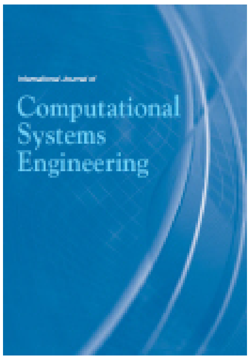

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Chaoqun Huang, Qianlan Liu, Wenbin Qian

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The regulation method of agricultural internet of things services based on dynamic multi-objective optimisation

Chaoqun Huang*

School of Economics and Management,
Hunan University of Science and Engineering,
Yongzhou 425199, China
Email: ChaoqunHuang_@outlook.com
*Corresponding author

Qianlan Liu

School of Information Engineering,
Hunan University of Science and Engineering,
Yongzhou 425199, China
Email: liuqianlan_nancy@163.com

Wenbin Qian

School of Economics and Management,
Hunan University of Science and Engineering,
Yongzhou 425199, China
Email: eye186@eyou.com

Abstract: In response to the complex and ever-changing environmental impacts faced in the current construction of agricultural internet of things technology. A supervision method for agricultural internet of things services based on dynamic multi-objective optimisation is proposed. The poor dynamic capabilities in the intelligent agricultural internet of things can be solved by constructing a decomposed algorithm. According to the findings, it performed well in convergence, hypervolume value and extreme point accuracy. This algorithm could propose the optimal service matching scheme based on a single-target service strategy, with good diversity. In addition, the calculation time of this algorithm was relatively short. Compared with the other two comparison methods, it led by 3.59s and 8.39s, respectively. Meanwhile, the average service cost of this algorithm was relatively low. It reduced the average service cost by 16.39% and 25.00%, respectively. Overall, the dynamic multi-objective optimisation agricultural internet of things regulation method has performed well in practical application, significantly improving accuracy. It can provide the highest quality service at the lowest cost within the shortest service time. In summary, this research provides an effective solution for the regulation of internet of things services in the intelligent agriculture.

Keywords: internet of things; IoT; MOO algorithm; dynamic multi-objective optimisation algorithm; agriculture.

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Biographical notes: Chaoqun Huang received her Bachelor's in Business Administration from Jilin University of Finance and Economics in China in 2010. She received her Master's in Economics from Hunan Normal University in China in 2013. At present, she is working as a full-time teacher in the School of Economics and Management of Hunan University of Science and Engineering. His areas of interest are agricultural economic development and urbanisation.

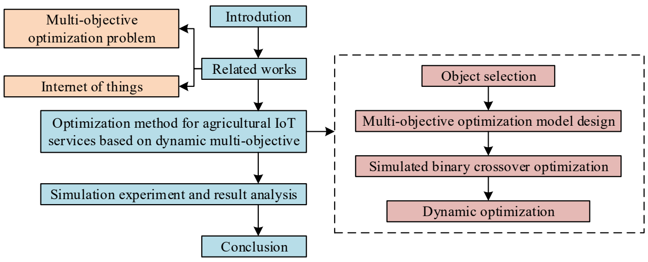
Qianlan Liu received her Bachelor's in Electronic Information Engineering from University of South China in 2010. She received her Master's in Electronic Science and Technology from Central South University in 2013. Presently, she is pursuing her PhD at Perpetual University of the Philippines. At the same time, she is engaged in full-time teaching work in the School of Information Engineering of Hunan University of Science and Engineering. Her areas of interest are computer vision and image processing.

Wenbin Qian received her Bachelor's in Mathematics and Applied Mathematics from Shanxi University of Finance and Economics in China in 2007. She received her Master's in Finance from Yunnan University of Finance and Economics in 2010. At present, she is working as a full-time teacher in the School of Economics and Management of Hunan University of Science and Engineering. Her area of interest is rural finance.

1 Introduction

With the progress of internet technology, the internet of things (IoT) technology has become a research focus. It effectively connects actual production and life with the network through various sensing devices. People can obtain and monitor data from various devices and systems in real-time, thereby achieving more intelligent and efficient operations and management (Wen et al., 2021). The IoT technology effectively connects actual production and life with the network through various sensing devices (Samaila et al., 2020). Combining artificial intelligence technology and IoT technology, intelligent agricultural IoT services can be achieved. For example, through sensors and data collection devices, information including soil moisture and temperature in farmland can be collected. Then, artificial intelligence algorithms are used to analyse and predict these data. Based on these predicted results, farmers can better manage and regulate water supply, fertilisation, irrigation, and other resources, achieving reasonable resource allocation and optimised utilisation. However, currently, there is a lack of effective regulatory methods in agricultural IoT services, resulting in uneven resource allocation (Yan et al., 2021). Artificial intelligence technology provides solutions. Computing and intelligent technologies are used to learn the laws of survival of the fittest in nature. These methods have the ability to adapt to complex environments (Shi et al., 2021; Singh et al., 2020). Therefore, an improved dynamic multi-objective optimisation (MOO) algorithm for decomposing IoT services is designed based on the decomposition MOO algorithm. To cope with environmental changes, dynamic monitoring factors are introduced in the algorithm to improve dynamic adaptability. The innovation of this research is that on the basis of MOO, a dynamic optimisation strategy is proposed. Dynamic monitoring factors are introduced to capture real-time changes in the environment and service status. The optimisation objectives and strategies are adjusted accordingly, which overcomes the limitations of traditional static optimisation methods in dealing with dynamic environments. Meanwhile, the idea of objective decomposition is adopted to deal with conflicting objectives in MOO problems. The study is divided into four parts. The first part provides an overview of the IoT and MOO issues problems. The second part is to achieve a dynamic multi-objective IoT service regulation method. The third part is to verify the effectiveness. The final part is a summary of the research results. The flowchart of the overall framework of the study is shown in Figure 1.

