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A Non-Linear Multi-Objective Service Composition Optimization for Smart Agriculture with Lagrange's Interpolation-based Evolutionary Algorithm

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ABSTRACT

Nowadays, digital technologies are being used to transform the agriculture sector into a more effective and environmentally friendly one by including technologies such as the Internet of Things (IoT), cloud computing, machine learning, and artificial intelligence (AI). These techniques are used to improve sustainability through more productive farming practices. Internet of Things is one of the most revolutionary techniques to provide improved agricultural services by efficiently managing and analyzing related processes. Traditional methods of a few agricultural services cannot satisfy the intricate needs of a growing population. Hence, a combination of multiple services or service composition is needed to meet user demand. This study addresses this problem by considering various agricultural services and integrating them into a composite service. The proposed work is divided into two phases. To ascertain the non-linear relationship between the cost and time of different services, Lagrange's interpolation model has been employed in the first phase. Subsequently, in the second phase, the Non-dominated Sorting Genetic Algorithm (NSGA-II), a multi-objective evolutionary algorithm, has been utilized to optimize the time and cost of services. The efficacy of the work has been evaluated by analyzing the results of the proposed method using the same multi-objective evolutionary technique, which has a linear relationship between the cost and time of various services.

***Index Terms*—**Lagrange's interpolation, multi-objective, pareto solutions, service composition, smart agriculture

I. INTRODUCTION

The primary necessity for all forms of production and the foundation of human life is agriculture. Every nation's national economy is built on this sector [1]. Population growth is positively correlated with an increase in the need for food production. The Food and Agriculture Organization (FAO) projects that by 2050, there will be 9.73 billion people on the planet, and by 2100, there will be 11.2 billion [2]. As a result, the world's population is growing, the climate is changing, and there aren't enough natural resources to support agriculture. Because numerous barriers to agricultural production lower crop productivity, there is a need to concentrate on surveying land resources for agricultural development. Furthermore, the climate influences agricultural yield and quality and may make soil more susceptible to desertification [3].

Through the integration of Information and Communications Technology (ICT), the agricultural industry is going through a revolution to usher in a new era of agriculture. This revolution boosts the yield of crops, enhances crop management decisions, lessens the negative environmental effects of agricultural practices by using fewer chemicals, and lowers expenses for things like water, electricity, and fuel. It is feasible owing to the emergence of new technologies like IoT, cloud computing, robots, and artificial intelligence that have the potential to completely alter farming. These technologies have a wide range of uses [4]. In smart agriculture, robots and drones are being used to increase the precision of herbicide, pesticide, and fertilizer applications along with other smart farming equipment. Farmers employ smart agriculture technologies to cultivate in a more organized manner and accurately forecast the results. From planting to sowing to harvesting, virtually every aspect of agriculture stands to gain from the impact of technology. As a result, the farmer has a thorough understanding of the land, which increases the production process's logic and reduces its arbitrary elements [5, 6]. Several domains and sub-domains of smart agriculture are shown in Fig. 1.

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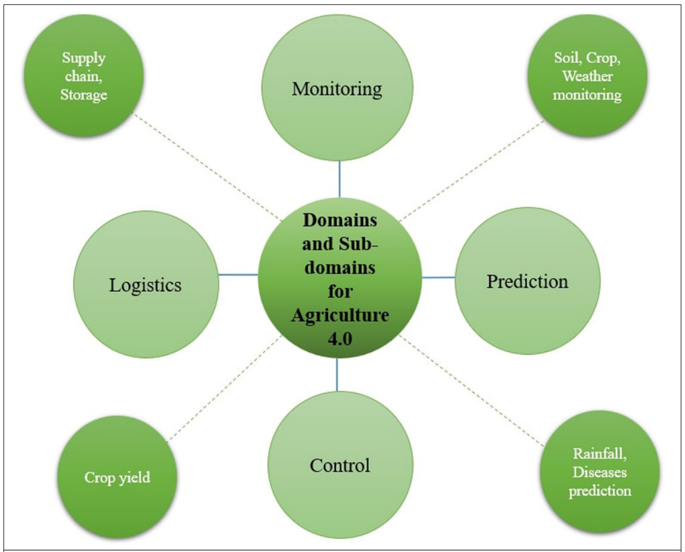

Fig. 1. Domains/sub-domains of smart agriculture.

Internet of Things can be defined as an interconnected system of smart devices and systems. These devices are utilized for sending and receiving vast volumes of data over an internet network with reduced human involvement. It is a smart and promising technology that provides innovative solutions that are beneficial in many fields, including smart homes, smart cities, smart healthcare, smart traffic management, smart agriculture, etc., as shown in Fig. 2 [7].

The use of IoT technology in agriculture has significantly transformed farming practices. With the use of IoT, all agricultural machinery and equipment may be connected to make predictable decisions regarding irrigation requirements, fertilizers, pesticide supply, crop harvesting etc. Internet of Things-based agricultural systems are applicable to diversified sub-domains such as smart farms, soil management, irrigation management, precision agriculture, animal farm monitoring systems, etc. All diversified sub-domains of smart agriculture applications are shown in Fig. 3.

In order to make agriculture more adaptable and in line with the demands of a growing population, nearly all applications of smart agriculture are discussed in the literature. However, no research on the optimization of service composition in smart agriculture has been discovered. The term "agriculture field" refers to a variety of services. It is often quite challenging to meet the demands of the growing population utilizing only a single service because they are becoming more and more complex every day. Internet of Things services fall under the categories of atomic or composite services [8]. An atomic service is a well-defined service that cannot be further separated whereas a composite service is a combination of services and is made from numerous different services that may give more extensive functionality to handle more complicated problems. For instance, a composite air conditioner could include temperature and humidity-based sensor services. A service composition method considers the functional characteristics of control flow and data flow to define a significant connection between services. Control flow refers to the order in which interactions happen, whereas data flow explains how data is transmitted between services. Any service composition problem's workflow can be defined in one of four possible ways: loop, parallel/fork, branch, and sequence [9]. They are becoming more and more crucial for IoT systems because they enable the integration of IoT services into a task to automate a particular context. A workflow that controls a room's temperature in response to fluctuations in the environment, for instance, can be automated in a smart home. Simultaneously, in the field of smart agriculture, a workflow can be established to analyze data from harvest sensors, forecast diseases, and take appropriate action. This situation gives rise to the emergence of the service composition problem in smart agriculture. A generalized workflow is shown in Fig. 4. It commences with task-1, uses branch conditioning to determine whether to execute task-2 or task-3, and then uses parallel mode to simultaneously conduct tasks 4 and 5. The workflow of tasks then comes to an end.

