Smart Agriculture with Autonomous Unmanned Ground and Air Vehicles: Approaches to Calculating Optimal Number of Stops in Harvest Optimization and A Suggestion

Chapter · December 2020

DOI: 10.4018/978-1-7998-1722-2.ch010

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Chapter 10
Smart Agriculture With Autonomous Unmanned Ground and Air Vehicles:
Approaches to Calculating Optimal Number of Stops in Harvest Optimization and a Suggestion

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ABSTRACT

This study researches smart agriculture and its components, robotic systems and machine learning algorithms, development of agricultural robots, and their effects on the industry. In application, it is aimed to collect the harvest of autonomous unmanned aerial vehicles and UGVs in communication with each other by means of time minimization of the target. It wanted to be tested with different approaches for an optimal number of stops by using particle swarm optimization. Deterministic, binary mixed (0-1) integer modeling was used to determine the optimal picking time of the apples allocated to the stalls with the k-means method. With this modeling, it has been determined which unmanned aerial vehicle will be collected and how it is calculated whether the air vehicle has collected the apple or not using 0-1 binary modeling. The route of the unmanned UGV was made by using the nearest neighbor, nearest insertion, and 2-opt methods. This study has been extended and reviewed by the summary paper at International OECD Studies Conference March 2020, Ankara, Turkey.

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INTRODUCTION

Twenty-first century robotics and sensing technologies have the potential to solve long-standing problems in the agricultural field. It is possible to make crops more efficient and more sustainable by switching to an agricultural system using robotic systems. Many researchers in the world carry out robotic automation studies that will reduce the cost and increase the quality in greenhouses where fruit and vegetable production is made. Autonomous robotic pickers are tested, monitoring vegetable and fruit growth and harvesting crops. For livestock farmers, sensing technologies help manage and control the health of their animals. In order to improve soil quality, monitoring and maintenance works are carried out to eliminate harmful pests and diseases without resorting to the indiscriminate use of agricultural chemicals.

Although some of these technologies are already available, most of them are still at the research stage in start-up companies. Large-scale companies that produce agricultural equipment do not want to invest in autonomous agricultural technology yet. The reason for this is the fear that the economic model established by these companies in the current production and sales markets will change. Start-up companies working with digital agricultural technologies will also change the way we produce food forever if they manage to implement their projects in the agricultural sector. Our current food production will double, and this rate will increase until 2050, and will meet the food demand of 70% of the global population.

After the industrialization process that started with the industrial revolution, engineers and scientists have been creating solutions by designing great inventions and systems for the great problems that humanity has faced for centuries. Agriculture 5.0 will be the first major problem that scientists and engineers will face in the first half of the 21st century. The concept of Agriculture 5.0 states that farms use sensitive farming features and implement digital agriculture by implementing equipment including unmanned operations and autonomous decision support systems. Therefore, Agriculture 5.0 refers to the use of autonomous robots and some artificial intelligence systems Zambon (2019).

In traditional farming in the world, the workers in the seasonal working class go to agricultural work from different regions in the world to different countries in order to meet the global agricultural labor force every year. Due to the global epidemic of Covid-19, seasonal workers cannot leave, so many countries face the danger of deterioration in the field Brelie (2020). In addition, the rate of migration from villages to cities continues to increase every year. As a result of these, The World is moving away from the agricultural society every year and the population is growing rapidly in the cities. These problems show us that we will have great labor problems in the agricultural sector in the coming years ILO (2020). Autonomous robotic systems in agricultural production provide production by working 30 times more than an agricultural worker Hooijdonk (2020); Walch (2020). We need to face the fact that the world will face other outbreaks like COVID-19 in the future, give up the classic human-worker method and accelerate the transition to robotic-agricultural production.

According to a research conducted by Forbes Walch (2020), agricultural robots can harvest crops in the field in higher amounts and faster than human labor. Although robots are not as fast and efficient as humans in most sectors today, this is not the case for the agricultural sector. Agricultural robots rapidly fulfill repetitive routine tasks on the farm everyday thanks to the rapidly developing autonomous robotics and artificial intelligence technologies Bechar (2017); Shamshiri (2018). These developments started a new era in agriculture as Agriculture 5.0.

According to the study of Reddy et al., In the countries with high rates of using digital agriculture, agricultural robots have been shown to greatly increase productivity and reduce farm operating costs. As mentioned earlier, robotic applications are rapidly increasing in the agricultural sector Shamshiri (2018).

Many of these agricultural technologies are still very expensive for farmers, especially those with small farms Lamborelle (2020). Farmers with small-scale lands and small-scale economies in direct proportion to this are not yet able to access robots and systems in this technology in the World. However, with the increase of production year by year, the cheapening of technology and state-supported agricultural development packages, small farmers will also use this technology.

Agricultural production and crop yields in the world decreased in 2015. In order to overcome these problems and meet the increasing demand with high efficiency, the concept of agricultural robot was introduced to the world. Robotic innovations have reached an increasing trend in the global agricultural sector and the stock market. According to the verified market intelligence report, agricultural robots can complete agricultural work in a much shorter time and with higher quality compared to farmers Verified Market Intelligence (2020).

The value of start-up firms working in agricultural technology between 2013 and 2017 has increased around 800 million dollars Cb Insight (2020). Start-up companies, which use robotics and machine learning to solve problems in agriculture, have been on the rise since 2014 in parallel with the development of artificial intelligence. Venture capital fund in the field of artificial intelligence has increased by 450% in the last 5 years. This new style of agriculture concept can also be explained as “less resources, more production”. Because when the reports of United Nations Food and Agriculture Organization (FAO) are analyzed, the world population will reach 9.1 billion in 2050, FAO (2009). Providing sustainable food production for the growing world population by preventing climate changes will be the most basic and critical agenda in the coming years.

In developed countries, modern farming systems are used and thanks to these modern systems, developed countries obtain more products than expected. Therefore, developed countries also started to have comparative advantages in agriculture. With the rapid increase in the world population, per capita consumption has increased, but it has brought many problems. These problems are;

- Unawares used chemical fertilizers and pesticides,
- Groundwater is not used efficiently,
- Decrease in productive agricultural areas,
- Property issues,
- Problems caused by mechanization,
- Destruction of forests for agricultural land or housing construction,
- Unawares agricultural activities in erosion regions Kılavuz (2019).

BACKGROUND

The agricultural sector is becoming an advanced technology industry, creating new opportunities for technology use and product development. Autonomous systems and agricultural tools with customized use come to the forefront in the progress of the industry. The agricultural platform can be broadly classified as area and task. Task-specific robots are designed to perform a specific task on a predefined product, while general purpose robots are designed to perform a variety of tasks in different areas.

