On Optimal Crowd-Sensing Task Management in Developing Countries

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***Abstract*—In developing countries, crop field productivity is particularly vulnerable to spreading diseases, including viruses and fungi. This is mostly due to the lack of skilled plant pathologists as well as to the scarce fund and poor infrastructure (e.g., roads, power and water lines) availability. The PlantVillage project through its mobile application named Nuru provides an AI digital assistant to recognize plants and their diseases through image analysis. Through the use of Nuru endowed smartphones, farmers can participate in a mobile crowd-sensing framework to improve their crop production. The crowd sensing framework also contributes to early detection of the outbreak of spreading diseases across geographical regions, and consequent adoption of appropriate countermeasures to ensure food security.**

As devices are often granted in a limited number by countries' government or charities, we propose a Farmer to Farmer (F2F) cooperation to achieve the required Quality of Information (QoI) for the system. In particular, only a selected crew of farmers receive smartphones to monitor their own farm as well as some other farmers' one. We formulate two variants of the problem of mobile device deployment and task assignment and propose related solutions. We evaluate the proposed approaches through simulations and apply them to a test-bed in Kenya.

***Index Terms*—pervasive computing, agriculture, deep learning, smartphones**

I. Introduction

The proliferation of smartphones and the improvement of their sensors, such as camera, GPS, and microphone, enables their use in complex monitoring applications. Data can be collected and analyzed close to the user [1], also exploiting his/her movements, which may be opportunistic or participatory. These improvements also enable a new paradigm of data collection, i.e., mobile crowd-sensing [2], [3]. In particular, in the agriculture domain, smartphones may be used to perform pervasive sensing and computing to determine the plants' health status. The collected data can be used to make informed decisions to improve food productivity, safety and sustainability [4].

Especially in developing countries, where agriculture has a huge social impact and most of the economy relies on it, widespread use of smartphones with computing capabilities can improve farming operations, while increasing awareness on plant diseases, health and growth requirements. In fact, most of the agriculture problems in developing countries are due to a general lack of knowledge of the main causes of plant diseases, for which reason farmers do not use the correct pesticides or proper countermeasures to diseases, failing in preventing their spread.

Governments sometimes hire skilled personnel to inspect crop fields in the region and help farmers understanding the ongoing issues. However, skilled personnel are not enough to support all the farmers with the necessary frequency to increase crop disease awareness as is desired.

To address this issue, PlantVillage [5] introduced a mobile application, called Nuru [6], which is able to collect data from crops, detect possible plant diseases, and suggest countermeasures. Farmers, provided with a Nuru endowed smartphone, can participate in a crowd-sensing framework which aims at improving crop production and data collection to monitor the agriculture situation at region scale, and eventually plan massive interventions. As farmers in developing countries can seldom afford the purchase of their own smartphone the country government may occasionally provide a limited number of them. For example, in our test-bed a limited number of smartphones were donated by Penn State University.

Considering the limited number of devices, a partially controlled mobility approach to foster Farmer-to-Farmer (F2F) interaction is proposed: only a selected crew of farmers receive the smartphones and they travel around to help some of their neighbors in monitoring operations. While a random distribution of devices to farmers seems reasonable, the irregular distribution of farms can produce zones with too many smartphones, and others with no smartphones at all.

To improve the deployment of sensing devices, i.e., the presence of people with smartphones along the region, we propose an analytical model that, given the available number of smartphones and farmers' positions, decides which farmers can receive the smartphones, and which monitoring tasks they should perform in the neighbor farms. The model aims at maximizing coverage (i.e., the number of farmers who benefit from the framework). Due to the high computational requirements of the problem, we propose a second model in which we reduce the computational complexity by relaxing the route optimization requirement.

We compare the two models by means of simulations against a random deployment. We show how the first model provides a better monitoring efficiency at the expense of huge processing time and resource requirements. Finally, we show an application in our real test-bed in Busia, Kenya. In the test-bed region, smartphone were initially distributed as gifts by charities and given to a subset of farmers, selected on the basis of the farmer social reputation and local elections. In this paper we show how the proposed approaches can be used to design a new device deployment scheme, to replace the original assignment. Simulation results highlight the improvements.

