Heterogeneous Resource Scheduling Method based on Energy Optimization under Price Constraints in Computing Force Network

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Keywords: Computing Force Network, Workflow Scheduling, Price-Sensitive.

Abstract: With the development of Computing Force Network (CFN), more and more resources are deployed in CFN which dynamically provide computing resources according to users' needs. In the CFN environment, scheduling workflow under deadline constraints is one of the fundamental issues. The number and size of heterogeneous resources in the CFN are gradually increasing, and the required costs are also constantly rising. As a result, it is necessary to consider users' budget limits while also reducing the energy consumption of end-side devices and edge servers. Aiming at workflow scheduling on time, cost, and energy consumption constraints, a scheduling algorithm that combines with NSGA-II is used to optimize scheduling time, cost, and energy consumption, with price as a soft constraint to ensure that the cost stays within the budget and the schedule is completed before the deadline while minimizing energy consumption. Our algorithm is validated by four typical scientific workflows, and the experimental results show that our algorithm can reduce the average energy consumption by 14.8%, and compared to the GPR-HEFT method, the average energy consumption can be reduced by 20.5%.

1 INTRODUCTION

In recent years, the computing infrastructure has undergone a significant transformation, moving from a centralized cloud-based model to a distributed architecture that includes the cloud, edge, and end-side computing (F. Liang, 2018). The cloud, represented by large-scale data centers, serves as the foundation of cloud computing, offering users the ability to store and process data through grid-based access to interconnected computers and servers. However, the rise of Multi-access Edge Computing (MEC) has shifted the focus towards bringing computing capabilities closer to the data source, addressing the limitations of latency and data volume associated with centralized cloud computing (Ahmad, S. Lembo, 2022). MEC enables the analysis and processing of data generated by Internet of Things (IoT) devices at the network edge, enhancing efficiency and security by eliminating the need to transmit data to remote cloud data centers. Additionally, the end-side computing encompasses various devices with networking and computing capabilities, such as PCs, smartphones, smart TVs, home set-top boxes, and IoT devices like smart meters for water and electricity (Baek, 2020). The proliferation of these terminal devices in the era of the Internet of Things presents an opportunity for leveraging their collective computing power through shared computing resources (B. Baek, 2020). By aggregating the idle computational resources of these devices, computing power sharing can be achieved, opening up new possibilities for distributed computing. These advancements in computing infrastructure offer potential for improved performance, reduced latency, enhanced security, and efficient utilization of computing resources. Researchers and industry professionals are actively exploring the opportunities and challenges associated with distributed computing models to harness the benefits of cloud, edge, and end-side computing in various domains.

With the increasing adoption of the three-level computing architecture comprising cloud, edge, and end-side, computing power is no longer confined to centralized data centers but is distributed across various locations at the edge and end-side. However, realizing the full potential of these distributed computing resources requires a robust network infrastructure that enables seamless interconnection and collaboration among the computing nodes. To address this challenge, the concept of the Computing Fabric Network (CFN) has been introduced. The

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CFN seeks to establish a network framework that facilitates the sharing, scheduling, utilization, and collaboration of computing resources across the distributed computing nodes. By enabling effective communication and coordination among these nodes, the CFN ensures that the computing power available at the edge and end-side can be harnessed efficiently and effectively. This concept holds great promise in unlocking the full potential of the three-level computing architecture and driving the development of innovative applications and services.

In the CFN, there are various heterogeneous resources in addition to computing power and storage space. Heterogeneous resources refer to different computing resources, such as CPUs, GPUs, FPGAs, etc., with different computing capabilities and characteristics. In the CFN (Seo, 2022), the use of heterogeneous resources can better meet the needs of different computing tasks and improve computing efficiency and flexibility.

Energy consumption of end-side devices is a crucial factor in computing scheduling, as these devices usually have limited computing power and storage space and need to complete various computing tasks through the CFN (Zhu, 2020). In computing scheduling, considering the energy consumption of end-side devices can help to maximize the battery life of devices, increase device usage time, and improve usage efficiency (Djigal, 2021).