With the advances in technology, agricultural robots can now perform various agricultural operations such as crop imaging, pest and weed control, spraying water and insecticide, harvesting. These processes are fully autonomous or semi-autonomous, depending on the farmland and application. Although there are agricultural robots with high speed and precision accuracy, their applications in agriculture remain limited due to unstructured environments and difficulties. For example, a robot with seed sowing capacity may not have distance information between the seeds to be sown to achieve maximum efficiency. A water / insecticide spraying robot may not have control over the amount of water / insecticide to be sprayed depending on soil conditions and crop type. Although robots have become part of agricultural practices, they are not yet smart enough to make their own decisions based on various physical, natural and environmental factors. Sub-algorithms used in machine learning together with the developing technology continue to optimize the current model by storing historical data. As a result, autonomous robots used in agricultural technology are getting more intelligent in the future.

Fruit harvesting platforms are used to reduce human movement during harvesting, to minimize the time outside picking and to achieve optimum working conditions. The use of these platforms, in other words, increases productivity during the harvest period.

Smart agriculture has the potential to provide a more productive and sustainable agricultural production based on a more resource efficient and precise approach. Smart agriculture should provide added value to the producer in the form of better decision making or more efficient business activities and management. In this sense, smart agriculture is strongly related to three technology fields such as interconnected management information systems, precision agriculture and agricultural automation-robotics.

Agricultural automation and robotics; It is the process of applying robotic, automatic control and artificial intelligence techniques in all kinds of agricultural production, including farmbots and farmUAVs.

Agricultural robots increase production efficiency for producers in various ways. Some of those; autonomous UAVs, autonomous tractors and robotic arms. These technological innovations are used in creative and innovative applications. Agricultural robots' autonomies slow, repetitive and boring tasks for farmers, allowing them to focus more on increasing overall production efficiency. Autonomous robots are electro-mechanical devices that can find a method to perform a task assigned to them, as well as autonomously capable of performing static tasks dynamically or dynamically to prevent possible hazards by using the data obtained from the environment with the help of sensors (sensors) to protect itself.

Agricultural robots, which are the most common uses in the agricultural sector, can be listed as follows:

- Weed control,
- Harvesting and picking,
- Autonomous mowing, pruning, seeding, spraying and thinning,
- Separation and packaging,
- Service platforms.

Harvesting and picking robots use image processing and an arrangement of robotic arms to determine what to choose. Apple's quality control and grading can only be done by preventing repetitive processing in a single operation. Data analysis about the product processed by the harvesting robot can assist in determining the business income and regulating the packaging and processing processes.

Nowadays, an operator using components that develop and become widespread with the advancement of technology only guides the main machine in the orchard; the remaining fruit harvesting machines are available on machines that are done automatically. Examples of these machines are the robotic fruit picker designed for apple harvesting ffrobotics (2020).

After the collector is positioned by the user in the area to be harvested, the sensors and cameras on the machine determine the location of the fruits in the three-dimensional space plane. In the next stage, the position information of the fruit is evaluated in the processor and the robotic arms move towards the fruit, tear it off in the axis of the fruit stem and leave it on the carriage. After this process, the conveyor transfers the fruits to the frame located on the back of the machine and rotating on its own axis on a tray. This machine is what a harvest worker should do; can decide whether the fruit is ripe or not, rip the fruit and place it in the case. Producing company ffrobotics (2020) emphasizes that the machine is ten times more efficient than a harvest worker.

There are also fruit harvesting machines that operate without the need for an operator. An example of this type of machine is the SW 6010 strawberry harvesting machine developed by Agrobot (2020). SW 6010 is the first autonomous robot on the market that can detect and collect strawberries, by analyzing the strawberries one by one and gently harvesting them so as not to damage the fruit. It is possible to use in the field and greenhouses, it has a working width of 6 meters and a length of 4 meters, and it is possible to adjust between the lines. By scanning the plants in the order, they entered with color and infrared sensors; It performs operations such as reaching the harvest maturity, determining the location of the fruit in the three-dimensional space plane. Then the robotic arms take the fruit off the handle and place it in the crates at the bottom.

Ben-Gurion University researchers have developed a pepper picking robot called SWEEPER. Working with a series of machine learning algorithms, SWEEPER robot travels on agricultural land and scans peppers. The robot, which also examines whether pepper is ripe with its data such as color and height, can collect peppers without damaging its flowers. Using the machine learning algorithm, the robot was trained using more than 1000 pepper photographs for pepper selection. Researchers also state that the robot's algorithm can be trained to collect fruits and vegetables such as oranges, tomatoes Arad (2020).

Tevel-tech start-up company in Israel has started to implement the apple harvesting project with autonomous unmanned aerial vehicles and UGVs Tevel-tech (2020). By contacting a program designed for the use of farmers, they found a collection process that required intensive labor and cost in a short time and less costly solution. In the coming years, we will encounter more projects with the harvest collection processes of UAV/UGVs for agriculture by working in interactive with swarm formation. The transition to Agriculture 5.0 will accelerate with the proliferation of active harvesting of such autonomous unmanned systems.

This study is founded by European Union. Russian, German, Turkish and Serbian partners work together on HARMONIC, Project Number: 217E138. This project supported by the Scientific and Technological Research Council of Turkey (TUBİTAK) and European Union.

Collaborative activity of groups of heterogeneous robots, as well as their delivery/transportation to the point of direct solution of applied problems, are ones of the main unresolved problems in the agriculture robotics. The main aim of the research in this project is development of theoretical basis of autonomous functioning of the mobile platform for serving group of unmanned aerial vehicle (UAV) under high level, mission based, remote control via intuitive user interface during agriculture operations. A distinctive feature of the project is the presence of built-in parking spaces for several UAVs.

Unlike the current works, an optimal joint functioning of groups of heterogeneous unmanned vehicles will be developed during the project. The main tasks of the project are:

1. development of theoretical basis of autonomous functioning the mobile platform served UAVs;
2. development of theoretical basis of group interaction of heterogeneous UAVs at solving agriculture operations;
3. development of theoretical basis of human-platform-UAV interaction and control including collaborative learning and time-critical interaction components via gesture, voice, etc.

The main impact of the project will be in creation of agriculture robotic system capable to minimize the effort and injuries of people in agrarian operations; maximize the coverage area of automation farming; minimize use of fertilizers through using UAVs and principles of precise agriculture. The project includes optimization applications for autonomous unmanned ground and air vehicles and smart agriculture.

Many studies are conducted in the literature including Vehicle Routing Problems (VRP) for different usage areas of unmanned aerial vehicles (UAV).

