Service migration across edge devices in 6G-enabled Internet of Vehicles networks

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***Abstract*—The Internet of Vehicles (IoV) environment consists of a number of latency-critical and data-intensive application (e.g., real-time video analytics). In this paper, we posit the potential of leveraging the sixth generation (6G) mobile networks to minimize communications delay, particularly for latency-critical task execution. In particular, 6G-enabled network in boxes (NIBs) deployed in the vehicles can communicate in real-time with the edge servers or the NIBs in other vehicles. Although, NIBs are capable of providing dynamic and flexible computing resources to support real-time IoV services, there are significant energy costs associated with the communication and computing activities. Seeking to achieve an optimal balance between energy consumption and time cost during service migration, we design a NIB task migration method (NTM) for IoV in this paper. In our approach, the IoV framework is designed and the routing mechanism is established. The Strength Pareto Evolutionary Algorithm (SPEA2) is then utilized to determine the migration strategy. Findings from our experiments demonstrate the reliability and efficiency of our proposed approach.**

***Index Terms*—IoV, Edge computing, 6G, Network in boxes, Service migration.**

I. Introduction

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INTERNET of vehicles (IoV) are increasingly becoming mainstream, as cities and nations become more digitalized and interconnected. A typical IoV setup includes participating smart vehicles (equipped with various technologies such as sensors, micro-controllers and intelligent cameras) and other supporting infrastructure (e.g., road side units, and IP-based CCTVs) [1], where vehicles and other smart entities communicate with each other. To support the computational demands of an IoV network, data collected from vehicles and other smart entities are sent to the cloud for processing.

However, many of the tasks in an IoV setting are time- and delay-sensitive tasks (e.g., traffic navigation and danger notification), and hence there have been attempts to utilize edge computing (EC) in IoV settings, where most of the time- and delay-sensitive tasks can be performed at the edge servers. Examples of edge computing-based approaches include those of [2]–[4]. There are various design considerations in such edge computing-based approaches. For example, one need to consider the allocation and coordination of resources between edge and cloud servers. Hence, researchers such as [5], [6] have proposed approaches to facilitate service migration. In addition, some researchers utilize the cache management policies to achieve better EC performance [7]. Although, most of the existing approaches are designed to facilitate service migration, focusing on the time cost or energy consumption. However, considering sixth-generation (6G) mobile networks, which achieves 10 to 100 times data rate, lower latency, and wider coverage than the fifth-generation mobile networks, the migration rate and delay can be acceptable with 6G, facilitating the interconnection of vehicles [8]–[12]. We posit the importance of designing a service migration method to optimize both energy consumption and time cost, as well as utilizing 6G to support IoV communications.

There are, however, challenges associated with a 6G-enabled IoV deployment. For example, how to ensure the users' quality of experience during service migration is not adversely affected by the migration, and how to minimize the energy consumption during service migration? To address these issues, the strength Pareto evolutionary algorithm (SPEA2) was used to optimize energy usage and migration time costs. The multiple criteria decision making (MCDM) and the technique for order preference by similarity to an ideal solution (TOPSIS) are then used to evaluate the solutions of migration strategies.

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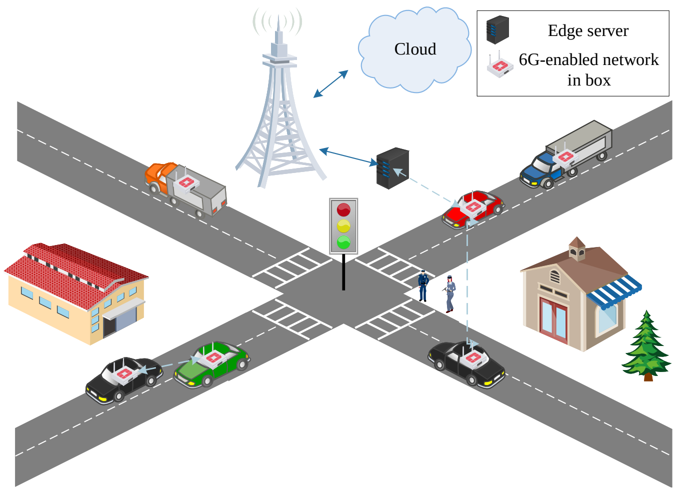

Fig. 1: A simplified use case

The rest of this paper is organized as follows. The system model and problem formulation are presented in the next section. The third and fourth sections present our proposed service migration method for IoV and simulation experiments and comparison analysis, respectively. Finally, the conclusion is presented in the last section.

