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Improving Non-Dominated Sorting Genetic Algorithm for IOT Service Composition Considering National Energy Consumption and User Experience

M. Bheemalingaiah[1,*], G. Sreenivasulu[1], L. Venkateswa Reddy[2], Khaja Mahabubullah[3], A. Ramesh Babu[1], D. Himagiri[1]

[1]Department of CSE, J.B. Institute of Engineering and Technology, Hyderabad, India

[2]Department of CSE, Joginapally B.R. Engineering College, Hyderabad, India

[3]Department of MCA, Deccan College of Engineering and Technology, Hyderabad, India

Email : bheemasiva2019@gmail.com; g.sreenivasulu@jbiet.edu.in; lakkireddy.v@gmail.com; hod_mca@deccancollege.ac.in; askarbabu@gmail.com; himagiri.danapana@gmail.com

Abstract

This paper proposes an enhanced Non-Dominated Sorting Genetic Algorithm -II algorithm to optimize IoT service composition by incorporating national energy consumption requirements and user experience, areas often overlooked in traditional models that primarily focus on time, cost, and quality. The original NSGA-II algorithm is prone to premature convergence and local optima issues during population iteration. To address these limitations, we introduce a novel evaluation model and improve the elite retention strategy of the NSGA-II algorithm. The improved algorithm balances exploration and exploitation through dynamic crowding distance adjustment and adaptive selection pressure, enhancing diversity and avoiding local optima. Experimental results demonstrate that the I-NSGA algorithm not only reduces running time by 5.916% but also achieves a smoother Pareto surface, indicating a more optimal distribution of solutions. The novelty of this approach lies in its comprehensive inclusion of energy consumption and user experience, the timeliness in addressing emerging IoT optimization challenges, and the relevance to current IoT service composition needs. This validates the effectiveness and advancement of the proposed model and algorithm, providing a robust and efficient solution for IoT service composition optimization.

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1. Introduction

An IoT service portfolio refers to the consolidation and integration of various types of IoT services, along with related resources and functions, to meet user needs and create higher levels of value. This combination includes multiple levels of services such as data analysis and mining, sensor data collection, remote operation, automated decision-making, and real-time monitoring, enabling more complex and intelligent application scenarios.

Key elements of the IoT services portfolio include service integration, automation, data interaction and sharing, intelligent decision-making, security and privacy protection, and scalability. Service integration involves bringing together different types of IoT services from various domains to achieve capabilities that are more comprehensive. Automation utilizes technology to automatically trigger, execute, or coordinate IoT services under specific conditions, thereby improving efficiency and response speed.

Data interaction and sharing facilitate the exchange of information between different IoT services, enabling more accurate analysis and decision-making. Intelligent decision-making advantages integrated IoT data to make informed choices, automatically adjust parameters, or perform specific tasks for optimized outcomes. Security and privacy protection ensure the safeguarding of data and user information during IoT service combinations, preventing potential security threats and risks. Scalability ensures that the IoT service portfolio can accommodate new services or resources as needed, adapting to changing requirements.

The enhancement of these elements is crucial in the context of the rapidly evolving technological landscape, where the integration of advanced algorithms can significantly influence the performance and efficiency of IoT services. In this study, we focus on improving the Non-Dominated Sorting Genetic Algorithm (NSGA) for IoT service composition, with an emphasis on national energy consumption and user experience. The NSGA is a popular multi-objective optimization algorithm used to solve problems where multiple conflicting objectives must be optimized simultaneously.

By refining the NSGA, we aim to develop a more efficient method for IoT service composition that not only optimizes resource allocation and operational efficiency but also considers the broader implications of energy consumption at the national level and the overall user experience. This approach seeks to balance technical performance with environmental sustainability and user satisfaction, leading to more sustainable and user-centric IoT applications.

