Chapter 24
Optimal Energy Consuming on Spraying an Agricultural Field by Using Multiple UAVs

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Abstract Recently, agricultural areas are decreasing day by day in the face of the constantly increasing population. As a result, it is inevitable that existing production techniques are made much more efficient. In this study, starting from this point, it was aimed to spray the spraying areas of the pre-determined targets in the agricultural land of autonomous unmanned aerial vehicles in communication with each other with time minimization. For this purpose, two scenarios were compared on how to use the drones in the stations placed in all four corners of the field in the most effective way. In the first scenario, the field is divided into four equal parts in a classical way. In the second scenario, the field was divided into 2–4 regions by using the k-means method according to the areas to be sprayed. The route that the drone will use in spraying has been analyzed using the segmental method developed for the traveling salesman problem. For calculations, Julia programming language was used. Each scenario has been examined 100 times for different number of spraying sites. In light of the results obtained, it was found that the k-means method improved the flight time by an average of 19% compared to classical segmentation. In addition, with the developed method, unnecessary flight times of drones were prevented, and their useful lives were extended by finding which stations should be used the least in different situations.

24.1 Introduction

Developing technology has taken place in the agricultural sector, which is important for the society as well as in all areas of life, and it has continued to do so rapidly. Technology has become an indispensable tool in agriculture to increase

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speed and efficiency in agricultural production in the face of the demand created by the increasing population. The use of the Internet in many fields and in fact the spread of "Internet of things (IoT)" started to constitute the fourth industrial revolution and this revolution was named as Industry 4.0 revolution. With this revolution, catching the developing and advancing age and technology is important in the agricultural sector as well as in all other sectors. It is aimed to minimize the risks in agricultural production and to reduce costs as well as increase productivity.

Providing controlled production and increasing productivity with the cooperation or integration of agriculture and technology are among the main objectives, in addition to reducing the workload and cost of producers by equipping agricultural tools and machines with digital sensors:

- How much and what kind of fertilizers should be put in which areas;
- Weather conditions;
- Minerals that plants need and irrigation;
- The condition of the soil;
- It is aimed to facilitate the work of the producers and to maximize the yield compared to traditional methods by showing the estimated harvest time in detail and in real time.

This system, which increases the use of the Internet, is also called "Smart-Farm Systems," that is, smart agriculture system. This system, which aims to bring agricultural production to a higher level, also ensures that the use of natural resources is full and effective. With smart agriculture, natural resources are used correctly and at the required level, reducing costs and preventing waste of resources. The farmer can observe the current state of the integrated machines with the help of a tablet or phone in electronic environment and can make fast and correct decisions. "All factors required for production are analyzed by smart systems on the farm and simultaneously transmitted to the producer."

In precision agriculture technology, collecting instant data from different sensors to determine machine performance, soil and plant properties and ensuring automation is important. In the continuation of the development of precision agriculture, sensor network technology is the main has become one of the technologies. Sensor networks, temporal, spatial, and predictive variations integration and determination of optimum agricultural management options are used.

Recently, in the communication between the sensors and the central control unit wireless sensor networks are used. Wireless sensor networks cost, size, power, flexibility, and it is preferred over wired sensor networks due to its advantages such as dispersibility.

According to a study conducted by Forbes [1], agricultural robots are able to harvest the crops in the field in much higher amounts and faster than human labor. Although robots are not as fast and efficient as humans in most sectors, this is not the case for the agricultural sector. Agricultural robots are performing repetitive routine tasks on the farm more rapidly, thanks to rapidly developing autonomous robotic and artificial intelligence technologies [2, 3]. These developments have started a new era in agriculture as Agriculture 5.0 [4].

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24.2 Background and Preliminaries

24.2.1 Main Stages of Agricultural Development

The level reached in digital agriculture is not a result of an instant development. Just like the stages of the industrial revolution, "Agriculture 4.0" has experienced an ongoing development phase over the years. These phases and their definitions can be explained as follows [5]:

- Agriculture 1.0: Combination of animal power and mechanization;
- Agriculture 2.0: Start the usage of engines and tractors in agriculture;
- Agriculture 3.0: Steering systems and precision agriculture applications and
- Agriculture 4.0: Smart farming technics.