II. System Model and Problem Formulation

In this section, we present the system model for service migration in IoV, which comprises both energy consumption and time cost models.

A simplified use case for the task migration method (NTM) is shown in Fig 1, which consists of a cross junction (P), some edge servers ($ES = \{es_1, es_2, \ldots, es_P\}$), and N NIBs in the moving vehicles ($NIB = \{nib_1, nib_2, \ldots, nib_N\}$). We assume each edge server contains a server with sufficient number of VM instances to execute service migration, and there are W VM instances in each NIB ($R = \{r_1, r_2, \ldots, r_W\}$), and Q VM instances in each edge server ($S = \{s_1, s_2, \ldots, s_Q\}$). We also denote X as the migration strategy, which is mathematically expressed as $X = \{x_1, x_2, \ldots, x_N\}$.

A. Time Consumption Model

As the significant elements for evaluating the strategy, the time consumption of the NIBs and ESs principally include the transmission, execution and feedback time. The execution time expenditure produced by c_m in NIBs is calculated by

$$t_{exec}(X) = \sum_{n=1}^{N} I_n(X) \cdot \frac{\delta_m}{\sum_{w=1}^{W} i_{m,w} \cdot k}, \tag{1}$$

where δ_m is the task size of c_m, k is the computing power of the VM instances in each NIB, which is related to the CPU frequency, and $I_n(X)$ is a binary variable to estimate whether c_m is existed in nib_n, which is calculated by

$$I_n(X) = \begin{cases} 1, & \text{if } c_m \text{ is existed in } nib_n, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

and $i_{m,w}$ is the dimension to estimate whether c_m occupies the w-th r_w on nib_n, which is calculated by

$$i_{m,w} = \begin{cases} 1, & \text{if } c_m \text{ occupies the } r_w \text{ in } nib_n, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The migration time is calculated by

$$trans_m(X) = \sum_{n=1}^{N} h_n^m(X) \cdot \frac{\omega_m}{\theta} \cdot (\lambda - 1), \tag{4}$$

where λ is the number of NIBs that transferred from nib_m to $nib_{m'}$, θ is the data transmission rate between NIBs, and ω_m is the data size of c_m. $h_n^m(X)$ is a binary variable employed to estimate whether c_m needs to be migrated, which is measured by

$$h_n^m(X) = \begin{cases} 1, & \text{if } c_m \text{ needs to be migrated to } nib_n, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

After the transmission and execution of the services migrated, the processed outcomes should be fed back to the vehicles, which is given by

$$feed_m(X) = \frac{\omega_{m'}}{\theta} \cdot \lambda, \tag{6}$$

where $\omega_{m'}$ is the datasize of Feedback results.

The execution time of c_m in ESs is calculated as

$$t'_{exec}(X) = \sum_{n=1}^{N} I'_n(X) \cdot \frac{\delta_m}{\sum_{q=1}^{Q} i_{m,q} \cdot g}, \tag{7}$$

where g is the computing power of VM instances in each ES and $I'_n(X)$ is a binary variable to estimate whether c_m is existed in es_p, which is calculated by

$$I'_n(X) = \begin{cases} 1, & \text{if } c_m \text{ is existed in } es_p, \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

and $i_{m,q}$ is the dimension to estimate whether c_m occupies the s_q in es_p, which is calculated by

$$i_{m,q} = \begin{cases} 1, & \text{if } c_m \text{ occupies the } s_q \text{ in } es_p, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

The migration time for transiting the service c_m from nib_n to es_n is calculated by

$$trans'_m(X) = \sum_{p=1}^{P} H_p^m(X) \cdot \frac{\omega_m}{\mu} \cdot (\lambda' - 1) + \frac{\omega_m}{\theta}, \tag{10}$$

where μ is the migration rate between NIBs and ESs, λ' is the number of ESs that transferred from nib_m to es_p. A binary variable $H_p^m(X)$ is employed to estimate whether c_m needs to be migrated, which is measured by

$$H_p^m(X) = \begin{cases} 1, & \text{if } c_m \text{ needs to be migrated to } es_p, \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

The feedback time of processed services c'_m is calculated by

$$feed'_m(X) = \frac{\omega_{m'}}{\theta}(\lambda' - 1) + \frac{\omega_{m'}}{\mu}, \tag{12}$$

Therefore, the total time consumption of the service migration can be calculated by

$$T(X) = trans_m(X) + trans'_m(X) + t_{exec}(X) + t'_{exec}(X) + feed_m(X) + feed'_m(X), \tag{13}$$

B. Energy Consumption Model

To the service migration strategy, the energy cost is a significant index. The energy expenditure produced by active VM in NIBs is calculated as

$$E_{emp}(X) = \sum_{n=1}^{N} I_n(X) \cdot \sum_{m=1}^{M} \sum_{w=1}^{W} i_{m,w} \cdot t_{exec}(X) \cdot \varphi, \tag{14}$$

where φ is the power rate of active VM in NIBs.