Each service in the IoT offers a certain functionality, and it is also possible for different services to offer the same functionality under different Quality of Service (QoS) attributes. To fulfilll the population's requirement, service discovery is the first step that is taken, in which

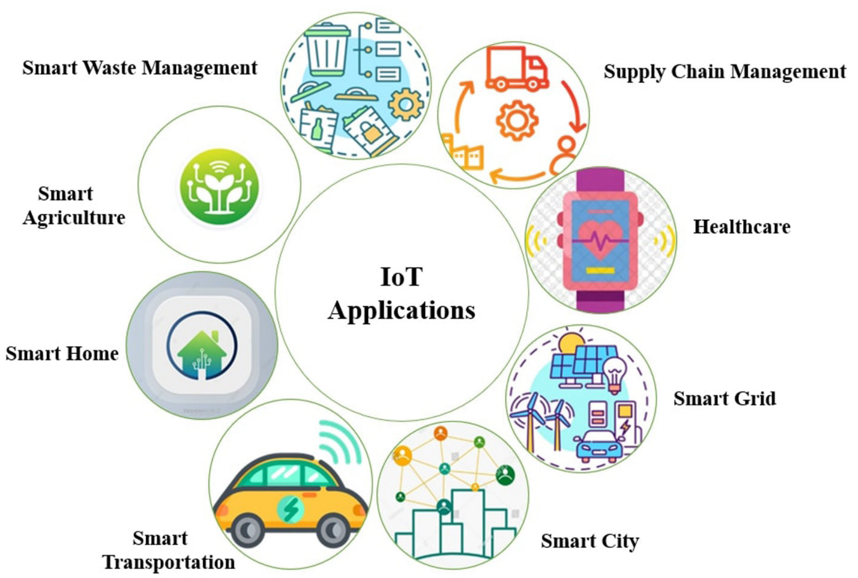

Fig. 2. Applications of Internet of Things in the real world.

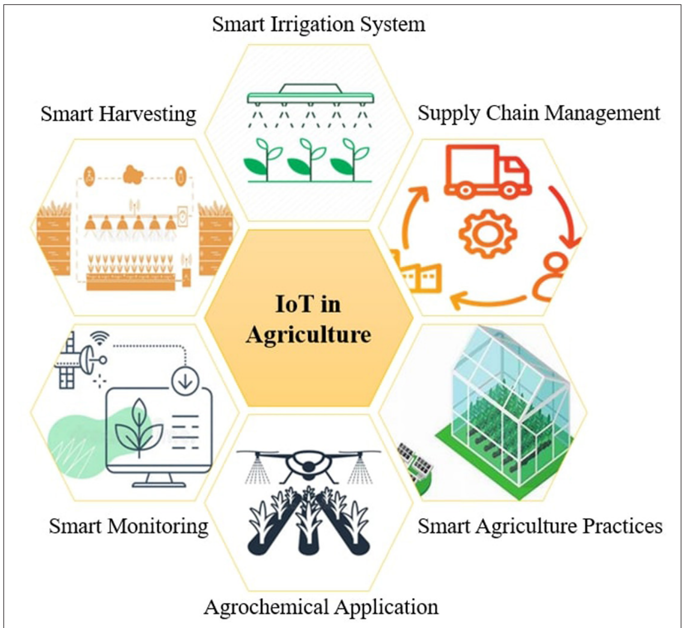

Fig. 3. Diversified sub-domains of smart agriculture.

it searches for the corresponding available services for a particular task. In the process of choosing the appropriate candidate services for a particular atomic service, QoS plays an important role. Next comes service selection, where services that satisfy the required QoS attributes are selected. Finally, services are composed that either employ local optimization or global optimization [10]. The growing number of devices is one of the biggest obstacles confronting IoT. It was already noted that IoT applications must be intelligent and operate without the need for human interaction. They ought to be able to think and act like people do. In such a search space, conventional search techniques are not meaningful. It would be practically difficult to look through every potential combination in search of the optimal solution. In reality, the service composition optimization problem is an NP-hard, non-deterministic polynomial-time problem [11]. Meta-heuristic approaches are thus helpful in solving problems of this nature. These approaches can be broadly classified into five categories: bio-inspired algorithms, physical algorithms, evolutionary algorithms, swarm intelligence algorithms, and miscellaneous algorithms [12]. These algorithms were primarily created to address problems with a single objective, but they can now be used to tackle problems with multiple objectives as well. The majority of real-world examples take into account competing goals, and maximizing one goal may have unfavorable effects on the other. Therefore, the answer to this problem is to have a collection of answers where each aim is achieved to some extent by each group of solutions without any of them dominating the others. Those are known as Pareto-optimal solutions [13, 14].

The goal is to consider multi-objective optimization of service composition, where the objectives of cost and time both have a nonlinear relationship between them. The objectives can be summed up as follows:

1) Service composition of various atomic services involved in apple crop production based on QoS attributes is done by taking cost and time as two objectives to be minimized.
2) Lagrange's interpolation method has been used to resolve the nonlinear relationship between the cost and time of each service.
3) Then, Non-dominated Sorting Genetic Algorithm II (NSGA-II) optimization was carried out to produce Pareto solutions.
4) A comparison of Lagrange's Interpolation-based NSGA-II approach (La-NSGA-II) has been done with Linear Interpolation-based NSGA-II (Li-NSGA-II) to see which one offers the best ideal solutions.
5) Statistical comparisons have been made to provide a clear picture of the outcomes.

The contribution of this paper lies in demonstrating how service composition optimization in smart agriculture applications can be achieved, enabling farmers to construct personalized agricultural plans based on their needs while maintaining an optimal balance between minimizing associated time and cost, ultimately contributing to profitable farming practices. Additionally, this work addresses the limitation of the work [2] where a linear relationship between the time and cost is assumed, which does not accurately represent real-world scenarios of smart agriculture. Rather, our work takes into account a more practical and non-linear relationship between these objectives.

The rest of the paper is divided as follows: Section 2 covers a few insights into the literature review in smart agriculture. The methodology and proposed framework are demonstrated in Section 3, whereas Section 4 presents the experimental setup and results of simulations. Finally, the complete paper is concluded in Section 5.