The paper is organized as follows. Section II introduces the overall mobile crowd-sensing framework. In section III we present the deployment problem of mobile sensing devices and we propose two analytical models for this problem. Finally, in section IV we discuss simulation results and the expected improvements when the models are applied to a real test-bed.

II. Overview of Mobile Crowd-Sensing Framework

The PlantVillage crowd-sensing framework, shown in Figure 1, includes two main components: *the users* (i.e., farmers), which collect data from the environment according to a participatory sensing model (i.e., they actively sense the data using a special purpose application); and the *system* which collects data, analyzes and stores them, and provides data visualization tools. The *system* allows plant pathology experts to access data to help *users* and to monitor the overall agriculture situation.

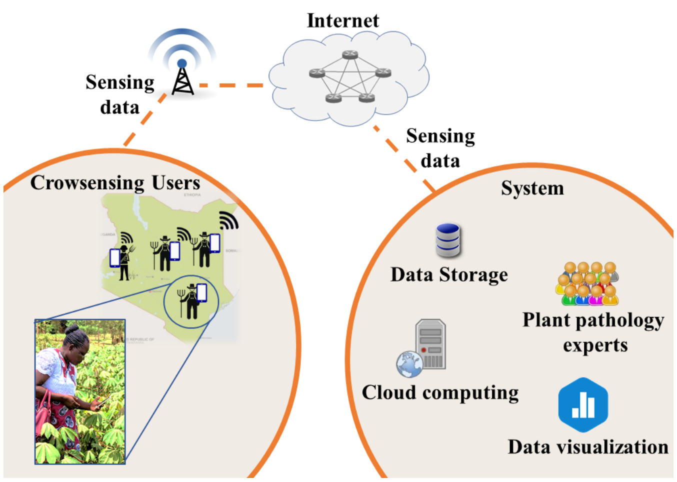


Fig. 1: Mobile Crowdsensing Framework

The *users* are endowed with smartphones and can participate in the crowd sensing framework by using a special purpose mobile application, called Nuru [6]. The application interface is shown in Figure 2. It allows the users to perform crop field measurements, detect potential plant diseases, and eventually receive advise on the appropriate countermeasures. It also allows users to: speak with plant pathology experts, to ask questions about diseases; access data concerning past and current agriculture status in the region; and access an online database with huge plant knowledge.

Notice that, as the application targets developing countries, it is developed with low computational requirements so as to work with low performance smartphones and poor network connectivity. More specifically, the application is designed to work offline and connect to the internet only when a reliable connection is available.

III. Smartphone Deployment and Task Allocation

In developing countries, where farmers are too poor to afford a smartphone, governments or charities can provide

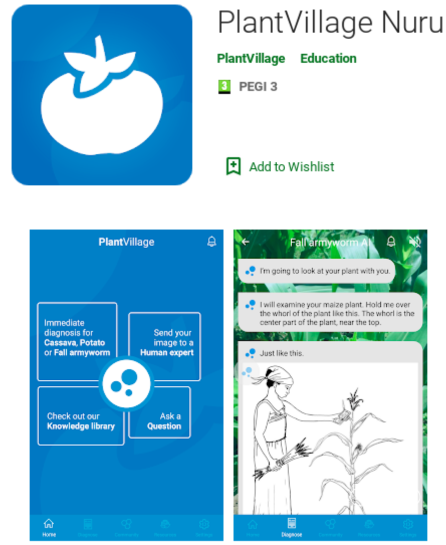


Fig. 2: Mobile Application

a limited number of them. To deal with this limitation, we propose a participatory sensing model, which includes Farmer-To-Farmer (F2F) interactions: selected farmers, the so called *lead farmers*, receive the smartphones, and assist and help their neighbor farmers, referred to as *basic farmers*, who do not have a Nuru smartphone.

To improve the number of covered farms, an optimized selection of lead farmers and their relative neighborhood assignment (monitoring task assignment) must be performed. In fact, a random distribution of smartphones to farmers does not ensure a uniform coverage of the monitoring service over the region, because of the non uniform distribution of farms. For simplicity, in the following sections, we assume that each farmer owns a farm that we consider as his home position. In this section, we propose two analytical models to maximize the number of covered farms within the region of interest by selecting the lead farmers, and their basic farmers assignment, given a fixed number of smartphones. Notice that, for a farmer, active participation in the crowd-sensing framework is encouraged through the prospect of receiving a free smartphone, and of gaining social reputation and prestige due to the contribution to the improvement of the crop yield of other farmers.