With the use of water and steam power in agriculture, mechanization in agriculture started. The situation in the early twentieth century is a labor-intensive agriculture system with low productivity. In this process, the food needs of the society were adequately met by participating in the basic agricultural products production process by actively working in a small number of small farms.

The researches that intensified in the nineteenth century literally turned agriculture into a branch of science. Thanks to the evolving mechanization, chemistry, and plant science, brand new products were produced, and unprecedented yields were achieved. Agriculture 2.0 began in the late 1950s when agricultural management practices such as supplemental nitrogen and new tools such as synthetic pesticides, fertilizers, and more efficient special machines benefited from relatively inexpensive inputs. Agriculture 2.0 is the use of mass production and internal farming mechanization applications in agriculture, such as tractor production using electricity. As a result, the harvest from the field has increased significantly.

The Agriculture 3.0, which started in the 1990s with the opening of GPS signals for everyone, is now called precision agriculture. Thanks to GPS technology, manual guidance, variable rate application (VRA) systems applied to harvesting machines, and especially following the fertilization process are the main technologies applied in this period. With sensitive farming methods, specific tracking and solutions are provided for each parcel of the land or for each animal in the herd, and the process is managed more effectively by reducing production costs.

Agriculture 4.0 (Smart Agriculture) is a modern understanding of agricultural management that uses digital techniques to monitor and optimize agricultural production processes. Smart agriculture determines the fertilization/harvesting strategy accordingly, by measuring the differences in the existing area and conditions, instead of applying the same amount of fertilizer to the entire farmland or feeding a large herd of animals with an equal amount of feed. Similarly, it assesses the needs and conditions of individual animals in larger herds and optimizes feed per animal.

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Smart farming methods aim to increase the amount and quality of agricultural production while using less input (water, energy, fertilizer, pesticides, etc.). It is also aimed to save costs, reduce environmental impacts, and produce more high-quality food. Smart farming methods are mainly based on a combination of new sensor technologies, satellite navigation-positioning technology, and the Internet of things (IoT).

Greenhouse agriculture is a methodology that helps to increase the yield of agricultural products such as vegetables, fruits, and plants. Greenhouses control environmental parameters with manual intervention or proportional control mechanism. This method is less preferred today, as production loss, energy loss, and labor costs increase when manual intervention is made. With the help of the Internet of things (IoT), a smart greenhouse can be designed, which intelligently monitors and controls the greenhouse climate and eliminates the need for manual intervention.

To control the environment in a smart greenhouse, different sensors are used that measure environmental parameters according to plant requirements. Since it is connected to the system using the Internet of things (IoT), it can create a cloud server for remote access. This eliminates the need for continuous manual monitoring, and the cloud server enables continuous processing of the greenhouse, enabling data processing. This design offers cost-effective optimum solutions for farmers with minimal manual intervention.

24.2.2 Internet of Things (IoT) Based on Intelligent Systems in Agriculture

It is aimed to maximize productivity with the Internet of things in agriculture. As natural resources are used at the required level, the cost is reduced. Similarly, with the smart systems on the farm, all factors required for production are analyzed and presented to the producer simultaneously. In this way, resource wastage is prevented, and quality products are produced. In addition, rapid decision-making mechanisms are created with machines that are in communication with each other and work synchronously. Producers are given the opportunity to manage and monitor the entire farm from a tablet or phone, and by reducing the labor force, productive, quality, and natural production opportunities are created [6].

