Optimal Task Allocation for Battery-Assisted and Price-Aware Mobile Edge Computing

Deng, Tao; You, Lei; Yu, Zhanwei; Yuan, Di

Published in:
IEEE Networking Letters

Link to article, DOI:
10.1109/LNET.2023.3274124

Publication date:
2023

Document Version
Peer reviewed version

Optimal Task Allocation for Battery-Assisted and Price-Aware Mobile Edge Computing

Tao Deng, Lei You, Zhanwei Yu, and Di Yuan

Abstract—**In this paper, we propose a battery-assisted approach to improve energy efficiency for mobile edge computing (MEC) networks by utilizing the space-time-varying characteristics of electricity price. We formulate a price-aware task allocation problem (PATA) that jointly considers the cost for task computation, the cost of task offloading, and the cost of battery degradation. PATA is seemingly a mixed integer non-linear programming problem. By a graph-based reformulation, solving PATA is mapped to finding minimum cost flows or convex cost flows in the graph. This discovery reveals that the global optimum of PATA is obtained in polynomial time. Performance evaluation manifests that the proposed approach significantly outperforms other approaches.**

Index Terms—**Battery-assisted, convex cost flow, minimum cost flow, mobile edge computing.**

I. Introduction

Mobile Edge Computing (MEC) is one of the key technologies of future sixth-generation (6G) networks, with the concept of deploying computing capabilities at the communication network edge [1], e.g., base stations (BSs). Some MEC systems provide energy-demanding services, for which the impact on energy consumption is non-negligible [2]. Thus, it is important to improve the energy efficiency in MEC networks. The existing works have made a lot of efforts. For example, the works in [3] and [4] propose a cloud-edge collaborative framework to optimize task offloading. The works in [5] and [6] optimize the training process of a system-level computing model in a cloud-edge collaborative framework. The work in [7] investigates nonorthogonal multiple access assisted computation offloading in multiaccess mobile edge computing, and models a minimization problem of energy consumption. For problem solving, the work proposes effective algorithms for a static channel scenario and a dynamic channel scenario, respectively. The works in [8] and [9] use energy harvesting devices. All these works target energy efficiency as a performance metric.

At present, in order to balance the energy usage and the peak-to-average energy consumption ratio, the grid corporations are allowed to dynamically adjust the electricity price [10]. The electricity price in off-peak periods is considerably lower than that of peak-demand periods. Thus, the electricity price varies in space as well as time. The works in [11]–[14] investigate this aspect. In [11], the authors propose a framework for optimizing the use of renewable energy, and formulate a energy cost minimization problem. For problem solving, two approaches, based on quadratic programming and variational methods, are developed. In [12], the authors assume that the BSs are equipped with batteries and renewable energy harvesting devices. The renewable energies can be shared with each other. In [13], the work proposes a genie-assisted strategy to optimize the renewable energy allocation. The strategy considers the distance-induced energy loss and the varying energy price. Simulation results show that the renewable energy allocation is affected by the transmission losses, the energy price, and the loads. In [14], the work considers geographically varying energy prices and carbon emission rates, and proposes a fuzzy set technique-based algorithm to optimize the resources of both communication and computation. Simulation results show that the proposed algorithm achieves the tradeoff between energy cost and carbon emissions. However, there is no work that utilizes the space-time-varying characteristics of electricity price for MEC networks with task offloading, thus motivating us to investigate this aspect. Our contributions are as follows.

- We propose a battery-assisted MEC approach where the batteries charge in off-peak periods, and then power MEC servers in peak-demand periods. The price gap between the two periods yields an energy cost gain. We consider the cost of battery degradation as the battery powered depth that is relevant to the battery lifetime. We formulate a price-aware task allocation problem (PATA) jointly considering the cost of task computation, the cost of task offloading, and the cost of battery degradation.
- A direct formulation of our optimization problem falls into the domain of mixed integer non-linear programming, for which it is generally hard to derive the global optimum of the problem. However, by a graph-based reformulation, we prove that solving PATA can be mapped to finding minimum cost flows or convex cost flows in a graph. Thus, the global optimum of PATA can be derived in polynomial time.
- Via performance evaluations, we compare the proposed approach to the energy sharing approach through the smart grid and the task offloading approach with sleeping mechanism. The results show that the proposed approach achieves significantly improvements.

