International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Delay Efficient Federated Learning based Plant Disease Detection and Monitoring (DFLPDDM) in Agricultural Fields: A UAV-IoT Environment

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Abstract:
Plant disease detection, monitoring and smart spraying using Unmanned Aerial Vehicle-Internet of Things (UAV-IoT) environment, has become extremely important in precision agriculture, this has to be performed in delay efficient manner so that prompt action can be taken to save as many plants as possible. Energy efficiency is an added advantage that incorporates sustainability in thesolution. However, to the best of authors knowledge, articles in relevant literature have neglected the concept of security which is indispensable if different regions of a big agricultural land belong to different owners and they want to keep their land status information confidential. In this article, we propose a delay efficient federated learning-based plant disease detection and monitoring scheme (DFLPDDM) that utilizes the concept of transmitting gradients among untrusted UAV's and transmitting data among trusted UAVs to ensure security and confidentiality. Also, mechanisms are proposed to incorporate delay and energy efficiency to improve overall performance effectiveness of the system. Simulation results shows that DFLPDDM produce much better performance compared to many other state-of-the-art agricultural field monitoring algorithms.

Keywords: Agricultural fields, energy, federated learning, follower, leader, plant disease detection and monitoring, precision agriculture.

1. Introduction

The importance of precision agriculture has increased these days, especially in the countries where economy is agriculture based. In those countries there are large agricultural lands belonging to a single owner or multiple owners. Temporal and spatial data from different parts of these large agriculture lands are collected by sensor nodes and sent to UAVs for necessary processing, analysis and decision making. Various techniques and tools have been invented to accomplish this purpose [1, 3-8]. These techniques have incorporated great technical development in monitoring of large lands, popularly termed as green movement [10-15]. The relevance of precision agriculture has gained more importance with increase in demand of food commodities and the trend is expected to continue beyond 2050 [15]. In order to save the plants from animals and various diseases, sensors and UAVs are being increasingly deployed for implementation of smart farming, that is, controlling irrigation, monitoring vegetation status, detection of contamination and use of fertilizers [20,21,23].
Earlier remote sensing was used to catch signals from satellite images but the cost was higher because of the requirement to take images of agricultural lands at short intervals and also resolution of those images

was poor lowering accuracy of the decision-making process. UAV-IoT environment enable more accurate and prompt decision making at a lesser cost. Also selected parts of the regions are observed with higher resolution while the others are assigned smaller resolution. However, implementation of security is difficult if various parts of a big agricultural land belong to different owners and they are not interested to share their land's data with others. In this case there are UAVs of trusted groups within which data can be shared and only gradients are forwarded to the leader if followers belong to different groups. One such concept has been illustrated in this paper along with techniques of delay and energy efficiency to make the process sustainable.

The rest of the article is organized as below. Related work is illustrated in section 2 whereas the system model appears in section 3. Section 4 describes the scheme of DSLPDDM and experimental results appear in section 5. Section 6 concludes the paper.

2. Related Work

Application of UAV technologies in the domain of agricultural field monitoring has recently gained attention of researchers [1-10]. Unmanned aerial vehicles are used to detect diseases and infections in agricultural fields and spray pesticides to treat those. Different types of techniques like AI, machine learning, deep learning etc. are applied in this context [11-18]. One important aspect of this is trajectory planning of the aerial vehicles in both single and multi-UAV systems [1, 2, 4, 17]. However, in multi-UAV systems trajectory planning is more difficult because collisions have to be avoided [1, 2, 4]. The process has to be energy as well as delay efficient so that UAVs continue to travel for a long time before the requirement of recharging and diseases of plants are treated in a timely fashion. This optimizes the cost and makes it very efficient. Energy efficiency is implemented by controlling i) positions of charging stations, ii) arranging sequences of sites to visit, and iii) energy efficient execution of tasks. Energy efficiency through controlling positions of charging stations is achieved only when UAVs get exhausted and need to be recharged. Different sites generate different types of tasks of different lengths and complexities. Strategies exist in literature to optimize execution of tasks. Deciding upon sequence of sites to visit is another important aspect of trajectory planning which we are going to consider in our current research effort. Flight paths are decided based on various methods like ant colony-based optimization, mixed integer linear programming-based technique and shortest path-based path planning.