Unmanned aerial vehicles used in the agricultural sector are a good example for us to see how advanced technology has changed over time. Today, agriculture continues to become an integrated technology area, including unmanned aerial vehicles. Unmanned aerial vehicles are used in agriculture to develop various agricultural applications. These applications: They are carried out in areas such as product health assessment, irrigation, crop spraying, planting, soil, and field analysis. The most important benefits of using unmanned aerial vehicles are product health monitoring, mapping, ease of use, time savings, and the potential to increase efficiency. Unmanned aerial vehicle technology, together with real-time data collection, processing-based

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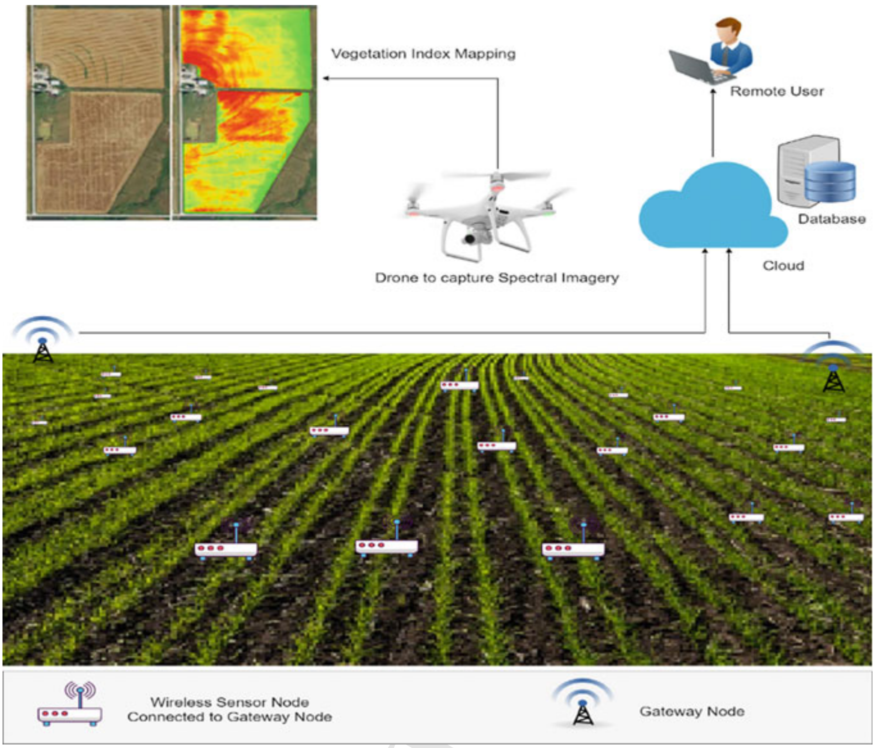

Fig. 24.1 IoT-based visualization system [7]

strategy, and planning, provides a great change in the agricultural sector with its high-tech quality products (Fig. 24.1). AQ1

Unmanned aerial vehicles collect multi-spectrum, thermal and visual images after they take off. From these flight data, many reports are obtained such as crop health indices, crop count and yield estimation, crop height measurement, canopy mapping, field water analysis, exploration reports, stock measurement, chlorophyll measurement, nitrogen content in wheat, drainage mapping, and weed [8]. Next, our method and simulation results are provided to validate our theoretical claims.

24.3 Methods and Results

In this part, two different scenarios are compared in terms of total flight time of four UAVs for spraying specified locations of a field. It is assumed that the spots to be sprayed are obtained through wireless sensors. For the first scenario, the field is divided into four parts. For this case, each UAV is supposed to spray given spots in their corresponding field. For the second scenario, the spots that need to be sprayed are divided into groups by using artificial intelligent methods.

24.3.1 Methods

The methods used in application will be explained in this section.

