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# Adopting an Improved Genetic Algorithm for Multi-Objective Service Composition Optimization in Smart Agriculture

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**Abstract**

In order to modernize numerous areas, the Internet of Things (IoT) is an emerging paradigm that connects various intelligent physical objects. As the rising global population depletes resources and causes unforeseeable environmental changes, producing sufficient food has now become a prime concern globally. Hence, to resolve this issue, agriculture is shifting to "smart agriculture," whose focus is to accelerate production using wireless sensor networks, cloud computing and IoT. The service composition is thought to be a crucial component in this technology for increasing functionalities and satisfying user's complex needs. This paper presents an improved version of the multi-objective genetic algorithm (iMOGA) for optimizing the time and cost associated with the services involved in the production of apple orchards to maximize the farmer's financial goals while reducing their potential time. It has been observed that (iMOGA) is a promising approach to obtaining Pareto optimal solutions for service composition optimization in smart agriculture.

*Keywords*: internet of things, multi-objective genetic algorithm, smart agriculture, crossover, mutation.

## 1. Introduction

In the past few years, IoT has gained immense popularity. It is demonstrating why it is the greatest means of bridging the actual and virtual worlds. In these systems, sensors, actuators, and other things are linked together. They communicate with one other via internet. As a result, it enables these objects to perform their functionalities by means of services Kaur (2018). These objects are heterogeneous in nature, spontaneous in interaction, supports dynamic network, and has no infrastructure. They include diverse real-time applications Razzaque, Milojevic-Jevric, Palade, and Clarke (2016), Sharma, Pathak, and Kumar (2023). Figure 1 shows the real-world applications of IoT in various domains.

The smart agriculture, industry, transportation, cities, waste management, and healthcare are all being affected by this new technology. Among all these applications, Agriculture 4.0

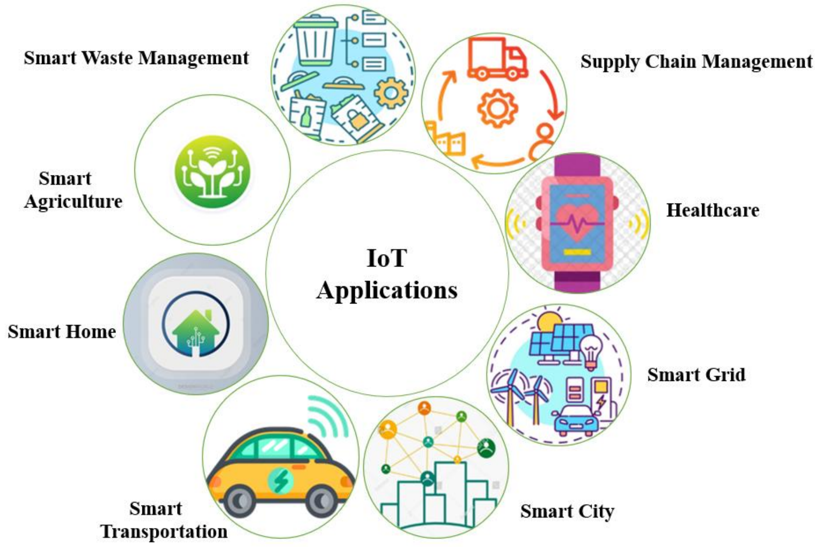


Figure 1: Real world IoT application

is gaining a lot of attention from researchers as it directly impacts the population's everyday life. Global urban population development has drastically altered people's eating patterns, increased their desire for better food as well as need for supplies. According to a new study released by UNESCO World Water Assessment Program, the requirement for food and water will increase by a factor of two in 2050 UNESCO (2016). For the entire world, but especially for the developing countries, this will have major repercussions. Smart agriculture is one of the most prominent applications of the widespread IoT technology. Farmers and researchers alike have recently shown a great deal of interest in smart agriculture techniques in an effort to fulfill rising food demand Ayaz, Ammad-Uddin, Sharif, Mansour, and Aggoune (2019).