II. System Model

A. System Scenario

Fig. 1 shows the battery-assisted MEC system scenario with B base station (BS) and one management system unit (MSU).

T. Deng is with the School of Computer Science and Technology, Soochow University, Suzhou, Jiangsu 215006, China (E-mail: dengtao@suda.edu.cn). L. You is with the Department of Engineering Technology, Technical University of Denmark, Denmark (E-mail: leiyo@dtu.dk). Z. Yu and D. Yuan are with the Department of Information Technology, Uppsala University, 751 05 Uppsala, Sweden (E-mail: zhanwei.yu; di.yuan@it.uu.se)

The work of Zhanwei Yu and Di Yuan has been funded by the Swedish Research Council.

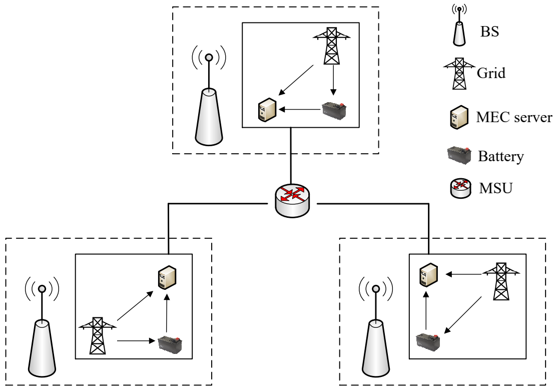

Figure 1. System scenario.

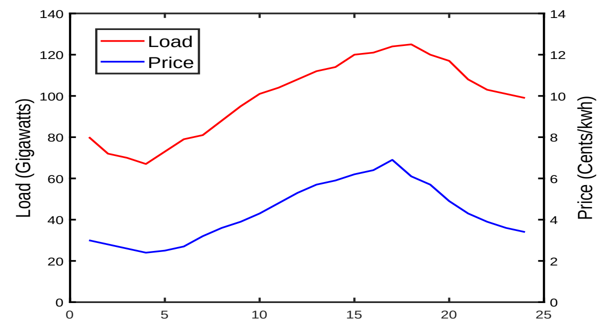

Figure 2. Electricity load and price in a summer day in Pennsylvania [10].

Table I
AVERAGE ELECTRICITY PRICE BY STATE IN USA (UNIT: CENTS PER KWH) [15].

State	Residential	Commercial	Industrial
California	27.27	24.62	19.91
Oregon	11.59	9.09	7.33
Washington	10.37	9.48	7.19
Oklahoma	14.45	12.23	8.16

Each BS is equipped with a local MEC server and a battery. Denote by $\mathcal{B}$ the set of BSs, $\mathcal{B} = \{1, 2, \ldots, B\}$. For each BS i, computation tasks arrive its MEC server i with arrival rate λ_i. We consider that λ_i is integer. The task arrival process is assumed to follow a Poisson distribution. The service process is assumed to follow an exponential distribution. Denote by μ_i the service rate of server i. The MSU is responsible for allocating computation tasks and energy management.

B. Electricity Price Model

Fig. 2 shows a typical electricity load and price shape in a summer day in Pennsylvania, USA [10]. We observe that the electricity price follows the load. When the load peaks, the price also peaks. In addition, the electricity price in the peak hour (at 18:00) is almost three times of that of an off-peak hour (at 4:00). Based on this, we propose the approach of charging the batteries in an off-peak period, and then battery-powering MEC servers in a peak period. The price gap between the two periods yields an energy cost gain. Denote by P_i^S the energy of battery i at the end of off-peak period. Denote by P_i^D the total consumed energy of battery i in the peak period. Denote by c_i^D and c_i^G the electricity prices during off-peak and peak periods for BS i, respectively, $i \in \mathcal{B}$. If we consider the case of dynamic loads and electricity prices over time in a day, the modeling aspect becomes very complex. In order to derive a tractable model, in our paper we consider the electricity prices of two periods, i.e., the off-peak and peak periods, and the load of the peak period. In fact, our model can tell the cost benefit of the battery-assisted approach for any two time periods by changing the values of c_i^D and c_i^G. Typically, there are a few periods of busy hours and off-peak hours of a day, and our approach target an off-peak period and the next peak period. Thus, our approach can optimize task allocation at an aggregate level, and a more micro-level adjustment can then be applied in a later stage. In the peak period, the tasks can be offloaded optimally among MEC servers, utilizing the heterogenous electricity prices. That is, the allocation tells the amount of tasks at aggregate level and therefore the time scale between the varying electricity price and the task offloading is consistent.