K-Means Clustering Algorithm. The K-means method was introduced in 1967 Developed by MacQueen [9]. It is one of the most widely used unsupervised learning methods among the existing clustering methods. The way this method is assigned is a sharp clustering algorithm, as it allows each variable to be assigned to only one cluster. It is a method based on the understanding that the center point of the cluster of variables expresses the set. The method tends to find clusters of equal amounts. The most common use for calculating the K-means method is sum of squared error (SSE). Clustering with the lowest SSE value gives the best results. Sum of squares the distances of the variables to the center points of the set to which they belong is calculated by Eq. (24.1).

$$\mathrm{SSE} = \sum_{i=1}^{K} \sum_{X \in C_i} \mathrm{dist}^2(m_i, x) \tag{24.1}$$

As a result of this division, it is aimed to distribute k clusters intensely within itself and separately from each other in a cluster. The aim of the algorithm is to determine k clusters that will reduce the SSE function. The algorithm divides the data set consisting of n data into k sets by using the k parameter determined by the user. The cluster similarity value measured by the average value of the variables in the cluster constitutes the center of gravity of the cluster.

2-Opt Heuristic Method for Traveling Salesman Problem. Many heuristic methods are used in the literature for traveling salesman problem (TSP). The heuristic methods used for TSP can be analyzed under two main titles as tour creation and development methods. In the method of creating a tour, it is aimed to reach the most optimal solution by connecting the points in order with some constraints. In tour development, it is aimed to develop the current solution through various movements. The 2-opt method described in detail below is in this group.

2-Opt is the in-route change approach first used by [9]. First, two springs of the current route are cut and connected and connected to two different nodes that are not consecutively to obtain a new route that has never been previously sorted. 2-opt change is also called transport [10].

As can be seen in the routes drawn as a sample in Fig. 24.2, the locations of the nodes in the route were changed by assuming that the activities in the route (1, 4) and (2, 5) were not optimum in terms of both total distance and cost. Thanks to the new activities in direction (1, 2) and (4, 5) on the changed new route, the route was

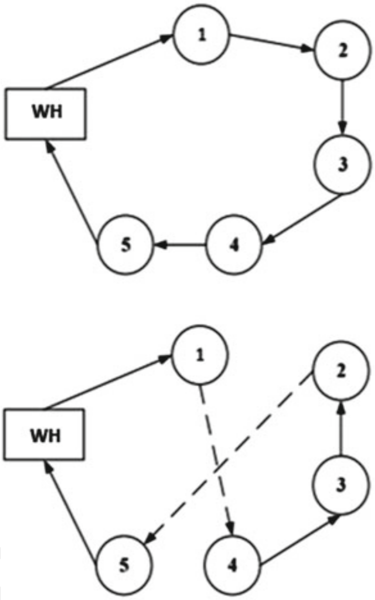

Fig. 24.2 2-opt heuristic method samples

shortened, and the new route gave a closer result to the optimum compared to the past.

Scenario 1: The field is divided into four equal subfields as given below. Then, the spraying areas produced were distributed according to the regions and sprayed in accordance with the route created by the drone at the defined station in each region, using the traveling salesman heuristic method. Flight time of all drones has been collected.

Scenario 2: The districts produced were composed of 2, 3, and 4 clusters, respectively. The k-means method was used to form clusters. The closest station to the center of each cluster was determined, and the spraying areas in the relevant cluster were sprayed in line with the route created by the drone at the defined station using the traveling salesman heuristic method (Fig. 24.3).

Figure 24.4 illustrates the field equipped with wireless sensors (blue dots) those are evenly planted on the ground and the spray drones on each corner of the field. The areas where the spraying is needed are marked with orange color based on the