The energy expenditure produced by unused VM in the NIBs is calculated by

$$E_{\text{unemp}}(X) = \sum_{n=1}^{N} I_n(X) \cdot \left(W - \sum_{m=1}^{M} \sum_{w=1}^{W} i_{m,w} \right) \cdot t_{exec}(X) \cdot \delta, \tag{15}$$

where δ is the power rate of the unused VM in NIBs.

The energy consumed in the data transmission process between the NIBs is given by

$$E_{tran}(X) = trans_m(X) \cdot p_m \tag{16}$$

where p_m denotes the transmission energy consumption power between the NIBs.

The energy cost of active VM instances in ESs is calculated by

$$E'_{emp}(X) = \sum_{n=1}^{N} I'_n(X) \cdot \sum_{m=1}^{M} \sum_{q=1}^{Q} i_{m,q} \cdot t'_{exec}(X) \cdot \gamma, \tag{17}$$

where γ is the rate of work of the active VM in ESs.

The energy cost of the unused VM in ESs is calculated by

$$E'_{\text{unemp}}(X) = \sum_{n=1}^{N} I'_n(X) \cdot \left(W - \sum_{m=1}^{M} \sum_{q=1}^{Q} i_{m,q} \right) \cdot t'_{exec}(X) \cdot \xi, \tag{18}$$

where ξ is the power rate of the unused VM in ESs.

The energy consumed in the data transmission process between the NIBs and ESs is given by

$$E'_{tran}(X) = trans'_m(X) \cdot p'_m \tag{19}$$

where p'_m denotes the transmission energy consumption power between the NIBs and ESs.

Hence, the energy expenditure produced by the service migration is calculated as

$$E(X) = E_{emp}(X) + E_{unemp}(X) + E'_{emp}(X) + E_{tran}(X) + E'_{unemp}(X) + E'_{tran}(X), \tag{20}$$

C. Problem Formulation

The optimization objective of this paper is consisted of the minimum of consumption of the energy and time of the service migration. The formalized problem is described as

$$\min T(X), \min E(X) \tag{21}$$

$$\text{s.t.} \sum_{m=1}^{M} \sum_{w=1}^{W} i_{m,w} \leq W \tag{22}$$

III. NTM Design

In this section, the NTM firstly using SPEA2 to deal with the multi-objective optimization problem. Then, NTM executes the optimization process by TOPSIS and MCDM.

A. Solution Generation Using SPEA2

SPEA2 has superior robustness and excellent capacity which is conducive to handle multifarious problems to generate the best solution [13]. With the utilization of the new archive truncation method, SPEA2 ensures the retention of boundary values and accuracy of the estimation. Due to the efficiency of SPEA2 in dealing with the multi-objective problem, SPEA2 achieve better performances in the service migration problems than other genetic algorithms and evolution algorithms.

After determining the optimization models, the best strategy for service migration in IoV based on SPEA2 is looked for. With the acquisition of the optimal migration strategy, NIBs reserve resources to achieve the best migration results according to the optimal migration strategy. NTM is designed based on the SPEA2, and the optimal service migration strategy is obtained by using TOPSIS and MCDM. The reason of using SPEA2 is that SPEA2 is capable of uniting with any clustering program to decrease to the scale of the non-dominant solutions with maintaining the integrity of the characteristics.

Firstly, the services which are needed to be migrated are coded. The migration strategy are formed as the chromosomes in the population. Suppose that the NIB which execute the migration process regard as the gene, and each gene t_i is set as $\{1,2, \ldots, I\}$. The best strategy, which is regarded as an superior individual, is calculated through the optimization process.

Then, to evaluate the strengths and weaknesses of the individuals, the fitness function is regarded as the decision criteria. (10) and (15) represent the energy consumption and the time cost, which are constituent parts of the fitness function. In addition, (17) shows the constraint.

The definition of the relevant parameters are given in the initialization process. About all, the optimal migration strategy is represented by the individual, and the scale of individual is the representation of the quantity of the service. In addition, the population size of the initial population set Q is M, and the initial archive Q_0 has the size M_0. The max interaction is n. $Q(n, M)$ represents the n-th population set. Besides, the probability of variation is denoted as Q_V. The crossover probability is denoted as Q_C.