In the study of Guzey et al., it is aimed to collect the harvest by the time minimization of the previously determined apples in the agricultural land in communication of autonomous unmanned aerial and UGVs. Due to the fact that the current problem is very large, the main problem is solved by dividing it into small sub-problems in order to make time optimization. K-means clustering method was used to determine the locations of the UGVs' stops and to analyze it. Julia programming language is used for calculations. In the study, the optimal number of stops for 500 apples was found to be 3. The model prepared to optimize the apple picking times of air vehicle at each stop was resolved with the help of the Gurobi solvent and the results were achieved. As a result of the study, the average waiting time of the UGV at each stop was approximately 439 seconds Guzey (2020).

In the study conducted by Murray and his colleagues, they first came up with the idea of a model that carried the truck first, and then the last point with the UAV. This idea is called "Flying Sidekick Traveling Salesman Problem". Within the scope of the study, a UAV and a truck were used in deliveries. Vehicles can carry simultaneously. After delivery, the UAV must return to the truck. Mixed integer linear programming (MILP) and heuristic methods were used in the study Murray (2015).

In the study of Olivares et al., The use of a UAV type Quadcopters in the internal logistics of a manufacturing plant, especially during the assembly and customization of products. The aim of this study is to model and optimize high energy consumption during operation, which is a major disadvantage. In the study, an internal logistics modeling was carried out to locate the warehouses, clusters and subsets. In addition to this process, a variety of ways have been created using a genetic algorithm for each Quadcopter. In addition, the weight, material and route to be carried by each Quadcopter were determined. Finally, the amount of electrical power to be discharged from the battery of each quadcopters for a specific route is also optimized, depending on the weight carried, the number of workstations visited and the number of quadcopter aerodynamic efficiency Olivares (2015).

In a study conducted by Bekhti et al., The route creation scenarios for autonomous unmanned aerial vehicles were analyzed using the monitoring capacities of regional wireless networks. The main purpose of the study is to minimize the transportation to the target point with the shortest route, and to achieve this purpose, monitoring the location information of unmanned aerial vehicles via wireless network. At the end of the study, the best solution could not be obtained, and an appropriate solution was offered by reducing the accuracy rate of the location information to be followed Bekhti (2017).

In a study conducted by Wang et al. "Vehicle Routing Problem with UAVs" In a system with multiple trucks and UAVs, in which transportation times were optimized. In this study, many bad scenarios were analyzed, and time-saving scenarios were proposed in which both trucks and UAVs were used instead of just trucks Wang (2016).

The article titled "Truck-UAV optimization in cargo distribution network using K-mean and genetic algorithm" conducted by Ferrandez et al. Is the basis for the application used in this study since it is the closest study to the harvest optimization area used in Unmanned Aerial Vehicle (UAV) and Unmanned UGV(UGV) Ferrandez (2016).

MAIN FOCUS OF THE CHAPTER

Issues, Controversies, Problems, Solutions and Recommendations

The rapid growth of the human population on a global scale forces us to find a permanent solution to the nutritional problem we need in the long term. It is estimated that the global population will reach approximately 10 billion in 2050 and it is estimated that the agricultural production capacity should increase by 70% in order to maintain our current nutrition standards FAO (2009). However, considering the decrease in arable agricultural lands as a result of the climate changes to be experienced in the following years, how this capacity increase will be faced is an important question today.

Today, industrial agriculture practices in the agricultural sector constitute 11-15% of global greenhouse gas emissions and it is a fact that if this uncontrolled increase continues, it will accelerate climate change. Another result of the global population growth is the rapid increase of the population in the cities. This increase also causes rural areas and labor to decrease. As a result of the high technology and input costs in the agricultural sector and the need for energy to increase in parallel with this, the process, which continues until 2050, should abandon old agricultural methods and implement digital transformation in agriculture as soon as possible to increase the production capacity by 70% FAO (2009).

Agriculture is experiencing a very important transformation in the world. The digitalization of agricultural applications enables the production of plant and animal products with higher productivity and lower environmental impact.

Agriculture on a global scale will face great challenges in the coming years. Some of these challenges are:

- Rapid population growth in the world,
- Climate change,
- Increased energy demand,
- Scarce resources,
- Rapid population growth in cities,
- Decreased productivity of arable land,
- Competition in increasing world markets and
- Lack of credit and arable land in many developing countries.

Agricultural production has increased more than threefold between 1960 and 2015 with the use of agriculture 2.0 (Green Revolution technologies), soil, water and other natural resources for agricultural purposes. In the same period, there were remarkable increases in the industrialization and globalization of food and agriculture. Although agriculture has become more productive at the global level, nature has again paid the losses of the increase in food production and economic growth. Almost half of the forests that once covered the planet have disappeared, groundwater resources are gradually decreasing, and biodiversity continues to be depleted. Our groundwater resources are contaminated with nitrates, herbicides and pesticides. Burning fossil fuels emits billions of tons of greenhouse gas emissions to the atmosphere every year, leading to global warming and climate change.

The development in digital technology and applications plays an important role in the increase of agricultural production and economic growth. When it comes to digitalization and modernization reform in agriculture, rural areas and especially farmers are important. Our ability to address these issues correctly is great importance for the future development of the agricultural sector on a global scale. In many studies conducted in the world, it was concluded that the development of digital technology and applications is seen as an important factor in economic growth and developments in agricultural production. Field work, improving the mechanization of machinery and equipment is a continuous process. We see the widespread use of more modern equipment reflected in the technical and technological level of the agricultural sector in today's applications.

The technological transformation that the agricultural activity, which dates back 10 thousand years, has undergone the last century, has brought the agricultural activity to a completely different level. This period brought intense production, increased efficiency and changing needs. Today, this new understanding, which can be called the "new version" of agriculture, which is not the only purpose, is that agricultural robots are actively used, is more sustainable, environmentally friendly and energy efficient, is called "Agriculture 4.0". Today, with the developing technology, the agricultural sector is experiencing a great digital evolution and now the future of the agricultural sector is shaped by this digital evolution. In order to reveal these digital technologies more clearly, it is important to analyze the main stages of agricultural development.

In agriculture, it is aimed to maximize efficiency with the internet of things. Since natural resources are used at the required level, the cost decreases. Similarly, all the factors required for production are analyzed and presented to the manufacturer simultaneously with smart systems on the farm. In this way, waste of resources is prevented, and quality products are produced. In addition, rapid decision-making mechanisms are created with machines that communicate and work synchronously. The producer is given the opportunity to manage and observe the entire farm from a tablet or phone, and by reducing the workforce, efficient, quality and natural production opportunities are created.

Smart agriculture; When it comes to livestock and crop farming, it is much more controlled and accurate than traditional farming. In this farm management approach that effectively uses Agriculture 4.0, the key component is the use of IT (Information Technologies), however, various technological applications such as sensors, control systems, robotics, autonomous vehicles, and autonomous equipment are used. The adoption of high-speed internet by farmers, the use and reliability of mobile devices, the use of low-cost satellites for image and positioning are important technological applications that affect the spread of smart agriculture.