Fig. 24.3 Equally divided fields

Field 1	Field 2
Field 3	Field 4

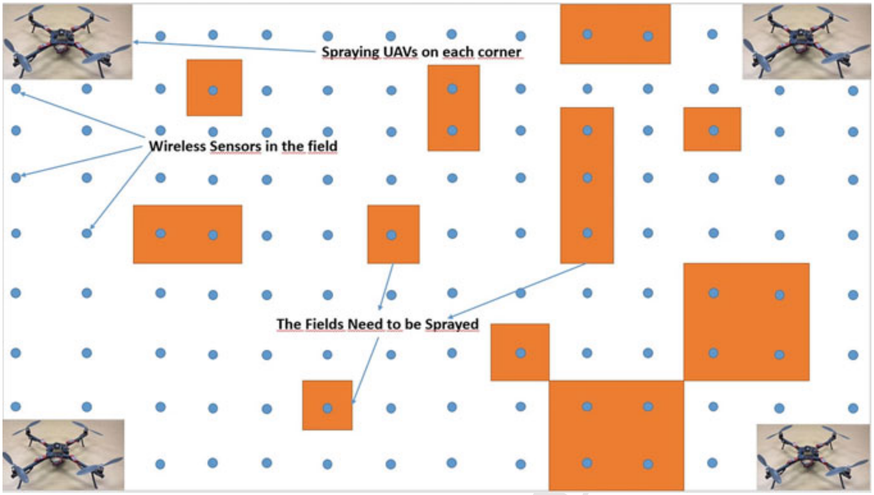

Fig. 24.4 Spraying areas, wireless sensors, and drones

sensor information. The challenge is finding the most energy-efficient solution to spray the orange areas by using some or all of the drones. By using two different artificial intelligence-based methods mentioned above, the task is accomplished, and the results are compared in the simulation results given next.

24.3.2 Algorithm and Simulation Results

The algorithm developed within the scope of this study examines the establishment of stations in four corners of the field. This algorithm can easily be developed for more than four stations. In order to examine the efficiency of the algorithm, the results obtained will be compared with the classical method. In the classical method, the field is divided into four equal parts transverse and longitudinally. Each spraying area is sprayed by the station on the corner of the part where it is located. At the end of this process, the total flight time of the drones gives the result of the classical method.

The developed algorithm (Tables 24.1 and 24.2, Pseudocode 1) consists of solving the problem by dividing it into two subproblems. First of all, the number of stations to be used is determined. This value is between two and four in this study. Then, the spraying zones are divided into clusters as many as the number of stations determined using the k-means method. The clusters obtained are assigned to the closest station to their center points. Afterward, the route of the drone at each selected station is determined using heuristic methods developed for the traveling salesman problem.

The number of stations to be used in the algorithm is run for all situations from two to four, and the total flight time of the drones is obtained. The process is terminated

Table 24.1 Inputs and its explanations

Inputs	Explanations
Y	kth assigned to the station, jth coordinates of the center of the area to be sprayed ($k = 1, \ldots$, nos, $j = 1, \ldots$, nsa, $i = 1, 2$) ($i = 1$ stands for: x-axes, $i = 2$ stands for: y-axes)
wof = 150	Width of the field
lof = 1200	Length of the field
mnos = 4	Maximum number of station
spdrn = 70	Drone's speed (m/min)
ust = 1/6	Drone's spraying speed (min/100 m^2)
nsa	Number of spraying areas in 5 different sizes. For example, sa1: is the number of spraying areas in 100 m^2 Then $\text{nsa} = \sum_{i=1}^{5} \text{SA}_i$
LSA	Two-dimensional locations of each spraying areas coordinate center ($j = 1, \ldots$, nsa, $i = 1, 2$) ($i = 1$ stands for: x-axes, $i = 2$ stands for: y-axes)
nos	Number of stations in a loop

Table 24.2 Outputs and its explanations

Outputs	Explanations
FPD	Route of the drone on the ith station, ($i = 1, \ldots$, mnos). Only optimal stations are counted
tft	Total flight time of all drones
eoa	Efficiency of the algorithm

by selecting the number of stations that minimize the total time. At the end of the process, which stations will be used, the routes of the drones for spraying and the efficiency of the proposed option compared to the classical method are obtained.

Julia programming language was used for the analysis [11]. The Julia package programs used are listed below:

- JuliaStats/Clustering.jl package,
- JuliaStats/Distances.jl package [11],
- TravelingSalesmanHeuristic [12],
- JuliaData/DataFrames.jl package,
- JuliaLang/Random.jl package [11].