Ant colony-based deployment of ground station appears in [4] whereas mixed integer-based trajectory planning appears in [5]. UAV infrastructure is built inside sensor nodes and a flat topology routing protocol is proposed to achieve the energy optimization objective. Among shortest path-based techniques, Dijkstra's shortest path algorithm is proposed in [4] where paths are restricted to two dimensions. Here, weights are assigned to individual edges based on distance between sites. If distance between two sites is high then weight of the link is less. On the other hand, if distance between two sites is low, weight of the link is high. However, this algorithm is not very appropriate in UAV-IoT context, because several other things need to be considered. Often there are many sites that need not be visited and visiting those eats up energy and time. Hence certain agricultural sites should be eliminated from consideration based on history of detection of diseases in those regions which cannot be done in Dijkstra's shortest path algorithm.

The algorithm A*-GA applies gravitational search and A* for path planning [5] where spraying of insecticides is made optimum by eliminating excess coverage of fields. Also, a genetic algorithm is applied to properly position the UAV in the beginning of the flight process. The authors also claim that this helps in visiting the sites by following shortest routes. However, for detection of certain parameters some portions of agricultural lands should be considered with higher importance, which has been ignored in A*-GA.

Planning trajectories based on artificial potential field method is illustrated in [25] and [26]. Here, obstacles can be present in the environment and paths are decided in such a manner that collisions are minimized. The concept of cooperation among multiple UAVs is proposed in [27] which consist of a theoretical framework that proposes to divide a large agricultural field into multiple regions with each region being under coverage of one UAV. The UAVs will plan trajectories consulting each other which is impossible if the regions belong to different owners and they don't want to cooperate with each other.

3. System Model

Background idea of the overall system model appears in 3.1 where the underlying problem is described along with the brief idea behind our proposed solution. System architecture appears in section 3.2 and basics of federated learning is illustrated in section 3.3. Procedure to select the clusterhead is shown in section 3.4 including formulation of parameters and calculation of weight.

3.1 Background

Figure 1 describes one such system where six regions are there R1, R2, R3, R4, R5, and R6. Each region has its own UAV. The regions have zero or more infected sub-parts inside them. The UAVs that belong to one single owner, form a trusted group and members belonging to one group are eager to share respective lands information with each other whereas members of different groups do not want that. Among the UAVs, the one with highest energy is the leader whereas others are follower. R1 has three small infected areas; R2 has two-one medium sized and one small; R3 has one small infected area; R4 has one big and R5 has two medium sized infected areas. R6 is not infected at all. R4 is almost entirely infected and it does not make sense to further notice spread of its disease unless pesticides are sprayed. Once pesticides are sprayed, only after that considerable change can be expected and we want to monitor changes only. Similarly, the other regions for which status has not changed in last few occasions, we can scan its images infrequently, expecting its current situation to prevail longer.

Figure 1: Picture of a big agricultural field

3.2 Architecture

The set of N UAVs is divided into two sets – 1 leader and (N - 1) followers. Among followers there are clusters of trusted UAVs which can safely transmit data to each other. If there are C number of clusters of UAVs and num(i) specifies number of UAVs in i th cluster s.t. $1 \leq i \leq C$, then

$$\sum_{i=1}^{c} num(i) = N - 1 \qquad (1)$$

Head of each cluster is chosen based on residual energy, energy depletion rate, latency of communication between clusterhead and each cluster member compared to leader UAV and those cluster members. A cluster member chooses to send its data to its clusterhead or computed gradient to the UAV leader, depending upon comparison of latencies they produce. Since our system is delay efficient, we primarily intend to minimize the latency. Model of the system appears in Figure 2, where the first cluster consists of three UAVs, second one contains four UAVs and three isolated UAVs are there which chose to communicate with the leader directly for latency minimization purpose. Therefore, five UAVs actually communicate their computed gradients to the leader UAV; two of these are clusterhead UAVs whereas three are isolated ones.