C. Computational and Offloading Costs

Table I shows an average electricity price for four states of USA in August 2022 [15]. It can be observed that there are large differences between the states. For example, the price of California is two times higher than that of Washington. Even in the same state, the prices of urban and rural areas are different [16]. The former is typically higher than the latter. Based on this, if some tasks are offloaded to other MEC servers with lower electricity price, the total energy cost of completing the tasks will be reduced. Denote by x_{ij} the number of tasks offloaded from server i to server j, $i, j \in \mathcal{B}, i \neq j$. We consider M/M/1 queuing model for a MEC server [17], by which the total response time of completing the computation tasks in server i, denoted by t_i, is expressed in (1).

$$t_i = \frac{1}{\mu_i}(\lambda_i - \sum_{j \in \mathcal{B}, j \neq i} x_{ij} + \sum_{j \in \mathcal{B}, j \neq i} x_{ji}). \tag{1}$$

In (1), if $B = 1$, The tasks are computed only by the MEC server with respect to the BS. Denote by δ_i the power of server i. Thus, the total energy for completing the computation tasks on server i, denoted by E_i, is expressed as

$$E_i = t_i \delta_i. \tag{2}$$

Thus, the total energy cost on server i, denoted by Δ_i^1, is expressed as

$$\Delta_i^1 = (E_i - P_i^D)c_i^G + P_i^D c_i^D, \tag{3}$$

where the term $E_i - P_i^D$ represents that the amount of consumed energy from the local grid. In (3), Δ_i^1 is a function with respect to the decision variables of x_{ij} and P_i^D. Denote by Δ_{ij}^T the transmission cost of a task from server i to server j, accounting for the energy consumption incurred by the transmission process [12]. The total transmission cost of tasks from server i to other servers, denoted by Δ_i^2, is expressed as

$$\Delta_i^2 = \sum_{j \in \mathcal{B}, j \neq i} x_{ij} \Delta_{ij}^T. \tag{4}$$

D. Cost Model of Battery Degradation

A battery-assisted system can achieve the energy cost gain, but it will also generate battery usage cost due to the shortening of battery lifetime. In general, the battery-powered depth is relevant to the battery lifetime [18]. For example, the results in [19] manifest that battery lifetime is an exponential function with respect to the battery-powered depth. However, the exponential relation may not represent all the battery types. For some battery technologies, the relation could be more toward a linear one. Based on this, we assume that if the battery powered depth increases, the battery lifetime decreases, and the battery degradation increases. Thus, the degradation cost of battery i, denoted by Δ_i^3, is modeled as

$$\Delta_i^3 = \alpha(\frac{P_i^D}{P_i^S})^n, \tag{5}$$

where P_i^D/P_i^S, α, and n ($n \geq 1$) denote the battery-powered depth, the normalization factor with respect to the grid's electricity price in the peak-demand period, and a given constant, respectively.