A. Optimization models

We consider a set of farmers $f \in \mathcal{F}$ displaced into a region of interest (RoI), which can be turned into lead farmers when endowed with a smartphone. We consider Z as the number of available smartphones to give them.

To improve crop production we empirically note that each farmer should be visited at least one time each month by a pathology expert to help farmers with diseases. Thus, we model a problem where we select the lead farmers that visit and help their neighbors with the use of their Nuru smartphone. The ultimate goal of the system is to cover the maximum number of farms, i.e., those that are visited at least once in a month, using the available smartphones. Notice that, while the proposed model considers a monthly period, with constraints, parameters and solution for this time horizon, it can be extended to any different period (day, week, or year), based on the application needs.

We assume that a farm f needs a monthly inspection which lasts τ_f seconds, and that a lead farmer i moves (walks) at an average speed of v_i. We also assume that each lead farmer i works for a limited amount of time in the framework, due to the farmer capabilities and free time available. His/her monthly workload is M_i, the time devoted to a single trip is bounded from above by a threshold b_i (i.e., the lead farmer wants to visit only close farmers). Then, considering d_{ij} the distance between farmer i and j, which is defined as the geographical distance between their farms, a candidate lead farmer i can visit only farmers j such that $\frac{2 \cdot d_{ij}}{v_i} + \tau_j \leq b_i$. Therefore, only farmers within a bounded round-trip time, which includes inspection time, can be visited.

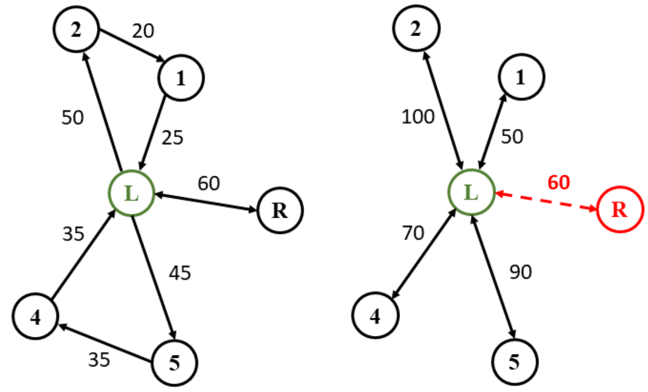
We now introduce the two optimization models. The first model, called *Lead Farmer Selection and Trajectory Planning Problem* (LFSTPP), decides which farmers should receive the smartphones and which not, and assigns a set of paths to lead farmers to visit basic farmers. Nevertheless, this model is complex and its computational time with large instances may become prohibitive. Thus, we introduce a simplified model, called *Lead Farmer Selection Problem* (LFSP), which selects lead farmers, and basic farmers to visit, using simple round-trip routes (i.e., a lead farmer visits only one basic farmer for each trip).

An example of the solution of two models solution is introduced in the Figure 3. Both the models select the lead farmer L which has a maximum workload of 350 ($M_L = 350$). In the first model (Figure 3a), which is referred to LFSTPP, the lead farmer L is associated with all the other farmers with a cost of 270, thanks to its optimal visit trajectories. Notice that, farmer 5 and 4 are visited in the same trip, without going back to its home farm. In the second Figure 3b, which is a solution to LFSP, the lead farmer L has only associated the basic farmers $\{2, 1, 4, 5\}$ with a cost of 310: due to round trip path, farmer R is not visited as he/she exceeds the maximum workload (310 + 60 > 350). Nevertheless, the time required to solve the first problem is fifty times bigger than the time required by the second model.

In general, considering the same problem instance, the second model, (LFSP), has shorter processing time, while the first one, (LFSTPP), due to path variables and constraints is extremely computational demanding. In some scenarios the models result equivalent (e.g., when a lead farmer carries some load, such as water, to basic farmers and he/she needs to return to his/her farm after each visit). In such a case the second model is preferable. Computational time is investigated in the section IV.

B. *Lead Farmer Selection and Trajectory Planning Problem*

We introduce the first optimization model, Problem 1, which aims at selecting lead farmers and assigning them monitoring tasks including visits to basic farmers, with optimized paths.