Unmanned aerial vehicles (UAVs) used in the agricultural sector are a good example to see how technology has changed over time. Today, agriculture continues to become an integrated technology field that includes UAVs. Unmanned aerial vehicles are used to develop various agricultural applications in agriculture. These applications are; product health assessment is carried out in areas such as irrigation, crop spraying, planting, soil and land analysis. The most important benefits of unmanned aerial vehicle use are product health imaging, mapping, ease of use, time saving and potential to increase efficiency. Unmanned aerial technology provides real-time data collection, processing-based strategy and planning, as well as a high exchange of high-tech products in the agricultural sector.

Unmanned aerial vehicles collect multi-spectrum, thermal and visual images after they take off. From this flight data, there are many reports such as crop health indices, crop count and yield estimation, crop height measurement, shade zone mapping, field water quantity analysis, exploration reports, stock measurement, chlorophyll measurement, nitrogen content in wheat, drainage mapping, and weeds.

Advanced technological developments enable autonomous agricultural robots to accomplish the agricultural tasks required for smart agriculture easily and safely. The advanced agricultural tools used today compress the soil over time, and this compression reduces the fertility of the soil over time. Compacted soil needs more than a decade to restore its fertility. Autonomous imaging and data collection tool, which works alone, is insufficient in large agricultural lands, and small vehicles that work in communication with each other rather than large and single vehicles provide a more effective solution. The technological studies required for the management and control of the system consisting of these autonomous tools by a single farmer have been carried out by the researchers for a long time. A task control center and intelligent coverage planning algorithms need to be developed to enable team members to communicate and collaborate with each other and to solve the assigned tasks safely and efficiently.

One of the topics that has been suggested by many researchers for a long time is the Multiple Robot system, also called "Swarm Robotics", which can work together to perform a specific agricultural task. Multiple robots need to use artificial intelligence and genetic algorithm methods to create an ecosystem in collaboration with each other. This system becomes even more useful when robots start learning interactively with each other and increase their performance over time. For example, a robot swarm can collect soil samples in coordination with the control center and contribute to the creation of food maps. The efficiency of this process may not be very good at first, but performances that punish the bad behavior of each robot can be improved over time by applying the "good behavior-bad behavior" method in the deep learning algorithm. These robots are of great benefit for the future of digital agriculture.

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

The K-Means algorithm is an unsupervised learning algorithm. Unsupervised learning is a machine learning technique where you don't need to check the model. Instead, you need to allow the model to work on its own to discover information and is mainly concerned with unlabeled data. Unsupervised learning algorithms enable more complex processing tasks to be performed compared to supervised learning.

Cluster analysis is defined as grouping the objects in the data set with their common properties or decomposing them into sub-data sets that are defined as clusters. In this process, the objects in the cluster are intended to be as similar as possible, but as different as possible from those in other clusters.

Another aim is; It is desired that the variance of the objects in the cluster is low and the variances between the clusters are high. Since the datasets used in clustering are divided into sections and existing data structure and patterns are revealed, they are constantly used in data mining to discover meaningful information.

Examples of clustering methods are classified in various ways, as there are a large number of them available today. These classifications are analyzed under 3 main headings. These; compartmental methods, hierarchical methods and mixed methods obtained by different ordering forms of these sets. The first method is the algorithms that divide the data sets used in clustering into k sub-sets. For this reason, one of these frequently studied topics is the selection of k, which should be known before the current analysis of an algorithm. The parameter here specifies the number of sets in the data set used. It can be said that the optimal choice of *k* depends on the successful and correct clustering of the clustering process. Classification algorithms will be obtained as a result of a positive or negative clustering regardless of *k*. However, there is no value that can be accepted as accurate in these clustering operations. Clustering method is used to find the closest number to this value and to reach the result. In other words, the correct selection of *k* makes cluster analysis more successful and it is also at the top of the classification clustering algorithm problems.

The K-means method was introduced in 1967 Developed by J.B. MacQueen MacQueen (1967). 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 Equation (1).

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

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.

Defining variables of a system by parameters and showing the connection between them by functions is called “mathematical model”.

Mathematical modeling is defined as the process of creating physical, symbolic and abstract models of situations that occur in real life. Mathematical modeling is a much more important process with its complex structure rather than just modeling a situation. All of the mental tools used in mathematical modeling are called mental models. In general, mathematical models are the external representations of the thoughts in our brains that have been transformed into a mathematical form, enabling the interpretation and solution of problems encountered in real life. In other words, mathematical modeling is a process that requires the mental modeling process Lesh (2003).

In the study conducted by Berry and Davies (1996), mathematical modeling is analyzed under seven basic steps. In the modeling process, the real-life problem is addressed in primary care. In the second step, a mathematical model that defines the current situation is created. Then, using the mathematical model, the mathematical solution of the problem is made. The results obtained from the solution are interpreted and their accuracy is analyzed. If the correctness of the results is suspected as a result of the analyzed, the existing model should be questioned again and revised when necessary. In the last stage, when the existing solution is analyzed according to real life, if a problem is not observed, the solution is turned into a written or oral report Berry (1996).

Linear programming (LP) is a method frequently used in optimization problems. The simplex algorithm, which is used effectively in the solution of linear programming problems, was proposed in 1947 by George Dantzig. With the simplex algorithm, linear programming has started to be used extensively in many sectors. Linear programming is still used in the solution of optimization problems in many sectors such as military fields, education and banking. As a result of a research conducted among Fortune 500 member companies, 85% of these companies used linear programming method.

Linear programming tries to make the objective function optimal (max-min) by adhering to variables and constraints. In general, linear programming can be said to be a deterministic mathematical technique that includes the optimum distribution of scarce resources.

In the linear programming model, there are three basic elements: goal function, constraints (constraint functions) and positivity (non-negative) constraints. A LP model includes constraint equations in the form of linear equations and / or inequalities and the linear goal function to be optimized. A LP problem is generally expressed as follows:

$$Z_{\max/\min} = \sum_{j=1}^{n} c_j x_j \tag{2}$$

Or,

$$Z_{\max} = C_1 X_1 + C_2 X_2 + \ldots + C_n X_n \tag{3}$$

Constraints,

$$\sum a_{ij} x_j \le, =, \ge b_i, i = 1, \ldots\ldots\ldots, m \tag{4}$$

$$x_j \ge 0, j = 1, \ldots\ldots\ldots, n \tag{5}$$

The assumptions required to achieve consistent results in Linear Programming are listed below.

- Severability,
- Proportionality,
- Summability,
- Certainty,
- Linearity.

Although the application areas of Linear Programming are very extensive, the most frequently used areas are:

- Production Program,
- Nutrition Program,
- Ad Environment Selection,
- Capital Budgeting,
- Distribution Program,

- Inventory Control,
- Production Line Balancing.

