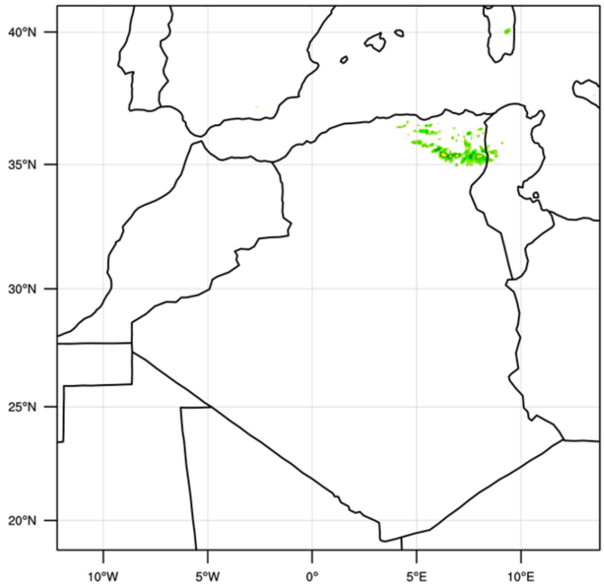

Figure 10. Accumulated total grid scale snow and ice in Algeria

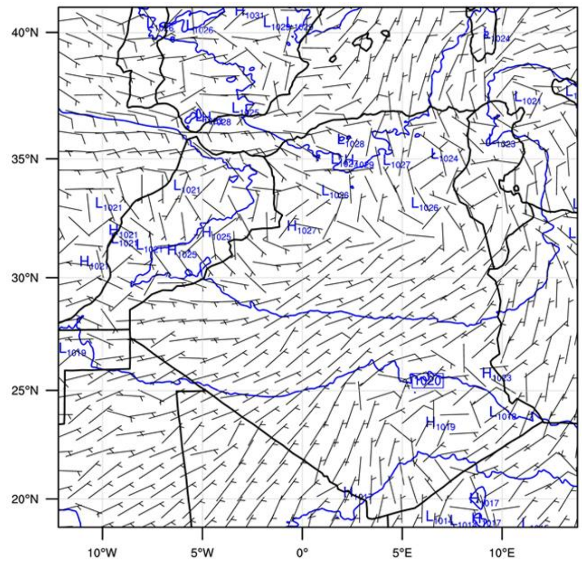

Figure 11. Sea level pressure contours

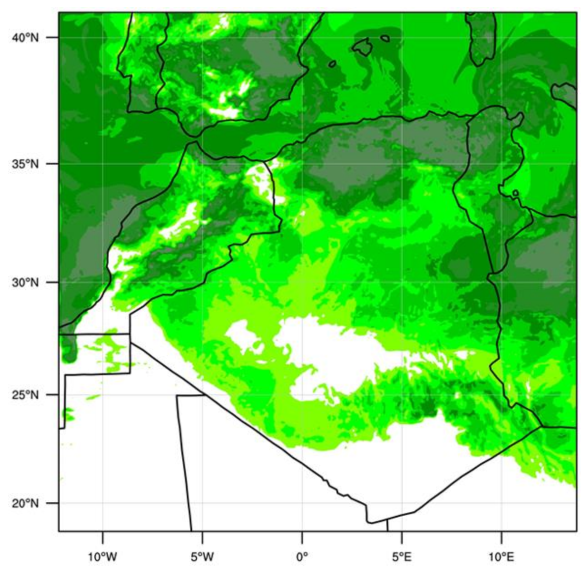

Figure 12. Relative humidity at 2 m above ground

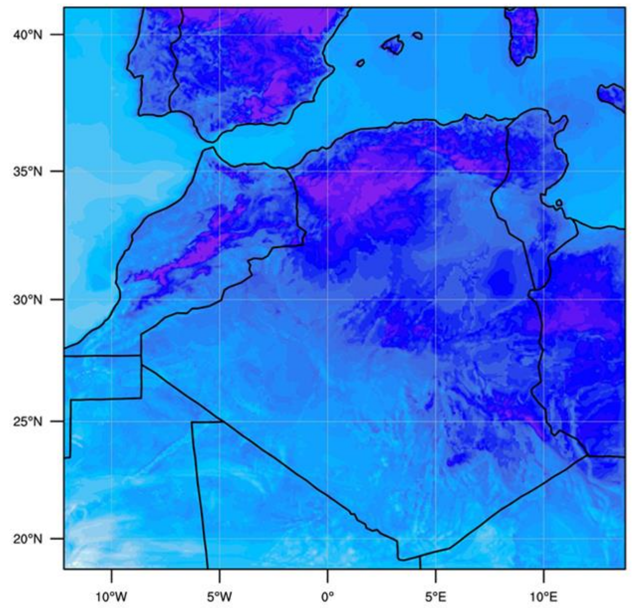

Figure 13. Surface temperature

All the figures are detected the month of January in Algeria. The information extracted from the figures in El Oued City is shown in the following Table 1.