Figure 1 Flow chart of the research framework (see online version for colours)



2 Related works

With the development of the economy, there are many MOO problems in various fields such as management, economics, and science. In multi-objective problems, there are often multiple optimisation objectives that constrain and conflict with each other. They often have unstable related parameters. The key to solving multi-objective problems is how to find the optimal solution set at a certain moment from the ever-changing environment. Lizotte et al. (2022) proposed a MOO solution for problems commonly affected by external multiple factors in practical engineering, successfully achieving robust optimisation for various types of unstable factors. To study the impact of work interruptions caused by uncontrollable forces on overall work in practical work, Zhang et al. (2020) proposed a robustness measurement method for repetitive projects based on floats. A balanced scheduling scheme was achieved through MOO method. Kuo et al. (2022) adopted the MOO to explore machining methods in tool machining. A polycrystalline diamond single wire cutting energy-saving machining method was proposed that couldn't affect the geometric shape and surface integrity of the cutting edge, ultimately achieving the best tool cutting method. Liu et al. (2022) conducted a research on the performance of organic Rankine cycle systems. Its performance was significantly affected by the temperature of the heat source and the cold source. The output power, thermal conductivity, and collider parameters of the system were optimised using MOO methods. Zhao et al. (2022) conducted a research on the non-monotonic projection gradient algorithm for solving convex constrained MOO problems. A new solving algorithm was proposed, which established a sequence with strong convergence for weak Pareto optimal solutions, providing a reference idea and method for solving this problem. Barros et al. (2022) proposed a MOO framework under uncertain influencing factors to address the challenges posed by land scarcity in solar planning in certain countries. The entire cycle of solar energy planning and construction has considered the performance. The result showed that this solution doubled the available area for solar energy construction.

The IoT technology, as a derivative of the internet technology, is essentially a complex heterogeneous network that connects real production and life with the network. The role of connecting physical objects with the network has attracted attention, which has been widely applied in various industries. Yadav and Ponged (2022) proposed an IoT routing technology based on bundle swarm algorithm to solve the excessive energy consumption caused by multi hop routing technology in the IoT. Experiments demonstrated the advantages of this method in stability, energy consumption, and response time compared with conventional methods. Priyadarshi et al. (2021) proposed a particle swarm optimisation solar power tracking algorithm based on the IoT. A solution was provided for power control in solar photovoltaic systems. According to the findings, it could accurately predict the maximum power, providing technical support for the development of the solar photovoltaic field. Qiao (2021) proposed a multimedia education resource fusion model based on the IoT to overcome the high error rate, low stability, and low efficiency in traditional models. It was designed using the internet architecture. According to the findings, it effectively reduced the error rate. It improved stability by 5.32% and operational efficiency by 4.5%. To meet the growing demand for energy management in residential areas, Vanitha and Vallimurugan (2022) proposed an artificial cross gender algorithm based on mixed gradient elevation decision trees to support an IoT system connected to residential electricity networks. This method achieved the best balance between electricity cost and waiting time, effectively maintaining the stability of the electricity network.

Therefore, a supervision method for agricultural IoT services based on dynamic MOO is proposed to address the regulatory difficulties caused by complex and variable environments and parameters in the current intelligent agricultural IoT. The intelligent optimisation algorithm is introduced into the IoT to achieve intelligent optimisation of IoT services, expanding the application fields of IoT services. The algorithm incorporates dynamic monitoring factors to realise dynamic monitoring of changing environments, thereby achieving dynamic adaptation of the algorithm.

3 Optimisation method for agricultural IoT services based on dynamic multi-objective

Based on the essential MOO problem of the agricultural IoT, a MOO model is first designed with the goal of minimising costs and service time. Then, combined with the impact of dynamic time factors on the IoT, dynamic time factors are added to enhance the adaptability of the model. The simulated binary crossover (SBX) method is used to enhance the indexing ability of the algorithm. The differential evolution (DE) method is used to enhance model diversity.

3.1 Optimisation method of IoT Based on MOO algorithm

The implementation and development of agricultural IoT is facing a series of intertwined challenges. In the field of data management, affected by massive heterogeneous data, devices must have efficient processing performance and integration. For its energy management, due to the large number of sensors in the field, the design of the central manager needs to take into account performance while ensuring energy efficiency. In some remote agricultural areas, network instability further reduces the reliability of the system. With these issues in mind, a agricultural IoT service optimisation based on dynamic multi-objective is proposed. The main feature of this method is that it can respond to and adapt to changes in the environment in real time. Simultaneously optimising multiple key performance indicators can not only realise efficient data integration and processing in data management, but also optimise energy consumption in energy management, so as to extend the service life of equipment and reduce maintenance cost. In terms of network connectivity, dynamic MOO can adjust data transmission strategies based on changes in network status to maintain stable and effective communication.