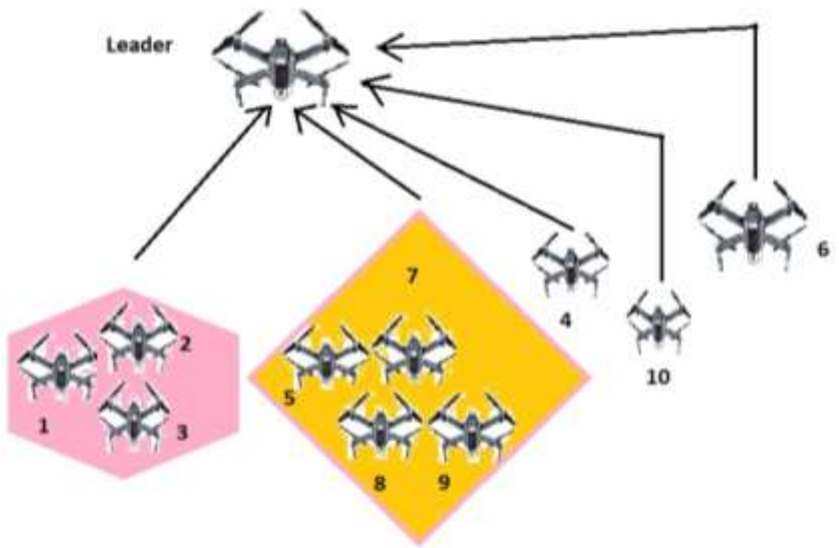

Figure. 2: Overall structure of the system

3.3 Federated learning model

The federated learning model consist of five steps, namely i) computation of local gradient ii) uploading of local gradient iii) aggregation of global gradient by the leader iv) updation of global gradient and v) broadcast of global parameters. Let ϕ denote the set of isolated and clusterhead UAVs. For each UAVi belonging to ϕ, local gradient $g_i(t)$ at time t is computed based on application of function f on their available local and/or non-local dataset $D_i(t)$ as shown in (2).

$$g_i(t) = f(D_i(t)) \qquad (2)$$

These local gradients are communicated to the leader UAV for aggregation purpose, this phase is termed as uploading of local gradients. During aggregation, the leader UAV computes weighted average of local gradients as in (3).

$$g'(t) = \frac{1}{|\emptyset|} \sum_{UAVi \in \emptyset} s_i g_i(t) \qquad (3)$$

Where $s_i$is size of sample data of i-th UAV which belong to ϕ.

Subsequently, the leader UAV updates parameters of aggregated gradients as in (4)

$p(t+1) = p(t) - \eta g'(t)$ (4)

Here, p(t+1) denotes global model parameters at time (t+1) where η is the learning rates t.η>0

After updation of global gradient global model parameters are broadcast to all members of ϕ. ϕ consists of isolated UAVs as well as clusterhead. Isolated UAVs obtain global model parameters and update local ones for next round. Clusterhead do the same and propagate to their respective members who repeat the procedure. The process continues till highest number of rounds is reached.

3.4 Selection of clusterhead

In a group of geographically nearby located segments of agriculture lands, the UAVs often fly close to one another. Here, we assume that no collision take place. The scheme of selection is computed based on optimization of the following factors:

- Residual energy
- Energy depletion rate
- Average latency improvement
- Member cardinality

Sub section 3.4.1 demonstrates formulation of above-mentioned parameters and subsection 3.4.2 illustrates calculation of weight along with necessary conditions to satisfy as a clusterhead.

3.4.1 Formulation of parameters

Residual energy - let ER(i) be highest energy of UAV i and er(i,t) be consumed energy of the same UAV till time t. The residual energy rs(i, t) of UAV i at time t, is given by (5).