In order to create a new chromosome with superior characteristics, the crossover operation merges the two different parental generations by complicated commutable processes. Firstly, the crossover probability Q_C is employed to choose a parental crossover place, and two associated genes surrounded the place are interchanged. Then, two new chromosomes are created around the place. Furthermore, with constant convergence, the probability of mutation

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Q_V implicates that the filial generation doesn't generate a better strategy than the parent.

B. Solution Evaluation Using TOPSIS and MCDM

TOPSIS is a sorting method to approximate the ideal solution. It evaluates the relative merits and demerits among the existing objects by sorting the limited evaluation objects according to the proximity to the idealized target [14] [15]. According to the model, two decision objectives are represented by $T(X)$ and $E(X)$, and in TOPSIS, the division of the ideal solution and nonideal solution is the premise of optimal solution selection.

By the dimensional Euclidean distance, the each alternative for the non-inferior solution is calculated as

$$D_i^+ = \sqrt{\left(T_i - T_i^{\min}\right)^2 + \left(T_i^{\max} - T_i\right)^2}, \tag{23}$$

Similarly, D_i^- can be calculated by

$$D_i^- = \sqrt{\left(E_i - E_i^{\min}\right)^2 + \left(E_i^{\max} - E_i\right)^2}, \tag{24}$$

With the intention of synthetically considering the ideal solution and the nonideal solution, the comprehensive evaluation index s is introduced. S is calculated by

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}, \tag{25}$$

Finally, the optimal solution OS in the solution set is selected by

$$S = \max\left[S_i\right], \tag{26}$$

$$\begin{aligned} \text{s.t. } & W_T, W_E \in [0,1], \\ & W_T + W_E = 1 \end{aligned} \tag{27}$$

In Algorithm1, we formulate the model of aggregating function and conduct the normalization through the TOPSIS and MCDM. First of all, the NIB data set and service set are input to process. Then, the function of time cost and the energy consumption is calculated (Line 3). In addition, the fitness function and non-inferior solution are calculated (Line 8,9). Finally, the least consumption criterion is confirmed. This process is repeated until the end of the iteration. Ultimately, the best migration S strategy is output.

C. Complexity Analysis

For the proposed algorithm NTM, the time complexity of the fitness calculation process is $O(N^2 \log N)$, where N is the population size. The worst time complexity of the environment selection is $O(N^3)$, and the number of operations that the filial generation needed is $O(NV)$, where V represents the amount of the control variable. Therefore, the computation complexity of NTM is $O(N^3)$.

Algorithm 1 Service migration using NTM

Require: NIB, C
Ensure: The optimal migration strategy S
1: n=1
2: **while** $i \leq I$ **do**
3: Evaluate the function by (13) and(20)
4: $i = i + 1$
5: **end while**
6: **for** i=1 to I **do**
7: Calculate T_i and E_i
8: Determine the non-inferior solution
9: Calculate the alternative for the non-inferior solution by (23) and (24)
10: Choose the optimal strategy S by (26)
11: **end for**
12: **return** S

D. Method Review

The purpose of seeking the optimal migration strategy is to achieve the minimum migration time cost and the energy consumption of the NIBs and ESs. In the first place, the genetic problem are abstracted from the model. In addition, the individuals are evaluated with the employment of the fitness function. The constraints are beneficial to the convergence of the individual. Afterward, the advantageous individuals are elected in the match pool during the election process. Due to the high elitism intensity and the boundary solutions, NTM achieves well convergence. What's more, with the intention of generating new individuals, the mutation and crossover process guarantee the variety of the filial generation. Ultimately, the optimal migration strategy is generated through TOPSIS and MCDM. The overall process of the NTM is shown in Fig 2.

IV. Experiment

In this subsection, a series of complicated simulations and experiments are conducted to get the assessment of the performance of NTM.

A. Experiment Initialization

In the experiment, the NTM is executed in personal computer that has the configuration with the Intel Core i7-10750H processor, 16GB memory and 1TB ssd. The size of services is randomly selected in [0.5, 0.8] GB. The processing power of NIBs and ESs are set as 200 MHZ and 1 GHZ, respectively. The power rate of active and unused VM in NIBs is set as 50 W and 30 W. The power rate of active and unused VM in ESs is 80 W and 40 W. The transmission rate between NIBs and ESs is set as 600 Mb/s and that between NIBs is set as 800 Mb/s. With the intention of protecting the fairness and variety of the experiment, three methods besides NTM are employed. The brief introductions of the other methods are as follows.