In this study, a MOO model should be designed for the IoT service, aiming at minimising the service cost and service time. A MOO model based on the number of service devices, service requests, sensors, and sensor distances is designed. According to the dynamic changes of the number of service devices, service requests, sensors and the distance of sensors, a dynamic model is constructed to achieve the dynamic optimisation of agricultural IoT with the goal of minimising the service cost and service time. Within the IoT, there are M requests per unit time and W available services. In the IoT services, there is the influence of geographic coordinate randomness in request allocation optimisation. The distance between sensors is different and dynamically changing, which provides necessary data for adjusting the deployment between sensors. The service device is S_i. The response request is R_j. The transmission cost in the service device and the request is $Dist(S_j, R_j)$. The Euclidean distance is used to calculate $Dist(S_j, R_j)$, as shown in formula (1) (Mosier and Banti's, 2021).

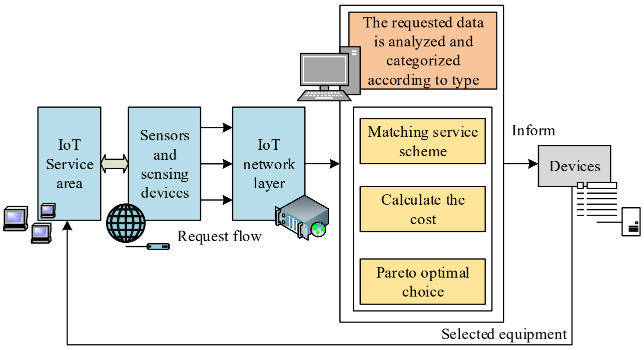
$$Dist\left(S_i, R_j\right) = \sqrt{\left(X_i - X_j\right)^2 - \left(Y_i - Y_j\right)^2} \tag{1}$$

In formula (1), X represents the corresponding device or requested abscissa. Y represents the corresponding device or requested ordinate. $EC(S_i, R_j)$ is the energy cost incurred when the service equipment requests it accordingly.

$$EC\left(S_i, R_j\right) = \begin{cases} R\_workload_j * p_i * \varepsilon_i, x_{ij} = 1 \\ 0, x_{ij} = 0 \end{cases} \tag{2}$$

In formula (2), p_i stands for the probability of workload allocation to server S_i. $R\_workload_j$ represents the workload that j needs to meet. ε_i represents the unit energy consumption cost of device i in service. x_{ij} stands for weather R_j is assigned to service provider S_i. Each service device is only assigned to one request, so $\sum_{j=1}^{M} x_{ij} = 1, i = 1 \cdots W$ (Karadag and Abubakar, 2021). The IoT service model is constructed, as shown in Figure 2.

Figure 2 IoT service model (see online version for colours)



In Figure 2, the total service cost is minimised, as shown in formula (3).

$$\text{Minimise } f1 = \text{service cost}$$
$$= \sum_{i=1}^{W} \sum_{j=1}^{M} x_{ij} \begin{pmatrix} Dist(S_i, R_j) \\ +EC(S_i, R_j) \end{pmatrix} \tag{3}$$

The total service time is minimised, as shown in formula (4).

$$\text{Minimise } f2 = \text{Service time} = \max_{i=1}^{W} \{ST_i\} \tag{4}$$

In formula (4), ST_i is determined by the capabilities of each service device and the amount of work completed. The specific representation is shown in formula (5).

$$ST_i = S\_workload_i / \beta_i \tag{5}$$

In formula (5), *S_workload* represents the workload completed by the service device. β_i stands for the capability value of provider S_i, which reflects the workload per unit time. A higher value indicates a stronger working ability of the device. The Unit Energy Consumption (UEC) is ε_i. The relationship in ε_i and the capacity value of the service equipment is shown in formula (6).

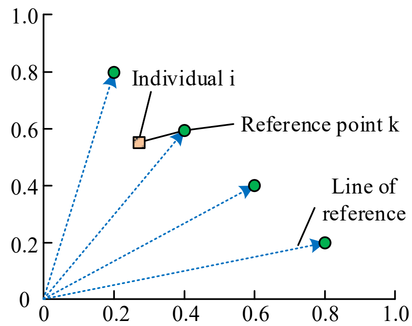
$$\varepsilon_i = \mu \cdot \beta_i \tag{6}$$

In formula (6), μ is the characteristic of the sensor in practice, which is a fixed value between the UEC and the service equipment capacity. When the capacity of the service equipment changes, the UEC also changes accordingly. For example, an increase in capability value can reduce total service time, but this increases UEC. Therefore, minimising service costs and service time constitutes a conflicting MOO problem (Barma and Modibbo, 2022). Encoding technology is very important in the research, providing a technical direction for visual representation to solve MOO problems. For the designed method, the new solution has an array. Each of them stands for an attribute of the information collected by the sensor. Based on the actual situation in the request, the length of the candidate solution is 5. The first three digits are *R_id* (unique identifier of the requesting device), *R_type* (request type), and *R_workload* (depending on the amount of data collected by the sensor) of the service request. The last two digits stand for the specific location of the service request, namely the *X*-axis and *Y*-axis. The data collected by each sensor is meaningful and not just ordinary numbers. Table 1 shows an example of array encoding under this setting.