Despite the intermittent nature of energy from the harvesting system, which is significantly impacted by weather conditions, sensor nodes can adjust their programming schedules according to best suit their energy production and battery levels residual, and this is what we have worked on in this paper.

In this paper, we ameliorated a metaheuristic algorithm called Particle Swarm Optimization (PSO) by using weather forecast data, and then we used this improved form to optimize the energy consumption of sensor nodes by minimizing the data transfer path from the source nodes to the destination ones.

3.4 Performance evaluation

The swarm algorithm is inspired by the behavior of swarms of birds [9] and fish [10] as they migrate from one place to another. The movement of a particle in the swarm is influenced by three things: it follows its current direction, it moves towards the best position it has already found, and it follows the best positions its neighbors have reached. Due to the alignment of the functionality of the algorithm with the requirements of our research, we have chosen it over other algorithms. It also it performs better in balancing exploration and optimization, making it an ideal tool for real-time data transmission, such as in wireless sensor networks.

Improving data transfer in networks means finding the most efficient path to send data from the source to the destination while minimizing delays and reducing energy consumption. In our research, we focused on a new principle for sending data between sensors, which is based on the battery level of neighboring (receiving) sensors after monitoring weather conditions for the lack of solar energy needed to charge sensor batteries.

This means that the transmission of information between the source and destination is done through sensors whose battery is sufficient to maintain the remaining sensors whose batteries are depleted, thus maximizing the lifetime of the network.

Based on this, we introduce the Improved Particle Swarm Optimization Algorithm. Our algorithm is based on weather data, specifically temperature, which means that on sunny days there are no problems because the sensors are powered by solar energy. But at night and on cloudy days, we need to optimize the energy consumption of the sensors. The optimization is achieved by choosing the right data transmission path, which passes through sensors with high battery levels to maintain the charge of other sensors for as long as possible. After determining the best position (Gbest) in the entire swarm according to the position of the most charged sensor, we have used the equations that we have listed in the Section 3.1 in our algorithm to show the effectiveness of our proposed method.

To improve the energy efficiency and extend the network's lifetime, we used weather forecast data in the improved PSO algorithm as shown in Algorithm 1, and since solar energy is consistent throughout the year in our region, we just focused only on temperature.

Algorithm 1. PSO Position update according to temperature

Require: temperature, equations 1, 2, 3, 4, 5, 6
Ensure: Best-Objective-Values
(1) X0: Initial Population
(2) S: necessary temperature to charge the sensor's battery
(3) Gbest: the best position found by the entire swarm
(4) Pbest: the best position found by each particle
(5) V: numbers of variables
(6) P: size of population
(7) **while** (temperature≤S) **do**
(8) Determine the most charged sensor
(9) M: the position of the most charged sensor
(10) Gbest= X0+M*0,08 (improvement factor)
(11) **end while**
(12) Update PSO position
(13) Determine the most charged neighbor sensor
(14) N: The position of the most charged neighbor sensor
(15) **for** (i=1:P) do
(16) **for** (j=1:V) do
(17) x(i,j) = x(i,j)+v(i,j)+(N*0,08)
(18) **end for**
(19) **end for**

The principle we have followed is that the sensors optimize their energy consumption depending on the temperature, on cloudy days we minimize the energy consumption due to the lack of solar energy in order to protect the batteries from draining, and this is where the importance of weather forecast data lies.

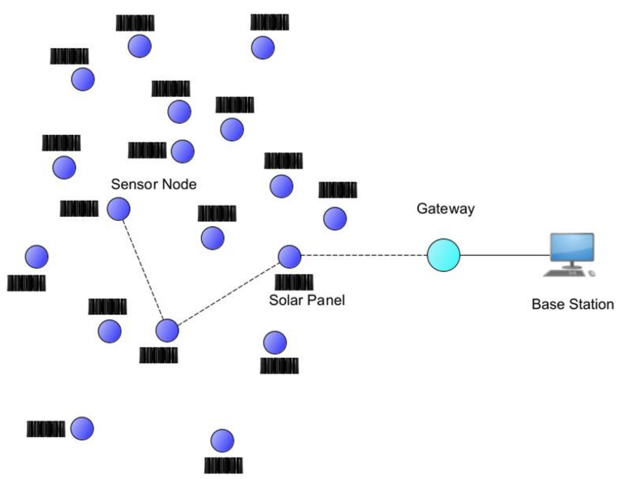

Figure 14. Network components

To concretize our proposals for three nodes (Sensors), see Figure 14, and to show the effectiveness of the proposed method See Figure 15, we used the Improved PSO algorithm on its MATLAB implementation. The results obtained are shown in Figures 16 and 17.