Through the I-NSGA algorithm, we anticipate enhancing the decision-making processes involved in IoT service composition, leading to more intelligent, adaptive, and sustainable systems. The integration of considerations for energy consumption and user experience highlights the importance of a holistic approach to IoT development, where technological advancements are aligned with societal and environmental goals. [1-4]

2. Related Researches

Recent research has made significant progress in optimizing IoT service portfolios. Asghari and Rahmani proposed method involves using a hybrid evolutionary algorithm in conjunction with an IoT conceptual model to create a privacy-aware service composition technique, which optimizes multiple Quality of Service (QoS) and security parameters during the composition process. [5]. Sefati and Navimipour developed a security (QoS) optimization approach combining the ACO (Ant Colony Optimization) algorithm and the Markov model (hidden), focusing on availability and high reliability but not energy efficiency [6]. Guzel and Ozdemir introduced IoT service portfolio framework a multi-objective for fiber optic gyroscopes, balancing security (QoS), energy consumption, and fairness, though it lacks scalability considerations [7].

Khan proposed a novel DSM (demand-side management) approach for the day-ahead dispatch of high-wind integrated smart grids, optimizing operating costs, load shedding costs, and emissions, using Monte Carlo simulations [8]. Ali and Ullah introduced a DSM strategy in smart grids for energy management relating distributed energy resources and diverse consumer types, utilizing a multi-objective wind-driven optimization algorithm [9].

Previous research on IoT service portfolio models has largely focused on parameters such as time, cost, and quality, with less emphasis on energy consumption and user experience requirements. Considering these factors, this research proposes a novel mathematical model for IoT service combination. Addressing the issues of early or local convergence in original algorithm NSGA-II during population iteration, this model incorporates task completion time, service response time, security, cloud platform energy consumption, and user experience as key indices. An improved elite retention strategy is designed, and an enhanced algorithm I-NSGA is employed to solve a model. This approach aims to optimize the IoT service portfolio comprehensively, considering both the demand side and the IoT platform's interests.

3. Methodology

3.1 IoT Service Portfolio Problem Description

Suppose a complex IoT service T can be decomposed into n subtasks, i.e., $T = \{ST_1, ST_2, ST_3, \dots, ST_{n-1}, ST_n\}$. In the resource pool of the IoT platform, several suitable services are combined to complete the IoT service collaboratively [10]. Each IoT subtask corresponds to the candidate service set, and the candidate service set corresponding to n subtasks is represented as $S_1, S_2, \dots, S_n$. Candidate set S_1 is represented as $S_1 = \{S_{1,1}, S_{1,2}, S_{1,3}, \dots, S_{1,m-1}, S_{1,m}\}$, indicating that candidate set S_1 has m candidate services. The candidate service set S_i is represented as $S_i = \{S_{i,1}, S_{i,2}, S_{i,3}, \dots, S_{i,m-1}, S_{i,m}\}$,, which indicates that the candidate service set S_i has m candidate services. Services are chosen from a set of candidate services based on specific requirements, and the selected services then work together to successfully execute the IoT service T. Figure 1 shows a schematic diagram of the IoT service portfolio.

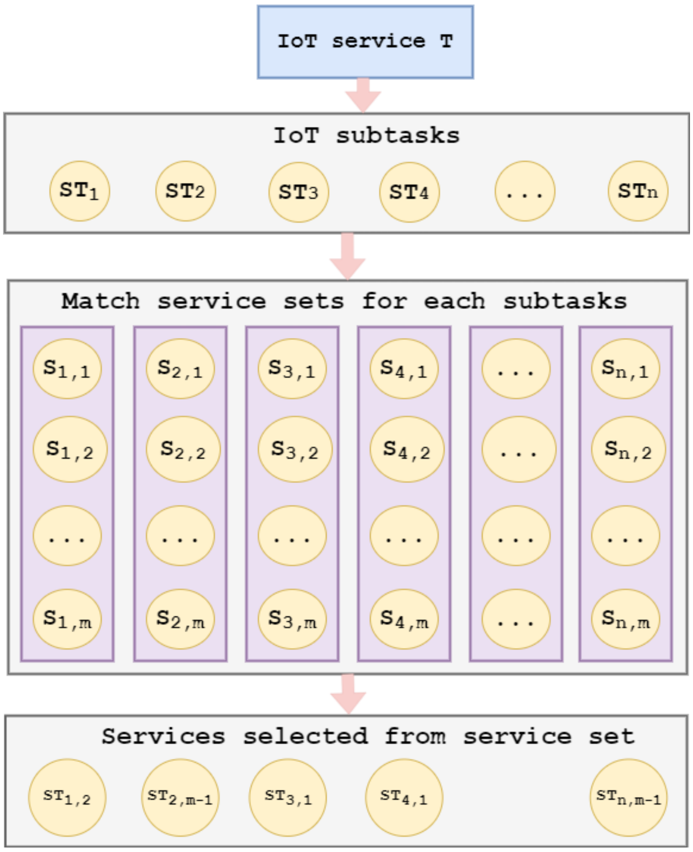

Figure 1. Schematic diagram of the IoT service portfolio.Mathematical modelling of IoT service portfolios