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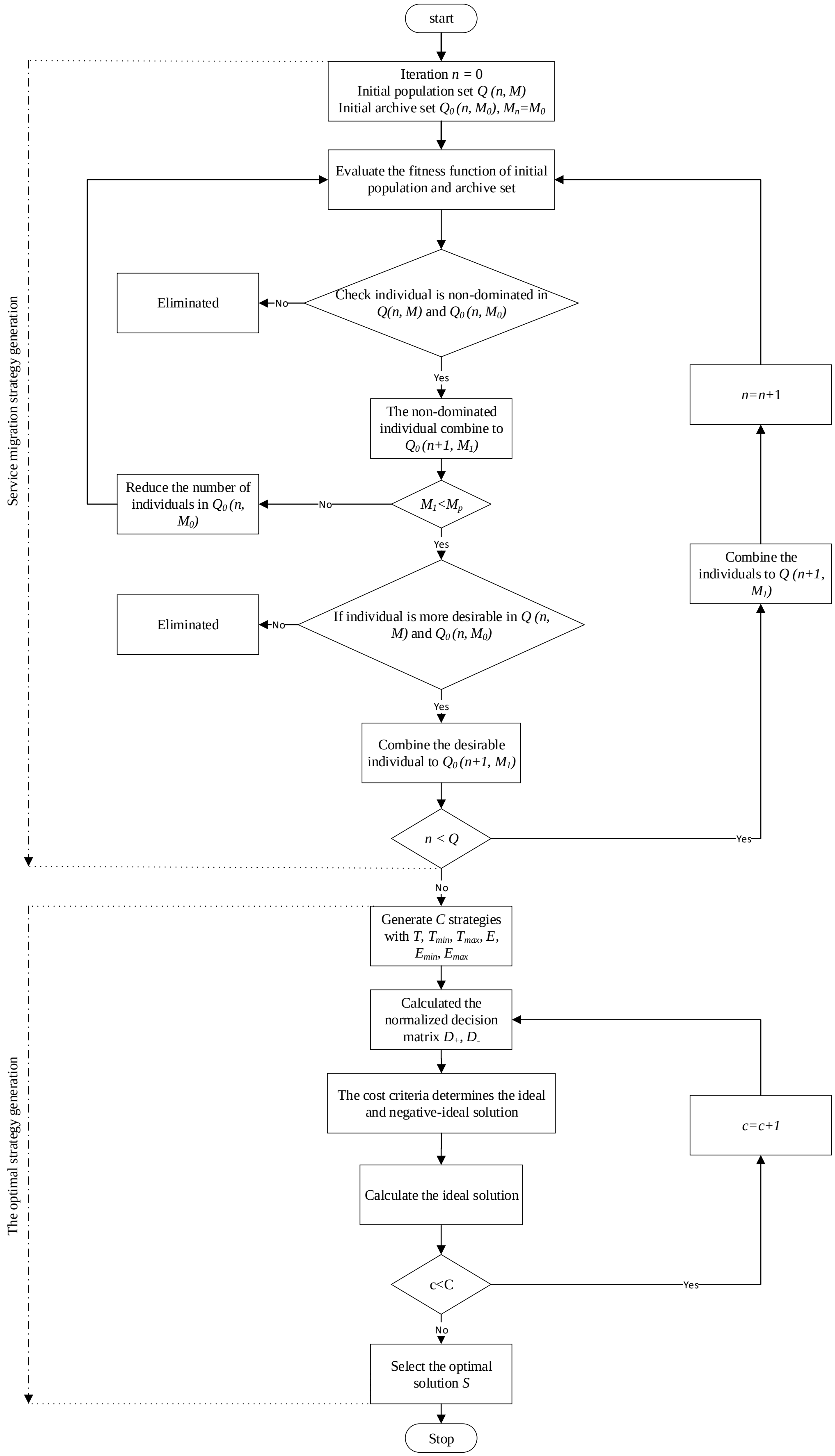


Fig. 2: The overall process of the NTM

1) Benchmark: Before migrating to the target NIB, the service first travels to the nearest NIB. If the computer resources of the nearest NIB are insufficient to meet the requirements, service is transferred to the next NIB with sufficient computing resources.
2) First Fit Decreasing (FFD): After the traversal search of the NIB, the service migrates to the NIB, which is the first fit. If the target NIB possesses enough computing resources, the service will migrate to it. [16].
3) Best Fit Decreasing (BFD): After the traversal research of the NIB, the service is intended to migrate to the NIB, which is the best fit. If the target NIB possesses enough computing resources, the service will migrate to it. This process will repeat until the migration ends [17].