Therefore, the total cost including the energy consumption cost for task completion, the task transmission cost, and the battery degradation cost, denoted by Δ, is expressed in (6).

$$\Delta = \sum_{i\in\mathcal{B}}(\Delta_i^1 + \Delta_i^2 + \Delta_i^3). \tag{6}$$

III. Problem Formulation

Our problem is to minimize Δ. PATA is expressed in (7). The constraint in (7b) requires that for each server, the total

$$\min_{\boldsymbol{x},\boldsymbol{P^D}} \quad \Delta \tag{7a}$$

$$\text{s.t.} \quad \sum_{j\in\mathcal{B},j\neq i} x_{ij} \leq \lambda_i, i \in \mathcal{B}, \tag{7b}$$

$$\frac{1}{\mu_i}(\lambda_i - \sum_{j\in\mathcal{B},j\neq i} x_{ij} + \sum_{j\in\mathcal{B},j\neq i} x_{ji})\delta_i \geq P_i^D, \tag{7c}$$

$$0 \leq P_i^D \leq P_i^S,\ x_{ij} \in \mathbb{N},\ i,j \in \mathcal{B}, i \neq j \tag{7d}$$

offloaded tasks to others do not exceed the number of tasks arrived locally. The constraint in (7c) states that the total consumed energy from the grid cannot be negative.

The objective function Δ in (6) can be reexpressed as

$$\Delta = \sum_{i\in\mathcal{B}}\frac{1}{\mu_i}(\lambda_i - \sum_{j\in\mathcal{B},j\neq i} x_{ij} + \sum_{j\in\mathcal{B},j\neq i} x_{ji})\delta_i c_i^G + \sum_{i\in\mathcal{B}}\sum_{j\in\mathcal{B},j\neq i} x_{ij}\Delta_{ij}^T + \sum_{i\in\mathcal{B}}\left[P_i^D(c_i^G - c_i^D) - \alpha(\frac{P_i^D}{P_i^S})^n\right].$$

In the above function, the first two terms denote the cost completing all the tasks' computation in the absence of batteries. The last term denotes the total cost gain due to using the batteries. We construct the function $f(\boldsymbol{P^D})$, which denotes the last term and is expressed as

$$f(\boldsymbol{P^D}) = \sum_{i\in\mathcal{B}}\left[P_i^D(c_i^G - c_i^D) - \alpha(\frac{P_i^D}{P_i^S})^n\right]. \tag{8}$$

In $f(\boldsymbol{P^D})$, there are two terms with respect to P_i^D, i.e., $\alpha(\frac{P_i^D}{P_i^S})^n$ and $P_i^D(c_i^G - c_i^D)$. The function represents the cost gain via using the batteries, and it is a convex function. Via solving $f(\boldsymbol{P^D}) = 0$, we obtain two solutions, i.e., $P_{i_1}^{D^*} = 0$ and $P_{i_2}^{D^*} = P_i^S\left[\frac{(c_i^G - c_i^D)P_i^S}{\alpha}\right]^{\frac{1}{n-1}}$. Comparing $P_{i_2}^{D^*}$ with the domain of P_i^D, we can determine the range of the optimum of P_i^D.

- If $\alpha \leq P_i^S(c_i^G - c_i^D)$, $P_{i_2}^{D^*} \geq P_i^S$. In this case, $f(\boldsymbol{P^D}) \geq 0$ for any $\boldsymbol{P^D}$.
- If $\alpha > P_i^S(c_i^G - c_i^D)$, $P_{i_2}^{D^*} < P_i^S$: 1) When $0 \leq P_i^D \leq P_{i_2}^{D^*}$, $f(\boldsymbol{P^D}) \geq 0$. 2) When $P_{i_2}^{D^*} < P_i^D \leq P_i^S$, $f(\boldsymbol{P^D}) < 0$. Therefore, the optimum of P_i^D will be in the range of $[P_{i_1}^{D^*}, P_{i_2}^{D^*}]$ in the global optimum of (7).

IV. Problem Solving

Although PATA is formulated as a mixed integer non-linear programming problem (MINLP), we will prove that obtaining the global optimum of PATA is tractable. The idea is that by a graph-based reformulation, solving PATA is mapped to finding minimum cost flows or convex cost flows in the graph, as shown in Fig. 3. The construction process of this graph, however, is non-trivial.