Considering the dynamics and instability of the IoT platform in the process of service execution, the following assumptions are made to facilitate the establishment of a mathematical optimization model: 1) In the process of IoT service combination, there is no situation where an IoT resource serves multiple IoT subtasks at the same time; 2) The sequential structure is used as the research object of the Internet of Things service portfolio.

3.2 Demand-side constraint metrics for IoT services

The present invention fully considers the needs of the service demand side and the operation characteristics of the Internet of Things service, and combines the quantifiable nature of the index, selects three indicators of task completion time, service response time, security, and constructs the index constraint system of the service demand side.

1) Task completion time T. The total amount of time it takes a service demander to submit a service request to achieve a service outcome. The expression is

$$T=\sum_{i=1}^{n} t_i$$

where t_i is the time for the service provider to complete the subtask corresponding to subtask, $i=1,2,\dots,n$.

2) Service response time R. Service response time is one of the key performance indicators for IoT applications, especially for applications that require high real-time performance. Optimization models can attempt to minimize the average service response time of a portfolio of services to ensure timely data exchange and processing. The total service response time from the time the service demand submits the task to the IoT platform and the time when the service result is obtained. The expression is

$$R=\sum_{i=1}^{n} r_i$$

where r_i is the service response time of the service provider corresponding to subtask $i=1,2,\dots,n$.

3) Security S. The security of IoT systems is essential to prevent malicious attacks and protect the privacy of data. The optimization model considers maximizing the security of the system and reduces potential security risks by selecting the appropriate services. The security S expression is

$$S = 1 - \frac{\sum_{i=1}^{n} s_i}{n}$$

where s_i is the failure rate of the service produced by the candidate service resource of subtask i, and the value range is [0, 1], where 1 indicates that no failure has occurred, $i = 1,2, \dots, n$.

The QoS Evaluation Expression is as follows:

$$QoS = W_T.\frac{T}{T_{max}} + W_R.\frac{R}{R_{max}} + W_S.\frac{S}{S_{max}}$$

$$S_{max} = 1 - S_{min}$$

where W_T, W_R, and W_S are the weights of task completion time, service response time, and security, respectively. T_{max} and R_{max} are respectively the maximum time and maximum service response time specified by the service demander; S_{min} is the minimum security required by the service demander.

3.3 IoT Platform constraint metrics

In order to reduce environmental damage and develop an economy with minimal environmental impact, characterized by reduced energy usage and decreased greenhouse gas emissions, the IoT platform operator will consider the national requirements for energy consumption, which will increase the energy consumption assessment of suppliers. In order to prevent the service provider from matching the service provider with too low service quality, the IoT platform will constrain the user experience A of the service provider.

1) Energy consumption: Energy consumption of IoT devices and services is an important consideration, especially in energy-constrained environments. Optimization models can attempt to minimize overall energy consumption to improve the sustainability of a system. The formula for calculating energy consumption E is:

$$E = \sum_{i=1}^{n} e_i$$

where: e_i is the energy consumption of subtask i; n is the number of subtasks, $i = 1,2, \dots, n$.