The energy consumption of end-side devices is closely related to computing scheduling. In computing scheduling, tasks need to be assigned to different computing nodes for execution, and these computing nodes often require a significant amount of energy to complete computing tasks. If the computing scheduling is unreasonable, it can cause some computing nodes to have a high workload, resulting in excessive energy consumption and affecting the performance and efficiency of the entire CFN (Wang, 2021). Therefore, computing scheduling needs to consider the energy consumption of end-side devices to maximize the reduction of computing node energy consumption and improve the energy efficiency performance of the entire CFN.

To reduce energy consumption, computing scheduling can adopt various measures, such as task merging, node sleep, load balancing, etc. Task merging can merge multiple small tasks into one large task, reducing nodes' startup and shutdown time and lowering energy consumption (Yadav, 2020). Node sleep can put idle nodes to sleep to reduce energy consumption. Load balancing can evenly distribute tasks to different computing nodes, avoiding high workload on some nodes and thereby reducing energy consumption.

The contributions of this paper are summarized as follows:

According to the CFN scenario, the resource scheduling problem was defined in a three-tiered collaborative environment of cloud, edge, and terminal, and a resource scheduling stability model based on energy consumption and price sensitivity was constructed.

A refined NSGA-II algorithm is introduced in this study, leveraging the resource scheduling model in the Computing Fabric Network (CFN). Alongside, a novel elite selection method is employed to efficiently match services with tasks, while considering cost, energy consumption, and execution time. The approach prioritizes selecting the best-suited service within budget and deadline limitations, leading to cost reduction without compromising success rates under various strict constraints.

Extensive simulation experiments were performed to evaluate the effectiveness of the proposed algorithm, comparing it against four state-of-the-art methods. The obtained results demonstrate that the proposed algorithm consistently achieves successful scheduling under all imposed constraints across all tested scenarios.

The remaining sections of the paper are as follows: Section II provides a review and discussion of the related work. Section III models the workflow scheduling problem in the CFN environment. Section IV presents the proposed optimization algorithm in detail. Section V provides the specific simulation settings and results, summarizes our work and points out the next steps.

2 RELATED WORK

Currently, there are increasing numbers of workflow scheduling algorithms proposed for cloud computing, which can be mainly classified into three types: heuristic algorithms, meta-heuristic algorithms, and reinforcement learning-based algorithms.

Heuristic algorithms have been extensively researched as a method for workflow scheduling, offering time-saving benefits by traversing tasks from the entry to the exit of the workflow. Researchers have made notable contributions in this area. Durillo et al. (Durillo, 2014) analyzed the multi-objective heterogeneous earliest finish time

(MOHEFT) algorithm, a Pareto-based list scheduling heuristic that provides a set of trade-off optimal solutions to users. Poola et al. (Poola, 2014) proposed a robust scheduling algorithm that utilizes a resource allocation strategy to schedule workflow tasks on heterogeneous cloud resources, aiming to minimize both completion time and cost. Faragardi et al. (Faragardi, 2020) introduced GPR-HEFT, a cost-benefit-driven resource allocation method for minimizing makespan in budget-constrained cloud environments. They considered different cost-benefit ratios among resource instances and proposed an improved version of the HEFT algorithm that schedules tasks on a fixed subset of resource instances. They optimized the calculation of the earliest finish time using an insertion strategy and sought a balance between instance renewal and budget constraints. However, while heuristic algorithms provide specific rules for task scheduling with lower time complexity, they face challenges in handling uncertainty in real-world scheduling scenarios and may not yield solutions close to optimality.

Meta-heuristic algorithms have gained significant popularity for scheduling workflows in the cloud due to their ability to find global optimal solutions while minimizing completion time and monetary cost. These algorithms operate based on a set of guiding principles or strategies. Deb et al. (K. Deb, 2002) proposed the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which is a generational evolutionary algorithm that employs Pareto sorting and crowding distance density estimation. Coello et al. (Coello, 2004) introduced the Multi-Objective Particle Swarm Optimization algorithm (MOPSO), which incorporates Pareto dominance into Particle Swarm Optimization (PSO) to handle multi-objective optimization problems. These meta-heuristic algorithms partially overcome the limitations of heuristic approaches and can generate near-optimal solutions. However, their high time complexity poses challenges for their widespread and deep application. These algorithms often require a large number of iterations in the evolutionary process to obtain good solutions, resulting in high computational costs and long convergence times.