II. LITERATURE WORK

Agriculture-based IoT has become an essential research area due to the population's increasing demand for food. Numerous studies have

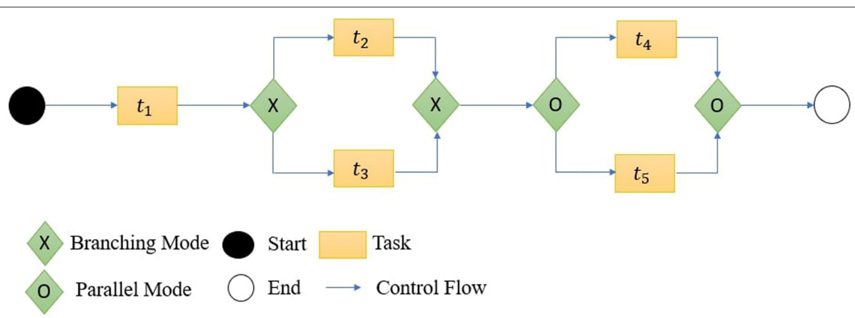

Fig. 4. A generalized workflow.

been conducted so far on smart agriculture. A few discussions from the literature in this smart agriculture field have been attempted to cover in this section.

P. P. Ray et al. [15] demonstrate a review of applications of IoT in smart agriculture, which includes pest and disease management, irrigation management, water quality management, soil monitoring, precision agriculture, cattle movement monitoring, and supply chain management. All IoT-supported technologies—hardware platform-based, wireless communication-based, and cloud-based—are discussed in detail along with a comparison of various IoT sensor systems available in the literature. The paper has been extended by providing case studies on seven different research topics in smart agriculture. The authors conclude the paper by highlighting a few key challenges that must be addressed, including node energy management, device heterogeneity, fault tolerance, and cost-effectiveness. Wen Tao et al. [16] also provides a systematic review of IoT applications in smart agriculture. Internet of Things sensors and various communication technologies used in agriculture are discussed in detail along with the challenges faced. The authors have concluded that cost, reliability of data, and standardization of IoT devices are major concerns that need to be dealt with. Another review provided by A. Srivastava et al. [17] not only discusses how IoT technology is solving many of the challenges faced by farmers in agriculture, but also explains that issues such as the cost of equipment, power saving of IoT nodes, data security, data privacy, and fault tolerance must be addressed for the effective implementation of technology to make agriculture smarter. E.G. Symeonaki et al. [18] present a review on the usage and impact of cloud-based IoT in climate-smart agriculture. A few applications such as cloud agro-systems and PDCA (plan-do-check-act) cycle-based agriculture cloud services are explained in detail. The authors found that, even though these technologies offer numerous advantages, they still lack integration in the experimental stage. Low-cost network coverage, farmer training centers, user-friendliness, and proper standardization for IoT devices are major problems that must be overcome. S. Wolfert et al. [19] provide a review of applications of big data in smart farming. They stated that its scope is influencing the entire food supply chain and providing predictive insights into farming. Aside from that, the considerable expansion of IoT devices is resulting in a vast volume of data with a wide variety that can be recorded, analyzed, and used for decision-making with the help of big data. The authors conclude the future of smart farming along a spectrum between two extreme scenarios: open collaborative systems and closed proprietary systems. A few issues have also been addressed, such as data privacy, security, openness of platforms, and intelligent analytics. A. Sharma et al. [20] demonstrate machine learning applications in smart farm management. They have explained that deep learning algorithms such as convolutional neural networks, support vector machines, random forests, and decision trees are good for recognizing plant diseases, whereas regression methods are best for determining weather forecasts, yield production, and soil properties. Smart harvesting, irrigation systems, robots, and drones all play vital roles in minimizing human labor. They have concluded the paper study by mentioning NLP-based chatbots and hybrid algorithms as potential solutions for making this sector more sustainable.

It can be seen that the review papers presented in the literature are focused on the use of modern technologies like machine learning, big data, IoT, and cloud computing to increase yield and make the agriculture sector smarter. Due to the increase in IoT devices, data are increasing day by day, so there is a need to optimize this huge data to extract the desired information. Various meta-heuristic approaches have been implemented by researchers to optimize the data generated by smart devices.

G. Sushanth et al. [21] have developed an IoT-based smart agriculture system in which decisions on watering plants are made by monitoring humidity, temperature, and moisture. A motion detector sensor is also used to sense the movement of animals in the field using an Arduino board, and notifications are sent to the farmer by SMS using Wi-Fi/3G/4G. Similarly, J. Muangprathub et al. [22] propose a wireless sensor-based system for optimally watering crops. This framework includes hardware, web-based applications, and mobile applications as three primary components. Data from soil moisture sensors are collected using a hardware module, and a web-based application has been created to manipulate the data gained through data mining, before using a mobile application to water the field either automatically or manually. The real experiment was carried out in three distinct villages in Thailand's Makhamtia area, using lime and home-grown vegetables as crops to be evaluated. The research demonstrated that the optimal temperature for good productivity of lime and home-grown vegetables in that area is within 72–81% and between 29 degrees and 32 degrees, respectively. S.K. Roy et al. [23] develops an architecture for outdoor and terrace gardening for predicting rainfall using a genetic algorithm with real data. In the case of terrace gardening, if rainfall is not predicted, a sensor-based system checks whether soil moisture is below a pre-defined threshold and, if so, a signal is sent to the relay and GSM module via Arduino UNO to turn on the water pump until the soil sensor reaches its threshold value. In outdoor areas, the signal from the moisture sensor is transferred to the smartphone through the ESP8266 Wi-Fi module, which leads the UAV to spray water in the specific region. A. Saha et al. [24] detail how researchers analyze IoT sensor data with machine learning and meta-heuristic approaches to obtain near-optimal solutions in smart transportation, smart cities, smart homes, smart agriculture, smart healthcare, smart parking, smart environment, and smart waste management. The authors have surveyed Ant Colony Optimization (ACO), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) algorithms used in conjunction with machine learning approaches. They emphasize that machine learning with meta-heuristics approaches is the future of optimization for IoT-based applications.

J.C. Alonso Campos et al. [25] demonstrated an NSGA-II algorithm-based system that minimizes energy costs while maximizing the pressure demands of an irrigation schedule from a pumping station. They explored five diverse scenarios, comparing both single-objective and multi-objective optimization approaches, as well as parallel and single-threaded evaluations. Their findings indicate that the multi-objective approach achieves better results than the single-objective approach within fewer iterations. Additionally, they found that parallel evaluation does not affect the algorithm's convergence rate but speeds up the process by increasing computational capacity. The authors concluded that a cost reduction of approximately 6–7% was achieved with parallel evaluations when compared to single-threaded evaluations.

With an emphasis on agricultural output and environmental impact, I. Kropp et al. [26] sought to optimize irrigation and fertilizer scheduling for sustainable intensification. The research combined the

Decision Support System for Agrotechnology Transfer crop model with the Unified Non-dominated Sorting Genetic Algorithm-III (U-NSGA-III), using multi-objective optimization strategies. The system discovered irrigation and nitrogen strategies that decreased water consumption by 48%, nitrogen leaching by 51%, and nitrogen usage by 26%.