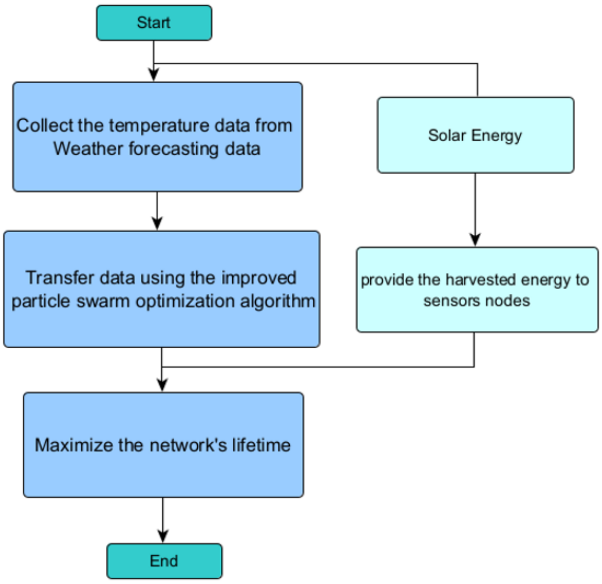

Figure 15. Flowchart of the proposed method

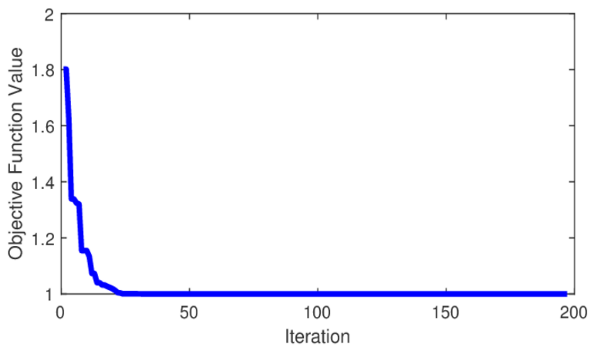

Figure 16. Particle swarm optimization convergence characteristics

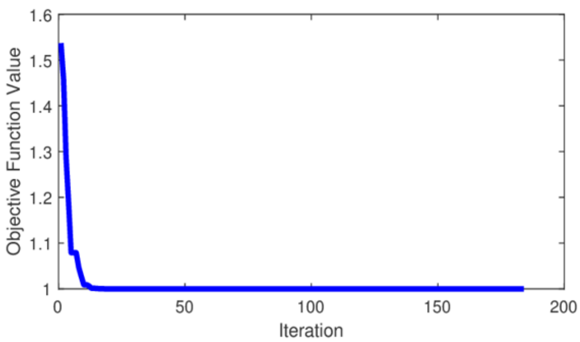

Figure 17. Improved Particle Swarm Optimization convergence characteristics using temperature weather prediction

We noticed in Figure 16 that the objective function value started dropping from 1,8 at 0 iteration to reach a value of 1 at 23 iteration where it remained at that value as the iterations increases which means that all the data was transmitted correctly and successfully reached its destination. As for the Figure 17, the objective function value started to drop from 1,54 at 0 iteration to reach a value of 1 at 14 iteration where it stopped at this value as the iteration increases, which means that all the data are transmitted correctly.

In addition, data transfer time is minimized from 11.052457 to 7.605885 seconds after using WRF data (temperature) so the harvested energy consumption is being optimized.

In addition, we validate the effectiveness and efficiency of our improved method by performing a simulation using Python. By reducing data transfer time, we save more energy in the sensors and extend the network lifetime. The results shown in Table 2 confirm that our improved algorithm is efficient in terms of energy savings as compared to the PSO algorithm.

Table 2. Comparison of data transfer time using PSO and improved PSO

Number of Sensors	03	05	20	100
Transfer time using PSO	11.05 Seconds	29 Seconds	2 minutes 30 Seconds	6 minutes 48 Seconds
Transfer time using IMPROVED PSO	7,60 Seconds	13,98 Seconds	58 Seconds	2 minutes 54 Seconds

The results showed that regardless of the number of sensors, the optimized algorithm consistently produced better results in terms of reducing data transfer time. This indicates that the sensor optimizes the harvested energy optimally, although the results are based on the worst weather conditions.