Table 1 Example table of candidate solutions

R_id	*R_type*	*R_workload*	*X*	*Y*
1	5	2	21	35
2	1	4	15	27
3	3	3	10	19
4	4	4	9	42
5	2	5	38	12

Figure 3 Two objective optimisation problem individuals are associated with reference points (see online version for colours)



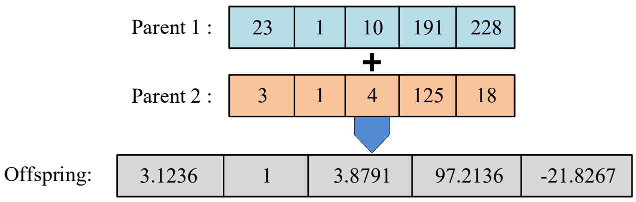
To better calculate the MOO problem in the research and optimise two conflicting objectives, the multi-objective decomposition is adopted. The Tchebycheff method is used to split the optimisation problem in the previous text into optimisation sub problems. To facilitate adjusting the parameter settings, the number of sub problems is *N*. The weight vector is λ. $\lambda^1, \cdots, \lambda^N$ are uniformly distributed weight vectors. z^* is a reference point, $\lambda^j = (\lambda_1^j, \cdots, \lambda_m^j)^T$ and $\lambda_1^j + \cdots + \lambda_m^j = 1$. In the research, it is a dual objective problem. Therefore, $m = 2$, and $z^* = (z_i, \cdots, z_m)^T$. z_j is the optimal value obtained. The objective function for the j^{th} sub problem is shown in formula (7).

$$\begin{cases} Minimise\ g^{te}\left(x \middle| \lambda^j, z^*\right) = \max_{1 \le i \le m} \left\{ \lambda_i^j \middle| f_i(x) - z_i^* \right\} \\ subject\ to\ x \in \Omega \end{cases} \tag{7}$$

In formula (7), $i = 1, \cdots, m$. Ω represents the decision space. For each λ^j, each reference point during the search process can be found. The optimal solutions of the j^{th} sub problem are preserved. Figure 3 is a diagram of the dual objective optimisation problem and reference points.

To further improve the search ability, the SBX method is used to optimise it. It is mainly used to generate new candidate solutions during the candidate solution generation stage. This method is used to enhance the diversity of candidate solutions. SBX contains two different coefficients. The coefficient is *beta*, which is usually evaluated by the *rand* value. The binary crossover probability in this simulation is σ. If $rand < \sigma$, then $beta = (2 * rand)^{\frac{1}{3}}$. If $rand > \sigma$, then $beta = \frac{1}{(2*(1-rand))^{\frac{1}{3}}}$. In the simulation of binary crossover operators, two randomly selected parent candidate solutions are used to generate two offspring. The probability of retaining the final two descendants is equal. The main contribution is to accelerate the filling process of Pareto Front by reconnecting different candidate groups. Figure 4 shows an example of simulating binary crossover.

Figure 4 Binary cross simulation (see online version for colours)



3.2 *Optimisation method for the IoT based on dynamic MOO algorithm*

To cope with the changing environment and parameters in the agricultural environment, and improve the dynamic adaptability of the IoT, based on the constructed MOO method, a dynamic MOO method for the IoT is further constructed. The set of service devices is $S(t)$, and $S(t) = \{1, \cdots, W\}$. The request set is $R(t)$, and $R(t) = \{1, \cdots, M\}$. There are W_{t0} service devices and M_{t0} requests in the IoT. $W(t)$ and $M(t)$ stand for functions (Mahmood and Ali, 2022). Within a specific time, the transmission consumption between service devices in response to service requests is $Dist(S_j^t, R_j^t)$. The distance is calculated using Euclidean method, as shown in formula (8).

$$Dist\left(S_i^t, R_j^t\right)\sqrt{\left(X_i^t - X_j^t\right) - \left(Y_i^t - Y_j^t\right)^2} \tag{8}$$

The energy consumption is further calculated. The energy consumption of service device S_i^t in response to request R_j^t is $EC(S_i^t, R_j^t)$. After further considering time dynamics, the calculation method is shown in formula (9).

$$EC\left(S_i^t, R_j^t\right) = \begin{cases} R\_workload_j^t * p_i * e_i, x_{ij} = 1 \\ 0, x_{ij} = 0 \end{cases} \tag{9}$$

In formula (9), e_i stands for the UEC cost. p_i represents the assigned work to S_i^t. $R\_workload_j^t$ stands for the workload. x_{ij} represents whether the request is assigned to S_i^t. A request has a service device. Therefore, $\sum_{j=1}^{M_{t0}} x_{ij} = 1, i \in S$. The optimisation objective is the same as above, which also minimises service cost and service time, as shown in formula (10).