(a) LFSTPP (b) LFSP

Fig. 3: Lead farmer to neighbors path

It achieves a maximum coverage of farmers while respecting the available number of smartphones.

Problem 1. We introduce $y_f \in \{0, 1\}$ as first decision variable which decides to provide the smartphone to the farmer f ($y_f = 1$) or not ($y_f = 0$), for $f \in \mathcal{F}$. We consider that each lead farmer can visit the associated basic farmers with several multi-trip paths, namely $|\mathcal{W}|$. Then, we introduce $x_{ij}^f(w) \in \{0, 1\}$, with $i \neq j$ for all $i, j, f \in \mathcal{F}$ and $w \in \{0, ..., |\mathcal{W}|\}$, as decision variable to move the lead-farmer f from farm i to farm j, exploring them in a sequence ($x_{ij}^f(w) = 1$) or not ($x_{ij}^f(w) = 0$) in the w-th path.

Notice that, an upper bound for the values of $\mathcal{W}$ can be the number of farmers $|\mathcal{F}|$.

We introduce an auxiliary variables $z_i \in \{0, 1\}$ that, based on the decision variables, indicates if i participates in the framework ($z_i = 1$), i.e., he is lead farmer or he has an associated lead farmer which visits him, or not ($z_i = 0$), for $i \in \mathcal{F}$.

To reflect the assignment variables we impose the following constraint to value of z_i:

$$z_i \leq y_i + \sum_{w \in |\mathcal{W}|,\ j,f \in \mathcal{F}, j \leq i} x_{ji}^f(w), \ \forall i \in \mathcal{F} \qquad (1)$$

Thus, the objective function can be expressed as:

$$\max \sum_{i \in \mathcal{F}} z_i \qquad (2)$$

that maximizes the number of farmers that participate in the framework.

We now introduce additional constraints to deal with farmer capabilities and to define the feasible set of solutions for the optimization problem. We impose that the number of lead farmers is less than or equal to the number of available smartphones Z:

$$\sum_{i \in \mathcal{F}} y_i \leq Z \qquad (3)$$

We add a constraint to guarantee that a basic farmer is visited only by a lead-farmer:

$$\sum_{i,j\in\mathcal{F},i\neq j,w\in|\mathcal{W}|}\frac{x_{ij}^f(w)}{|\mathcal{W}|\cdot|\mathcal{F}|^2}\leq y_f,\ \forall f\in\mathcal{F} \tag{4}$$

We impose that each lead farmer has a valid cyclic path by means of the MZT formulation [7]. In details, we introduce some auxiliary integer variables $o_i^f(w)\in\{1,\ldots,|\mathcal{F}|\}$, to enforce an order in the farmers visited by the lead farmer. The constraint is proposed as follows:

$$\sum_{i\in\mathcal{F},i\neq j}x_{ij}^f(w)=\sum_{i\in\mathcal{F},i\neq j}x_{ji}^f(w),\ \forall j,f\in\mathcal{F},\ w\in|\mathcal{W}| \tag{5}$$

$$\begin{gathered}o_j^f(w)-o_i^f(w)\geq x_{ij}^f(w)+|\mathcal{F}|\cdot(x_{ij}^f(w)-1)\\ \forall i,j,f\in\mathcal{F},i\neq j,\ \forall w\in|\mathcal{W}|\end{gathered} \tag{6}$$

Then, we consider the capacity constraint of a lead farmer. To comply with the different lead farmer capabilities and time expenditure for travel, we define $\omega_{ij}^f\triangleq\frac{d_{ij}}{v_f}+\tau_j$, which is the cost for lead farmer f to travel from farmer i to visit j, $\forall f,i,j\in\mathcal{F},i\neq j$. We recall b_f is the maximum workload for a single trip and M_f is the monthly workload, for a lead farmer $f\in\mathcal{F}$. The constraints are formulated as follows:

$$\sum_{i,j\in\mathcal{F},i\neq j}\omega_{i,j}^f\cdot x_{ij}^f(w)\leq b_f,\ \forall f\in\mathcal{F},\ \forall w\in|\mathcal{W}| \tag{7}$$

$$\sum_{i,j\in\mathcal{F},w\in|\mathcal{W}|,i\neq j}\omega_{i,j}^f\cdot x_{ij}^f(w)\leq M_f\cdot y_j,\ \forall f\in\mathcal{F} \tag{8}$$

Finally, as we consider that any farmer could be a lead-farmer if he/she receives a smartphone, when some farmers are not suitable to become lead-farmers (i.e., they are not willing to collaborate) an optional constraint must be added to the model:

$$y_i\leq 0,\ \forall i\in\hat{F} \tag{9}$$

where $\hat{F}$ are the farmers not available to be lead farmers.