Problems that some variables should be integers and others are real numbers are called mixed integer programming problems. Mixed integer programming and integer programming have many similarities in terms of solution method. As in integer programming, the optimal solution is obtained by the simplex method without requiring an integer condition. The mixed integer linear programming problem can be expressed as a model as follows.

$$Z_{\max} = 5x_1 + 3x_2 \tag{6}$$

Constraints,

$$2x_1 + x_2 \leq 12 \; (7) \;\; x_1, x_2 \geq 0, integer \tag{8}$$

A.Land and A.Doing proposed a general counting method for use in integer programs in a study they conducted in 1960, Land (1960). This method, which is referred to as “Doing method” in the literature, was applied to traveling salesman problems in the following years. In 1965, Egon Balas developed an algorithm used in 0-1 integer programming Balas (1965).

In some cases, more than two possible (0–1) value options are needed in decision variables. These variables can also show the problem that will turn into an integer form as 0-1. In 0-1 integer programming applications, we see that many divisibility assumptions are not valid, and some problems are related to “yes” or “no” decisions. In such decisions, two possible choices are only “yes” or “no”. For example, should we make this investment? or should we set up the factory in this area? Similarly, two-choice decisions are shown with decision variables whose values are constrained by 0 and 1. Thus, the j, “yes” or “no” decision is shown as follows:

$$X_j = \begin{cases} 1, & if\ j\ yes \\ 0, & if\ j\ no \end{cases}$$

The general structure of 0-1 integer problems is expressed as follows Hillier (1986).

$$Z_{\min} = \sum_{j=1}^{n} c_j x_j \tag{9}$$

$$\sum_{j=1}^{n} c_j x_j \geq b_i, i = 1, \ldots\ldots\ldots, m \tag{10}$$

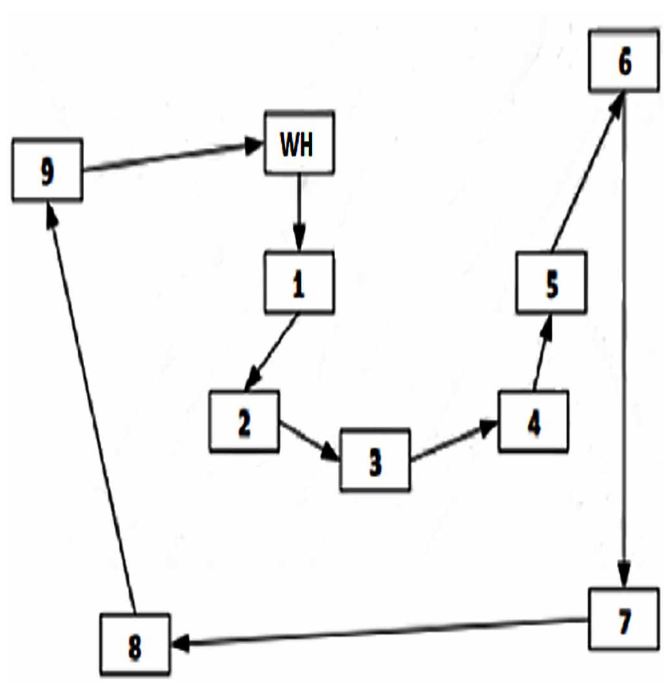
$$x_j = 0 \, or \, 1, j = 1, \ldots\ldots, n \tag{11}$$

In Nearest Neighbor Algorithm Method, one stop is randomly selected among the available stops and assigned as the starting point of the tour. Afterwards, the closest stop to the selected stop is determined and added as the next stop in the current tour. Adding is continued until all stops are included in the tour and the tour is not allowed to close until all the stops are added. In this method, the decision of which stop is selected as the beginning and which end of the current route to lead causes different length tour results. However, the solutions that are far from the global best are obtained because there are long returns to join the other stops left during the selection of the nearest stop.

Bellmore and Nemhauser (1968) brought the Nearest Neighbor algorithmic heuristic method to the literature (Bellmore, 1968). In this study, they have achieved an exemplary TSP by using this algorithm to the optimum result. Generally speaking, this heuristic method is very simple to use and can be used on TSP and Vehicle Route Problems (VRP) with small-scale samples.

It can be shown as an example of the Nearest Neighbor algorithm, starting from the nearest customers on the route of the vehicle and returning to the warehouse, provided that it does not exceed the time and capacity constraints after meeting all the demands, respectively. A sample route drawn using the Nearest Neighbor Heuristic is shown in Figure 1.

Figure 1. Nearest Neighbor Heuristic Sample[1]

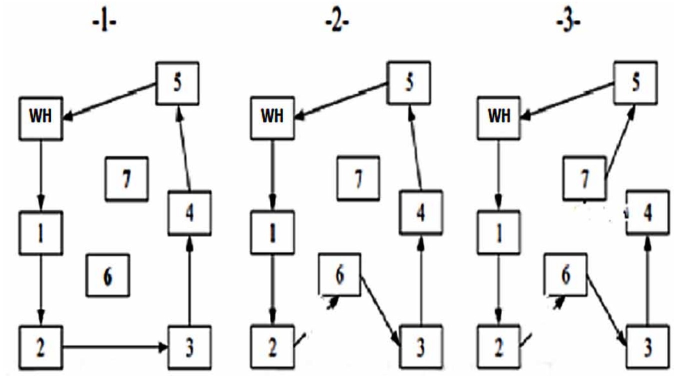


In Nearest Insertion Algorithm Method, the solution starts with a tour between two stops. Afterwards, it is ensured that the stops nearest to this tour are included among the stops in the current tour, and the inclusion of the tour is tested. After this process, the stop that will provide the smallest possible growth in the tour is determined and included in the tour.

This process is repeated until all the stops are included in the tour. In this method, the selection of the stop where the solution is started, and the addition order rule can change the solution. The solution stages of the tour starting from the warehouse are shown in detail in Figure 2.

The Nearest Insertion and Neighboring methods are often used to create a starting solution. But DePuy et al. (2005), in their study, propose a meta-heuristic method that can be used to solve Traveling Salesman Problems and similar combinatorial problems DePuy (2005).

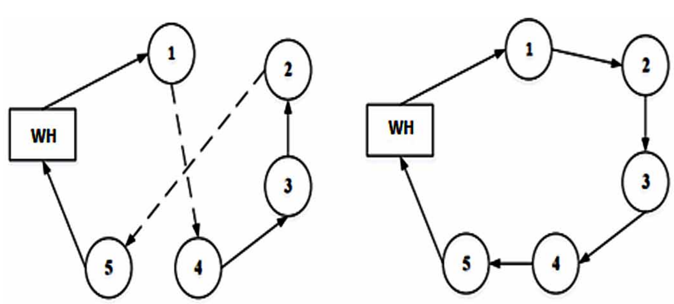
Figure 2. Nearest Insertion Heuristic Sample[2]



2-Opt Algorithm Method is the in-route change approach first used by Croes (1958). 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, Croes (1958).