A. Minimum Cost Flow Problem

The minimum cost flow problem (MCFP) is to send flow(s) from supply node(s) to demand node(s) in a directed graph, at minimum possible cost. Each arc in this graph has two attributes, i.e., the cost per unit flow and flow capacity. A feasible flow solution must satisfy two constraints, i.e., flow balance constraint and capacity constraint. The former states that for any node, the total incoming flow to the node plus the supply of itself (if any) is equal to the total outgoing flow of the node plus the demand of the node (if any). The latter requires that for any arc, the flow does not exceed the capacity of the arc.

B. Convex Cost Flow Problem

In MCFP, the cost of the flow on an arc is a linear function with respect to the amount of flow. Different from MCFP, in a convex cost flow problem (CCFP), the cost is a convex function with respect to the amount of flow.

C. Graph-Based Reformulation

In Fig. 3, the red nodes are supply nodes, the black node is a sink node, and the other nodes are transshipment nodes. The red and yellow nodes represent MEC servers, and the green nodes represent the batteries. The flows represent task allocation, i.e., the optimization variable x_{ij} in PATA. There are six types of entities, i.e., supply node i, arc (i, i'), arc (i, j), arc (i', D_i), arc (i', S), and arc (D_i, S), $i, j \in \mathcal{B}$, $i \neq j$, where i' is an auxiliary node defined for node i.

1) Supply Nodes: The supply of node i represents tasks that arrive MEC server i. Its amount supply is set to be λ_i.

2) Arc (i, i'): The arc (i, i') models that some tasks are computed in the supply node i. The cost of this arc is zero.

This article has been accepted for publication in IEEE Networking Letters. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/LNET.2023.3274124

3) Arc (i, j): The arc (i, j) allows the supply node i to offload some tasks to node j, $i, j \in \mathcal{B}$, $i \neq j$. The cost of this arc is Δ_{ij}^T due to task transmission. The total cost of these arcs is expressed as $\sum_{i\in\mathcal{B}}\sum_{j\in\mathcal{B},j\neq i} x_{ij}\Delta_{ij}^T$, which corresponds to the second term of our objective function in (6). Due to the flow balance constraint, for any supply node i, the total outgoing flow to other nodes does not exceed the supply of this node, i.e., $\sum_{j\in\mathcal{B},j\neq i} x_{ij} \leq \lambda_i, i \in \mathcal{B}$, which corresponds to constraint (7b).

4) Arc (i', D_i): The arc (i', D_i) represents that the battery i powers server i. The cost of this arc is equal to $\frac{\delta_i}{\mu_i} c_i^D$, and the capacity of this arc is equal to the maximum number of tasks that can be supported by this battery, i.e., $\left\lfloor \frac{\mu_i}{\delta_i} P_i^S \right\rfloor$. Here, note that our optimization variable P_i^D in fact is the flow on this arc multiplied by $\frac{\delta_i}{\mu_i}$. The total cost of these arcs corresponds to the second term of Δ_i^1. Due to the capacity and flow balance constraints in the graph, constraints (7c) and (7d) are satisfied.

5) Arc (i', S): The arc (i', S) represents that server i is powered by the grid. The cost of this arc is $\frac{\delta_i}{\mu_i} c_i^G$, and the capacity of this arc is infinity. The total cost of these arcs corresponds to the first term of Δ_i^1.

6) Arc (D_i, S): The arc (D_i, S), $i \in \mathcal{B}$, represents the cost of battery degradation. The cost of this arc is $\alpha(\frac{\delta_i}{\mu_i P_i^S})^n$. If $n = 1$, the cost is a linear function with respect to the flow. For $n > 1$, it is a nonlinear but convex function with respect to the flow. The capacity of this arc is $\frac{\mu_i}{\delta_i} P_i^S$ due to the flow balance constraint. The total cost of these arcs corresponds to the last term of our objective function in (6).

By the above analysis, the objective function and constraints in PATA are mapped to the total flow cost of the arcs and the flow balance constraints, respectively. Therefore, solving PATA corresponds to finding minimum cost flows ($n = 1$) or convex cost flows ($n > 1$) in the graph.