S. Sharma et al. [27] have proposed a fuzzy inference system to check the impact of uncertainties on the time and cost of various composite services involved in apple plant production and optimize those services using NSGA-II, resulting in diversified optimal solutions. However, one limitation of this work is that it considers a linear relationship between the time and cost objectives, which does not accurately represent real-world scenarios of smart agriculture applications.

Thus, the work presented in this paper proposes a Lagrange interpolation-based NSGA-II optimization approach for implementing service composition in smart agriculture, where Lagrange's interpolation is used to define the non-linear relationship between the time and cost of each service.

III. PROPOSED FRAMEWORK

This section introduces the concepts of service composition, Lagrange's interpolation, and optimization methods for use in smart agricultural challenges. Each of the three concepts is well explained concerning the proposed architecture as well as the proposed La-NSGA-II.

A. Service Composition Model

The term "service composition" can be defined as a combination of numerous services. There is no set method for defining the service composition that must match user criteria. However, web services are defined by several QoS characteristics such as scalability, availability, time, throughput, and cost. User requests are routed through a service pipeline. Then, for each atomic service, a candidate services list is created. These services are functionally equivalent to the user's request, but each atomic service has a unique set of QoS criteria [28].

The goal of this research is to provide an optimum solution for apple crop production to tackle the multi-objective problem of related cost and time in the growing environment. Assume that there are "t" services engaged in cultivating apple harvests, each of which is treated as an atomic service with unique QoS metrics. This notion can be specified using the following equations, whose symbol descriptions are given in Table I.

TABLE I. DESCRIPTION OF NOTATIONS AND SYMBOLS USED IN EQUATIONS

Symbol	Description
G	Atomic services
g_i	ith atomic service
CS_{ik}	kth candidate service belonging to ith atomic service
Qos	Quality of service parameter
C	Final composite service
CS^*_{tj}	tth possible options of all jth candidate services

Equation (1) provides the atomic services, and (2) identifies the candidate services that belong to those atomic services [29].

$$G = \{g_1, g_2, g_3, \ldots, g_i, \ldots, g_t\} \tag{1}$$

$$g_i = \left\{CS_{i1}, CS_{i2}, \ldots, CS_{ij}, \ldots, CS_{ik}\right\} \quad i = 1,2,3,\ldots..t \tag{2}$$

Equation (3) shows how candidate services are influenced by non-functional QoS parameters as follows:

$$CS_{ij} = \left\{QoS\left(CS_{ij}\right)\right\} \qquad j = 1,2,3,\ldots..k \tag{3}$$

Thus, the final service composition can be determined by (4):

$$C = \{CS^*_{1j}, CS^*_{2j}, CS^*_{3j}, \ldots CS^*_{tj}\} \tag{4}$$

B. Phase-1: Lagrange's Interpolation

Lagrange interpolation can find a polynomial that exactly takes the value that has been observed at each observed point [30].

There is a unique k-degree polynomial Lk (x) satisfying L_k $(x) = f(x_i)$, given $k+1$ different interpolation points x_i where ($i = 0, 1, 2, \ldots$ k) and corresponding numbers $f(x_i)$ who may or

may not be samples of a function f. Let

$$l_i\left(x\right) = \prod_{j=0, j\neq 1}^{k} \frac{x - x_j}{x_i - x_j}, \qquad \left(i = 0,1,\ldots..k\right) \tag{5}$$

Equations (5) and (6) are showing $l_i(x)$ which is an n-degree polynomial that also satisfies

$$l_i\left(x_j\right) = \begin{cases} 1, & j = 1 \\ 0, & j \neq 1 \end{cases}, \qquad \left(i = 0,1,\ldots..k\right) \tag{6}$$

The k-degree polynomial $L_k(x)$ can thus be expressed in Lagrange form as shown in equation (7).

$$L_k\left(x\right) = \sum_{i=0}^{k} f\left(x_i\right) l_i\left(x\right) \tag{7}$$

Selecting any $k+1$ points from a k——degree polynomial function gives the function expression [31].

C. Phase-2: Non-dominated Sorting Genetic Algorithm-II

Agricultural systems are multi-functional because their behavior involves consideration of variables such as the utilization of energy, labor time, labor cost, maintenance cost, and implementation costs as well. As a result, several evolutionary approaches can be used to evaluate various optimization goals and find the optimum solution.

Using meta-heuristic evolutionary computational algorithms to find optimal solutions is the best way. One of the most popular meta-heuristic evolutionary algorithms is NSGA-II, proposed by K. Deb in 2002 [32]. The method uses non-dominated sorting and the crowding distance idea to locate a collection of uniformly distributed solutions and to boost diversity for any multi-objective problem. To begin the process, any random collection of individuals is sorted using a non-dominated sorting approach. In this stage, all non-dominated

NSGA-II Algorithm

Begin
  Solution Representation, $t \coloneqq 1$, Maximum allowed generation = T;
  Initialize random population $P(t)$;
  Evaluate $P(t)$ and assign rank using dominance depth method and diversity using crowding distance method to P(t);
  while t < T do
    $M(t) \coloneqq Selection\ (P(t))$; %Crowded Binary Tournament Selection%
    $Q(t) \coloneqq variation\ (M(t))$; % Crossover and Mutation%
    Evaluate $Q(t)$; % Offspring%
    Merge population $\hat{P}(t) = (P(t) \cup Q(t))$;
    Assign Rank using dominance depth method and diversity using Crowding distance operator to $\hat{P}(t)$;
    $P(t+1) \coloneqq Survivor\ (\hat{P}(t))$;
    $t \coloneqq t+1$;
  end while
End

Fig. 5. Non-dominated Sorting Genetic Algorithm-II.

solutions are ranked first and are temporarily removed from the initial population. Similarly, the following set of solutions is placed second. This approach is repeated until all viable sets of solutions have been ranked. The parent population is formed in the following step by utilizing the binary tournament selection method on the existing population. The binary tournament's selection method entails selecting any two solutions from the existing population and then ranking them. The better option is not necessarily on the same side. In that case, the crowding distance concept is used. Following the selection of parents, the population of parents is subjected to the crossover and mutation operators to create offspring. The next population is made up of the best solution from the combined population of parents and children. This process will continue until a termination condition is met. It can run for a defined number of generations or until all potential solutions are explored. Figure 5 defines the pseudocode of the NSGA-II algorithm [33].