C. Lead Farmers Selection Problem

We now introduce the second optimization model, Problem 2, as special case of the previous one. The problem selects lead farmers and assigns them the basic farmers with simple round-trip paths to achieve a maximum farmers coverage, while respecting the available number of smartphones.

Problem 2. We again set $y_i\in\{0,1\}$ to be the decision of selecting farmer i as lead farmer ($y_i=1$) with a smartphone or not ($y_i=0$), for $i\in\mathcal{F}$. We introduce a new variable $x_{ij}\in\{0,1\}$ which determines the assignment of farmer j to a lead farmer i (i.e., j is assigned to i then $x_{ij}=1$, or not $x_{ij}=0$), considering a simple round-trip path.

Then, we introduce the binary variables $z_i\in\{0,1\}$ which reflects if a farmer i participates in the system ($z_i=1$) or not ($z_i=0$), for $i\in\mathcal{F}$. Formally, we impose the following constraint for the value of z_i:

$$z_i\leq y_i+\sum_{j\in\mathcal{F},j\neq i}x_{ji},\ \forall i\in\mathcal{F} \tag{10}$$

$$\begin{array}{lr}
\max\sum_{i\in\mathcal{F}}z_i & (a)\\
s.t. & \\
z_i\leq y_i+\sum_{w\in|\mathcal{W}|,\ j,f\in\mathcal{F},j\leq i}x_{ji}^f(w),\ \forall i\in\mathcal{F} & (b)\\
\sum_{i\in\mathcal{F}}y_i\leq Z & (c)\\
\sum_{i,j\in\mathcal{F},i\neq j,w\in|\mathcal{W}|}\frac{x_{ij}^f(w)}{|\mathcal{W}|\cdot|\mathcal{F}|^2}\leq y_f,\ \forall f\in\mathcal{F} & (d)\\
\sum_{i\in\mathcal{F},i\neq j}x_{ij}^f(w)=\sum_{i\in\mathcal{F},i\neq j}x_{ji}^f(w),\ \forall j,f\in\mathcal{F},\ w\in|\mathcal{W}| & (e)\\
o_j^f(w)-o_i^f(w)\geq x_{ij}^f(w)+|\mathcal{F}|\cdot(x_{ij}^f(w)-1) & \\
\qquad\forall i,j,f\in\mathcal{F},i\neq j,\ \forall w\in|\mathcal{W}| & (f)\\
\sum_{i,j\in\mathcal{F},i\neq j}\omega_{i,j}^f\cdot x_{ij}^f(w)\leq b_f,\ \forall f\in\mathcal{F},\ \forall w\in|\mathcal{W}| & (g)\\
\sum_{i,j\in\mathcal{F},w\in|\mathcal{W}|,i\neq j}\omega_{i,j}^f\cdot x_{ij}^f(w)\leq M_f\cdot y_j,\ \forall f\in\mathcal{F} & (h)\\
 & \\
y_i\leq 0,\ \forall i\in\hat{F} & (i)\\
y_f,z_f,\ \forall f\in\mathcal{F} & (l)\\
x_{ij}^f(w)\in\{0,1\}\ \forall i,j,f\in\mathcal{F} & (m)\\
o_i^f(w)\in\{1,\ldots,|\mathcal{F}|\} & (n)
\end{array}$$

Problem 1: Lead Farmer Selection and Trajectory Planning Problem.