In the agricultural sector, an improved PSO algorithm can optimize the performance of wireless sensor networks that are used for crop monitoring. The lifetime of the network has been maximized by selecting the most energy efficient data transfer paths. The algorithm dynamically selects the best path for real-time data transmission based on changing conditions such as weather and battery levels. Minimizing energy consumption makes the network more efficient and allows continuous monitoring without the need for frequent maintenance or recharging, improving the sustainability and productivity of smart farming.

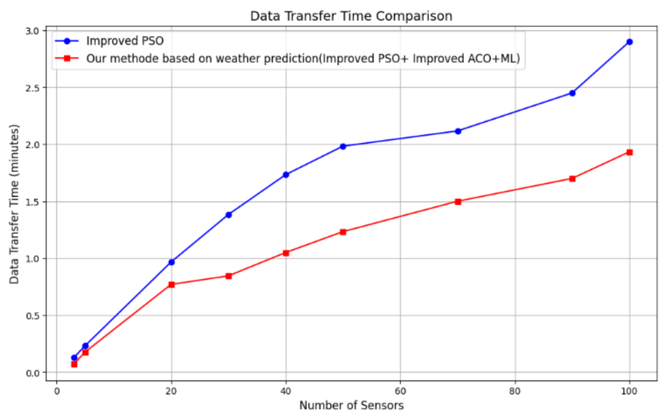

Figure 18. Data transfer time comparison using Improved PSO and the combined method

In addition, we have combined the concept of weather forecasting with machine learning (supervised learning), Improved PSO Algorithm, and Improved ACO (Ant Colony

Optimization [29, 30]) Algorithm to get better results. The following steps explain the scenario.

(1) Based on weather forecast data and historical battery level data, SVM (Support Vector Machine) model [31] predicts the effect of temperature on the sensors (battery charge level).
(2) The Improved PSO works as described above.
(3) The improved ACO selects the best path with sensors that have the highest battery level based on weather forecast and using the equations in Section 3.1, to prolong the network's lifetime.

This combination gives us better results than using Improved PSO. See Figure 18.

The results show that regardless of the number of sensors, the combined method gives better results than the improved PSO in terms of data transmission time, which proves the effectiveness of our approach.

The reduction in transmission time conserves sensor energy and maximizes network lifetime.

4. DISCUSSION

The use of the improved algorithm to select the best data transfer path between sensors in agricultural systems to reduce energy consumption has some technical limitations that can affect its deployment and performance. Choosing the optimal path based on battery level can cause delays in data transmission, especially if frequent calculation based on energy consumption is required. Also, sensors with higher charged batteries can become overloaded if energy is not managed efficiently. In addition, increasing the number of sensors can make the algorithm more complex. This requires additional processing resources.

Despite the significant energy efficiency benefits of this system, it also has an impact on the environment. For example, the deployment of large numbers of sensors can have an impact on the natural environment, especially if the infrastructure requires digging up the soil or installing equipment in sensitive areas. In addition, the haphazard placement of equipment without proper planning can have a negative impact on biodiversity.

By relying on renewable energy to power the sensors and using the optimization algorithm only when necessary, our system reduces these impacts and achieves a balance between system efficiency and environmental protection.

5. CONCLUSIONS

In wireless sensor networks used in agricultural IoT, each sensor can collect, transmit, and receive data. These operations consume energy, which leads to complete battery depletion. Therefore, we use the concept of solar energy harvesting to feed the batteries and prevent them from going empty, especially when the agricultural zone is located in a very sunny region like the Algerian Sahara.

In our work, we considered an optimal scheduling when data is represented by a DAG with two types of backup copies under the assumption that there will be a single failed node. The use of our Improved Particle Swarm Optimization (PSO) algorithm, which we developed based on weather forecast data, gives better results compared to the PSO algorithm and minimizes the data transfer time. The use of our combined method based on weather forecasting (Machine learning, Improved PSO and Improved ACO) improved the results even more.

The combination of the use of solar energy harvesting and energy consumption optimization extends the network's lifetime.

We chose critical weather conditions (in the middle of the winter) to show that our solution is also effective even in other conditions. Smart farming system based on weather forecast data has high productivity and authenticity, so it will help farmers increase agricultural yield and effectively manage food production. In the future, a comparison between the used method and other methods will be conducted, to choose the best one to be implemented in an Arduino testbed.

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