$$\begin{cases} \min f_1 = \sum_{i=1}^{W(t)} \sum_{j=1}^{M(t)} x_{ij} \begin{pmatrix} Dist\left(S_i^t, R_j^t\right) \\ +EC\left(S_i^t + R_j^t\right) \end{pmatrix} \\ \min f_2 = \max_{i=1}^{W(t)} \{ST_i\} \end{cases} \tag{10}$$

In formula (10), ST_i stands for the time to complete the assigned task. The workload $S\_workload_i$ and capability value β_i are shown in formula (11).

$$ST_i = S\_workload_i / \beta_i \tag{11}$$

The relationship between UEC and capacity is shown in formula (12).

$$e_i = \mu \cdot \beta_i \tag{12}$$

In the dynamic service systems, the priority and quantity of services are considered. Different requests require different quantities of collaborative services. Therefore, the dimension of the decision variable depends on the services required between requests. The required quantity of services is shown in formula (13).

$$CoSerNum_j^t = \left[\sigma \cdot R\_workload_j^t \cdot R\_priority_j^t\right] \tag{13}$$

In formula (13), $CoSerNum_j^t$ represents the quantity required for the service. $R\_workload_j^t$ stands for the workload. $R\_priority_j^t$ stands for the priority of the request. σ stands for the probability of the service device being available at t. In this service request work, service equipment failures are not considered. The constraint is shown in formula (14).

$$\sum_{j=1}^{M(t)} CoSerNum_j^t \leq W_{t0} \tag{14}$$

In multiple requests, formula (14) indicates that the services are less than the total available services. Furthermore, the concurrent requests and corresponding services generated within a certain period are shown in formula (15).

$$\begin{cases} M(t) = \left[rand \cdot M_{t0}\right] \\ W(t) = \left|\left\{S_i \middle| x_{ij} = 1, i \in S, j \in R_t\right\}\right| \end{cases} \tag{15}$$

Optimising the target service time and service cost are two conflicting goals. Therefore, it is in line with MOO problems. In the research, the new solution consists of a real number encoded array. It represents the id attribute value of the information attribute collected by the sensor. For the collaborative services faced in the research, the dimensions of the solution need to be calculated based on formula (13). Table 2 shows some candidate solution examples.

Table 2 Sample table of partial candidate solutions

id	*id*	*id*	*id*	*id*
1	8	11	15	18
2	6	9	17	29
3	2	6	11	7
4	5	12	9	15
5	7	13	4	8

For the dynamic IoT services in the research, a multi-objective decomposition method is used for optimisation, dividing the objective problem into sub objectives. Formula (16) displays the function of the N^{th} sub problem.

$$\begin{cases} \text{minimise } g^{te}\left(x \middle| \lambda^j, z^*\right) = \max\limits_{1 \le i \le m}\left\{\lambda_i^j \left| f_i(x) - z_i^* \right.\right\} \\ \text{subject to } x \in \Xi \end{cases} \tag{16}$$

In formula (16), $j = 1, \cdots, N$. The decision space is Ξ, which is the candidate solution set for the dynamic IoT problem. λ^j displays a sub problem. Furthermore, to further optimise the algorithm and accelerate the optimal solution time in the MOO problem, the diversity of candidate solutions in the algorithm is strengthened. In the research, a DE operator with a fixed probability *CR* is chosen to generate new candidate solutions to enhance the diversity (Zhang and Wang, 2022). By adding candidate solutions to the algorithm, the search ability of the algorithm can be improved. The convergence performance of the algorithm can be improved. Moreover, increasing the diversity of candidate solutions can effectively increase the solution set space coverage of the algorithm. In generating candidate solutions, whether to generate candidate solutions depends on whether the random generation probability *rand* exceeds the *CR*. If *rand* > *CR*, a new offspring *y* is generated. The expression is $y = x^{r1} + F \cdot (x^{r2} - x^{r3})$. Among them, *rand* is a random number with a range of (0, 1). *F* is the calculation parameter. If *rand* < *CR*, no calculations will be performed, but a new solution will still be generated. The new child is one of the parents. The expression is $y = x^{r1}$. To further increase the diversity, the new generation *y* generated by this method is also applied to the polynomial mutation operator for calculation. Figure 5 shows an example of a specific DE operator generating new offspring. The parameter is 0.5. *CR* is 1. To ensure the smooth completion, the attributes of each parent are randomly generated within a valid range. The corresponding range is line with the experimental section.

For the dynamic IoT scenario in the study, the dimensions of the decision variables will change over time. To effectively adapt to this dynamic nature, the activity of sensors and equipment needs to be monitored in real time to accurately grasp the amount of resources required for agricultural scenarios at a particular point in time. On this basis, according to different dimensions of decision variables, different service strategies need to be adopted to obtain the best results. Therefore, the number of service devices required for a service request needs to be detected in real time. The formula (13) is used to calculate the number of service providers required at a given time. The decision variables are then encoded in real time within the framework of MOO to achieve resource optimisation and ensure response speed. Through continuous data flow and sample updates, the method ensures that the optimisation process reflects changes in the real-time agricultural environment, while taking into account key objectives such as energy efficiency, cost control, and service quality. Then the algorithm is used to obtain better service solutions. The specific process is shown in Figure 6.