D. Proposed Architecture

The architecture proposed for solving the optimization service composition problem is shown in Fig. 6. It has five layers: sensor layer, network layer, cloud layer, service composition layer, and application (user interface) layer.

1) Sensor Layer—This layer is responsible for collecting data from several IoT sensors such as soil sensors (temperature sensors, moisture sensors, motion sensors), cameras, and so on.
2) Network Layer—This layer provides a communication link between the data collected from sensors and the servers present. For example, Bluetooth, Zigbee, LoRa, LoWPAN, Wi-Fi, etc.
3) Cloud Layer—It serves as virtual storage and offers a variety of sub-services via several private, public, or hybrid clouds. Software as a Service (SaaS), Infrastructure as a Service (IaaS), and Platform as a Service (PaaS) are all available. Our work has taken 14 services related to apple crop production from the cloud and defined them in a sequential workflow.
4) Service Composition Layer—This is the architecture's most important layer. It composes several sub-services in response to the user's demands to meet their complex requirements. Initially, services in the cloud are discovered; next, required services are selected from available cloud options, and finally, services are composed. This layer is connected with optimization algorithms in our work (here, the NSGA-II technique is employed as an optimization approach) to optimize the composite services based on the user's demands.

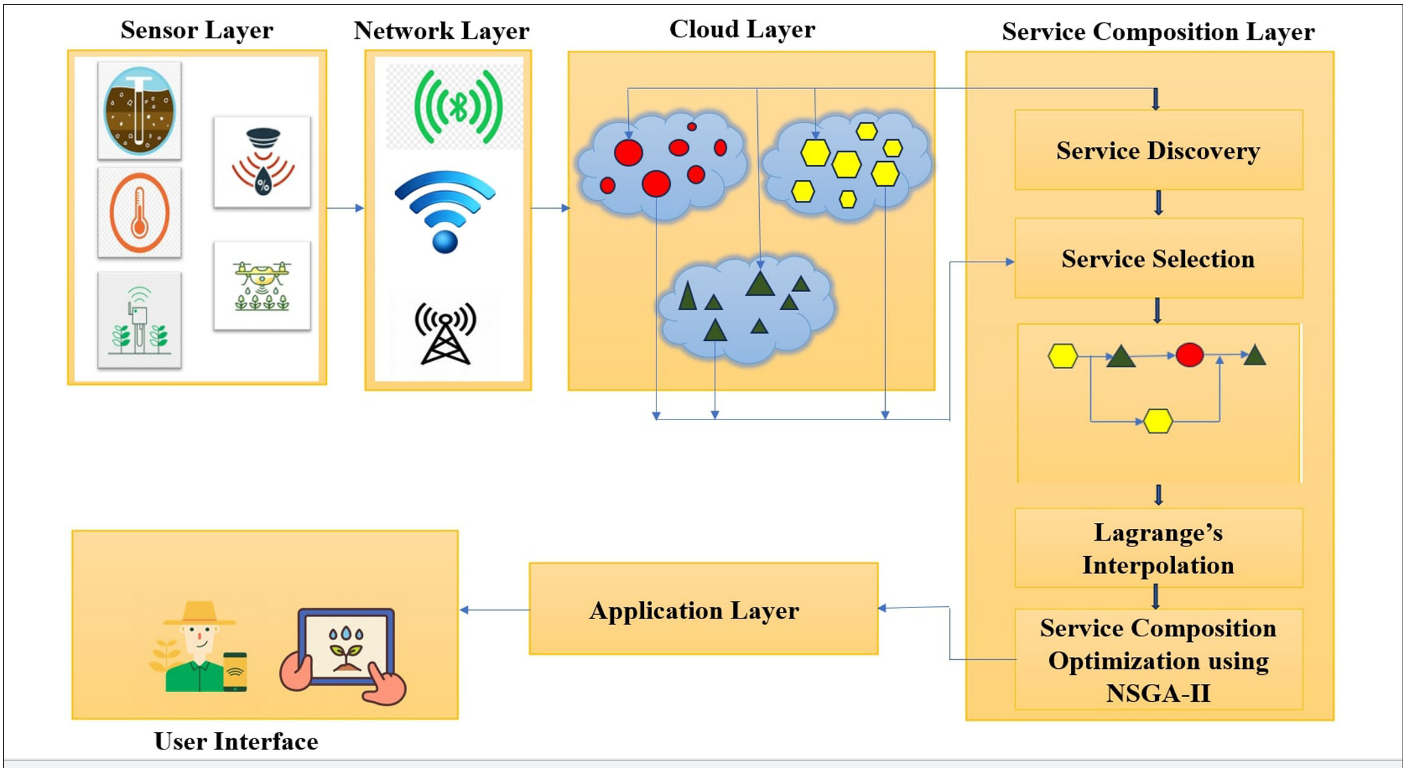

Fig. 6. Proposed architecture for service composition optimization.

5) Application Layer—The services compiled in the previous phase are required to be made available to end users via the application layer.

E. Lagrange's Interpolation-based Non-dominated Sorting Genetic Algorithm-II Approach

This paper has presented a novel La-NSGA-II for service composition in smart agriculture. Initially, all the genetic operators, such as population size, number of generations, crossover, and mutation probability, are initialized. Then, during the population initialization phase, Lagrange's interpolation is used to determine the cost of each service corresponding to the random time generated between the minimum and maximum time of each service. The process is further followed by generating non-dominated solutions and calculating crowding distance. Finally, selection, crossover, and mutation operations are done to generate the offspring. The whole process is repeated until the convergence criterion is satisfied. The steps involved are shown in the flow chart illustrated in Fig. 7.

IV. EXPERIMENTAL SETUP AND RESULT ANALYSIS

This section provides a detailed overview of solution encoding, simulation parameters, dataset used, and result analysis of the proposed framework.

A. Solution Encoding

Our work has focused on choosing 14 atomic services along with their corresponding candidate services for apple crop production. There exists a set of solutions "S" for the population "P" and it is described by using a string as shown in Fig. 8. The string size is equivalent to the total number of services taken, with indices representing the corresponding number and their values describing the particular candidate of the given service. For example, in Fig. 8, a string having an index equal to 6, defining the third candidate of service-6, has been finalized to become a part of the solution set.

B. Dataset Description

It can be observed from the literature that the majority of research is carried out on increasing crop yield, minimizing the use of fertilizers and pesticides, and using UAVs (Unmanned Aerial Vehicles) for crop monitoring. However, combining services and optimizing them with multiple objectives to achieve the desired output in one run is the least explored concept yet. Thus, to accomplish this, a dataset related to apple plant production from a survey of farmers in the Shimla and Kullu regions of an Indian state is taken [34]. Table II shows a tabular description of the dataset in detail.