The objective function can be expressed as:

$$\max\sum_{i\in\mathcal{F}}z_i \tag{11}$$

Again, we impose that the number of lead farmers (i.e., the farmers which receive the smartphones) is less or equal to the number of available smartphones Z:

$$\sum_{i\in\mathcal{F}}y_i\leq Z \tag{12}$$

We impose that a basic farmer can be assigned only to an actually deployed lead farmer:

$$\sum_{j\in\mathcal{F},j\neq i}x_{ij}\leq y_i,\ \forall i\in\mathcal{F} \tag{13}$$

Then, we consider the capacity constraint of a lead farmer. To comply with different lead farmer capabilities and their time expenditure for travel, we denote with w_{ij} the workload of lead farmer i to visit farmer j, such that $w_{ij}\triangleq\frac{2d_{ij}}{v_i}+\tau_j$. We recall that τ_j is the inspection time required by farmer j for his farm. Thus, the lead farmer workload constraints are modeled as follows:

$$w_{ij}\cdot x_{ij}\leq b_i\cdot y_i,\ \forall\ j,i\in\mathcal{F},j\neq i \tag{14}$$

$$\sum_{j\in\mathcal{F},j\neq i}w_{ij}\cdot x_{ij}\leq M_i\cdot y_i,\ \forall i\in\mathcal{F} \tag{15}$$

Finally, we impose that farmers, which cannot be lead farmers, are not selected to receive the smartphone:

$$y_i\leq 0,\ \forall i\in\hat{F} \tag{16}$$

where $\hat{F}$ are the farmers not able to be lead farmers.

IV. Performance Evaluation

In this section we evaluate the performance of the proposed approaches first through simulations and then with real experiments in Western Kenya, in the Busia region. The model parameter tuning is based on estimates derived from the analysis of previous data or provided by local farmers, which are the end-users of the crowd-sensing framework.

$$
\begin{array}{ll}
\max \sum_{i \in \mathcal{F}} z_i & (a) \\
s.t. & \\
z_i \leq y_i + \sum_{j \in \mathcal{F}, j \neq i} x_{ji}, \ \forall i \in \mathcal{F} & (b) \\
\sum_{i \in \mathcal{F}} y_i \leq Z & (c) \\
\sum_{j \in \mathcal{F}, j \neq i} x_{ij} \leq y_i, \ \forall i \in \mathcal{F} & (d) \\
w_{ij} \cdot x_{ij} \leq b_i \cdot y_i, \ \forall \ j, i \in \mathcal{F}, j \neq i & (e) \\
\sum_{j \in \mathcal{F}, j \neq i} w_{ij} \cdot x_{ij} \leq M_i \cdot y_i, \ \forall i \in \mathcal{F} & (f) \\
y_i \leq 0, \ \forall i \in \hat{F} & (g) \\
y_i, z_i \in \{0,1\} \ i \in \mathcal{F} & (h) \\
x_{ij} \in \{0,1\} \ \forall j, i \in \mathcal{F} & (i)
\end{array}
$$

Problem 2: Lead Farmer Selection Problem.

A. Simulation results

To give the intuition of the characteristics of the deployment achieved by the proposed models, in Figures 4 and 5 we show their solution for a scenario with only 3 smartphones, providing service for 23 local farmers. In particular, Figure 4, which employs the solution of Problem 1, evidences a complete coverage of all the farmers: it visits them using multiple optimized paths. Likewise, Figure 5 shows the solution of Problem 2 in the same setting. This small example highlights that the second model, which is simpler and more computationally tractable than the first, shows a good performance, with only a moderate loss in coverage with respect to the first model, i.e., only 2 farmers are left out from the framework.

Figure 6 shows the computation time required by our approaches. The models are solved using the Gurobi Optimizer [8] on a Lenovo X3550 M5, with 2 CPUs Intel(R) XEON(R) E5-2650 @ 2.20GHz with 16 cores each and 80 GB RAM [9]. The figure suggests the need to tradeoff computation time with deployment performance. In fact, working with medium size instances, LFSTPP requires several hours of computation (e.g., around 6 hours for 50 farmers) while LFSP requires only few minutes. The following experiments show that when the number of farms is high, the two algorithms' performance is very close, motivating the use of LFSP. In fact, when the number of farmers is high, LFSP produces a deployment solution in a considerably shorter time with respect to LFSTPP, at the expense of a negligible loss in coverage.