The adoption of IoT technology for faraway, autonomous monitoring of the agricultural fields and taking remedial steps to make the environment most favourable for crop growth are two important reasons that drive smart agriculture systems. For the best results, these systems depend on a mix of hardware and software technologies. They may now be deployed in enormous numbers throughout vast indoor and outdoor agricultural fields because to the accessibility of affordable, portable, power-efficient technology with wireless communication. To evaluate soil conditions, robust hardware modules may be implanted under-ground. Other modules may be able to survive adverse weather conditions including sunlight, rain, and high humidity. The latest reverberation in artificial intelligence holds up an enormous amount of data from hardware unit so that it can be provided to artificial intelligence-based models to give the farmers more informed choices. It can include crop yield, reduced usage of harmful chemicals found in pesticides, fertilizers and conservation of water for irrigation systems. The farmer now has more freedom and insight to attain a level of control over agriculture, including the ability to choose the crops that will yield the most under current and projected climatic conditions Qazi, Khawaja, and Farooq (2022). These advancements in use of artificial intelligence have also increased the expectations of population, thus, resulting in complicated user demands in everyday life. New services are acquired by composing atomic ones in order to guarantee them. Composite Services are the name given to these services. Composite services offer new functionality that atomic services cannot offer on their own. In reality, the integration of smart objects services to address complicated needs is made possible by IoT composite services Lemos, Daniel, and Benatallah (2015). IoT services are created by the massive proliferation of smart objects and have the same functionalities, but they differ due to their qualities of service (QoS) characteristics. Because of this, meeting user requirements can often be difficult. Considering the large number of potential services for the composition, it is difficult to adhere to the QoS constraints (user requests in terms of QoS). This issue involves choosing the best services to ensure that the composite service satisfies the user's both functional and non-functional QoS needs Baker, Asim, Tawfik, Aldawsari, and Buyya (2017).

The method of composing QoS-aware IoT services typically entails four steps- Composition of plan, Service discovery, QoS based service selection, implementation of service composition. Basically, two types of service are there- abstract and concrete services. Several concrete services with an identical function but different QoS values make up an abstract service class. In general, there are two processes in the composition of an IoT application. As a new service class, the existing classes containing a set of concrete services are first put together using a variety of action flows. Secondly, the best possible candidate services from these classes are picked to be the IoT application's components. The composition plan displays the order in which candidate services are invoked as well as the rules for data flow between them Chai, Du, and Song (2021a).

After that, service discovery phase selects the tasks from set of services with similar functionalities by considering the factor of QoS. Next comes the service selection phase where latter selects the required services as per user's needs Khansari, Sharifian, and Motamedi (2018). Eventually, services are composited by considering techniques that either employ local selection or global optimization. The former enables individual determination of the best concrete service in terms of QoS for each abstract service in the composition plan. These methods, despite having an acceptable time complexity, cannot ensure that a composite service complies with user provided global QoS demands. The latter considers QoS parameters at composite level. The service composition with maximum aggregated value satisfying the global constraints is finalized, leading to a NP hard problem Alrifai and Risse (2009). Since, our work in this paper is focused on global optimization, meta-heuristic techniques can be useful in obtaining the best solution. These approaches are categorized into five categories according to their nature: evolutionary algorithms, bio-inspired algorithms, swarm intelligence algorithms, physical algorithms and miscellaneous Sharma and Tripathi (2022). These optimization techniques provide only single solution but in order to optimize multiple objectives in a single run, multi-objective feature is required to get the set of Pareto optimal solutions. Population based evolutionary algorithms are one of the oldest and widely used algorithm.

Here, the idea is to reframe the service composition optimization problem using improved genetic algorithm (iMOGA) in smart agriculture field. The objective can be summarized as follows

**a)** Service Composition of fourteen services involved in the production of apple orchards.

**b)** Using improved multi-objective genetic algorithm (iMOGA) to optimize the time and cost associated with all fourteen services.

**c)** Obtaining Pareto optimal solutions to analyse the trade-off between both objectives.

**d)** Statistical analysis explanation to get the clear view of results.

Rest of the paper is organized as follow- Section-2 gives a few insights of literature work done using genetic algorithm in smart agriculture. Section-3 is detailing the composition of existing and proposed algorithm. Experimental setup and result analysis is explained in Section-4. Finally, Section-5 concludes the paper.

## 2. Literature work

High demand and dependability of the world's population on agriculture has made it an ominous research field. Enough work has been done in this field by using IoT, cloud computing, fog-computing, machine learning artificial neural networks which involves maximizing crop yield, minimizing water usage for irrigation in fields, lowering down the use of fertilizers and pesticides, crop monitoring using UAVs (Unmanned aerial vehicles) and other related factors. Few glimpses of related work is explained in this paper.