3 SOLUTIONS

3.1 Workflow Model

The workflow is represented by a directed acyclic graph (DAG), G=(T, E), where T represents a set of nodes, $T = \{t_1, t_2, t_3 \dots t_N\}$, and each node is a microservice. In addition, E represents a set of edges between tasks, $E = \{e_{i,j} | t_i, t_j \in T\}$, where these edges are control or data dependencies, and the amount of data transferred between t_i and t_j is denoted by $CR_{i,j}$. If microservice t_j depends on microservice t_i, then $e_{i,j}$ is 1, otherwise $e_{i,j}$ is 0.

There are M different combinations of computing resources in the entire CFN, $P = \{p_1, p_2, p_3 \dots p_M\}$, where $p_i = \{CPU_i, GPU_i, ASIC_i, FPGA_i, MEMORY_i, BANDWITH_i | i \in M\}$ represents the number of heterogeneous resources provided by different resource combinations.

The processing capacity of different computing resource combinations varies, and $ExecTime_{i,j}$ is used to represent the execution time of t_j on p_i. If resource combination A takes less time to execute the same task than B, then A is faster than B. The reasons for this may be: (1) the MIPS rate of the virtual processors of instance types is higher. (2) there are more virtual cores. (3) the memory size and storage capacity are larger, and the storage access time is faster.

3.2 Energy Consumption Model

Consider the following three types of energy consumption: (1) energy consumption when running tasks on computing resource combinations; (2) energy consumption when computing resource combinations are idle; (3) energy consumption of communication links. Assuming that the hardware facilities support DVFS technology (S. Wang, 2017), the system-level power model used in (Y. Chen, 2018) and (Z. Long, 2020) is adopted, and the power estimation at running frequency f is shown in Formula 1:

$$P(f) = P_s + h(P_{ind} + P_d) = P_s + h(P_{ind} + C_{ef} * f^m) \tag{1}$$

Where P_s is the static power, which is always present by default and can only be eliminated by turning off the entire system's power; h is the system state, indicating whether the current system is consuming dynamic power. When the system is in an active state, h=1; otherwise, h=0. P_{ind} represents the frequency-independent dynamic power, which can only be eliminated by putting the system into sleep mode; P_d represents the frequency-dependent dynamic power (Y. Chen, 2018); C_{ef} represents the effective switching capacitance; m represents the dynamic power exponent, and its value should not be less than 2.

In this study, the static power P_s is not considered in the computation. For various types of heterogeneous resources in the CFN, such as FPGA and ASIC, the mainstream calculation method for their power consumption is to follow the computation form of CPU, which consists of three parts: chip static power, design static power, and design dynamic power (Xu, 2016)(Taghinezhad-Niar A., 2020). The power consumption of the first two parts depends on the FPGA chip itself, so the main focus is still on the dynamic power consumption as the variable to be considered in the computation:

$$P_{total} = P_{static} + \alpha C V^2 f \tag{2}$$

3.3 Cost Model

Cloud computing resources are composed of a set of virtual machines with different unit prices. Therefore, let $Cost(t_i, p_m, f_m, h)$ denote the execution cost of task t_i running on node p_m with $f_{m,h}$, which can be expressed as:

$$Cost(t_i, p_m, f_m, h) = w_{i,m} \times price_m \times \frac{f_{m,max}}{f_{m,h}}. \tag{3}$$

Where $price_m$ is the unit execution price of a task on node p_m. The total execution cost of a DAG application can be calculated as follows:

$$Cost(G) = \sum_{i=0}^{|N|} Cost(t_i) = \sum_{i=0}^{|N|} Cost(t_i, p_m, f_m, h). \tag{4}$$