$rs(i,t) = ER(i) - er(i,t)$ (5)

Energy depletion rate - Let UAV i started operating at time ζm(i) and current time is t. Then energy depletion rate ed(i, t) of the same UAV at time t is formulated in (6), as follow:

$ed(i,t) = \frac{er(i,t)}{(t-\zeta m(i))}$ (6)

Average latency improvement – This specifies the difference between time delay of communication between a potential clusterhead and its members compared to summation of communication delays with each individual of those UAVs. This is computed based on latency of communication i) between leader UAV and those members, ii) between those members and clusterhead, iii) between clusterhead and leader. Let UAV i be a potential clusterhead candidate and its trusted UAVs are UAV (i + 1), UAV (i +2), UAV (i + 3) … UAV (i +n). Also, assume that latn(i, i + j) denote latency from UAV i to UAV (i +j) when 1≤ j ≤ n. UAV (i +j) chooses to be member of the cluster of UAV if latency of communication between UAV (i + j) and leader UAV through clusterhead, is lesser than the same required for direct communication between UAV (i + j) and leader UAV.

$latn(i+j, leader) > \left(latn(i+j, i) + latn(i, leader)\right)$ (7)

$latn(leader, i+j) > (latn(leader, j) + latn(i, i+j))$(8)

Where, $latn(i+j, i) = \frac{sz(w_{i+j})}{R(i+j,i)}$(9)

$(sz(w_{i+j}))$ denotes size of model parameters.

$R(i+j, i)$specifies data rate of communication from UAV (i+j) to UAV i as formulated in (10).

$R(i+j, i) = B(i+j)\log_2\left(1 + \frac{P_{i+j}G_{i+j}}{B(i+j)\gamma_0}\right)$ (10)

B(i+j) denotes bandwidth of communication of sender node that is UAV (i+j). P_{i+j} and G_{i+j} are signal power gain of UAV (i+j) and power gain of the same channel from UAV (i+j) to UAVi. Υ_0 specifies spectral power density of background noise. Similarly, significances of symbols in (11) and (12) can be explained.

$$latn(i, leader) = B(i)\log_2\left(1 + \frac{P_i G_i}{B(i)\gamma_0}\right) \quad (11)$$

$$latn(leader, j) = B(leader)\log_2\left(1 + \frac{P_{leader} G_{leader}}{B(leader)\gamma_0}\right) \quad (12)$$

Average latency improvement avg-lat-imp(i)produced by UAV i is formulated in (13). This is based on the assumption that UAVs (i+p) to (i+q) satisfied conditions C1 to C9.

$$avg - lat - imp(i) = \left[\sum_{j=p}^{q}(latn(i+j, leader) + latn(leader, i+j) - (latn(i+j, i) - latn(i, leader) - latn(leader, i) - latn(i, i+j))\right]/r \quad (13)$$

Number-of-members(i) = q-p+1

3.4.1 Computation of Weight and Associated Conditions to Satisfy as Clusterhead

Weight W(i) of a clusterhead is computed in (14).

$$W(i) = avg - lat - imp(i) \times ed(i,t) \times rs(i,t) \quad (14)$$

Selection of clusterhead is an optimization problem:

$$\max(W(i))$$

S.t. C1:$0 \leq ER(i) \leq E_{max}$

$E_{\max}$ denotes Maximum possible energy of an UAV

C2: $0 \leq er(i,t) \leq ER(i)$

C3: $0 \leq ed(i,t) \leq er(i,t)$

C4: $0 \leq \rho_i \leq \rho_{max}$

ρ_{max}denotes Maximum signal power gain

C5: $0 \leq G_i^k \leq G_{max}$

G_{max}denotes Maximum channel power gain

C6: $0 \leq avg - lat - imp \leq F(i)$

C7: $0 \leq Number - of - members(i) \leq TR(i)$

C8: $0 \leq B_i \leq B_{max}$

B_{max}denotes Maximum possible bandwidth in the system

C9: $0 \leq TR(i) \leq num - all - UAVs$

$TR(i)$denotes set of UAVs that trust UAV i and UAV k ∈ (TR(i) ∪ leader)