Sinha and Dhanalakshmi (2022) presents a review on how significant is to use IoT in smart agriculture for cost optimization and increasing crop production. Importance of IoT is defined in irrigation management, livestock monitoring, precision farming, nutrient management, crop management etc. Along with it, types of sensors like pH sensors, soil moisture sensor, UV sensors, temperature sensors, global positioning system (GPS) etc. also discussed in detail. Further the use of data analytics, apps, software and hardware in smart agriculture is shown. The authors concludes the paper by considering cost and security as the critical issues to be solved in the future for taking the full benefit of IoT in smart agriculture.

Saiz-Rubio and Rovira-Mas (2020) provides a review on how the data driven management can be used for a sustainable agriculture terming it as Agriculture 5.0 for cost optimization while saving the environment. The authors discuss the concept of Agriculture 5.0 as use of precision agriculture with unmanned equipment and independent decision systems or in simple form, the use of artificial intelligence and robotics. They have divided the field data management into five cycles as crop, platform, data, decision and actuation.

Masdari, Nozad Bonab, and Ozdemir (2021) demonstrates a systematic review on QoS based service composition using meta-heuristics in literature. They classify the literature in seventeen distinct meta-heuristics and compare each of them with some meta-heuristic properties they have deployed to solve web service composition problem. The authors conclude the paper as genetic algorithm is the most deployed algorithm for solving service composition problem after particle swarm optimization (PSO) with MATLAB holding the first position for majorly being used as a simulator. Evaluation parameters like fitness value covered most of the part followed by time related parameters. QWS dataset is used in many papers, followed by random datasets for web service composition. The authors conclude the paper by suggesting the adoption of methods to increase security and energy constrained resources.

It can be seen that reviews in agriculture field are focussed on the use of IoT, data analytics, cloud computing, artificial intelligence like machine learning, deep learning and nature inspired meta-heuristics to make it smarter, sustainable, predictable in future by determining crop diseases, water requirement for irrigation, intruder's attacks etc. Evolutionary meta-heuristic techniques are currently in trend to optimize the requirements in smart farm. Almost in every aspect of agriculture use of genetic algorithm has been done in the literature.

Ocampo and Dadios (2017) demonstrates a study to minimize the energy cost of two motor pumps in a smart farm with a necessary condition of ample amount of energy to be available to both pumps by using genetic algorithm. Constraints were also added. They take each solution as set of weights that should be multiplied by the matching sensor readings. Population size is varied from 50-500 with a spacing of 10, generations = 500, tournament selection, crossover probability = 50%, six crossover operators (Scattered, single point, two-point, intermediate, heuristic and arithmetic), three mutation operators (Uniform, adaptive feasibility, gaussian). The authors test a number of parameters and concludes that different simulations are required to reach to optimal solution. The conclusion is not cleared in the paper as they have considered neither trade-off points nor any particular optimal solution.

Hakli (2017) proposes a novel technique for automatic land partioning using the concept of genetic algorithm. Three conflicting parameters- location of cadastral parcels, degree of cadastral parcels and fixed facilities multiplied by a factor of two are taken as objective function. Unique no. within the block is taken for initializing the random population. The authors implement their proposed model on a completed project of Alanozu where genetic operators are population size = 20, no. of generations = 50, roulette wheel selection method, single point crossover, swapping mutation, mutation probability = 0.1, and crossover probability = 0.8. Comparison is done with another study where 4.8 hours has been taken by model to optimize only 3-hectare block with 6 parcels whereas the proposed algorithm is optimizing the 109-hectare containing 18 block and 33 parcels in just 8 hours. The authors shows their achievement by comparing the results of objective function with the same land portioning done by designer and have found that proposed Automated land portioning genetic algorithm (ALP-GA) is far superior.

Roy and De (2022) proposes an architecture for terrace gardening and outdoor regions for predicting the rainfall by using genetic algorithm on a real data set in Kolkatta, West Bengal region of India. In case of terrace gardening, if the rainfall is not predicted then a sensor-based system checks whether soil moisture is below the pre-defined point and if yes, then a signal is sent to relay module & GSM module using Arduino UNO to start the water pump until the soil sensor reaches to its threshold value whereas for outdoor regions, the signal from moisture sensor is sent to mobile via ESP8266 wifi module which guides UAV to spray water in the desired region. Roulette wheel selection is used but no information of crossover and mutation is provided in the paper.