3.4 Optimization Model

This study considers completing the scheduling before the deadline while minimizing energy consumption as much as possible while ensuring that the cost is within the budget. The optimization model can be formulated as follows:

$$MinF(X) = MinMakespan(X) + EnergyConsumption(X) \tag{5}$$

$$s.t \sum_{k=1}^{M} X_{i,k} = 1, \quad \forall i \in [1, N], X_{i,k} \in \{0,1\}.$$

$$Task_{i,j} \le CurrNode_{i,j}, \forall i \in [1, N], \forall j \in [1,4].$$

$$|Cost(G) - Budget_i| \le q, \quad \forall i \in [1, N].$$

3.5 Baseline

The Spread algorithm is an innovative approach for solving multi-objective heterogeneous earliest finish time scheduling problems. It is a Pareto-based list scheduling heuristic algorithm that offers users a range of trade-off optimal solutions. The Binpack algorithm, on the other hand, proposes a robust scheduling approach that incorporates a resource allocation strategy. It schedules workflow tasks onto a set of heterogeneous cloud resources while minimizing both the maximum completion time and cost. GPR-HEFT, a greedy heuristic method, takes into account resource allocation under budget constraints. To establish a baseline for comparison, the essence of these three algorithms was reproduced, and energy and time calculations were incorporated into the algorithms.

3.6 Algorithm Based on NSGA-II

The workflow scheduling problem is a typical multi-objective optimization problem, and it is also NP-Hard. Traditional single-objective optimization algorithms cannot solve multi-objective optimization problems. Non-Dominated Sorting Genetic Algorithm (NSGA) is a commonly used method for solving multi-objective optimization problems. However, NSGA has drawbacks such as high computational complexity and the inability to perform elite selection.

To address these issues, Deb et al. proposed the NSGA-II algorithm in (K. Deb, 2002), which improves on NSGA in the following ways: (1) proposes a fast non-dominated sorting method, (2) introduces the concept of crowding distance and crowding distance sorting, and (3) introduces an elite selection strategy. In NSGA-II, a portion of the best solutions is retained in each offspring to ensure the algorithm maintains diversity in the search space and accelerates convergence. Therefore, NSGA-II has significant improvements over NSGA in terms of algorithm efficiency, diversity in the search space, offspring quality, and convergence speed. NSGA-II is an effective method for solving multi-objective optimization problems, and this paper will also design a workflow scheduling algorithm based on NSGA-II to solve the microservice scheduling problem in the CFN.

The algorithm takes as input a set of user tasks and a set of computing nodes, and outputs the Pareto front. The following is the algorithm and its flowchart.

Algorithm 1 The proposed algorithm

```
Input: Input the initial population size, number of generations to run the algorithm,
number of offspring, crossover and mutation rates, and fitness function.
Output: Return the final population, non-dominated solutions or Pareto front,
diversity of the population, convergence performance, and execution time.
1.    Initialize population P(0) with N individuals randomly
2.    for each generation G = 1 to T do
3.        M = 2N offspring created through crossover and mutation of P(G-1)
4.        Q = P(G-1) ∪ M
5.        Compute non-domination of Q
6.        Assign a rank to each individual based on the non-domination levels
7.        Perform crowding distance calculation for each individual
8.        Create a new population P(G) by selecting the best individuals based on
      their rank and crowding distance
9.    end for
```

The input of the proposed algorithm is a set of user tasks and a set of computing nodes, and the output is the Pareto front.

4 EXPERIMENT

To ensure reproducibility and statistical significance, simulation methods were employed to evaluate the proposed method. Conducting repeatable experiments in a real data center or cloud platform can be challenging. Therefore, a simulation approach was adopted, enabling a substantial number of experiments to be conducted across various application configurations. This approach allows for rigorous testing and analysis, resulting in more reliable and statistically significant results.

The purpose of the experiment is to verify the superiority of the improved algorithm over other algorithms in the same optimization indicators, including energy consumption, cost, and scheduling delay. In terms of hardware, a physical machine with an Intel(R) Core(TM) i5-1135G7 @ 2.40GHz processor and running the Windows 11 operating system was used for the experiment.

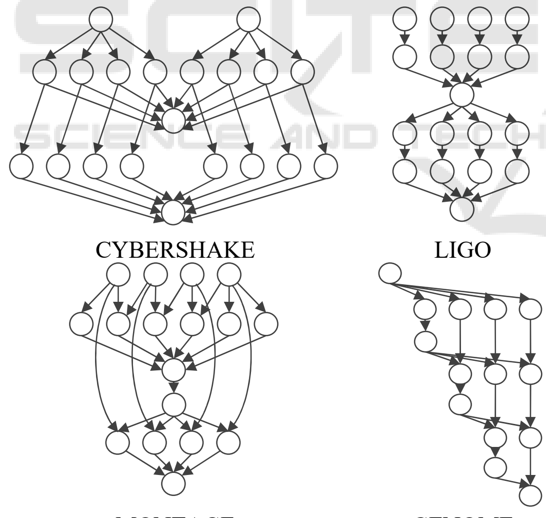


Figure 1: Four kinds of workflow diagrams.