As can be seen in the routes drawn as an sample in Figure 3., 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 shortened, and the new route gave a closer result to the optimum compared to the past.

Figure 3. 2-Opt Heuristic Method Sample[3]



Particle Swarm Optimization is a population-based optimization algorithm based on the behavior of bird swarms that search. This method was proposed by Kennedy and Eberhart. Each solution in the PSO algorithm is considered to be the social particle that makes up the swarm. While these particles move in the solution space and search on their own, they are also affected by the search behavior of other particles in the swarm Kennedy (1995).

Pang and his colleagues studied the PSO algorithm and TSP problems solving methods by aiming the transformation between continuous-discrete solution spaces. In this study, while position update and speed calculation are performed in continuous space, local search operations are performed in discrete space. Using the chaotic operator, the problem of jamming to the local best solution is avoided and it changes the position and velocity vectors positioned in space by random numbers and randomly changes them. In order to analyze the effectiveness of the use of chaotic operators, four different versions of the algorithm have been tested in different comparison problems Pang (2004).

The model developed in this study consists of modeling the problem by dividing it into two sub-problems.

First stage; UGV must stop at one point in order to find the optimal time. Ferrandez et al. Proposed the K-Means Method to find optimal stop coordinates Ferrandez (2016). This method is used in the model proposed in this study. This process is managed by a conditional loop.

In the second stage; Deterministic, Binary Mixed (0-1) Integer Modeling was used to determine the optimal picking time of the apples allocated to the stops with the K-Means Method. With this modeling, it has been determined which UAV will collect and how it is calculated whether or not the UAV collects the apple using 0-1 Binary Modeling. The 5 UAVs on the UGV platform are calculated to reach the optimal time, regardless of which apples are collected.

In the third stage; First, the route of the UGV was made by using the Nearest Neighbor and Nearest Insertion Methods, which are included in the heuristic solution paths in the Traveling Salesman Problem. Secondly, 2-Opt, one of the Heuristic Traveling Salesman Problem solution methods, was used again Field (2020). This method is called tour developer and it was used to improve the current route of UGV.

In the last stage; The object we created by using these three stages gives us the time used by UAVs for harvest in a certain number of stops and the total harvest time of UGV. The PSO algorithm that uses this object will allow us to find the optimal stop that gives us the minimum harvest time from the possible stops. Therefore, as a result of this proposed model, the ideal number of stops and locations where UGV will stop, and the information about which apples and which UAV will be collected at these stops can be easily accessed.

Finding the locations of these stops with the minimum number of stops; When using the PSO Method, it is necessary to find the smallest number of stops. In order for the object developed in the proposed model to work properly, the number of stops must be in accordance with the range of UAVs, and the lower limit of the number of stops must be found at this step.

The algorithm works as follows in the process of finding the locations of these stops with the minimum number of stops. Initially, the number of stops was taken as three. The coordinates of the apples were found using the K-Means Clustering Method and apples were assigned to three clusters to obtain the center point of each cluster. If the distance of this center point from the farthest apple in the cluster is within the collection area (Maximum flight range of UAV) of the UAV, the cycle is terminated, otherwise the cycle is repeated by increasing the number of stops by “1”.

Table 1. Indices, Descriptions and Definition Sets

Indices	Descriptions	Definition Sets
Э	Apple indices	I= {1, 2,…,i_{max}}i_{max}: Total number of apples on the field
J	Stop indices	J= {1, 2,…j_{max}} j_{max}: Total number of stops on the field
K	UAV indices	K= {1, 2,…,k_{max}}k_{max}: Total number of UAVs on UGV

Table 2. Parameters and Descriptions

Parameter	Description
A_{ij}	A is a matrix that shows at which stop each apple should be collected. If the value is "0" apple i will not be collected from the stop j, if it is "1" it will be collected.
U_{ij}	U is the distance of each apple in minutes to the stops.

Harvest time used by UAV; According to the number of stops found with K-Means Method; The coordinates of the stops begin with the information assigned to these stops and the distance from these apples to their stops.

The indices used in the model are given in Table 1, parameters and definition sets are given in Table 2 and the decision variables are given in Table 3. Later, constraints and objective function were explained, and an optimization model was established.

Table 3. Decision Variables and Explanations

Decision Variables	Explanations
D_{ijk}	It is a variable that takes the value "1" if the apple i is collected by the UAV k at the stop j and "0" if it is not collected.
SE_{ijk}	It is a continuous type variable that shows the charging time in minutes the UAV k spends to collect the apple i in the Stop j.
SD_{jk}	It is a continuous type variable that shows the total time, in minutes, UAV k spent to collect and charge apples at the stop j.
SDM_j	It is a continuous type variable that shows the total time in minutes spent by the UGV at the stop j. This period is obtained from the UAV with the highest collection and charging time of the UAVs at the stop j.

Decision variables and explanations for the proposed model are presented in Table 3.

The constraints in the proposed model for the problem are as follows:

With the constraint given in Equality (12), each apple is ensured to be collected at any stop by any UAV.

$$\sum_{j=1}^{j_{max}}\sum_{k=1}^{k_{max}} D_{ijk} = 1, \forall i \in I \tag{12}$$

With the constraint in Equality (13), the UAV is provided to collect apples only within their range at each stop. The UAV consumes the charging time as much as it goes on collecting apples. The UAV consumes 120% (30/25) of charging time since it carries the apple on return. Therefore, the total flight time of the apple, 2.2 times the distance from the station in duration, must be less than 30 minutes.

$$2{,}2 * A_{ij} * U_{ij} * D_{ijk} \leq 30, \forall i \in I, j \in J, k \in K \tag{13}$$

The value obtained with the Equation (13), Equation (14) ensures that the UAV k in the model acquires the charging time in minutes that it takes to collect the apple i at the stop j.

$$2{,}2 * A_{ij} * U_{ij} * D_{ijk} = SE_{ijk}, \forall i \in I, j \in J, k \in K \tag{14}$$

Equality (15) and the total time in minutes the UAV k spends to collect apples and charge at the stop j.

$$\sum_{i=1}^{i_{max}} 2 * A_{ij} * U_{ij} * D_{ijk} + SE_{ijk} = SD_{jk}, \forall j \in J, k \in K \tag{15}$$

With the equation (16), the total time in minutes spent by the UAV, which has the highest time of collecting apples in the stop j, is obtained.

$$SD_{jk} \leq SDM_j, \forall j \in J, k \in K \tag{16}$$

The objective function for the suggested model can be created as in Equation (17).