Figure 5 Schematic diagram of differential evolution (see online version for colours)

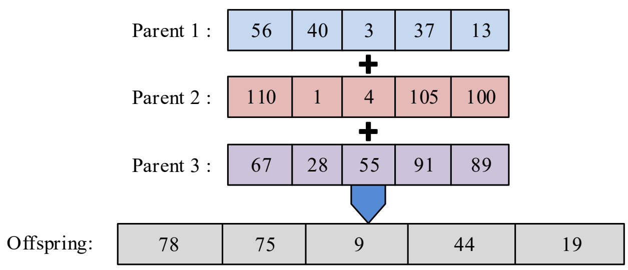
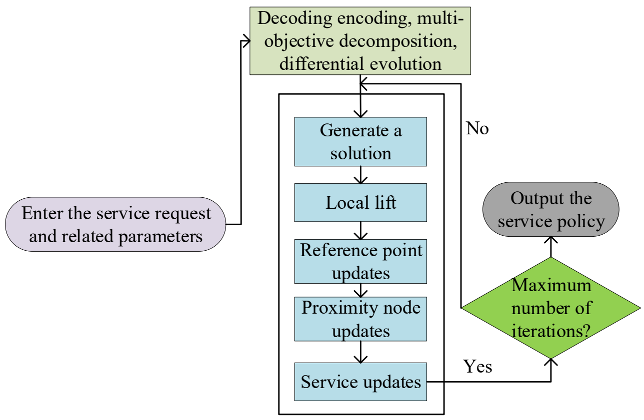


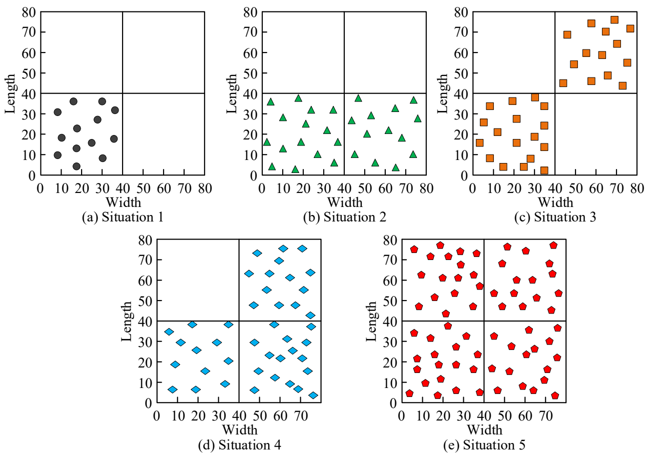
Figure 6 Schematic diagram of the MOO algorithm of the IoT (see online version for colours)



The flow diagram of the dynamic MOO algorithm is shown in Figure 5. Firstly, the service request and related setting parameters are input, including the target service cost and service time. Then the decoding is carried out, and the feasible solution is explored by DE method in the multi-objective framework. After local optimisation and improvement, reference points are updated to guide the search direction, and neighbouring nodes are adjusted to refine the search process. This process continues to loop until a preset maximum number of iterations is reached, finding an optimal solution or one that satisfies a specific criterion. Finally, the algorithm outputs the final service policy, which will guide the implementation of agricultural IoT services. For agricultural IoT services, an agricultural

IoT area is set up for testing. The size is 80 × 80, and 120 sensors are set up to accept service requests. The sensors are evenly distributed. 121 sensors are set up as service devices, which are evenly distributed in the region using the 11 × 11 matrix. All fields are the same corn crop, and all maintain nearly the same environmental conditions, with the same soil conditions, fertilisation conditions, irrigation conditions and care conditions. To maximally simulate the dynamic situation in the optimisation problem of the IoT, the entire service block is divided into four regions. The dynamic distribution of IoT services is maximised through different distributions. It can be divided into 5 situations, as shown in Figure 7.

Figure 7 Schematic diagram of IoT service block distribution (see online version for colours)



4 Simulation experiment and result analysis of agricultural IoT service regulation based on dynamic MOO

To validate the proposed dynamic multi-objective optimisation algorithm (DMOOA), it is applied to actual dynamic agricultural IoT services to verify the actual performance. To fully validate the effectiveness of the DMOOA, multi-objective particle swarm optimisation (MOPSO) and non-dominated neighbourhood immune algorithm (NONIA) are used as comparative methods. Table 3 displays the specific parameters.

Firstly, the Single-Target Service (ST) strategy of the three algorithms are evaluated. Based on the dynamic agricultural IoT distribution defined above, independent experiments are conducted on all five distributions. Each algorithm is assigned tasks with different service costs, and then the task completion time of each algorithm is recorded. To eliminate errors that may be caused by a single environmental condition, the average value is taken to compare Pareto frontiers of the three algorithms. The results are shown in Figure 8. From Figure 8, the proposed DMOOA had relatively better convergence performance. It achieved the best service matching scheme. The lowest service cost and shortest service time were obtained when assigning tasks. The DMOOA could better solve the optimisation problem of ST in dynamic IoT.