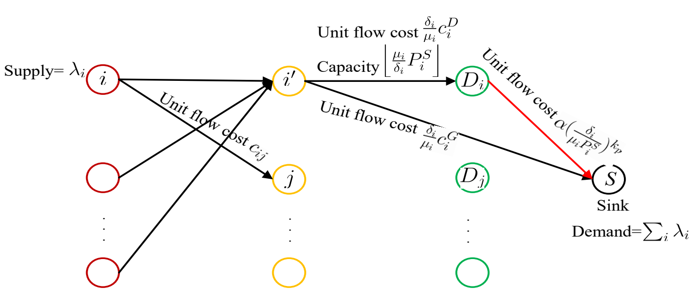

Figure 3. Solving PATA corresponds to finding minimum cost flows or convex cost flows from the supply nodes to the sink node.

D. Algorithm Summary

As the capacities of all the arcs and the supplies of all the nodes are integer, the global optimum of MCFP can be derived in polynomial time, e.g., by Orlin's algorithm [20]. CCFP has been widely studied in the existing works. For example, the work in [21] has proposed a capacity scaling algorithm to derive the global optimum of CCFP in polynomial time. The proposed network flow algorithm (NFA) is summarized in Algorithm 1.

Theorem 1. *The global optimal solution of PATA can be derived in polynomial time.*

Algorithm 1: NFA algorithm

1: Map the objective function and constraints of PATA in (7) to the total flow cost of the arcs and the flow balance constraints in the graph, as shown in Fig. 3.
2: **if** $n = 1$ **then**
3: Solve PATA in (7) as to finding minimum cost flows in the graph, and obtain its global optimum by Orlin's algorithm [20].
4: **else**
5: Solve PATA in (7) as to finding convex cost flows in the graph, and obtain its global optimum by a capacity scaling algorithm [21].

Proof: When $n = 1$, the graph in Fig. 3 can be solved in polynomial time, with complexity $O(E\log(E(E + V\log V)))$ (Orlin's algorithm [20]), where E and V are the total number of arcs and nodes, with $E = B^2+3B$ and $V = 3B+1$ respectively. When $n > 1$, the graph in Fig. 3 can be solved in polynomial time, with complexity $O((E\log U)(VE + V^2\log V))$ (capacity scaling algorithm [21]), where U is the maximum capacity of any arc. Hence the theorem. ■

V. Performance Evaluation

The proposed approach is evaluated by comparing it to the energy sharing approach (ESA) in [12] and the task offloading approach with sleeping mechanism (TOAS) in [22]. In the ESA algorithm, the total cost is minimized by exchanging energy among BSs through the smart grid. In the TOAS algorithm, the lightly loaded BSs are switched off in order to save power. The tasks of a sleeping BS are offloaded to other active BSs. The sleeping initiator is determined by the average arrival rates of tasks The task arrival rate λ_i follows a uniform distribution in [20, 50], and the task service rate μ_i follows a uniform distribution in [1, 5], $i \in \mathcal{B}$. The power of MEC server i is set to be one, $i \in \mathcal{B}$. The constant n is set to be 2 [18]. The cost unit in Figs. 4-6 can be set to cents as the unit of electricity price is cents/kwh, as shown in Fig. 2.

Figs. 4-6 show the comparison results. We have the following observations. First, in Fig. 4, with the increase of MEC servers, the total cost grows. This is because the number of computation tasks increases. Second, in Figs. 5 and 6, when c_i^G/c_i^D and the total energy of battery increase, the total cost decreases. This is because with the increase of c_i^G/c_i^D, the gap between the electricity price between the off-peak and peak periods grows, thus the cost benefit increases due to using batteries. With the increase of the total energy of battery, more cheaper energy can be stored and utilized. Finally, the proposed approach outperforms TOAS and ESA. The reason is that for TOAS, its sleeping initiator is associated with only the average arrival rates of tasks and ignores the impact of electricity price. As a result, a lightly loaded BS with cheap electricity price may be switched off and a highly loaded BS with expensive electricity price may be active, thus generating a higher cost. For ESA, energy loss will happen during the transmission process, thus reducing energy utilization efficiency. In addition, ESA ignores the impact of the battery degradation cost, resulting in a higher degradation cost as some batteries deeply discharge.