2) User experience A: The user experience of IoT applications is critical for widespread adoption. The optimization model can consider maximizing the user experience and providing better user perception by selecting the appropriate combination of services. The user experience A of the IoT service portfolio is the historical score of each service provider by the service demander, with a value between $0 \sim 1$, A higher value indicates a better quality or higher level of service of the IoT platform service provider. The expression is

$$A = \frac{\sum_{i=1}^{n} A_i}{n}$$

where: A_i is the user experience of the service provider corresponding to the subtask i by the service demander; n is the number of subtasks, $i = 1,2, \dots, n$.

i OPTIMIZE YOUR GOALS

The total goal of a IoT service portfolio is to complete IoT services with the lowest QoS on the demand side, the lowest energy consumption on the IoT platform, and the highest user experience. Considering comprehensively, a mathematical model of IoT service portfolio is established:

$$F(X) = (\min QoS, \min E, \max A);$$

$$s.t \begin{cases} T \leq T_{max}, \\ R \leq R_{max}, \\ S \geq S_{min} \ , \\ E \leq E_{max}, \\ A \geq A_{min}, \end{cases}$$

The five constraints indicate that the task completion time T in the model does not exceed the maximum time T_{max} specified by the service demander, the service response time R does not exceed the maximum service response time R_{max} specified by the service demander, the security S is not lower than the minimum security S_{min} specified by the service demander, the energy consumption E does not exceed the maximum energy consumption E_{max} generated during the IoT service process required by the IoT Platform operator, and the user experience A is not lower than the minimum user experience A_{min} specified by the IoT platform.

3.4 Non-Dominated Sorting Genetic Algorithm-II algorithm

The IoT service composition model constructed in this paper is a multi-objective optimization problem, which is different from the traditional single-objective optimization in that it considers the simultaneous optimization of multiple interrelated objectives. In single-objective optimization, we try to find a solution that makes a single objective function optimal. However, in many practical cases, there are multiple conflicting objectives, and improving one of them may have a negative impact on the others. In contrast to single-objective optimization, multi-objective optimization requires finding a set of solutions in the solution space, which are called Pareto solution sets, also known as non-dominated solution sets [11]. In the Pareto solution set, there is no one solution that can outperform all the others, but rather that each solution outperforms others on some goals and may perform worse on others. The Pareto solution set presents a balanced frontier that represents a solution with different trade-offs. The goal of multi-objective optimization is to find the optimal solution or a set of optimal solutions in the Pareto solution set to achieve a balance between multiple objectives [12]. In order to compare different solutions, the concept of Pareto domination is often used, one solution to another means that at least one goal is better than the other on all objectives is, and at least one goal is strictly superior to the other.

The algorithm NSGA-II [13] suggested by Deb and Srinivas on a basis of NSGA, is an evolutionary algorithm based on genetic algorithm, which can discover a set of non-dominant Pareto solutions when dealing with multi-objective problems, and these solution sets have trade-offs between multiple objectives. The algorithm NSGA-II is designed to provide better performance and convergence, as well as efficient handling of non-dominant solution sets.

Compared to the traditional NSGA algorithm, the NSGA-II algorithm boasts three significant enhancements [14]: the algorithm NSGA-II has the following advantages, compared to NSGA:

1) Rapid non-dominated solutions: NSGA-II uses a fast non-dominant ranking algorithm, which reduces a complexity of calculating non-dominant relationships and improves the execution efficiency of the algorithm.
2) Diversity maintenance: NSGA-II introduces the crowding distance to maintain the variety of solution set, so that the algorithm can distribute the solutions more evenly in the solution space and avoid falling into the local optimum.
3) Better convergence: NSGA-II considers the individual's level and congestion distance in the selection operation, which is conducive to the selection of high-quality solutions, so that the algorithm converges to the Pareto frontier faster.
4) More stable performance: NSGA-II is relatively less sensitive to the selection of parameters, so it is more stable and has increased versatility and adaptability to tackle a broader variety of problems..

Figure 2 shows the specific steps of using algorithm NSGA-II to resolve the optimal combination model of IoT services.

Step 1: $g = 0$, randomly generate an initial population of P_g, the number is N, each individual represents a potential solution, and the P_g is ranked non-dominantly and the whole individual crowding is calculated.

Step 2: Through the tournament method, select some individuals from the population, and perform crossover and mutation operations on the selected individuals to generate the next generation of population, and the population number is. Cross-operation can fuse the information of two individuals to produce a new individual, mutation operations, on the other hand, make small, random changes to individuals in order to maintain population diversity.

Step 3: The new individual obtained through selection, crossover and mutation operations is combined to the original population to form the new population with a quantity of for the next generation of iteration.