num-all-UAVs denotes number of all UAVs in the network

4. Description of The Scheme of DFLPDDM

Each agricultural field is divided into some parts and each part is monitored by one UAV. The plants inside region under each UAV may or may not have disease. If area of the diseased portion is greater than or equal to a predefined threshold A, then gradients of those UAVs are simply eliminated. Those are termed as negligible UAVs which do not take part in communication of data or gradients. Also, certain UAVs are termed as inactive that do not show significant difference in output of consecutive interaction. Others upload their data to respective cluster heads or directly to the leader and subsequently receive global update from the leader or server and accordingly update their own information for refinement in next round.

4.1 Detection of negligible nodes

Let A1,A2,…,Ak be areas of k different parts of a large agriculture field. Among these, Av is the maximum area.

$$\text{Av} = \max_{i=1}^{k} A_i \quad (15)$$

$$75\%\ of\ Av = \frac{3Av}{4} \quad (16)$$

Also, assume that area of diseased plants monitored by UAV i is AREA(i), UAV i is considered negligible provided condition (17) is true.

$$AREA(i) > \frac{3Av}{4} \quad (17)$$

Outputs of these UAVs are not considered because most plants in those regions are diseased, and there is no point to further monitor their status unless pesticides are sprayed.

4.2 Detection of inactive nodes

A node or UAV will be termed as inactive provided its contribution in the global gradient is negligible. In each round t, corresponding to the global model ρ(t-1), local gradient $f(\rho(t-1))$ is calculated and uploaded to the server. Characteristic of the inactive nodes is identified in (18), where ∪ is the set of all UAVs and INC is set of all inactive nodes. Then

$$\frac{||GRAD_{INC}(t-1)||^2}{|INC|} \leq \frac{||GRAD_{\cup}(t-1)||^2}{|\cup|} \quad (18)$$

$GRAD_A(t-1)$is the weighted sum of all gradients uploaded in the leader by others belonging to set A. Please note that

$$||GRAD_{INC}(t-1)||^2 \leq \frac{|INC|\,||\rho(t)-\rho(t-1)||^2}{\eta^2(|\cup|-1)} \quad (19)$$

As the overall gradient is supposed to converge after interaction t,

$$\rho(t)-\rho(t-1) \approx \rho(t-1)-\rho(t-2) \quad (20)$$

Putting this in (19) we get,

$$\frac{||GRAD_{INC}(t-1)||^2}{|INC|} \leq \frac{||\rho(t-1)-\rho(t-2)||^2}{\eta^2(|\cup|-1)} \quad (21)$$

Each UAV (including ordinary cluster members, clusterhead and isolated nodes) locally verify whether they will be active or inactive in the next iteration.

From consideration of mean equality to ensure fairness,

$$\frac{||GRAD_{INC}(t-1)||^2}{|INC|} \leq \frac{\sum_{i\in\cup}||s_i GRAD_I(t-1)||^2}{\sum_{i\in\cup} s_i^2} \quad (22)$$

Where s_i is size of sampled data produced by UAV i. Putting this in (21)we get,

$$||s_i GRAD_i(t-1)||^2 \leq \frac{\sum_{i\in\cup} s_i||\rho(t-1)-\rho(t-2)||^2}{\eta|INC|(|\cup|-1)} \quad (23)$$

An UAV checks if sample data satisfy equation (23). If they do, then it does not upload its sampled data (to clusterhead) or local gradient (to the leader). This not just helps to reduce latency, but also contributes in preserving energy because number of communications is reducing, along with amount of computation. We are consciously reducing latency, but at the same time, energy consumption is also expected to reduce significantly.