Shivgan and Dong (2020) proposes a genetic algorithm-based UAV path planning technique to minimize the energy consumption by reducing the number of turns while covering an area. The experiment is performed for waypoints = 10, 25, 50 and 100. Tournament selection, two-point crossover and swapping mutation is used as parameters. To evaluate the results, authors compares the optimized solutions with greedy approach. The authors concludes proposed GA is consuming energy 2-5 times less than the greedy approach.

Gaofeng (2020) demonstrates the use of genetic algorithm for reducing the cost by optimizing the path coverage of 40 sensors nodes connected to greenhouses with hop-to-hop delivery method. Total of 30 iterations were run in which 20th iteration is giving the best value of 3838 for optimal path determination.

Use of meta-heuristics along with artificial intelligence like machine learning, deep learning is also taking the smart agriculture to the next level. Sharma, Jain, Gupta, and Chowdary (2020) have demonstrated the applications of machine learning in smart farm management. They have explained that deep learning algorithms like Random Forest, Support Vector Machines, Convolutional neural networks,Random Forest and Decision trees are good solutions for recognition of diseases in plants whereas regression methods are best suitable for determining the weather forecast, yield production and soil properties. For reducing the human labour, smart harvesting, irrigation systems, robots and drones plays an important role. They concluded the paper by mentioning NLP based chatbots and hybrid algorithms for making this industry sustainable.

Acharjya and Rathi (2022) proposes a model for crop identification using a hybridization of fuzzy rough sets, real coded GA, regression and k-nearest neighbour (KNN) technique. In the first phase, redundant attributes are removed using fuzzy real set and then dividing the data into training part, testing part and validation part. Analysis of training data is done using real coded genetic algorithm (RCGA) together with KNN and regression. For this, six possible combinations using tournament selection, roulette wheel selection, laplace crossover, flat crossover and simple crossover are taken- Tournament with Laplace (TSLX), Roulette with Laplace (RWLX), Tournament with simple (TSSX), Roulette with simple (RWSX), Tournament with flat (TSFX), Roulette with flat (RWFX). All these combinations are compared for success rate, accuracy and execution time with minimum mean squared error as objective function by taking information from Krishi Vigyan Kendra of Tiruvannamalai district of Tamil Nadu. FRRWLX (Fuzzy rough set roulette wheel selection with laplace crossover) is found to be the best among these combinations.The authors further compares their results with rough set real coded genetic algorithm with roulette wheel and laplace crossover (RSRWLC) along with five other techniques for various vegetables grown in Tiruvannamalai district. The paper is concluded by declaring FRRWLX approach to be the superior one from others.

Cloud computing, IoT, machine learning, fog/edge computing, deep learning and meta-heuristic methods have all been extensively studied by researchers for optimum solutions in smart agriculture but the service composition problem has not received any attention, according to a thorough analysis of the literature in this field. Thus, the uncharted nature of service composition in smart agriculture is coming to a conclusion. As a result, the work that is suggested in our research is a novel method of composing the services and optimizing using improved multi-objective genetic algorithm.

# 3. Composition algorithm

Making decisions using several criteria includes multi-objective optimization. It has been used in many scientific domains, such as logistics and engineering, where it is necessary to make the best choices when there are trade-offs between two or more competing objectives Pathak and Srivastava (2014) Meta-heuristics are a reliable method for solving optimization problems with insufficient data and information. They sample a collection of solutions that is too large to be fully illustrated. By searching across a vast set of possible solutions, they can frequently identify outstanding solutions with less calculation than heuristics and iterative methods. There isn't a single solution for a complex multi-objective optimization problem that concurrently optimizes all of the objectives. As a result, it is claimed that the objective functions are incompatible, and several Pareto optimal solutions exist Hojjati, Monadi, Faridhosseini, and Mohammadi (2018). The solution is referred to as non-dominated Pareto optimum if none of the objective functions can be elevated in value without degrading some of the other objective values. Without additional subjective prior data, all Pareto optimum solutions are equally taken into account. The goal is to identify a typical collection of Pareto optimal solutions, which is capable of identifying the trade-offs involved in achieving the various objectives so that a single solution can be achieved as per the priority Kapoor, Pathak, and Kumar (2023). This can be formulated in the form of equation (1) as follows Chitra and Subbaraj (2012)