4.1 Dataset

The simulation incorporated four commonly used scientific workflow models: CYBERSHAKE, GENOME, LIGO, and MONTAGE. Figure 1 illustrates the smaller workflow structures of each application. CYBERSHAKE is a data-intensive workflow that places high demands on memory and CPU resources. It plays a significant role in modeling seismic disasters in a particular region. GENOME is designed for automating various genome sequencing operations, essentially serving as a data processing pipeline. LIGO is utilized for the detection and analysis of gravitational waves in physics. It primarily requires substantial CPU resources.MONTAGE is an astronomy workflow model used to generate customized sky mosaics. In MONTAGE, most tasks are I/O-intensive and do not necessitate high CPU processing capabilities (Gideon Juve, 2012).

In our experiment, we assume that the CFN provides six types of virtual machines, each with different resource and price characteristics.Each virtual machine has different attribute values that are randomly generated based on the resource requirements of the dataset. The pricing was based on the existing Alibaba Cloud pricing for cloud resources. For the resource requirements, the same dataset as (S. Tao, 2023) was used.

The parameters of the algorithm greatly affect the performance of the algorithm. Table 1 is the parameters used in the implementation of the algorithm.

Table 1: NSGA-II parameter setting.

Parameter	Value
Population size	80
Number of iterations	100
Cross probability	1
Mutation probability	0.1

The performance metric employed to evaluate the different algorithms on various workflows is the normalized cost. The normalized cost is calculated as the ratio of the cost of the current solution to the cost of the cheapest solution. In the cheapest solution, all tasks are scheduled on the cheapest virtual machine, resulting in the minimum cost. The total execution time and cost of the cheapest solution are denoted as M_t and C_t, respectively. Similarly, in the fastest scheduling solution, all tasks are scheduled on the fastest virtual machine. The HEFT algorithm is used to determine the fastest scheduling method in our experiment. The total execution time and cost of the fastest solution are denoted as M_f and C_f, respectively. To control the variation of the deadline, a deadline factor μ is introduced, with $\mu \in [0,1]$. The deadline for each repeated experiment can be calculated based on the value of μ. This allows for the assessment of algorithm performance under different deadline constraints.

$$Makespan = M_f + \left(M_t - M_f\right) \times \mu \tag{6}$$

For certain workflows, the cost can be much higher due to their special structures, making it difficult to show differences when considering budget constraints. To overcome this problem, a budget factor λ (λ∈[0,1]) is introduced to represent the looseness of the budget. To make it easier to control the factor, we set λ = 1−μ and calculate the budget based on λ.

$$Budget = C_t + (C_f - C_t) \times \lambda \tag{7}$$

A higher value of μ indicates looser deadline constraints and stricter budget constraints. In such cases, the scheduling method is more likely to prioritize slower services to meet the budget restrictions. On the other hand, a higher value of λ increases the likelihood of the scheduling method selecting faster services, as it emphasizes meeting tighter deadline constraints.

The success rate measurement was employed to assess the effectiveness of each method in generating solutions that satisfy the given constraints. It is determined by dividing the number of successful plans by the total number of plans evaluated. This metric provides an indication of how well each method performs in meeting the specified constraints and achieving satisfactory outcomes.

4.2 Results Analysis

The experiment employed the total delay of scheduling and the energy consumption of resources as evaluation indicators for microservice scheduling. These indicators were calculated using formulas 2 and 4, respectively. To assess the performance of the proposed algorithm, benchmark methods such as Spread, Binpack, and GPR-HEFT were utilized. These methods are well-established optimization techniques in the field of workflow scheduling. Considering the stochastic nature of certain properties of the methods, the experiments were conducted using datasets of different sizes (50, 100, 200). Each experiment was repeated 10 times to obtain average values, ensuring the reliability and robustness of the results.