C. Parameters Description

The proposed algorithm is executed on a personal computer running the MATLAB R2013a version on a 12th Gen Intel Core (TM) i5 @ 2.00 GHz with 16 GB RAM. Table III shows the parameters utilized to validate the performance of the proposed algorithm. As a multi-objective optimization, the fitness function is determined by minimizing cost and time. The search is stopped when the trade-off points remain constant for three consecutive iterations, which is achieved in the 1000 generations.

D. Results and Comparative Analysis

Since the goal of this study is to optimize the cost and time of a service composition problem in smart agriculture, this paper has checked the impact of non-linearities on cost. The whole problem is solved using La-NSGA-II approach. Pareto optimal solutions obtained are

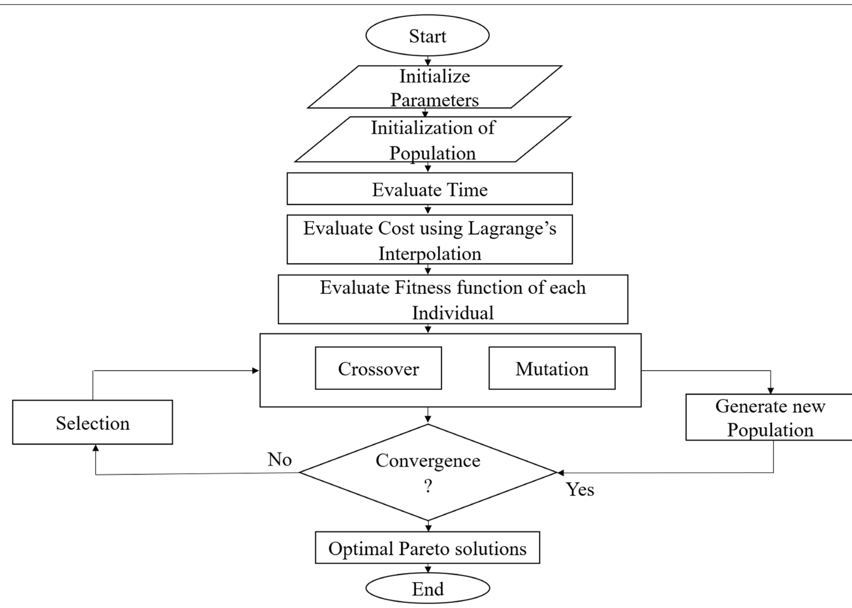

Fig. 7. Flow chart for the proposed La-Non-dominated Sorting Genetic Algorithm-II.

S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}
8	3	54	4	10	21	15	27	91	23	13	17	89	167

Fig. 8. Solution encoding for fourteen atomic services with time as an objective function.

TABLE II. DATASET FOR APPLE CROP CULTIVATION

Service Number	Atomic Services	Time (in days)	Cost (in rupees)
1	Soil testing and analysis	7	10,000
		8	9500
		10	7000
		13	5700
		14	5000
2	Apple variety selection	1	4000
		1.5	3700
		2	3000
		2.5	2400
		3	2000
3	Orchard establishment	30	2,00,000
		45	1,74,000
		54	1,25,000
		77	65,000
		90	50,000
4	Tree planting	2	10,000
		3	9600
		4	8200
		5	7400
		6	7000
5	Irrigation system installation	7	1,50,000
		9	1,27,000
		10	97,000
		13	75,000
		14	50,000
6	Fertilizer application	14	1,00,000
		17	96,000
		21	81,000
		25	73,000
		28	50,000
7	Pruning and training	7	30,000
		12	27,000
		15	21,000
		19	19,000
		21	15,000

(*Continued*)

TABLE II. DATASET FOR APPLE CROP CULTIVATION (CONTINUED)

Service Number	Atomic Services	Time (in days)	Cost (in rupees)
8	Pest and disease control	14	1,00,000
		17	97,000
		21	87,000
		27	76,000
		28	70,000
9	Crop monitoring and management	60	50,000
		77	46,000
		91	34,000
		111	25,000
		120	20,000
10	Harvesting	14	70,000
		19	68,000
		23	49,000
		25	41,000
		28	35,000
11	Sorting and grading	7	30,000
		8	28,000
		11	26,000
		13	19,000
		14	15,000
12	Packaging and labeling	14	90,000
		17	88,000
		22	76,000
		26	69,000
		28	60,000
13	Storage and cold chain management	60	50,000
		72	48,000
		89	42,000
		107	29,000
		120	25,000
14	Marketing and distribution	90	80,000
		97	78,000
		122	61,000
		167	44,000
		180	40,000

TABLE III. SIMULATION PARAMETERS OF NON-DOMINATED SORTING GENETIC ALGORITHM-II

S. No.	Parameters	Values
1	Population size	200
2	No. of generations	1000
3	Crossover probability (P_c)	0.9
4	Mutation probability (P_m)	0.07

shown in Fig. 9. It can be analyzed that the profile is moving toward the coordinate axes, minimizing both cost and time while achieving trade-off points. Additionally, to demonstrate the efficacy of the suggested approach, it has been examined with a Li-NSGA-II approach, which illustrates a linear cost–time relationship. A comparison of both approaches is illustrated in Fig. 10. Comparative study reveals that La-NSGA-II has a lower standard deviation value than Li-NSGA-II, indicating more reliable and consistent solutions. Further evidence that the algorithm is outperforming Li-NSGA-II is provided by the fact that the mean, median, and mode values of La-NSGA-II are, on average, 1% lower in time and cost objectives (refer to Table IV). Thus, it is apparent that La-NSGA-II is yielding more diversified Pareto optimal solutions.

E. Statistical Analysis

Statistical analysis is the most effective way to comprehend the results thoroughly. Therefore, Table IV provides a statistical summary of both La-NSGA-II and Li-NSGA-II, allowing for the quantitative evaluation of both approaches. As can be observed, La-NSGA-II is reaching a mean value of 476.3, whereas La-NSGA-II is getting a mean value of 456.1. Additionally, the median value for Li-NSGA-II is 446, and for La-NSGA-II is 425.3, indicating that the latter has better solutions than the former. Moreover, the minimum and maximum values for Li-NSGA-II are 335.1 and 689.4, respectively, whereas for La-NSGA-II they are 328 and 688.6, respectively. Furthermore, the difference between the standard deviations of both approaches demonstrates that La-NSGA-II is producing more consistent outcomes that demonstrate stability throughout the optimization process.