Step 4: The individuals of population are ranked by non-dominance and divided into different frontier ranks, and non-dominant solution sets are obtained. The individuals in the population are divided into multiple frontier classes according to the non-dominant relationship. In each rank, other individuals do not dominate individuals, while individuals in higher ranks dominate individuals of lower ranks. This step determines the variety and spread of solutions within the solution set.

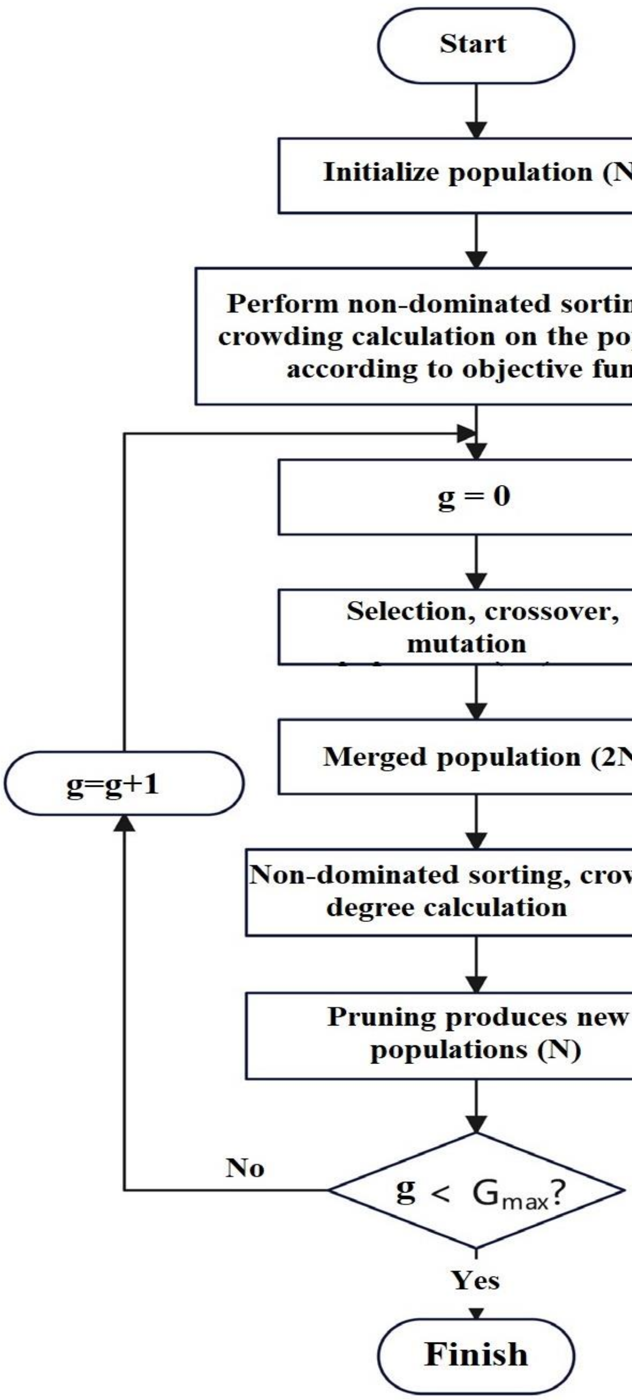

Figure 2. NSGA-II (Non-Dominated Sorting Genetic Algorithm –II) flow diagram.

Step 5: Choose individuals from the combined population R_g in the order of the non-dominated solutions until the desired population size of N is surpassed, stopping when the non-dominated set F_j is obtained.

Step 6: If the total number of individuals across $F_1, F_2, F_3, \ldots, F_i$ is greater than the population size N, the crowding degree is calculated for all individuals in F_j. The crowding distance indicates a distribution density of individuals in a solution space, which is used to maintain the diversity of the solution set. Individuals with larger distances are retained to avoid over-dense solutions. Based on the elite strategy, select the superior individuals from F_j and retain all individuals from the higher-ranked sets $F_1 \sim F_{j-1}$.

Step 7: Perform steps 2 through 6 repeatedly with $g = g + 1$ till a predetermined number of iterations is reached. At this time, the Pareto solution set of the IoT service combination model is solved.