Table 3 The relevant parameters of the three parameters

Parameter name	*DMOOA*	*MOPSO*	*NONIA*
Population	180	80	160
Crossover rate	-	1	-
Difference rate	0.8	0.8	-
Subproblem number (N)	1	-	-
Neighbour (T)	180	-	-
Iterations	20	-	-
Active population (n_a)	500	500	500
Dominant	15	20	-
Population	60	80	-
Clone population (cs)	60	80	-
Inertia weight damping ratio	-	-	1
Leader selection pressure parameter	-	-	4
Extra repository member selection pressure	-	-	1

Figure 8 Pareto frontier comparison result plot of the three algorithms (see online version for colours)

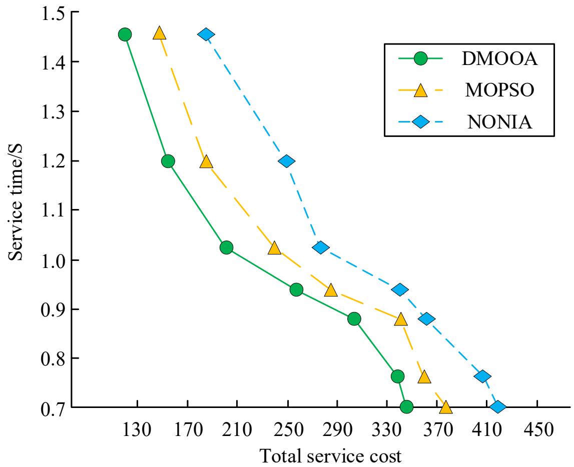


Figure 9 Hypervolume value comparison result plot of the three algorithms (see online version for colours)

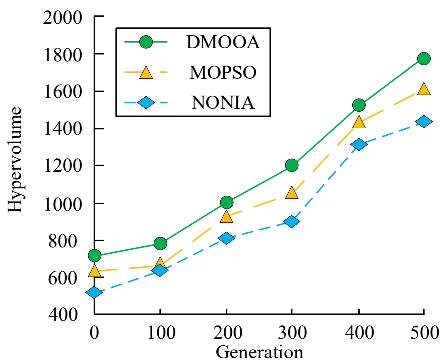


Table 4 Extreme point accuracy comparison results of the three algorithms

Experimental results	*DMOOA*		*MOPSO*		*NONIA*	
	Minf₁					
	$Minf_1$ (f_1, f_2)	$Minf_2$ (f_2, f_1)	$Minf_1$ (f_1, f_2)	$Minf_2$ (f_2, f_1)	$Minf_1$ (f_1, f_2)	$Minf_2$ (f_2, f_1)
Best	199.313, 1.745	0.671, 627.981	205.146, 1.745	0.734, 658.412	219.475, 1.745	0.814, 679.587
Worst	236.467, 1.745	0.784, 649.108	258.718, 1.745	0.896, 668.294	265.896, 1.745	0.980, 691.347
Average	216.489, 1.745	0.752, 634.240	228.386, 1.745	0.816, 662.336	247.562, 1.745	0.896, 687.452

The hypervolume value (HV) of the three algorithms is compared to analyse the comprehensive performance of their solution sets, so as to judge the diversity of the algorithms. A collaborative service strategy (CS) is used to compare the average HV of the three algorithms under five distributions. Each algorithm is applied to the same set of agricultural service scenarios. The operation data of the algorithm under each distribution is collected. To avoid the influence of experimental errors, the average HV of all test cases is taken for statistical comparison. The test results are shown in Figure 9. From Figure 9, the average HV of the DMOOA performed extremely well compared with the other two algorithms. The comprehensive HV also performed best. The proposed algorithm performs well in both CS and ST.

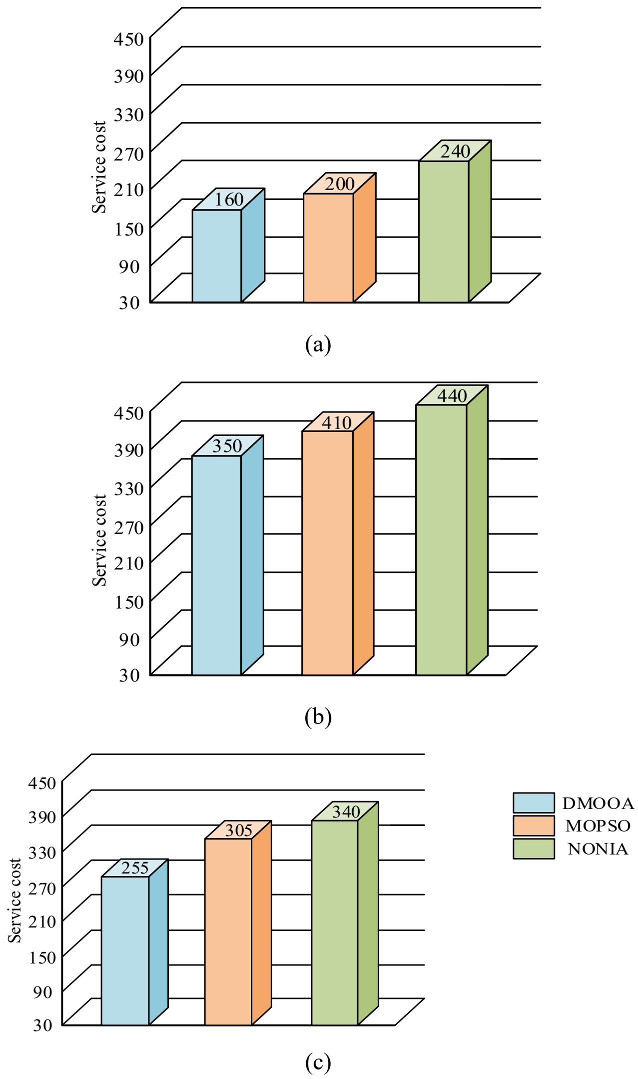
Then, the extreme point accuracy of the three algorithms is tested and compared. To conduct detailed testing on the three algorithms, the best, worst, and average test results are recorded, as shown in Table 4. From Table 4, the proposed DMOOA performed best in optimal accuracy, worst case accuracy, and average accuracy, indicating that the research had better accuracy in actual services.