4.3 Computation of global gradient

Please consider Figure 2 again, UAV_1sends $D_1(t)$ to $UAV_2$and UAV_3 sends $D_3(t)$ to UAV_2.Based on this the gradients are as follows:

$$g_2'(t) = \frac{1}{3}[s_1 g_1(t) + s_2 g_2(t) + s_3 g_3(t)]$$
$$g_1(t) = f(D_1(t))$$
$$g_2(t) = f(D_2(t))$$
$$g_3(t) = f(D_3(t))$$
$$g_9'(t) = \frac{1}{4}[s_5 g_5(t) + s_7 g_7(t) + s_8 g_8(t) + s_9 g_9(t)]$$
$$g_5'(t) = f(D_5(t))$$

5. Experimental Setup, Results and Discussion

In this section, validity of the proposed method is tasted in a framework that is designed by python. The leader UAV hovers around center of the large agricultural field whereas follower UAVs are distributed around it, one in each region. Trajectories of the UAVs are planned in such a manner that they do not collide. Performance of our proposed scheme DFLPDDM is compared with SN-UAV and A^* – GA and results appear in Figure 3 and 4. Figure 3 compares Overall UAV Energy Consumption (OEC) for these three competitors whereas the Overall Latency (OL) is compared in Figure 4.Further, the experimental setup and simulation parameters of the proposed methodology has been shown in Table 1.

Table 1: Experimental setup and simulation parameters

Parameter	**Value**
Coverage area	500×500 m^2
Number of IoT devices	15,35,55,75, and 95
Maximum number of regions in an agriculture field	15
Maximum number of UAVs in a cluster	7
Maximum possible number of followers	15
Total number of UAVs	40
Number of CPU cycles/s in an UAV	0.5G cycles/s
Speed of UAV	10m/s – 30 m/s
Hovering altitude of UAVs	2m – 9m
Transmission bandwidth	100-200 kHz
Channel gain	-20dB – -10dB
Noise power	-50dBm
Local model size	2MB
Global model size	1MB
Learning rate	0.01
Noise power density	-175 dB m/Hz
Fraction ID diseased portion	0.01-0.99
Number of runs	5

In SN-UAV, all sensor nodes have UAV capability embedded but when the agriculture field is very large the associated energy consumption is high. Also, the associated required time is high due to traversal of sensor-cum-UAV, from one part of region to another. The time to fly in SN-UAV is higher than others. On the other hand, in case of A^* – GA, a genetic algorithm-based approach is adopted where fitness function is concerned with energy only and latency is completely ignored. In the current context, we assume that all the follower UAVs have to report to the leader and that communication is valid for SN-UAV and A^* – GA as well. Application of federated learning in our proposed protocol DFLPDDM identifies inactive as well as negligible nodes that do not take part in computation and communication of local gradients. Hence, load of computation on leader UAV is also reduced. This saves a lot of energy in our proposed technique of communication, as shown in Figure 3. Along with that, it saves the time delay of computation and communication of local gradients, as shown in Figure 4. However, it should be noted that federated learning ensures security because data is transferred in raw from only among the trusted entities and among untrusted ones, only gradients are exchanged. Leader does not have to be trusted by all. This facility is not there in SN-UAV and A^* – GA.