3.5. Improved elite retention strategy

In the unusual NSGA-II algorithm, individuals with higher dominance ranks, having lower values, were included in the new population according to the dominance relationship, and individuals with high crowding were placed into the population when the same rank was placed until the population size reached N [15]. This elite retention strategy is to retain all elites, which may lead to rapid convergence or convergence to the local optimal solution. Therefore, an enhanced elite retention strategy is designed in this paper, as shown in Figure 3. Set the parameter α to add the first $N \times \alpha$ individuals directly to the new population, and remaining $N \times (1 - \alpha)$ individuals are chosen randomly from the less optimal solutions.

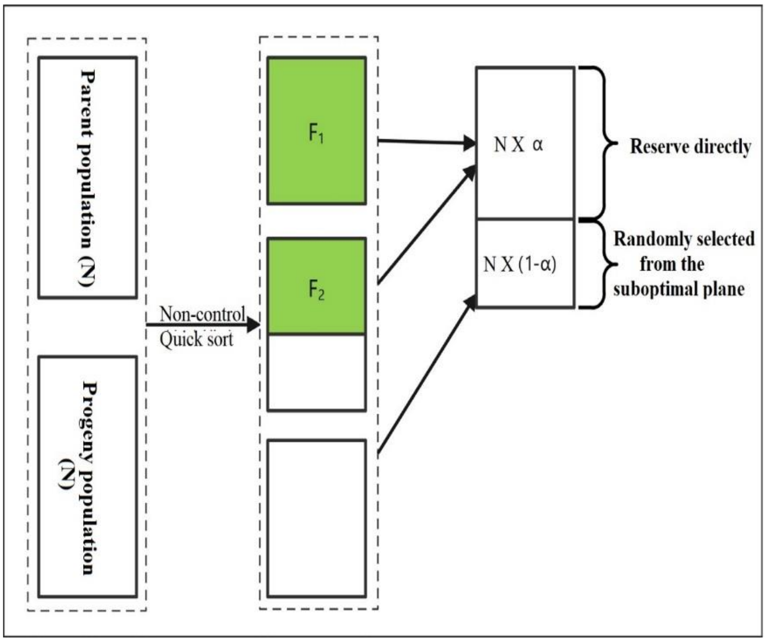

Figure 3. Improved elite retention strategy.

4. Simulation and Analysis

4.1 Study model

In the IoT service combination environment, a complex IoT service is decomposed into six simple sub-tasks according to certain normative criteria, and each simple sub-task can find the relationship between the sub-tasks and the candidate resource service set that meet the conditions from the IoT service pool. Each candidate task has a different QoS metric value corresponding to it, and the detailed QoS metric value and energy consumption.

The study parameters required in the IoT service combination are W_T = 0.15, W_R = 0.5, W_S = 0.35, T_{max} = 800 h, R_{max} = 3800 seconds, S_{min} = 0.93, E_{max} = 2500 kW·h, and A_{min} = 0.92.

4.2 Simulation results of the study

Take the maximum number of iterations G_{max} = 200, crossover rate P_c = 0.9, mutation rate P_m = 0.1, population N_p = 50. The experimental results of the non-dominating layer of the original NSGA-II algorithm to solve the IoT service combination model are shown in Figure 4. Figure 5 shows the original NSGA-II Pareto front and Pareto solution set, each dot in the figure represents a Pareto optimal service combination scheme, it can be seen that the number of service combinations obtained by solving the model by the original NSGA-II algorithm is 31, and the specific values of the 31 service combinations are used. The experimental results of the non-dominance layer of the I-NSGA algorithm to solve the IoT service composition model are shown in Figure 6. Figure 7 shows the I-NSGA Pareto front surface and Pareto solution set, and each dot in the figure represents a Pareto optimal service combination scheme, and it can be seen that the number of service combinations obtained by solving the model by the I-NSGA algorithm is 13, and the specific values of the 13 service combinations are used. Figure 8 shows a comparison of the Pareto frontiers of the two algorithms. The Pareto solution set of the original NSGA-II algorithm, and the Pareto solution set of the I-NSGA algorithm are put into table.