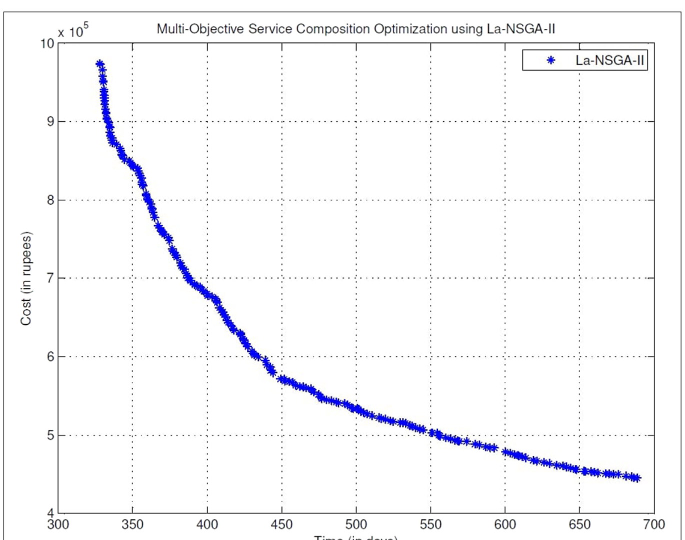

Fig. 9. Pareto optimal solutions obtained from Lagrange's interpolation-based Non-dominated Sorting Genetic Algorithm-II approach.

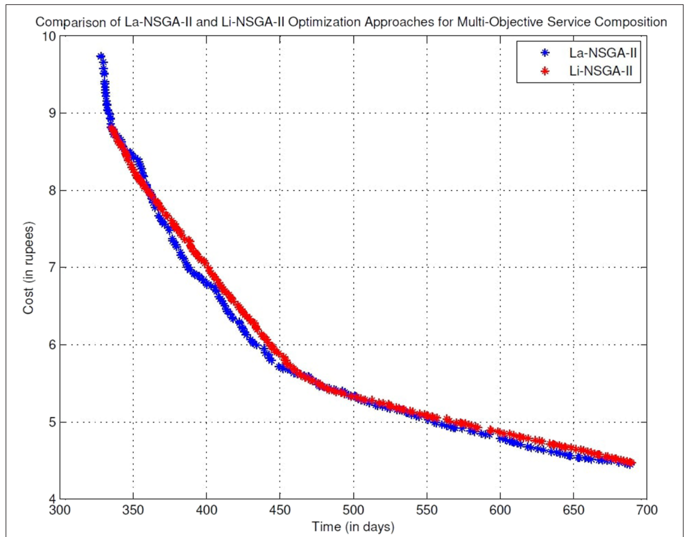

Fig. 10. Comparative analysis of Pareto solutions obtained from Lagrange's interpolation-based Non-dominated Sorting Genetic Algorithm-II and Linear interpolation-based Non-dominated Sorting Genetic Algorithm-II.

V. CONCLUSION

This study presents a novel approach to addressing non-linearities in multi-objective service composition optimization in smart agriculture. It has taken two scenarios. The first scenario has considered

TABLE IV. STATISTICAL ANALYSIS

Algorithm	Statistics	Time	Cost
La-NSGA-II	Min	328	4.451e+05
	Max	688.6	9.737e+05
	Mean	456.1	6.504e+05
	Median	425.3	6.188e+05
	Mode	328	4.451e+05
	Standard deviation	106.5	1.576e+05
	Range	360.6	5.286e+05
Li-NSGA-II	Min	335.1	4.473e+05
	Max	689.4	8.805e+05
	Mean	476.3	6.21e+05
	Median	446	5.937e+05
	Mode	335.1	4.473e+05
	Standard deviation	106.8	1.32e+05
	Range	354.3	4.331e+05

a non-linear relationship between cost and time by implementing Lagrange's Interpolation and analyzing the corresponding Pareto optimal solutions. To assess the impact of non-linearities on a fitness function, the same experiment has been conducted by considering a linear relationship between both objectives termed Li-NSGA-II. The overall setup is tested on a dataset comprising 14 services pertaining to apple plant production. It has been concluded that non-linearities show a significant impact on the Pareto optimal solutions. This approach to composing and optimizing services can help farmers construct personalized agricultural plans based on their demands, resources, and ability to maintain an optimal balance between minimizing time for operations and lowering associated costs. It will further contribute to profitable and sustainable farming practices. However, there are a few limitations to this study. The dataset used for this study, specifically focusing on apple crop production in the Kullu and Shimla regions, may not provide direct generalizability for other regions or agricultural contexts. Furthermore, other important considerations like energy consumption, environmental impact, and crop yield quality are omitted due to its emphasis on time and cost optimization only. Additionally, the proposed system's static nature may not fully account for the dynamic nature of agricultural environments, which include changes in weather patterns, pest attacks, and market prices. Future research directions encompass exploring other meta-heuristic algorithms, hybrid algorithms, and neural networks. To further enhance this work, it might be modeled as a discrete optimization problem to reflect real-world scenarios and incorporate various other constraints.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – B.K.P.; Design – B.K.P.; Supervision – B.K.P.; Resources – S.S.; Materials – S.S.; Data Collection and/or Processing – S.S.; Analysis and/or Interpretation – S.S.; Literature Search – S.S.; Writing – S.S.; Critical Review – R.K.