$$f_i(x), i = 1, 2, 3, ......N_{objectives} \tag{1}$$

where, $f_i(x)$ can be either maximized or minimized.
Subject to Constraints

$$g_k(x) = 0, k = 1, 2, 3, ......K \tag{2}$$

$$h_l(x) \leq 0, l = 1, 2, 3, ......L \tag{3}$$

Equation (2) and (3) are defining the linear and non-linear constraints, respectively.
Here, $f_i = i^{th}$ objective function, $N_{objectives}$ = number of objectives, $x$ = decision variable representing solution, $L$ = inequality constraints, $K$ = equality constraints.

## 3.1. Genetic algorithm

Genetic algorithm is a nature inspired population-based optimization technique which mimics the behaviour of genetic process. It is a computerized and an automated search technique first proposed by Johan Holland in 1990 Holland (1992). The GA commence the search process from a randomly generated initial set, known as the population, in contrast to the conventional searching algorithms. Each individual makes up one chromosome in the population. A chromosome is a string of characters that resembles a binary code. The fitness function is evaluated for each iteration to assess how well the existing chromosomes are performing. It is a quality that must constantly be at its best, whether it is minimization or maximization.

Next step is parent selection which is crucial in GA since the outcomes of optimizations directly depend on the fitness of the subsequent generation. Then the selected parents undergo crossover and mutation to create the new chromosomes called offspring. Because the chromosomes in the new population are chosen based on their fitness function, some undesirable chromosomes will be deleted and only fittest chromosomes survives. After a number of repetitions, population converges on the ideal chromosomes called pareto optimal solutions Zhai, Martinez Ortega, Lucas Martinez, and Rodriguez-Molina (2018). The flow chart of GA is shown in Figure 2.

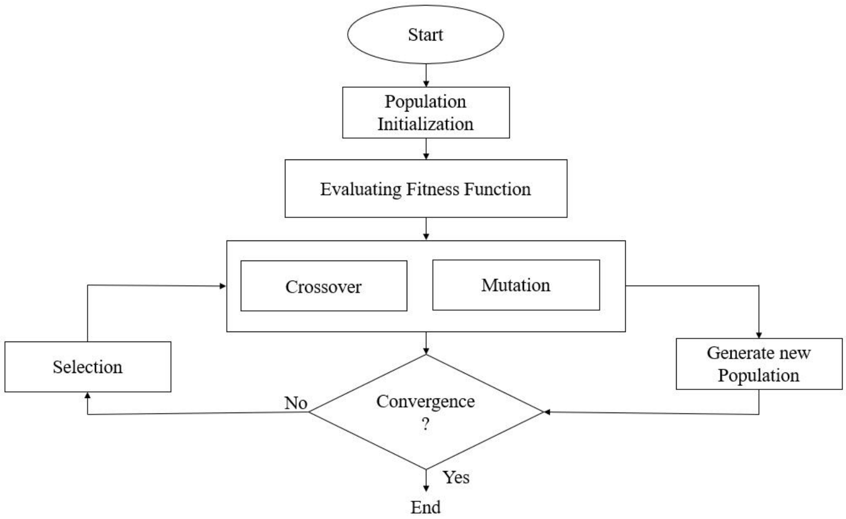


Figure 2: Flow chart of genetic algorithm

Genetic Algorithm works step by step Kim and Ko (2015) which are described below in Figure 3.

### 3.2. Service composition problem

The goal of this work is to offer the apple crop production an optimal solution. For achieving this goal, "t" no. of heterogeneous atomic services is taken with each of them having distinct QoS attributes. This can be described further in equation (4) given below Kashyap, Kumari, and Chhikara (2020)

$$G = \{g_1, g_2, g_3, .......g_t\} \tag{4}$$

Each one of the atomic services is having "k" no. of candidate services defined in equation (5) shown below-

$$g_i = \{CS_i^1, CS_i^2, CS_i^3, ......CS_i^k\} \tag{5}$$

Candidate services further depend upon quality-of-service attributes presented in equation (6) as follows-