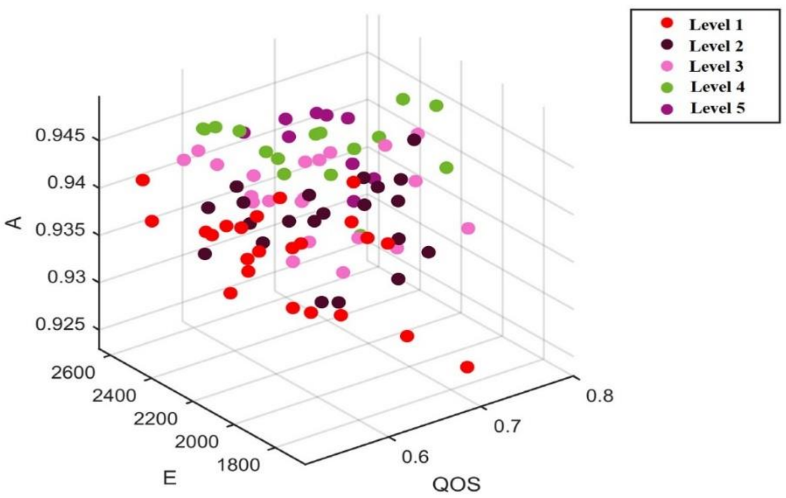

Figure 4. The algorithm NSGA-II. Solves non-dominant layer of IoT service composition model.

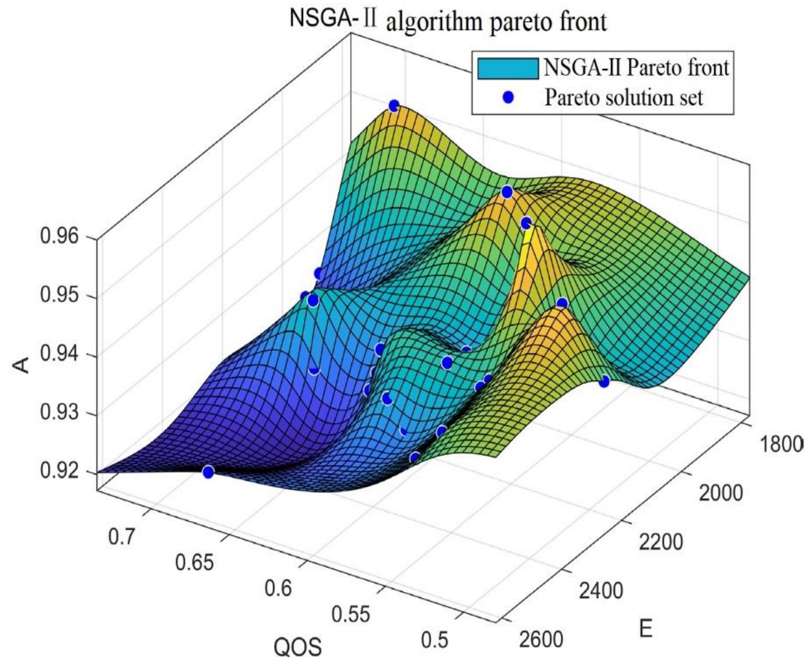

Figure 5. Pareto front plane with Pareto solution set of Original NSGA-II.

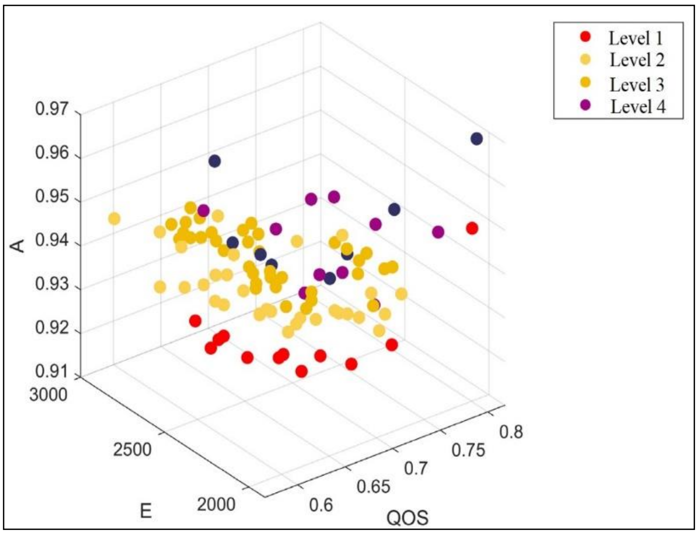

Figure 6. The algorithm I-NSGA is improved to solve the non-dominant layer of the IoT service composition model.