$$Z_{\min} = \sum_{j=1}^{j_{\max}} SDM_j$$

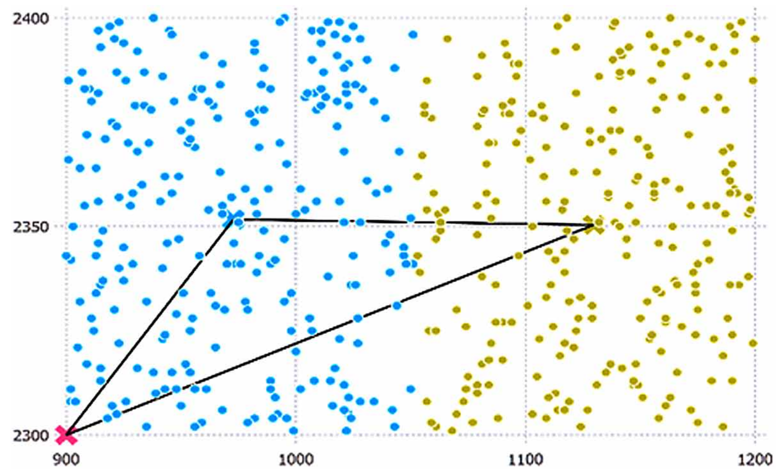
The objective function given in Equation (17) tries to minimize the total time spent in minutes by the UAV with the highest picking and charging time at each stop.

Harvest time used by UGV; By using the heuristic methods of the Traveling Salesman Problem with the stop coordinates found with the K-Means Method, analysis is performed.

The route of the UGV was made by using the Nearest Neighbor and Nearest Insertion Methods, which are included in the heuristic solution paths in the Traveling Salesman Problem. Secondly, 2-Opt, one of the Heuristic Traveling Salesman Problem solution methods, was used again. This method is called tour developer and it was used to improve the current route of UGV.

Optimum number of stops for minimum harvest time; The object we created by using three stages in optimization model gives us the time used by UAVs for harvest in a certain number of stops and the total harvest time of UGV. The PSO algorithm that uses this object will allow us to find the optimal stop that gives us the minimum harvest time from the possible stops. Therefore, as a result of this proposed model, the ideal number of stops and locations where UGV will stop, and the information about which apples and which UAV will be collected at these stops can be easily accessed.

Figure 4. Cluster Structure and Stops



The model proposed in this study was analyzed on a computer with Intel® Core ™ i7-2670QM @ 2.2GHz processor and 6 GB RAM hardware. Julia programming language was used for the analysis of the coordinates of the apples, the clustering, the calculation of the distances and the software of the mathematical model for analysis Bezanson (2017). The Julia package programs used are listed below:

- JuMP package Dunning (2017),
- JuliaStats/Clustering.jlpackage,
- JuliaStats/Distances.jlpackage,
- TravelingSalesmanHeuristic Field (2020),
- JuliaData/DataFrames.jlpackage,
- Giovineltalia/Gadfly.jlpackage,
- JuliaGraphics/Cairo.jlpackage,
- JuliaGraphics/Fontconfig.jlpackage,
- Giovineltalia/Compose.jlpackage,
- JuliaLang/Random.jlpackage,
- JuliaPlots/Plots.jlpackage,
- Sglyon/PlotlyJS.jlpackage,
- Stdlib/LinearAlgebra.jlpackage,
- Felipenoris/XLSX.jlpackage,
- Jump-dev/cbc.jlpackage.

In application, the number of apples (i_max = 500) and the number of UAVs on UGV (k_max = 5) were taken. JuliaStats / Clustering.jl package was used for the "rand" function and K-Mean Clustering Method to obtain the positions of the apples. The fact that the UGV is in motion during distribution or collection in the Flying Sidekick Traveling Salesman Problem (FSTSP) causes inefficiency in application. This is because the stop is at the optimal point to collect a certain number of apples. Heuristic TSP method was used in the route of the UGV.

In order to avoid problems in black and white printing, simulations obtained with multiple stops are not preferred, and as seen in figure 4., the scenario with UGV stop number 3 is preferred.

In application, the UAVs are allocated to the stops within its range and the minimum number of stops meeting this condition has been used. In figure 6., optimal values regarding the total harvest collection times at the determined stops are given. JuliaStats / Distances.jl package was used to calculate the distance of the stops obtained from apples. In the iterations made to find the number of stops (number of clusters) and their positions, the number of stops (j_max = 3) was obtained. In figure X., clustering structure and stops for 500 apples are presented. The “X” given in the figure 4. represent the stops.

In application, using the object obtained from the first three stages is optimized with the PSO algorithm at the last stage.

By using the algorithm developed for harvest optimization, it is aimed to find the optimal number of stops provides the lowest duration. Accordingly, when all possible stops are analyzed, it requires; i_{max}-2 times K-Means, (i_{max}* i_{max}+1)/2 times mathematical model and i_{max} times analysis of Traveling Salesman Algorithm. When it is necessary to analyze all the stops according to the number of 500 apples, it requires the analysis of 498 times K-Means, 125250 times the mathematical model and 500 times the Traveling Salesman Algorithm.

It takes more than 36 hours to reach the final solution, even if the time required to resolve each of these 125250 mathematical models is considered to be 1 second. For this reason, under the assumption that the harvest time has a function that decreases up to a certain number of stops and increases after this number of stops, Particle Swarm Optimization technique is thought to be used in this study to find the optimal number of stops.

Accordingly, the code was written in the Julia programming language and results were obtained. In all testing’s, the optimal solution was found as 500th stop in maximum 5 iterations. The results obtained show that the harvest time has a monotonous decreasing trend according to the number of stops. For a more detailed analysis, the algorithm was run for all possible stops and the results given in Figure 5. was reached.

As can be seen in Figure 5., the harvest time is a decreasing function except that it is stationary between 50 and 250 stops. Therefore, it is clearly seen that the optimal stop to be reached by using any