$$CS_{ij} = \{QOS(CS_{ij})\} \tag{6}$$

Thus, Composite service can be described in equation (7) given as follows-

| **Genetic Algorithm** |
|---|
| Step-1 Initialize the random population $(N)$ |
| Step-2 Evaluate the fitness value corresponding to initial population using the defined fitness function. |
| Step-3 Repeat the process until the desired fitness value is achieved. |
| Step-4 Using Selection process, select two parents represented as $P_1$ *and* $P_2$. |
| Step-5 Crossover operation is performed on the selected parents corresponds to $(N+1)$ population. |
| Step-6 Mutation operation is performed on the population obtained after applying crossover operator. |
| Step-7 Finally, calculate the fitness of the $(N+1)$ population and compare it with best fitness value. In case, if the fitness value obtained is found to be better than the previous best value then updates the best value. |

Figure 3: Procedure of genetic algorithm

$$C = \{CS_1^a, CS_2^b, ......CS_3^k\} \tag{7}$$

There are four possible composition modes in service composition- branch, sequence, fork and loop Asghari, Rahmani, and Javadi (2022). Overview of QoS based service composition approach is shown in Figure 4.

This paper is optimizing multi-objective service composition problem using sequential flow of services. Services are first found in the cloud, then required services are selected and finally, composited according to the user's complex needs. In order to optimize these services, improved genetic algorithm has been used.

## 3.3. Improved genetic algorithm for service composition problem

For achieving global optimized solution using GA, following steps are required to be followed in sequence.

*Encoding and population initialization*

Population is defined as the total no. of possible solutions for any particular problem. Chromosome is a term to represent a single solution whereas a gene is the index of any element. Hence, genes together form a chromosome and multiple chromosomes forms a population. In our case, random initial population is generated. It can be defined as follows-

Step-1: Start from i =1 and j = 1.

Step-2: Create random chromosomes.

Step-3: Increment $i = i + 1$ and $j = j + 1$. If $i \leq N$ and $j \leq M$ then go to step-2 otherwise hault.

Here, N is the population size and M is the no. of objectives. Thus, the initial population can be represented as in equation (8) given below-

$$P_{ini} = \{Ch_1, Ch_2, ......Ch_N\} \tag{8}$$

where, $Ch_N$ is the $N_{th}$ chromosome.

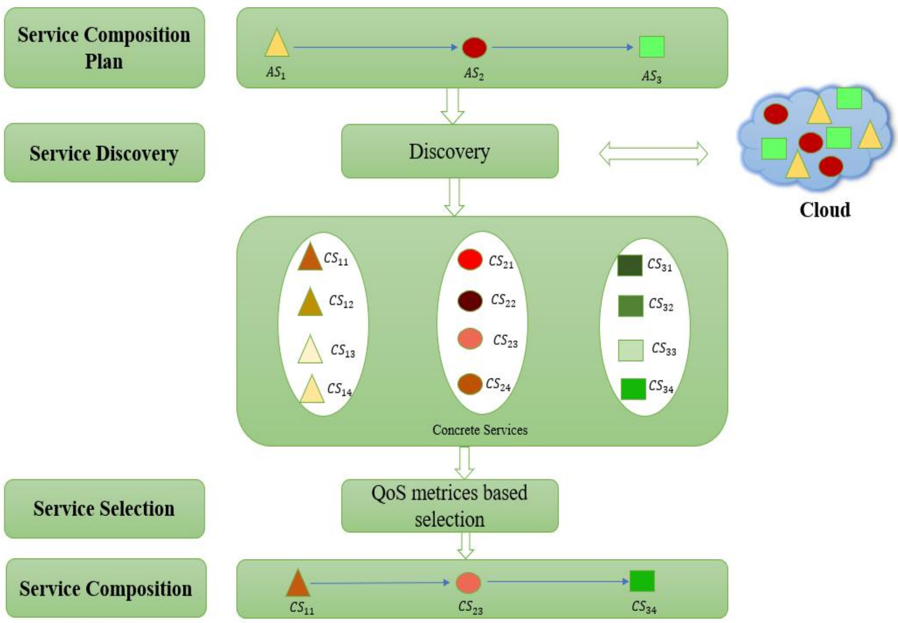


Figure 4: QoS based service composition problem

Our work is representing the chromosome by an array with number of items equivalent to number of atomic services whereas each of the services corresponds to a concrete service index.