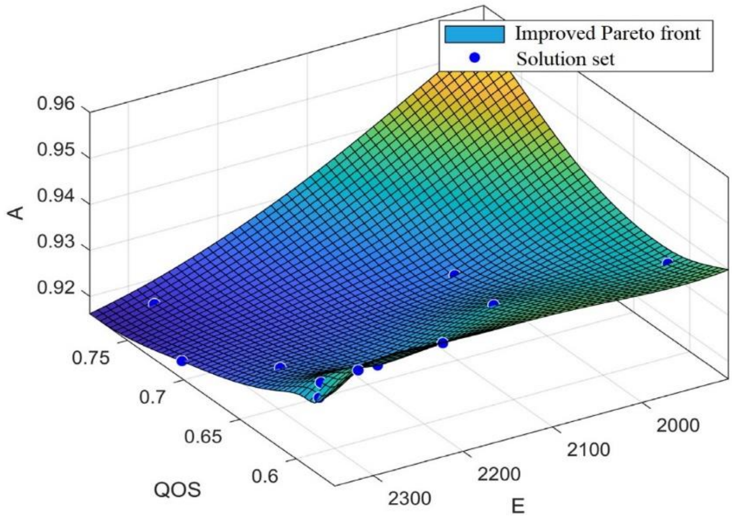

Figure 7. I-NSGA Pareto front with Pareto solution set.

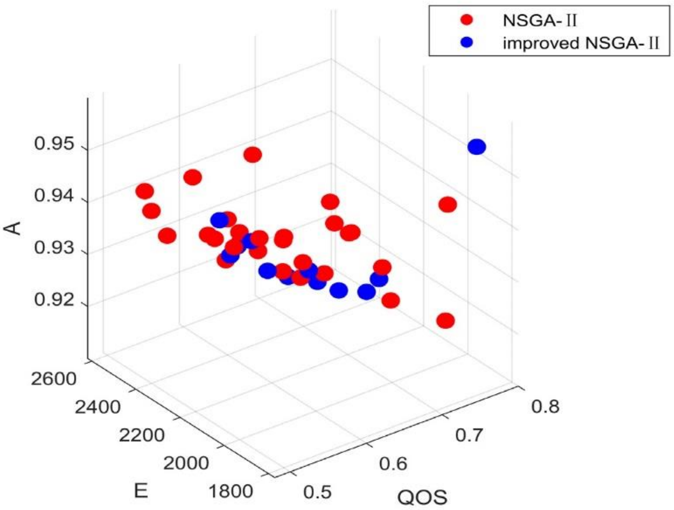

Figure 8. Pareto frontier comparison of two algorithms.

Related with the original NSGA-II algorithm, the running time of I-NSGA algorithm is reduced by 5.916%, and the Pareto surface of the proposed algorithm I-NSGA is smoother.

5. Conclusion

This study proposed an I-NSGA algorithm for optimizing IoT service composition, considering national energy consumption requirements and user experience. The original NSGA-II algorithm, while effective in handling multi-objective optimization problems, tends to suffer from premature convergence and local optima issues, which can limit its performance in complex environments such as IoT service composition. By introducing a novel evaluation model and enhancing the elite retention strategy, the I-NSGA algorithm demonstrates significant advancements over the original.

Highlights of performance Improvements, includes the running time of the I-NSGA algorithm is reduced by 5.916% compared to the original algorithm. This efficiency gain demonstrates the algorithm's enhanced performance and its ability to handle large-scale IoT service composition problems more effectively. The proposed algorithm produces a smoother Pareto surface, indicating a better spread and distribution of optimal solutions. This improvement is crucial for providing a diverse set of high-quality solutions, enabling more effective decision-making in IoT service composition.

Future Work, while the I-NSGA algorithm shows significant advancements, there are still areas for further research on exploring the algorithm's scalability for even larger and more complex IoT service composition scenarios, integration with Other Techniques, combining the I-NSGA with other optimization techniques, such as machine learning, to further enhance its performance and applicability.

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