In the following experiments we study our approaches comparing them with a random deployment of devices to the users. Such a baseline approach, hereafter shortly called *Random*, mimics a current deployment of devices in our test-bed experiment in Kenya, where deployment of smartphone is uniquely based on the selected farmer's social role. Where not otherwise stated, we consider a region of around $100km^2$, and homogeneous parameter setting with: maximum monthly workload $M_i = 10hr$; farm inspection time $\tau_i = 45$; maximum path workload $b_i = 2hr$; an average speed of farmers $v_i = 3m/s$ for all $i \in \mathcal{F}$.

The algorithms are compared in terms of *Percentage of Covered farmers* ρ, which reflects the number of farmers who benefit from the use of the framework, either because they are lead farmers endowed with a Nuru smartphone, or because their farm is included in the task schedule of a lead farmer: $\rho \triangleq \frac{1}{|\mathcal{F}|} \cdot \sum_{i \in \mathcal{F}} z_i$. In the following plots, the error bars denote one standard deviation of uncertainty.

Figure 7 show how ρ varies when the number of farmers in the area increases. For this experiment, we set the number of available smartphones to $1/10$ of the number of farmers (e.g., for 40 farmers we deploy 4 smartphones). The figure highlights that, as expected, the proposed approaches LFSP and LFSTPP produce a better coverage than the *Random* deployment. The figure also highlights that the performance of two proposed algorithms is only slightly different, despite the fact that LFSP requires a considerably lower computational time. In particular, the percentage ρ of covered farmers under LFSP model is only 10% worse than under LFSTPP.

Also, the performance of LFSP and LFSTPP converges when the density of farmers (nr. farmers / size of the area) increases: for 50 farmers over 100km^2 the coverage achieved by LFSP is very close to that of LFSTPP. When more farmers are close to each other, path optimization is less critical.

Figure 8 shows the percentage of covered farmers by varying the number of available smartphones in the case of 30 farmers. LFSTPP achieves a coverage close to 1 with only 3 smartphones while the random deployment does not cover all farmers, neither with 5 smartphones. In contrast, the performance of LFSP is close to that of LFSTPP, and it requires only one more smartphone to achieve full coverage.

In the following, we consider larger size scenarios with a more realistic number of farmers. Due to the large size of the problem instance and considering the high computation time of LFSTPP, in the following experiments, we examine only LFSP and Random. We consider an area of 225 km^2 and a ratio of smartphones to farmers equal to $1/15$. Figure 9 shows the percentage of covered farmers ρ by varying the number of farmers and 10 show. Figure 10 shows how ρ varies with the number of smartphones, with 160 farmers. Both plots confirm the algorithms trends and the superiority of the LFSP solution with respect to the random algorithm.

Finally, Figure 12 shows the applicability of the LFSP model in our real test-bed in the Busia region, Western Kenya. We collected the position of around 175 farmers, shown in Figure 11 and applied the LFSP model. Figure 12 shows how the LFSP model can cover all the 175 farmer with the only 25 smartphones received from the PlantVillage [5] research group, while meeting the workload constraints (i.e., 15 hours each month and 2 hours for each visit).

V. Conclusions

We consider a crowd-sensing framework for diagnosing crop field diseases. The framework is designed to work in developing countries with limited availability of sensing devices and poor infrastructure. Considering the above limitation, we introduce two optimization models to improve device deployment and service coverage through the region of interest. We show that the proposed models, along with a farmer-to-farmer collaboration, provide a better data collection even when the number of available devices is limited.