B. Comparison Analysis

The experiment results of the Benchmark, FFD, BFD, and NTM are compared and analyzed. Migration time cost and energy consumption are the key indicators to evaluate the performance of NTM.

The energy cost of the service migration contains the active VM instances and unused VM instances in NIBs and ESs. The consumption of the active and unused VM should be considered firstly. The Fig3 illustrates the comparison of the total energy consumption in the service migration through Benchmark, FFD, BFD, and NTM with diverse service scales. It can be seen that the energy consumption increase constantly with the growing services.NTM is the best solution that consumes the least energy, and Benchmark produces the most energy consumption because it consumes a great deal of energy during the upload period. When the number of services is 30, the four methods achieve similar performance in terms of total NIBs energy consumption, which is because the service scale is small, and the advantages of the NTM cannot be well-reflected. And when the service scale is 150, NTM exceeds the other methods, and the improvements compared to Benchmark, FFD and BFD are 44.29%, 26.42% and 31.58%, respectively.

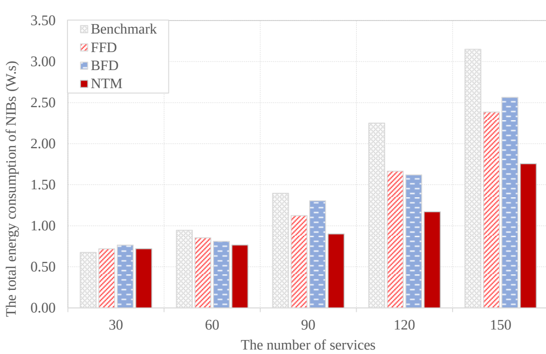
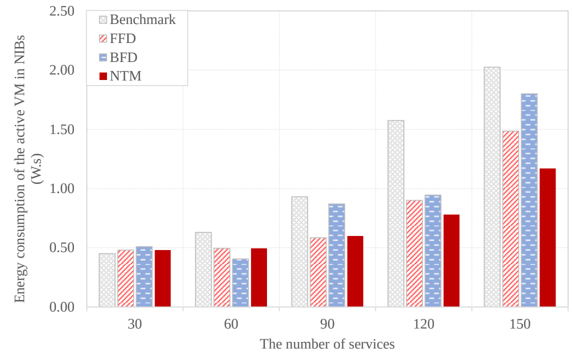
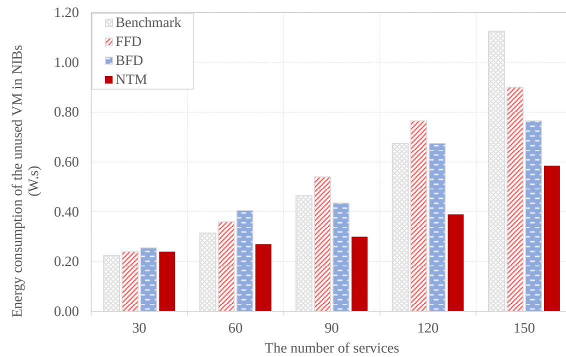


Fig. 3: Total energy consumptions of the NIBs



(a) The energy consumption of the active VM in NIBs



(b) The energy consumption of the unused VM in NIBs

Fig. 4: The energy consumption of the NIBs

In Fig4, the energy expenditure produced by the active and unused VM instances with diverse service scales are compared. In the Fig4(a), with the increase of the service scale, the energy consumption of the active VM in the NIBs increases. For the Benchmark method, the computing services are migrated to the nearest NIB firstly until migrating to the target NIB, whcih causes the consumption during transmission. The FFD migrates the computing services to the NIB which is first fit, and BFD migrates the services to the NIB, which is the best fit. Benchmark consumes the maximum energy, and NTM consumes the least energy. Fig4(b) shows the energy consumption of the unused VM in the NIBs. NTM consumes the least energy, and as the increase of the service scales, the consumption of FFD and NTM verge to the same. When the service scale is 30, the four methods achieve nearly performances in the light of energy consumption of unused VM in NIBs. Benchmark exceeds FFD and BFD due to the nearest selection mechanism. When the number of services is growing to 120, NTM achieves the best performance and improvements compared to Benchmark, FFD and BFD are 46.15%, 35.27% and 23.53%, , respectively.