To comprehensively assess the effectiveness of each method under varying degrees of constraints, the evaluation process began by setting μ and λ to small values to evaluate performance under strict constraints. Subsequently, μ and λ were varied within the range of [0.005, 0.03] with a step size of 0.005. The average success rate of each method under different configurations is depicted in Figures 2 and 3. These figures provide insights into the performance of each method across a range of constraint settings, allowing for a comprehensive evaluation of their ability to generate effective solutions.

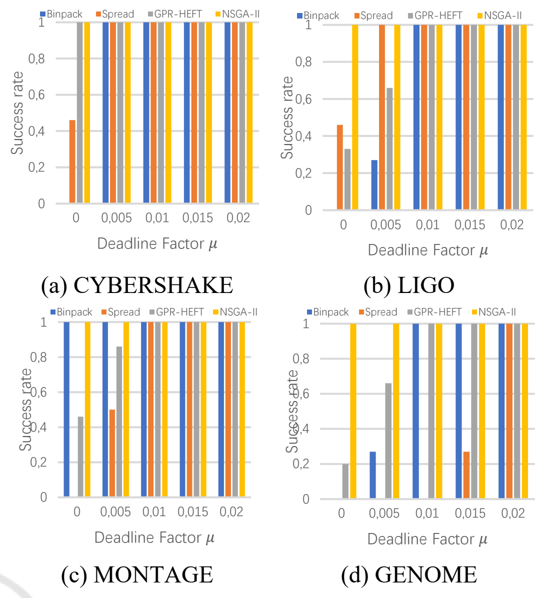


Figure 2: The average scheduling success rate of each workflow data under the deadline constraint.

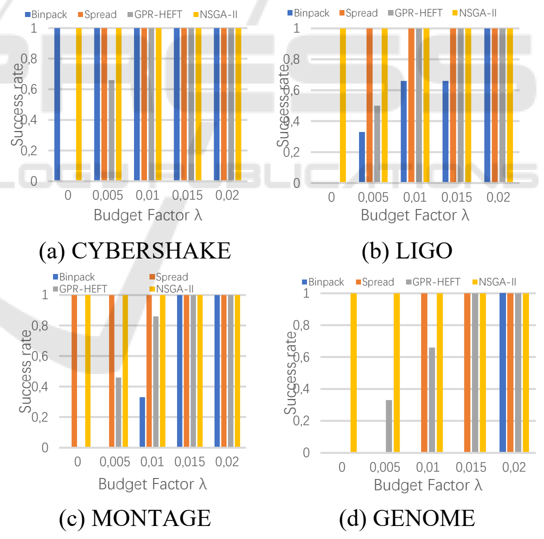
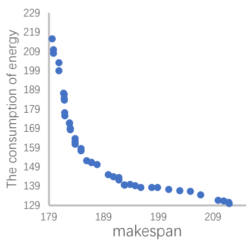


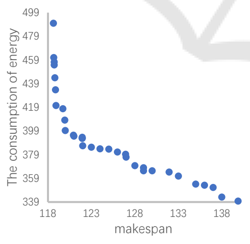
Figure 3: The average scheduling success rate of each workflow data under budget constraints

As shown in Figure 2, as the deadline factor μ increases and the budget factor λ decreases, the success rate of each method also increases, and when μ equals 0.025, all methods can achieve a success rate of 100%. The Spread method does not perform well on every workflow. When used on CYBERSHAKE and LIGO, it can quickly reach 100%, but performs the worst on GENOME. When μ is less than 0.025, the Binpack method cannot complete the scheduling 100% and performs relatively poorly on GENOME and LIGO. the GPR-HEFT method performs better than the first two methods, but there are still cases where it cannot complete scheduling when the deadline constraints are strict. The proposed agorithm performs the best in terms of performance and can successfully schedule under all workflows in this experiment.

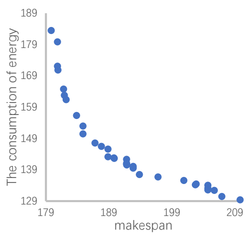
As depicted in Figure 3, an interesting observation is that when the budget factor λ is extremely small, only our proposed method consistently achieves a 100% success rate across all workflows. In contrast, the Binpack method fails to satisfy the constraints in most cases, achieving a 100% success rate only for GENOME when λ exceeds 0.02. The Spread method performs well for MONTAGE, reaching a 100% success rate in every case. However, it struggles to satisfy the constraints when the budget is at its minimum for MONTAGE. On the other hand, the Binpack method demonstrates robustness, with a relatively stable success rate at small values of μ and λ. The performance of GPR-HEFT under budget constraints remains steady, with a success rate that gradually increases as the budget constraint becomes more stringent. This aligns with the design intention of the GPR-HEFT algorithm. Overall, these findings shed light on the comparative performance of different methods under varying constraint settings and highlight the strengths and limitations of each approach.