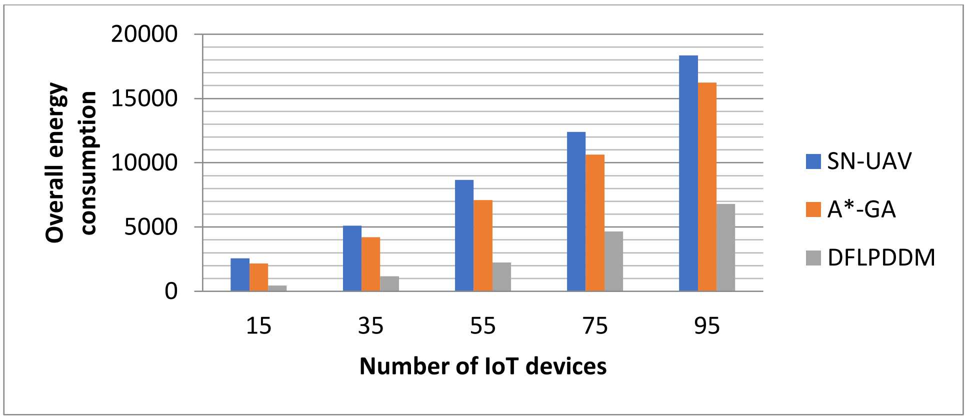

Figure 3: OEC vs number of IoT devices

Figure 5 shows convergence of accuracy curve of DFLPDDM with respect to number of iterations corresponding to various values of proportion of active nodes denoted by β. Accuracy of 0.97 is achieved when iteration round approaches 40. This is not just acceptable but very good accuracy which denotes that diseased regions are identified accurately and measures can be taken. Also, it saves the amount of medicines and pesticides that are sprayed on the fields. When β is higher than 0.3 slope of the curve decreases gradually with decreased iterations, which means that we should takes values of β higher than 0.3.