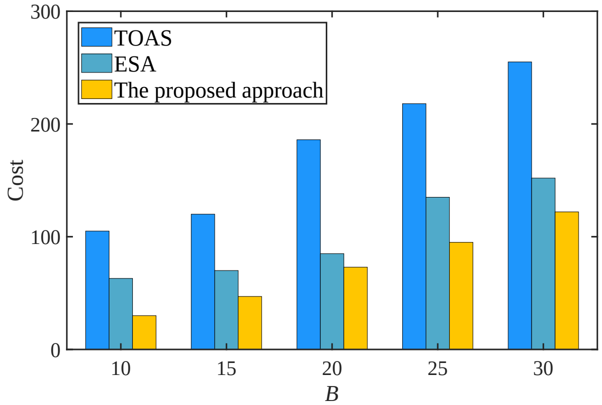

Figure 4. The total cost as function of B.

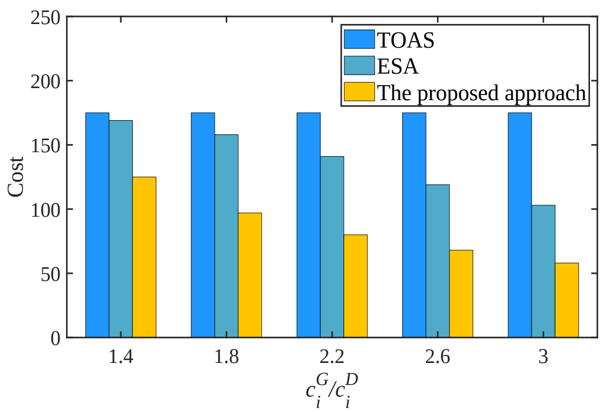

Figure 5. The total cost as function of c_i^G/c_i^D.

VI. Conclusion

We have proposed a battery-assisted approach for MEC networks and formulated a price-aware task allocation problem. By a graph-based reformulation, we have proven that the global optimum of the problem can be derived in polynomial time. The numerical results manifest that by utilizing the space-time-varying characteristics of electricity price, the proposed approach significantly reduces the total cost and makes the task allocation more cost efficiently.

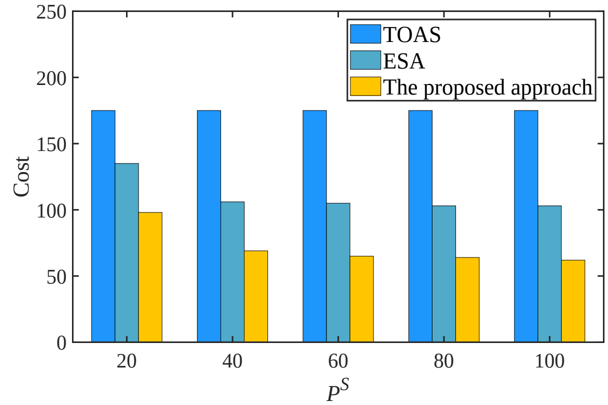

Figure 6. The total cost as function of P^S where $P_i^S = P^S$.

References

[1] Z. Zhang, Y. Xiao, Z. Ma, M. Xiao, Z. Ding, X. Lei, G. Karaginnidis, and P. Fan, "6G wireless networks: Vision, requirements, architecture, and key technologies," *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 28–41, 2019.

[2] N. Shalavi, G. Perin, A. Zanella, and Michele Rossi, "Energy efficient deployment and orchestration of computing resources at the network edge: A survey on algorithms, trends and open challenges," *arXiv: 2209.14141v1*, 2022.

[3] X. Hu, L. Wang, K. Wong, M. Tao, Y. Zhang, and Z. Zheng, "Edge and central cloud computing: A perfect pairing for high energy efficiency and low-latency," *IEEE Trans. Wireless Communications*, vol. 19, no. 2, pp. 1070–1083, 2020.

[4] T. Wang, Y. Jiang, K. Zhao, and X. Liu, "Energy-efficient edge-cloud collaborative intelligent computing: A two-timescale approach," in *Proc. IEEE SCC*, 2022, pp. 1–10.