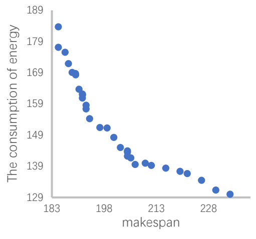
(a) CYBERSHAKE



(b) LIGO



(c) MONTAGE

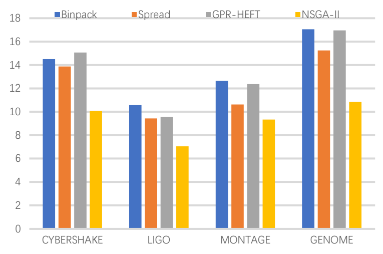


(d) GENOME

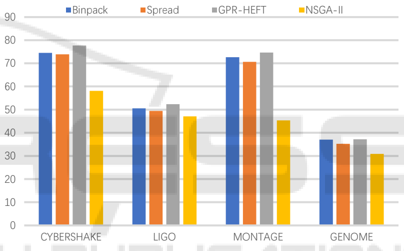
Figure 4: The number of tasks is 100 when the NSGA-II algorithm Vilfredo Pareto front.

Figure 4 shows the Pareto front of the proposed algorithm for four different workflow datasets with a task count of 100. It can be seen that for the four different datasets, our algorithm can converge quickly and obtain a set of Pareto front solutions for selection, with a moderate number of solutions that are evenly distributed.

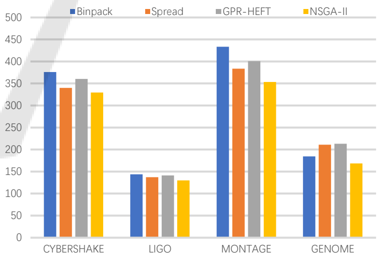
Figures 5 and 6 show the comparison of delay and energy consumption of three algorithms under different task counts in four datasets. From the figure, it can be seen that as the number of microservices increases, the overall delay continues



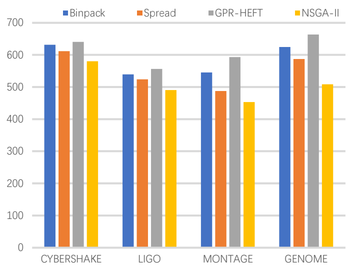
(a)10



(b) 50



(c)100

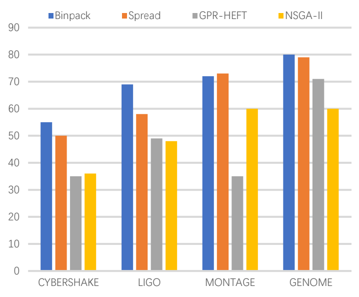


(d) 200

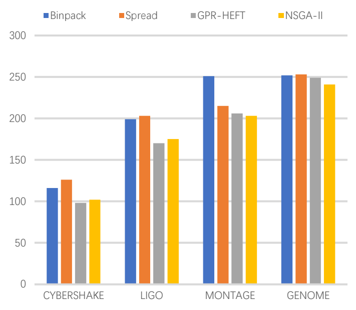
Figure 5: The energy consumption of the four algorithms was compared with the data from different tasks.

to increase, and the proposed algorithm has a much lower delay than the Spread algorithm, slightly lower than the Binpack algorithm. This is because Spread always schedules microservices to different nodes, resulting in an increase in microservice data transmission. Binpack schedules microservices to one node, reducing this delay. Due to its greedy strategy, the GPR-HEFT method often falls into local optima during the search process, resulting in overall inefficiency, while our algorithm has global search capabilities and can find globally optimal solutions to some extent. In terms of load balance, our algorithm has significant improvements compared to the above two algorithms. The experimental results show that the proposed algorithm optimizes both scheduling delay and energy consumption, effectively ensuring the QoS of user applications.