*Fitness function*

After the initialization of population, the next step involves defining the fitness function in order to obtain the fitness value for each chromosome. Among all the chromosomes compared at each iteration, it takes the value of the best fitting chromosome. Fitness function either minimizes or maximizes as per the user's requirements. Our work has taken two objective functions of minimizing time and maximizing cost.

*Selection operator*

By passing on the higher-quality chromosomes to the following generation, selection contributes significantly to raising the population's average quality. "N" number of pre-existing individual parents produces "N" number of fresh individual offspring on each iteration. In order to be included in the next iteration, both parents and children must compete with one another. Our paper is using tournament selection method where $p$ random chromosomes are taken into account and top $p$ chromosomes are selected Gupta and Panwar (2013).

*Crossover operator*

Crossover is the initial genetic operation performed on the chromosomes in mating pool. The purpose of crossover is to establish a communication pathway between two chromosomes. The algorithm will do this to explore new offspring in the hopes of discovering superior off-springs on the basis of fitness value obtained. In our work, simulated binary crossover has been used having a probability equals to *sigma*. The SBX operator has two distinct coefficients *beta* to evaluate depending on the values of rand function where rand contains random values between 0 and 1. Two cases are defined in equation (9) given below-

$$\begin{cases} (2 \cdot \text{rand})^{1/3} & \text{if rand} < \sigma \\ \frac{1}{(2\cdot(1-\text{rand}))^{1/3}} & \text{otherwise} \end{cases} \tag{9}$$

Additionally, SBX produces two offspring from two randomly chosen parent solutions drawn from the present population. Finally, based on equal likelihood, one of the offspring is kept Chai, Fang, and Li (2021b). SBX's main addition to the entire algorithm is that it accelerates the Pareto Front blending by recombining various solutions.

*Mutation operator*

To create the new chromosome, a mutation operation is carried out on the new offspring chromosome to alter one or more than one gene in the original chromosome. As a result, the mutation preserves population diversity and early convergence. In this work, the replacement of gene is done by using polynomial mutation operator Deb (2011). Polynomial mutation operator along with SBX crossover has been used in solving multi-objective service composition problem in smart agriculture as a result of the aforementioned study findings Deb (1995).

# 4. Simulation and result analysis

## 4.1. Experimental setup

As can be observed from the literature, the majority of researchers concentrated on reducing the use of fertilizers, improving crop production but combining these different services and then optimizing to achieve several targets in one run has not yet been investigated. In order to accomplish this, our study has taken fourteen atomic services required for the production of an apple orchard which is tabulated in Table 1. Per acres data has been taken for the simulation analysis. The proposed algorithm is run on a personal computer 12th Gen Intel Core (TM) i5 @ 2.00 GHz with 16 GB RAM on MATLAB R2013a version.

Fitness function is defined by taking time and cost as multiple objectives to be minimized. The search is stopped when the trade-off points remain constant for three consecutive iterations that is achieved in 1000 generations. Population size (represented by N) is defining maximum number of possible solutions to this service composition problem. Table 2 lists other more parameters that were used when running the simulations.

## 4.2. Experimental results

Simulation results for service composition optimization problem are shown in Figure 5 where the Pareto optimal solutions are obtained after running for defined number of iterations. It can be analysed from the results that iMOGA is providing diversified Pareto optimal solutions for multi-objective optimization problem, thereby, generating a trade off points between time and cost parameters in the field of smart agriculture. The solutions presented demonstrate the various choices farmers can make based on their diverse and complex requirements.

For the clear view of results obtained, statistical analysis of the simulation results is depicted in Table 3.