242 **Pseudocode 1**

```
nos=4

#Total spraying time
  for i=1:5
    tst=tst+(i*SA[i]*ust)
  end

#CTFT: Classical technique flight time.
  nos = 4
  for j=1:nsa
    if jth  area, kth  station,
      Y[k,j,:] = LSA[j,:]
    end
  end

#Total flight time for four stations is being calculated
  for i=1:nos
    DISTMAT
    #The distances among the spraying areas those are as-
    signed to the ith station is calculated first. Then,
    the route and the total flight times are calculated
    by using #TravelingSalesmanHeuristics.jl julia pack-
    age.
    @time path, cost = solve_tsp(distmat; quality_factor
    = 100)
    CTFT = CTFT+(cost/spdrn)
  end
  ctft = ctft+tst
      KMTFT(best)

#Calculation of total flight time based on ideal number
of clusters by using K-Means
  #KMTFT is a vector which stores total flight time when
  the ith station, (i=1,…,mnos), is in charge.
  KMTFT

  #KMFP is two dimensional matrix which stores flight
  routes on the jth station when there are i number of
  clusters (i=1,…,mnos, j=1,…,mnos).
  KMFP
```

```
for i=1:mnos
  kmtfti=M  #M is a very big number
  for j=1:mnos
    kmfpij=0
  end
end
for noc=2:mnos
#All possible routes and flight times are being ob-
tained for all number of clusters from 2 to mnos.
#Spraying areas are being clustered with noc number of
clusters by using K-means Clustering.jl julia package.

  kmeans(LSA, noc; maxiter=200)

  for i=1:noc
    for j=1:4
      #Distances between ith cluster's center to jth
      station is being calculated. jth station is being
      assigned to the ith cluster which satisfies
      min(DIST[i,:])
      DIST[i,j]
    end
  end

  for j=1:nsa
    if jth area belongs to the kth cluster, then
      Y[k,j,:] = LSA[j,:]
    end
  end

  for i=1:noc
    #the distances among the spraying zones assigned to
    ith station and their distances to the ith station.
    DISTMAT
    #the route and the flight time are being calculated
    by using TravelingSalesmanHeuristics.jl julia pack-
    age
    @time path, cost = solve_tsp(distmat; quali-
    ty_factor = 100)
    kmtftnoc = kmtftnoc+(cost/spdrn)
    kmfpnoc,i = path
  end
  kmtftnoc = kmtftnoc+tst
end
```

Table 24.3 Comparison of total flight time in two scenarios for different number of spots to be sprayed

Number of stops to be sprayed	Scenario 1	Scenario 2		
		Total cluster: 2	Total cluster: 3	Total cluster: 4
20	19.52	15.26	17.14	18.87
30	24.22	19.92	21.64	23.30
40	25.99	21.54	23.31	25.30

```
#optimal number of clusters is being obtained by finding
the situation which provides the minimum flight time.
  for i=2:mnos
    if kmtfti = min(KMTFT[:]) then
      opt=i #optimal number of clusters is being obtained
    end
  end

  for i=1:mnos
    FPD[i] = KMFP[opt,i]
  end
#results
tft = KMTFT[opt]
eoa = (ctft-tft) / ctft
end
```

When the drones available in the market were examined, it was determined that they could spray all the areas to be sprayed at one time for a normal-sized field due to their high spraying capacity and flight time. For this reason, the algorithm has been developed in this direction. In the simulation study, 20 random spraying areas of 5 types (100, 200, 300, 400, and 500 m^2) were created on a field of 18 ha (1200 m $\times$ 150 m). The results obtained from 100 repetitions of the algorithm are presented in Table 24.3.

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Next, some concluding remarks are provided.

24.4 Conclusion

The results show that the clustering method has produced more effective results than classical segmentation in all cases. When the same number of clusters were formed by the k-means method instead of the four clusters created in classical segmentation, an improvement of approximately 3% was achieved. In addition, the low number of clusters enabled more effective results to be achieved. Reducing the number of clusters and ensuring that only relevant stations operate has achieved an average 19% improvement. Finding out which stations should work in every situation with the method developed allows avoiding unnecessary energy use and has extended the lifetime of drones.

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