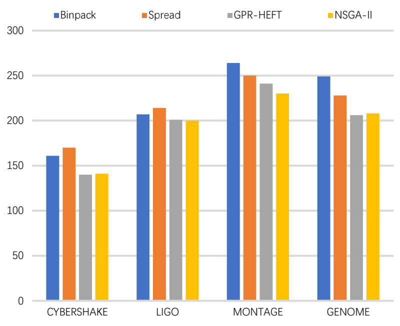
In summary, the LIGO workflow's complex topological structures may limit the impact of NSGA-II in the elite selection step, leading to a less significant reduction in scheduling execution costs. In the CYBERSHAKE workflow, tasks with numerous parent tasks but no intermediate child tasks can be scheduled flexibly, with their execution having a varying impact on the overall plan depending on the constraints and budget. The GENOME workflow, with its simpler structure and consistent scheduling order, exhibits similar cost and energy consumption patterns across different scheduling methods. These observations emphasize the role of workflow characteristics in influencing scheduling method performance and highlight the specific challenges posed by each workflow.



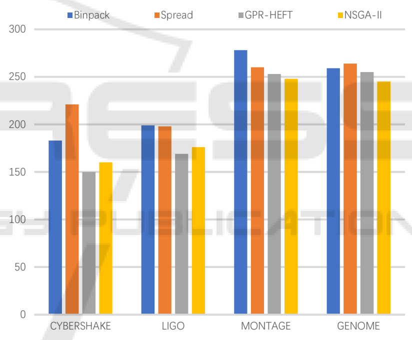
(a) 10



(b) 50



(c) 100



(d) 200

Figure 6. Under the data of different tasks, the Makespan of the three algorithms is compared.

In summary, the proposed algorithm performs well on each dataset with different numbers of tasks, as shown in Figure 5. On the four datasets, the scheduling energy consumption of the NSGA-II algorithm is on average 19.4% lower than Binpack, 14.8% lower than Spread, and 20.5% lower than GPR-HEFT. Especially on the MONTAGE dataset, the average energy consumption is 24.7% lower than Binpack. In Figure 6, the NSGA-II method still has an advantage in scheduling delay, with an average delay that is 15.4% lower than Binpack, 14.1% lower than Spread, and 3.7% lower than GPR-HEFT. Especially on the CYBERSHAKE dataset, the average scheduling time is 23.7% lower than Spread.

Regarding scheduling delay, our method also performs well. Figure 6 shows the average scheduling delay of the four methods on four datasets. The scheduling delay of our algorithm is on average 15.4% lower than Binpack, 14.1% lower than Spread, and 3.7% lower than GPR-HEFT. Especially on the CYBERSHAKE dataset, the average scheduling time of our method is 23.7% lower than that of Spread.

5 CONCLUSION

In this article, we analyzed the scheduling problem of workflow in the existing CFN environment and found that energy consumption and price constraints are important in the scheduling process in a real environment. Therefore, we concluded that the scheduling problem in the CFN is a multi-objective optimization problem. Then, we modeled the energy-aware and price-sensitive scheduling problem in the CFN.

A comparative analysis between the proposed algorithm and existing algorithms showed that the proposed algorithm achieved the highest success rate, satisfying constraints with low energy consumption, especially under tight constraints. It also maintained good performance as the constraints became looser. The algorithm performed exceptionally well on the CYBERSHAKE dataset, with a consistently lower average Makespan compared to other algorithms. In summary, the comparative analysis demonstrated the superior performance of the proposed algorithm in terms of success rate, constraint satisfaction, energy consumption, and Makespan. This highlights its potential as a promising solution for microservice scheduling.

In future research, we plan to enhance the update strategy of the algorithm to improve convergence speed and achieve better results across workflow processes. Our goal is to optimize the algorithm's efficiency, enabling faster generation of high-quality solutions. We will also focus on refining the comprehensive budget allocation and service selection methods, particularly for relaxed constraint conditions. This will allow the algorithm to be applied effectively in a wider range of real-world scenarios with varying constraints and budget allocations. By addressing these areas, we aim to advance the algorithm's performance, expand its applicability, and contribute to the field of microservice scheduling research.

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