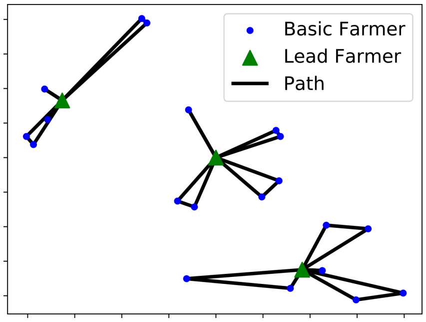


Fig. 4: LFSTPP solution

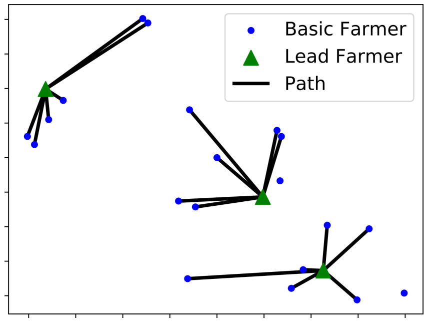


Fig. 5: LFSP solution

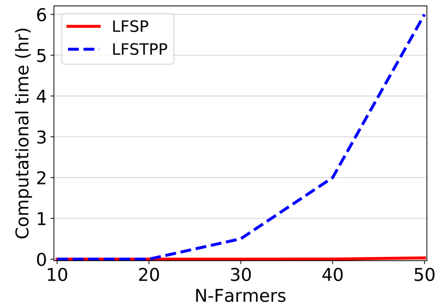


Fig. 6: Time by varying nr. farmers

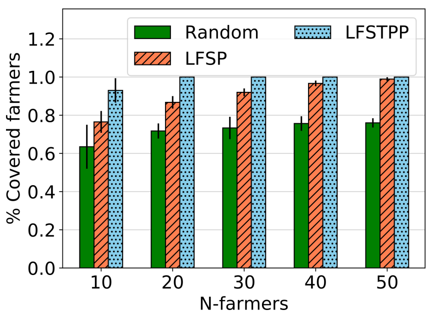


Fig. 7: Algorithms by varying nr. farmers

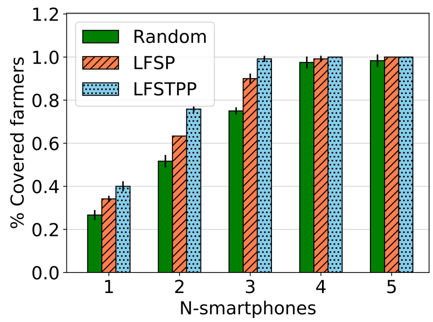


Fig. 8: Algorithms by varying nr. smartphones (30 farmers).

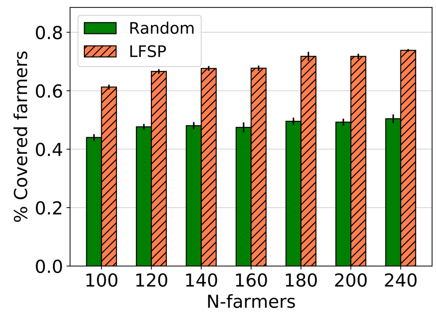


Fig. 9: Random vs Star by varying nr. farmers

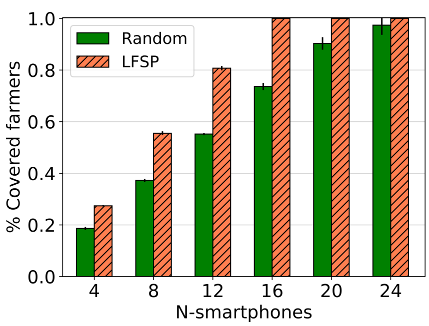


Fig. 10: Random vs Star by varying nr. smartphones (160 farmers)

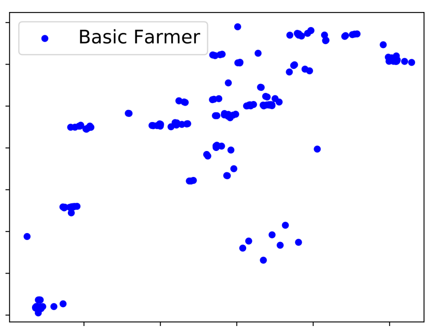


Fig. 11: Farmers in Busia

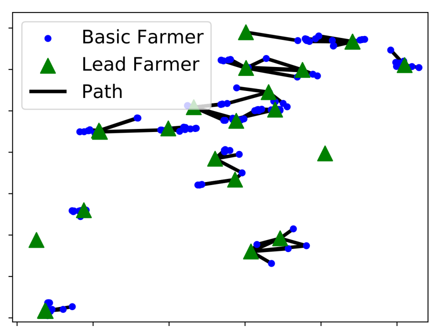


Fig. 12: LFSP in Busia

Thanks to the optimal deployment, the model can increase the system participation to sufficiently large number of users to ensure the required pervasiveness and retrieve enough data. We evaluate the models and compare them with a Random deployment approach which mimics the current solution in our test bed in Kenya. Results demonstrate that our models outperforms the previous approach in terms of number of people who benefits from the use of the framework, and meets the required Quality of Information (QoI) for the whole system.

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