Table 1: Dataset of atomic services in smart agriculture

| Service Number | Atomic Service | Time(in days) | Cost(in thousand rupees) |
|---|---|---|---|
| 1 | Soil Testing and Analysis | 7 | 10 |
| | | 14 | 5 |
| 2 | Apple Variety Selection | 1 | 4 |
| | | 3 | 2 |
| 3 | Orchard Establishment | 30 | 200 |
| | | 90 | 50 |
| 4 | Tree Planting | 2 | 10 |
| | | 6 | 7 |
| 5 | Irrigation System Installation | 7 | 150 |
| | | 14 | 50 |
| 6 | Fertilizer Application | 14 | 100 |
| | | 28 | 50 |
| 7 | Pruning and Training | 7 | 30 |
| | | 21 | 15 |
| 8 | Pest and Disease Control | 14 | 100 |
| | | 28 | 70 |
| 9 | Crop Monitoring and Management | 60 | 50 |
| | | 120 | 20 |
| 10 | Harvesting | 14 | 70 |
| | | 28 | 35 |
| 11 | Sorting and Grading | 7 | 30 |
| | | 14 | 15 |
| 12 | Packaging and Labelling | 14 | 90 |
| | | 28 | 60 |
| 13 | Storage and Cold Chain Management | 60 | 50 |
| | | 120 | 25 |
| 14 | Marketing and Distribution | 90 | 80 |
| | | 180 | 40 |

Table 2: iMOGA parameters

| Parameters | Values |
|---|---|
| Number of Generations | 1000 |
| Population Size (N) | 200 |
| Selection Operator | Tournament Selection |
| Crossover Operator | SBX |
| Crossover Probability | 0.9 |
| Mutation Operator | Polynomial Mutation |
| Mutation Probability | 0.07 |

Table 3: Statistical results

| Statistics | Cost | Time |
|---|---|---|
| Min | 485.2 | 351.3 |
| Max | 875 | 630.7 |
| Mean | 629.9 | 468.6 |
| Mode | 485.2 | 351.3 |
| Median | 602.6 | 449.4 |
| Range | 389.8 | 279.4 |
| Std Dev | 113.8 | 83.8 |

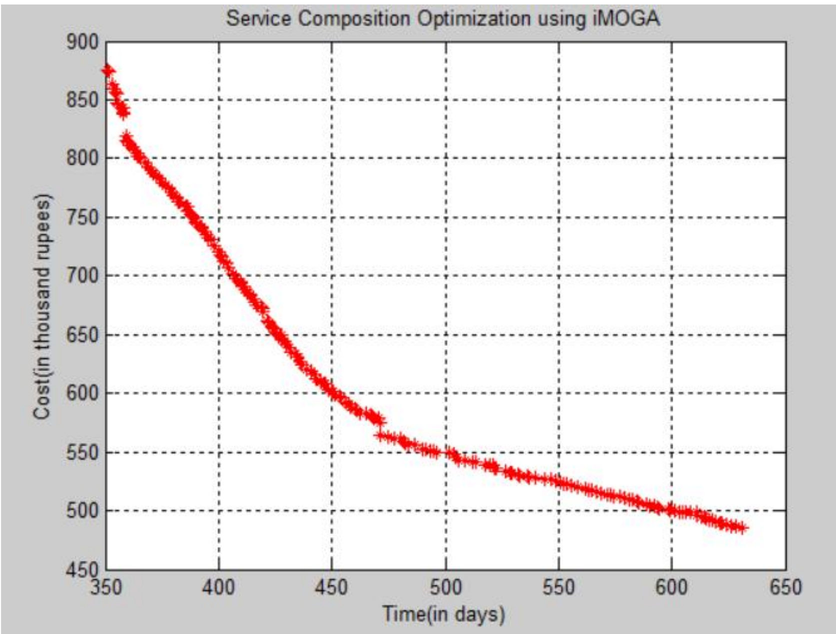


Figure 5: Pareto optimal solutions obtained using iMOGA

## 5. Conclusion

The research presented in this paper offers a fresh perspective on smart agriculture. Studies published in the literature till date have offered hopeful options for reducing the use of fertilizers, using UAV for monitoring crops and animal intrusion in the field, improving crop output, thereby, improving agriculture. However, no study has demonstrated how the user's complicated requests may be fulfilled without service composition. Thus, in order to advance smart agriculture, our effort has concentrated on composing the services and improving the QoS metrics. For this purpose, an improved genetic algorithm has been proposed by using SBX crossover operator and polynomial mutation for obtaining the best off-springs. For checking its efficiency, it is implemented on a dataset which takes the services associated with apple orchard production. It can be concluded from the simulation analysis that Pareto optimal solution set are the trade-off points that can further be used by the farmer as per his choice to fulfill their complex requirements. This effort is merely the beginning of service composition in smart agriculture; there is still a sizable amount of unfinished scope in this area. Work can be further extended by considering more QoS parameters together as well as using this concept in irrigation systems, weather forecasts and others by using machine learning and artificial neural networks.

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