[5] S. Shinde, A. Bozorgchenani, D. Tarchi, and Q. Ni, "On the design of federated learning in latency and energy constrained computation offloading operations in vehicular edge computing systems," *IEEE Trans. Vehicular Technology*, vol. 71, no. 2, pp. 2041–2057, 2022.

[6] S. Savazzi, S. Kianoush, V. Rampa, and Mehdi Bennis, "A framework for energy and carbon footprint analysis of distributed and federated edge learning," in *Proc. IEEE PIMRC*, 2022, pp. 1–6.

[7] L. Qian, Y. Wu, F. Jiang, N. Yu, W. Lu, and B. Lin, "NOMA assisted multi-task multi-access mobile edge computing via deep reinforcement learning for industrial internet of things," *IEEE Trans. Ind. Informatics*, vol. 17, no. 8, pp. 5688–5698, 2021.

[8] W. Zhou, L. Xing, J. Xia, L. Fan, and A. Nallanathan, "Dynamic computation offloading for MIMO mobile edge computing systems with energy harvesting," *IEEE Trans. Vehicular Technology*, vol. 70, no. 5, pp. 5172–5177, 2021.

[9] X. Chen, H. Wen, W. Ni, S. Zhang, X. Wang, S. Xu, and Q. Pei, "Distributed online optimization of edge computing with mixed power supply of renewable energy and smart grid," *IEEE Trans. Communications*, vol. 70, no. 1, pp. 389–403, 2022.

[10] Real-time pricing for electricity- Penn State Extension. [Online]. Available: https://extension.psu.edu/real-time-pricing-for-electricity.

[11] J. Leithon, S. Werner, and V. Koivunen, "Storage management in a shared solar environment with time-varying electricity prices," *IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 7420–7436, 2019.

[12] J. Leithon, T. Lim, and S. Sun, "Energy exchange among base stations in a cellular network through the smart grid," in *Proc. IEEE ICC*, 2014, pp. 1–6.

[13] J. Leithon, S. Werner, and S. Talebi, "Price-aware renewable energy management with transmission losses," in *Proc. IEEE ICASSP*, 2019, pp. 1–5.

[14] E. Ahvar, S. Ahvar, Z. Mann, N. Crespi, R. Glitho, and J. Garcia-Alfaro, "DECA: A dynamic energy cost and carbon emission-efficient application placement method for edge clouds," *IEEE Access*, vol. 9, pp. 70 192–70 213, 2021.

[15] U.S. Energy Information Administration monthly electric power industry report. [Online]. Available: Electric Power Monthly-U.S. Energy Information Administration (EIA).

[16] S. Silva, I. Soares, and C. Pinho, "Electricity residential demand elasticities: Urban versus rural areas in Portugal," *Energy*, vol. 144, no. 1, pp. 627–632, 2018.

[17] L. Kleinrock, *Queueing Systems: Theory*. John Wiley Sons, 1975.

[18] I. Duggal and B. Venkatesh, "Short-term scheduling of thermal generators and battery storage with depth of discharge-based cost model," *IEEE Trans. Power Systems*, vol. 30, no. 4, pp. 2110–2118, 2015.

[19] M. Meyer, M. Elizondo, P. Balducci, V. Viswanathan, C. Jin, X. Guo, T. Nguyen, and F. Tuffner, "Energy storage for power systems applications: A regional assessment for the northwest power pool (NWPP)," *U.S. Department of Energy, Rep. PNNL-19300*.

[20] J. Vygen, "On dual minimum cost flow algorithms," *Mathematical Methods of Operations Research*, vol. 56, no. 1, pp. 101–126, 2002.

[21] R. Ahuja, J. Batra, and S. Gupta, "A parametric algorithm for convex cost network flow and related problems," *European Journal of Operational Research*, vol. 16, no. 2, pp. 222–235, 1984.

[22] A. Alnoman and A. Anpalagan, "Computing-aware base station sleeping mechanism in H-CRAN-cloud-edge networks," *IEEE Trans. Cloud Comput*, vol. 9, no. 3, pp. 958–967, 2021.