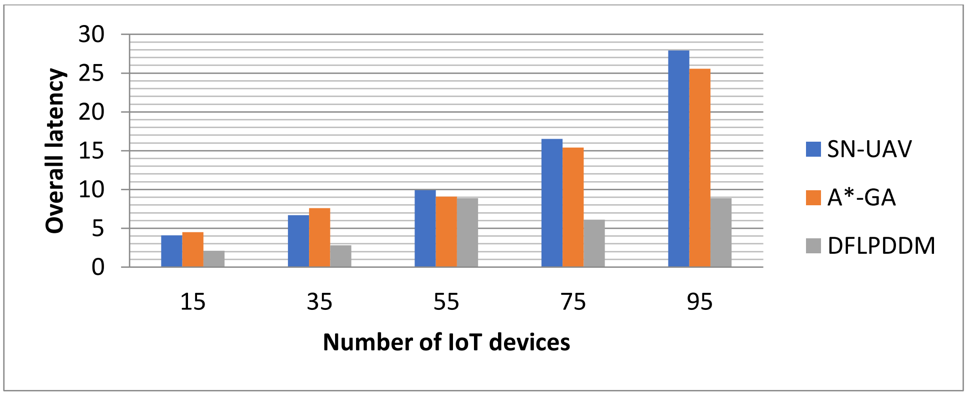

Figure 4: OL vs number of IoT devices

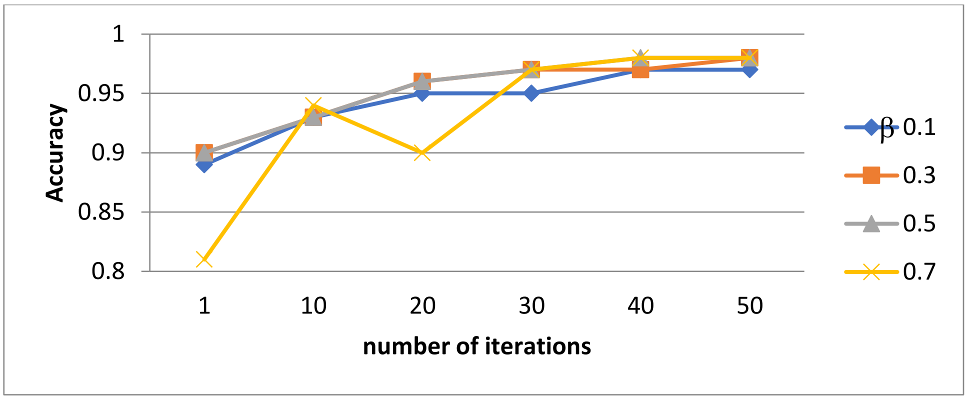

Figure 5: Accuracy vs value of β

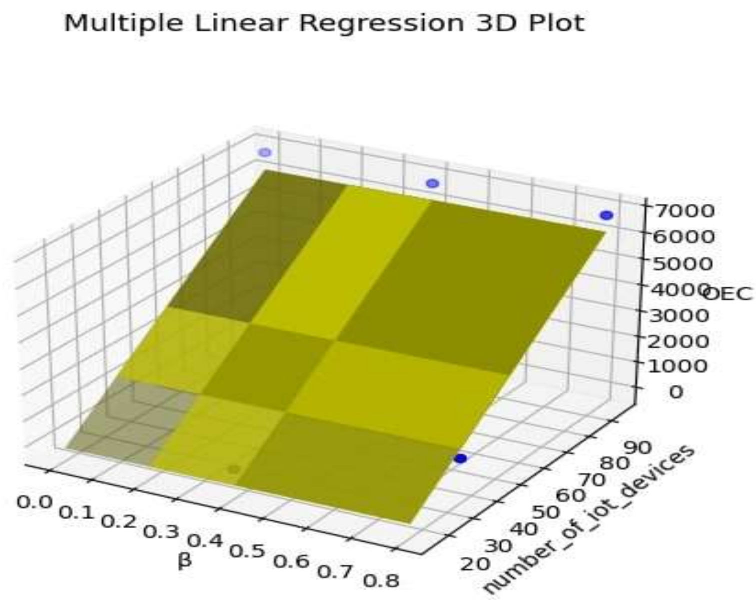

Figure 6: OEC with respect to β and number_of_iot_devices

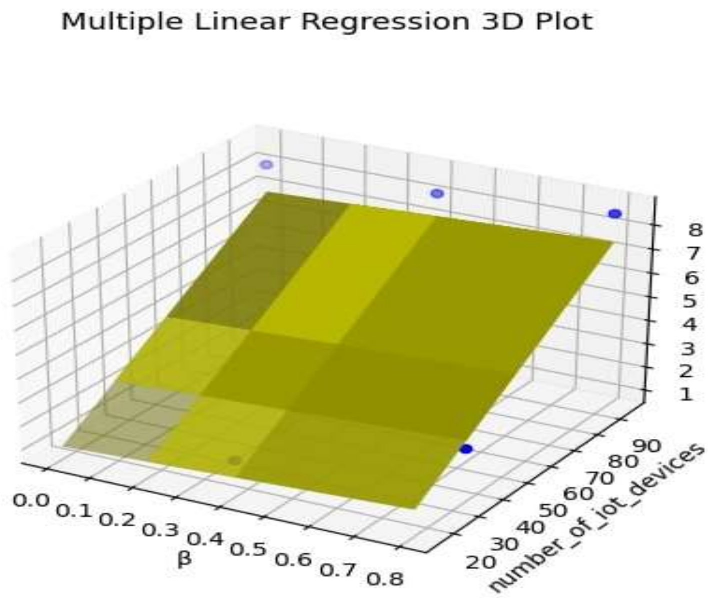

Figure 7: OL with respect to β and number_of_iot_devices

From Figure 6 it is evident that with increase in number of devices OEC increase and with increase in β value of the same initially increase and then converge after β goes above 0.6. Similar finding can be seen from Figure 7 where value of OL increases with increase in number of IoT devices and ultimately converges after β goes above 0.6. This happens because of the clustering facility in DFLPDDM. When participation ratio of UAVs increase, multiple UAVs often come under a single clusterhead and therefore negligible additional energy consumption and latency is needed for communication between the clusterheads and its new members. This phenomenon is responsible for converge of OEC and OL with increase in β.

5. Conclusion and Future Scope

The plant disease detection and monitoring can be very efficiently implemented using DFLPDDM scheme where overall energy consumption and delay are much lesser than other state-of-the-art schemes like SN-UAV and A*-GA. The improvement caused by DFLPDDM, on an average, is 67.67% with respect to SN-UAV and 62.24% with respect to A*-GA in context of the performance metric overall energy consumption. Similarly overall delay in our proposed scheme is 63.44% lesser than the same of SN-UAV and 61.52% lesser than the same of A*-GA. From Figure 5, it can be noticed that the accuracy of detection is above 90% for all the cases except one where accuracy is 89%. All these justify the effectiveness and efficiency of our proposed scheme. In future, we feel encouraged to test this scheme in real world environment so that it can be effectively applied in precision agriculture for well being of plants as well as mankind.

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