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REFERENCES

1. J. Yang, A. Sharma, and R. Kumar, "IoT-based framework for smart agriculture," *Int. J. Agric. Environ. Inf. Syst.*, vol. 12, no. 2, pp. 1–14, 2021. [CrossRef]
2. Food and Agriculture Organization of United Nations, "The future of food and agriculture–trends and challenges," 2017. Available: https://www.fao.org/3/i6583e/i6583e.pdf. .[Accessed: Jun. 2024].
3. M. K. Abdel-Fattah *et al.*, "Quantitative evaluation of soil quality using principal component analysis: The case study of El-Fayoum Depression Egypt," *Sustainability*, vol. 13, no. 4, p. 1824, 2021. [CrossRef]
4. B. B. Sinha, and R. Dhanalakshmi, "Recent advancements and challenges of Internet of Things in smart agriculture: A survey," *Future Gener. Comput. Syst.*, vol. 126, pp. 169–184, 2022. [CrossRef]
5. M. A. Ferrag, L. Shu, H. Djallel, and K.-K. R. Choo, "Deep learning-based intrusion detection for distributed denial of service attack in agriculture 4.0," *Electronics*, vol. 10, no. 11, p. 1257, 2021. [CrossRef]
6. M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Enhancing smart farming through the applications of Agriculture 4.0 technologies," *Int. J. Intell. Netw.*, vol. 3, pp. 150–164, 2022. [CrossRef]
7. S. Sharma, B. K. Pathak, and R. Kumar, "Understanding of network resiliency in communication networks with its integration in Internet of things-A Survey," *Electrica*, vol. 23, no. 2, pp. 318–328, 2023. [CrossRef]
8. D. Arellanes, and K.-K. Lau, "Evaluating IoT service composition mechanisms for the scalability of IoT systems," *Future Gener. Comput. Syst.*, vol. 108, pp. 827–848, 2020. [CrossRef]
9. P. Asghari, A. M. Rahmani, and H. H. S. Javadi, "Privacy-aware cloud service composition based on QoS optimization in Internet of Things," *J. Ambient Intell. Hum. Comput.*, vol. 13, no. 11, pp. 5295–5320, 2022. [CrossRef]
10. A. Souri, and M. Ghobaei-Arani, "Cloud manufacturing service composition in IoT applications: A formal verification-based approach," *Multimedia Tool. Appl.*, vol. 81, no. 19, pp. 26759–26778, 2022. [CrossRef]
11. H. Jin, C. Jiang, S. Lv, H. He, and X. Liao, "A hybrid teaching-learning-based optimization algorithm for QoS-aware manufacturing cloud service composition," *Computing*, vol. 104, no. 11, pp. 2489–2509, 2022. [CrossRef]
12. V. Sharma, and A. K. Tripathi, "A systematic review of meta-heuristic algorithms in IoT based application," *Array*, vol. 14, p. 100164, 2022. [CrossRef]
13. Y. Hua, Q. Liu, K. Hao, and Y. Jin, "A survey of evolutionary algorithms for multi-objective optimization problems with irregular pareto fronts," *IEEE CAA J. Autom. Sin.*, vol. 8, no. 2, pp. 303–318, 2021. [CrossRef]
14. S. Peng, and T. Guo, "Multi-objective service composition using enhanced multi-objective differential evolution algorithm," *Comp. Intell. Neurosci.*, vol. 2023, no. 1, p.8184367, 2023. [CrossRef]
15. P. P. Ray, "Internet of things for smart agriculture: Technologies, practices and future direction," *J. Ambient Intell. Smart Environ.*, vol. 9, no. 4, pp. 395–420, 2017. [CrossRef]
16. W. Tao, L. Zhao, G. Wang, and R. Liang, "Review of the internet of things communication technologies in smart agriculture and challenges," *Comput. Electron. Agric.*, vol. 189, p. 106352, 2021. [CrossRef]
17. A. Srivastava, and D. K. Das, "A Comprehensive review on the application of Internet of Thing (IoT) in smart agriculture," *Wirel. Personal Commun.*, vol. 122, no. 2, pp. 1807–1837, 2022. [CrossRef]
18. E. G. Symeonaki, K. G. Arvanitis, and D. D. Piromalis, "Cloud computing for IoT applications in climate-smart agriculture: A review on the trends and challenges toward sustainability," in *Innovative Approaches and Applications for Sustainable Rural Development*, Eds. Cham: Springer, 2019, pp. 4301–4304. [CrossRef]
19. S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming – A review," *Agric. Syst.*, vol. 153, pp. 69–80, 2017. [CrossRef]
20. A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," *IEEE Access*, vol. 9, pp. 4843–4873, 2021. [CrossRef]
21. G. Sushanth, and S. Sujatha, "IoT based smart agriculture system," International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, India, 2018, 2018, pp. 1–4. [CrossRef]
22. J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, "IoT and agriculture data analysis for smart farm," *Comput. Electron. Agric.*, vol. 156, pp. 467–474, 2019. [CrossRef]
23. S. K. Roy, and D. De, "Genetic Algorithm based Internet of Precision Agricultural Things (IopaT) for agriculture 4.0," *Internet Things*, vol. 18, p. 100201, 2022. [CrossRef]
24. A. Saha, C. Chowdhury, M. Jana, and S. Biswas, "IoT sensor data analysis and fusion applying machine learning and meta-heuristic approaches," in *Stud. Comp. Intell.* Cham: Springer, pp. 441–469, 2021. [CrossRef]
25. J. C. Alonso Campos, M. A. Jiménez-Bello, and F. Martínez Alzamora, "Real-time energy optimization of irrigation scheduling by parallel multi-objective genetic algorithms," *Agric. Water Manag.*, vol. 227, p. 105857, 2020: [CrossRef]
26. I. Kropp *et al.*, "A multi-objective approach to water and nutrient efficiency for sustainable agricultural intensification," *Agric. Syst.*, vol. 173, pp. 289–302, 2019. [CrossRef]
27. S. Sharma, B. K. Pathak, and R. Kumar, "Multi-objective service composition optimization in smart agriculture using fuzzy-evolutionary algorithm," *Oper. Res. Forum* SN Operations Research Forum, vol. 5, no. 2, 2024. [CrossRef]
28. N. Kashyap, A. C. Kumari, and R. R. Chhikara, "Service composition in IoT using genetic algorithm and particle swarm optimization," *Open Comput. Sci.*, vol. 10, no. 1, pp. 56–64, 2020. [CrossRef]

29. P. Kumar, S. Shetty, D. R. Janardhana, and A. P. Manu, “QoS aware service composition in IoT using heuristic structure and genetic algorithm,” *Mathematical Statistician and Engineering Application*, vol. 71, no. 3, pp. 750–766, 2022. [CrossRef]
30. Z.-F. Wang, Y.-W. Ren, Z.-Y. Cao, and L.-Y. Zhang, “LRBFT: Improvement of practical Byzantine fault tolerance consensus protocol for blockchains based on Lagrange interpolation,” *Peer-to-Peer Netw. Appl.*, vol. 16, no. 2, pp. 690–708, 2023. [CrossRef]
31. A. Fu, X. Zhang, N. Xiong, Y. Gao, H. Wang, and J. Zhang, “VFL: A verifiable federated learning with privacy-preserving for big data in industrial IoT,” *IEEE Trans. Ind. Inform.*, vol. 18, no. 5, pp. 3316–3326, 2022. [CrossRef]
32. H. Ghiasi, D. Pasini, and L. Lessard, “A non-dominated sorting hybrid algorithm for multi-objective optimization of engineering problems,” *Eng. Optim.*, vol. 43, no. 1, pp. 39–59, 2011. [CrossRef]
33. K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multi-objective genetic algorithm: NSGA-II,” *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, 2002. [CrossRef]
34. S. Sharma, R. Kumar, and B. K. Pathak, “Analyzing the impact of uncertainties with fuzzy logic on service composition in smart agriculture,” International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, vol. 2024, 2024, pp. 1–5. [CrossRef]

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