Similarly, the energy consumption of the ESs consists of the active and unused VM instances in the ESs. Fig6 illustrates that with the increase of the service scale, the

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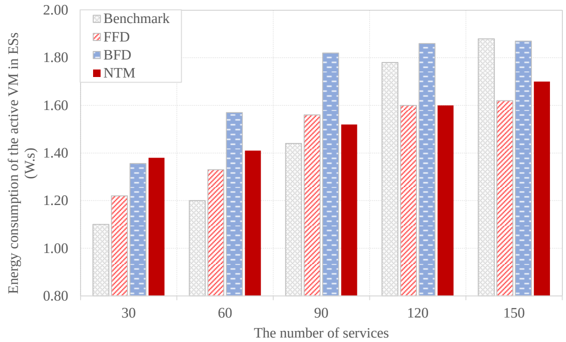
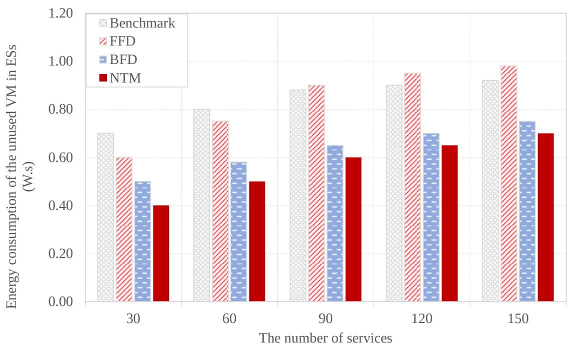


(a) The energy consumption of the active VM in ESs



(b) The energy consumption of the unused VM in ESs

Fig. 5: The energy consumption of the ESs

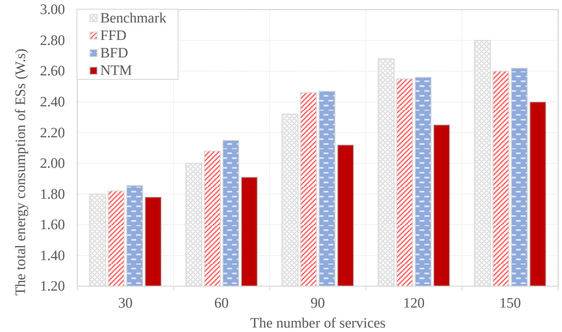


Fig. 6: The total energy consumption of ESs

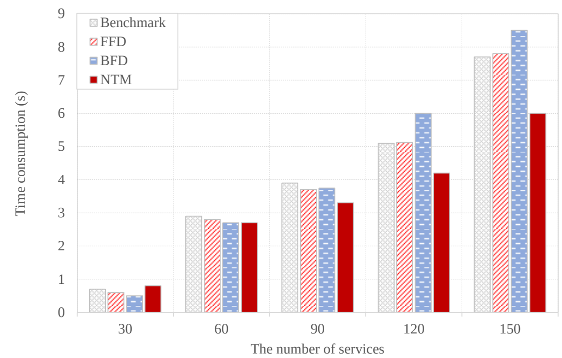


Fig. 7: Comparison of the migration time consumption

energy expenditure produced by the four method increase. On the other hand, the cost of NTM is the least and verges to harshness. Taking the performance contrast under 120 services as an example, NTM exceeds Benchmark, FFD and BFD, and the improvements are 16.04%, 11.76% and 12.11%. Fig5(a) shows that energy consumption of the active VM instances with the four methods all increase as the increasing of number of vehicles. The BFD spends the most energy because it trends to find the best next nodes, and the NTM costs least. From Fig5(b), with the increase of the service scales, the energy cost of FFD exceeds the Benchmark due to the selection strategy, and the performance of NTM is superior.

Fig7 illustrates the contrast of the migration time cost of the four methods with various service scales. When the service migration is executed, the time consumption of the migration is capable of bearing the identity of criterion of evaluating the performance of the migration strategy. The FFD always chooses to migrate the service to the first fit NIB without consciousness of decreasing the migration time consumption. In addition, BFD aims at migrating the service to the best fit NIB and without regard to the time consumption. Since the migration time consumption is the optimization objective of NTM, NTM performs well in decreasing the time consumption. When the number of the services is 30, the performance of four methods in time consumption are not too different, and NTM even costs more time than the other three methods. But with the growth of service scale, NTM achieves relatively excellent performance in terms of time consumption. Taking the performances of four methods with a service count of 150 as an example, NTM exceeds the other three methods and the improvements of NTM compared to Benchmark, FFD and BFD are 22.08%, 23.07% and 29.41%, respectively.