Figure 5. Time used by UAV/UGV and total time with charge

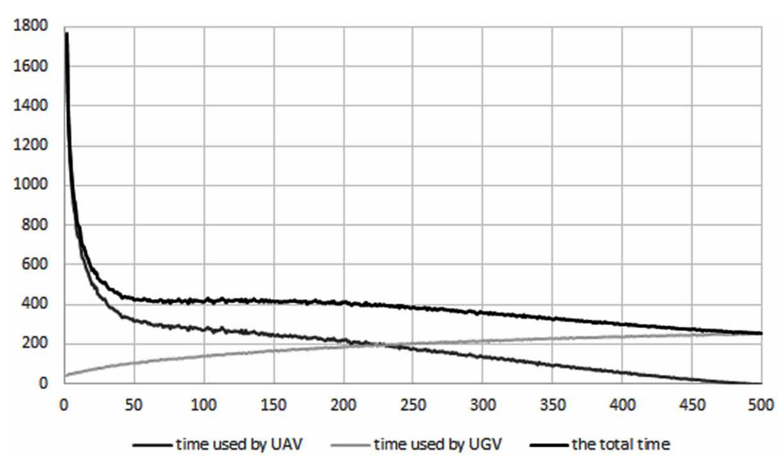
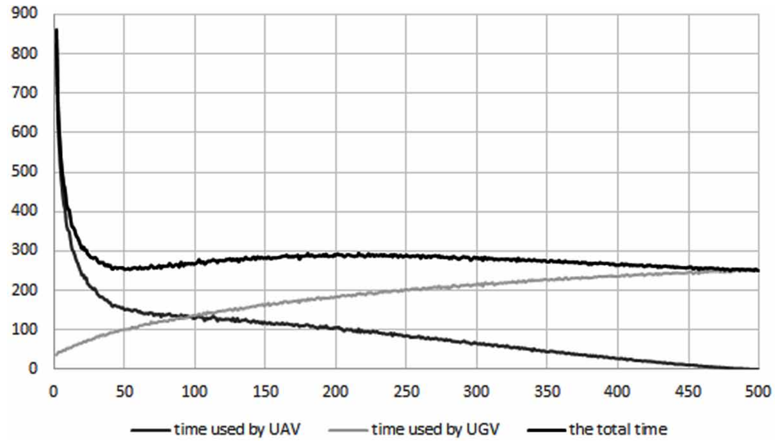


Figure 6. Time used by UAV/UGV and total time with no charge

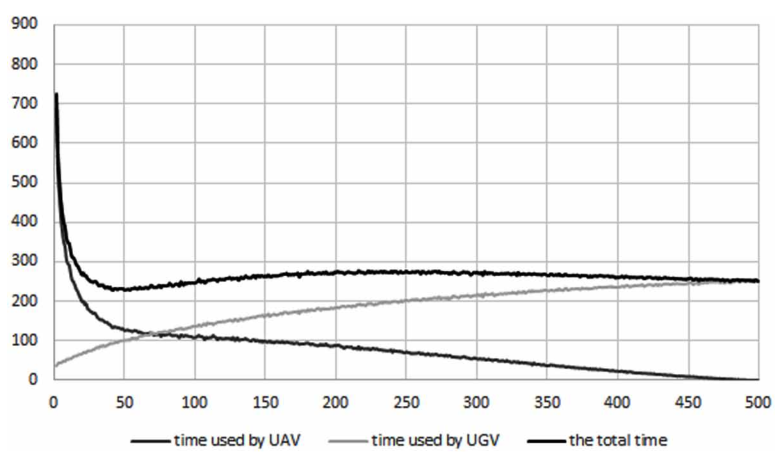


mathematical model will be the 500th stop. When the process was analyzed, it was understood that UGV was acting without recurring, without returning between stops, without spending time for recharging. On the other hand, UAVs spend more time for charging than their flight time. They have to go back and forth between each target and the stop while tracking the same speed as UGV.

As a result of all this, the process carried out with UAVs is less efficient when compare to the process carried out with UGV. In the study conducted by Ferrandez et al., it was proposed to have a spare battery for each UAV (Ferrandez, 2016). Thus, the time spent by UAVs for charging is planned to be reduced to zero. When the scenario used in this study is updated accordingly, the Figure 6. was reached.

As can be seen in Figure 6., the harvest time is a function that decreases rapidly to the 50th stop, increases between 50 and 200 stops and decreases between the 200 and 500 stops. Although the times around the 50th and 500th stops are very close to each other, the optimal stop is found as the 500th stop, with very little difference. Finally, when a 20% improvement in the speed of UAVs considered, the Figure 7. was reached.

Figure 7. Time used by UGV, UAV (%20 speed improvement) and total time with no charge



The positive effect of all these improvements is clearly visible between the 25th and 75th stops. The minimum point of the function for the harvest time is clearly in this range. In this way, the optimum number of stops can be found using the Particle Swarm Optimization Algorithm without making calculations for all stops.

After the current improvements were made, the PSO algorithm was run with the parameters presented in table 4 and the 42nd stop was found as the optimal stop with 228.25 min. The result obtained is exactly the minimum point of the total time in figure 7.

Table 4. Parameters

Parameter	Value
Variable Number	1
Particle Number	5
Minimum inertia weight	0.4
Maximum inertia weight	0.9
Cognitive acceleration constants C1	2
Social acceleration constants C2	2
Initial velocity	10
Maximum iteration number	50

In order to use the PSO algorithm for harvest optimization, the following assumptions must be provided. Otherwise, the optimum number of stops will be equal to the number of apples.

1. Charging time should be left out of the process by using a spare battery in UAVs,
2. UAVs should be faster than UGVs.

The algorithm should be added to the PSO algorithm until the result produces a different result from the number of apples, so that the result is not affected by the trap zone in the first part of the graph, which is the rapid decrease. In addition, instead of repeating the PSO algorithm for a certain number of times, running the best values of all particles until they equal the global best value produced healthier results in less time.

FUTURE RESEARCH, DIRECTIONS

This study can set an example for future studies. When smart agriculture can be applied with all its components, it will also provide great benefits to environmental problems through optimization of inputs. In our next study, the load carrying capacity of the UAV will be added and flight ranges and battery ratios of different weights will be simulated. In addition to that developing fault diagnosis and fault tolerant control of UAVs and UGVs will be integrated to the model.

CONCLUSION

In this study, it is aimed to collect the harvest of the autonomous UAVs and UGVs in the agricultural land, in accordance with the time minimization of the apples whose targets have been determined previously. Due to the fact that the problem studied is very large, the main problem is separated into small sub-problems in order to optimize the solution and the solution is provided.

It is understood from the UN reports that the world population will increase to 10 billion in 2050 and the food demand will increase by 70%. Countries that do not consider this population increase and do not invest in technology in the field of technology will have to purchase food and agricultural machinery from abroad. Today, in agricultural reports, there is more room for innovative agriculture, agriculture 4.0 and sensitive agriculture practices.

This change also affects farmers, manufacturers, marketers, retailers, consumers, governments that interfere with the flow of goods and products. Today, value of the smart agriculture market is almost$ 26.8 billion. It is expected that smart agriculture practices will reach the volume of 30 billion dollars in 2030 and this will be the factor that will affect the agriculture sector the most with this positive momentum caught by the market.

Although there is a lot of agricultural land available in the world, it is not possible to obtain a productive harvest due to reasons such as labor cost and technology shortage. Countries with small surface measurements, such as the Netherlands and Israel, have a voice in the world in the agricultural field by implementing successful and long-term digital agriculture policies. If the Agriculture fully fulfills the requirements of 4.0 and plans to switch to Agriculture 5.0 in the long term, the world will be able to meet the need for food that will increase in the future.

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ENDNOTES

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