Table 5 The average calculation time

Situation	*Service policy*	*DMOOA*	*MOPSO*	*NONIA*
Situation 1	ST	9.47	10.59	11.84
	CS	11.54	15.76	19.91
Situation 2	ST	10.15	12.94	14.37
	CS	12.29	14.37	18.92
Situation 3	ST	10.28	13.05	14.27
	CS	12.02	14.26	19.64
Situation 4	ST	9.34	12.43	16.48
	CS	12.49	19.62	26.43
Situation 5	ST	10.14	12.67	13.37
	CS	13.47	21.39	39.84
Average	-	11.12	14.71	19.51

The average calculation time of the three algorithms is compared. The testing environment consists of five different distribution scenarios constructed in the previous section. To conduct more comprehensive testing on the three algorithms, the ability to handle ST and CS is compared. The test results are shown in Table 5. From Table 5, the proposed DMOOA had the shortest computational time in all scenarios, whether for ST or CS. Compared with the MOPSO and the NONIA, the average calculation time decreased by 3.59s and 8.39s, respectively, indicating that the research could output experimental results more quickly in practical applications.

Figure 10 Service cost comparison of three algorithms, (a) the best of the three models (b) the worst of the three models (c) the average of the three models (see online version for colours)



The average service cost of the three algorithms is compared and tested. The service cost of the algorithm is defined as the resource usage and energy consumption test during the service cycle. Each algorithm is assigned the same service task. The highest service cost, lowest service cost, and average service cost are recorded. Figure 10 displays the test results. From Figure 10, the proposed

DMOOA had the lowest service cost. Compared with the MOPSO and the NONIA, the average service cost reduced by 16.39% and 25.00%. In summary, the DMOOA has better convergence performance. The HV performs well and has better diversity. The extreme point accuracy performs best, which has better accuracy in practice. In actual testing, it has the shortest calculation time performance and the lowest service cost.

5 Conclusions

At present, the IoT is a necessary way to build an intelligent architecture. The intelligent agricultural IoT is often greatly affected by complex and ever-changing environments. Therefore, a supervision method for agricultural IoT services based on dynamic MOO was proposed. A decomposition-based IoT DMOOA was constructed to solve the poor dynamic capability in the current intelligent agricultural IoT. Dynamic monitoring factors were added to the algorithm to improve the dynamic adaptability. According to the findings, the DMOOA performed well in convergence. Faced with a ST, the optimal service matching scheme was proposed. The HV performed well. The solution set had the best comprehensive performance, and the algorithm had the best diversity. The extreme point accuracy performed best, indicating that it had better accuracy in practice. Compared with the MOPSO and NONIA, it had the lowest average calculation time for multi-objective and ST, leading by 3.59s and 8.39s, respectively. The average service cost performance was the best. Compared with the MOPSO and the NONIA, the average service cost decreased by 16.39% and 25.00%, respectively. In summary, the proposed dynamic MOO agricultural IoT regulation method performed well in practical applications, greatly improving accuracy. It can maintain the shortest service time while having the best service cost performance, achieving the optimal service strategy for the IoT. In large-scale farm management as well as intelligent agriculture, this approach can directly reduce operational cost by optimising resource allocation. Meanwhile, it can improve the quality of agricultural products through dynamic adjustment, and then increase agricultural income. Due to the dynamic adaptability of the method, with complete equipment, it has high applicability and can be applied to various types of farmland. When it is applied to new farmland, it only needs to adjust some parameters to complete the adaptation. This method can provide more technical support for the further promotion and application of agricultural IoT technology. It can provide different perspectives for the optimisation and adaptation of agricultural IoT. However, the study did not consider the loss of IoT services in practice, nor did it take into account the further impact of more complex realities on parameters. In addition, the cost of this method in large-scale applications also has room for optimisation. Because of the large number of data, data security and privacy issues are also worth considering. Faced with older infrastructure, the usability of this method is also limited. Future studies should further optimise the cost of the method, strengthen its safety, and expand its adaptation.

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