V. Conclusion

This paper proposed a NIB task migration method for the 6G-enabled IoV network to support latency-critical and data-intensive tasks. We also evaluated the performance of the proposed approach using experiments to demonstrate utility. However, this is not ideal because numerous factors can affect the performance and security of communications and task transfer activities in a real-world scenario. Hence, in the future, we intend to implement a prototype of our proposed approach for evaluation in a more realistic setting.

References

[1] J. Cheng, G. Yuan, M. Zhou, S. Gao, C. Liu, H. Duan, and Q. Zeng, "Accessibility analysis and modeling for iov in an urban scene," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4246–4256, 2020.

[2] B. Chen, J. Wan, A. Celesti, D. Li, H. Abbas, and Q. Zhang, "Edge computing in iot-based manufacturing," *IEEE Communications Magazine*, vol. 56, no. 9, pp. 103–109, 2018.

[3] X. Pei, H. Yu, X. Wang, Y. Chen, M. Wen, and Y.-C. Wu, "Noma-based pervasive edge computing: Secure power allocation for iov," *IEEE Transactions on Industrial Informatics*, 2020.

[4] S. S. Vladimirov, D. A. Karavaev, A. B. Stepanov, M. A. Yurchenko, and A. G. Vladyko, "An application of lora technology for sd-iov network," in *2019 11th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE, 2019, pp. 1–4.

[5] K. Wang, H. Yin, W. Quan, and G. Min, "Enabling collaborative edge computing for software defined vehicular networks," *IEEE Network*, vol. 32, no. 5, pp. 112–117, 2018.

[6] C. Dai, X. Liu, W. Chen, and C.-F. Lai, "A low-latency object detection algorithm for the edge devices of iov systems," *IEEE Transactions on Vehicular Technology*, 2020.

[7] G. Jia, G. Han, J. Du, and S. Chan, "A maximum cache value policy in hybrid memory-based edge computing for mobile devices," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4401–4410, 2018.

[8] G. Gui, M. Liu, F. Tang, N. Kato, and F. Adachi, "6g: Opening new horizons for integration of comfort, security, and intelligence," *IEEE Wireless Communications*, vol. 27, no. 5, pp. 126–132, 2020.

[9] W. Saad, M. Bennis, and M. Chen, "A vision of 6g wireless systems: Applications, trends, technologies, and open research problems," *IEEE network*, vol. 34, no. 3, pp. 134–142, 2019.

[10] S. Chen, Y.-C. Liang, S. Sun, S. Kang, W. Cheng, and M. Peng, "Vision, requirements, and technology trend of 6g: How to tackle the challenges of system coverage, capacity, user data-rate and movement speed," *IEEE Wireless Communications*, vol. 27, no. 2, pp. 218–228, 2020.

[11] J. Wang, C. Jiang, K. Zhang, T. Q. Quek, Y. Ren, and L. Hanzo, "Vehicular sensing networks in a smart city: Principles, technologies and applications," *IEEE Wireless Communications*, vol. 25, no. 1, pp. 122–132, 2017.

[12] J. Wang, C. Jiang, Z. Han, Y. Ren, and L. Hanzo, "Internet of vehicles: Sensing-aided transportation information collection and diffusion," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 3813–3825, 2018.

[13] G. Acampora, G. Tortora, and A. Vitiello, "Applying spea2 to prototype selection for nearest neighbor classification," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2016, pp. 003 924–003 929.

[14] K. P. Yoon and W. K. Kim, "The behavioral topsis," *Expert Systems with Applications*, vol. 89, pp. 266–272, 2017.

[15] Ž. Stević, D. Pamučar, A. Puška, and P. Chatterjee, "Sustainable supplier selection in healthcare industries using a new mcdm method: Measurement of alternatives and ranking according to compromise solution (marcos)," *Computers & Industrial Engineering*, vol. 140, p. 106231, 2020.

[16] P. H. Raj, P. R. Kumar, P. Jelciana, and S. Rajagopalan, "Modified first fit decreasing method for load balancing in mobile clouds," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*. IEEE, 2020, pp. 1107–1110.

[17] K. Braiki and H. Youssef, "Fuzzy-logic-based multi-objective best-fit-decreasing virtual machine reallocation," *The Journal of Supercomputing*, vol. 76, no. 1, pp. 427–454, 2020.

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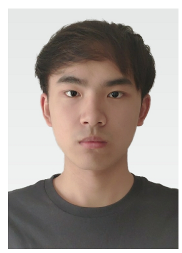

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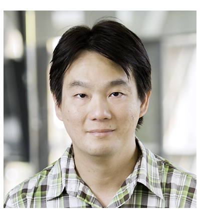

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