Quantum Optimization for Bidirectional Telecom Energy Exchange and Vehicular Edge Computing in Green 6G Networks

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***Abstract*—The latest 6G innovations envision various global benefits beyond connectivity. One of the pressing issues which can be potentially addressed by 6G is environment sustainability and reaching net-zero. Recent research proposes 6G-enabled communications for peer-to-peer energy exchange among various entities including grid and Electric Vehicles (EVs). The surplus energy stored in EVs is proposed to meet the increasing demands and reduce burden on grid through Vehicle-to-Grid (V2G) technology. However, the supply from EVs may not completely meet the rising energy demands. Meanwhile, the backup batteries of 6G base stations (BSs) can be effectively utilized to supply energy to the EVs or grid. This paper explores the concept of bidirectional Telecom-to-Grid (T2G) and Telecom-to-Vehicle (T2V) energy exchange and its integration with vehicular edge computing. The utility model of BSs and EVs for bidirectional energy trading and edge computing service is designed for efficient resource utilization. An optimization problem maximizing sum of utilities is solved by two solutions, which are Gale-Shapley (GS) matching and quantum algorithm. The theoretical bounds of time consumed in an edge computing task are also derived. The optimization solution results in less emissions through quantum approach as compared to classical GS algorithm.**

***Index Terms*—6G, base stations, EVs, energy, quantum**

I. Introduction

Environmental sustainability is one of the growing interests of telecommunications industry, specifically in the implementation of 6G systems. The use of renewable resources to power telecommunication systems is a promising step towards net-zero. However, the fluctuations in supply of renewable resources and rising energy demands while going towards green 6G communications is a serious challenge [1]. The potential of cellular Base Stations (BSs) with backup batteries to supply energy when needed is recently being investigated [2] - [3]. The deployment of BSs has already been increased to ensure seamless 6G network coverage. Ultimately, the increased number of backup batteries of BSs with spare capacities can potentially be utilized for bidirectional Telecom-to-Grid (T2G) energy exchange between BSs and grid.

At the same time, road transport is encountering the challenge of rapidly growing energy demands due to increase in number of Electric Vehicles (EVs). However, energy supply from renewable sources is unstable and existing renewable infrastructures are inadequate to meet the rising demands of EVs. To address this problem, battery storage systems in EVs supplying their surplus energy through Vehicle-to-Grid (V2G) technology has become a well-established and effective solution [4] - [5]. EVs can supply their energy at times of high demand and later charge their batteries during off-peak hours. However, supply from EVs can still be insufficient. Meanwhile, BSs are already equipped with backup batteries which often remain unused. Keeping in view the capability of backup batteries of BSs to provide energy, the concept of bidirectional Telecom-to-Vehicle (T2V) energy exchange is worth investigating. Since both EVs and BSs are integral elements of 6G networks, they can complement each other in terms of energy provision, connectivity and computing.

Mobile edge computing is the form of edge computing in cellular networks where edge nodes, such as vehicles, are capable of performing computing tasks to meet the stringent latency or energy requirements in a resource-efficient manner. Offloading a task from BS to vehicle is considered as an efficient utilization of computing resource in Internet-of-Vehicles [6]. As most of the vehicles are now expected to be electric, the synergistic approach of energy management combined with edge computing by EVs is evolving to avail the optimum benefits of computation resources and waiting times during charging [7] - [8]. A parked EV can perform edge computing while being charged and earn incentive. Since BSs are commonly employed in edge computing tasks [6], [9], their involvement in energy exchange can further enhance their utilization beyond their conventional role of network coverage.

Recent research aims to maximize the utilities of vehicles and BSs in edge computing tasks through various classical optimization algorithms and machine learning techniques [7] - [9]. However, it is expected that quantum machine learning and optimization techniques will revolutionize computing algorithms [10]. Quantum computers use quantum bits (qubits) to perform multi-dimensional computational tasks at a much faster rate than standard computers. Quantum computing is not only faster but is also observed as more energy-efficient [11] with lower CO_2 emissions than classical computing [12].

This paper consolidates bidirectional T2G, T2V and V2G

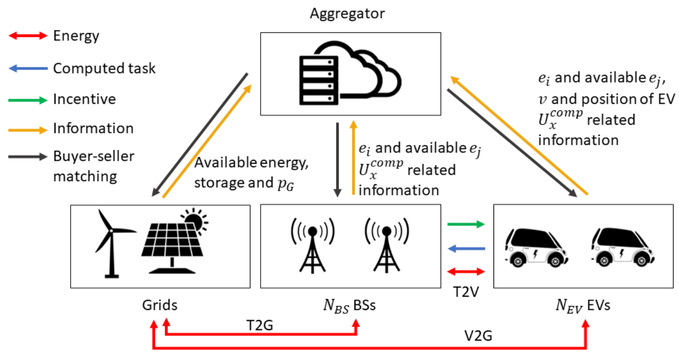


Fig. 1: The proposed system architecture.

energy exchange, and vehicular edge computing for green 6G networks. We conceptualize a model where energy can be distributed among BSs, EVs and grid. The EVs also perform edge computing tasks for BSs during the energy exchange. Additionally, a quantum optimization approach, i.e., Quadratic Unconstrained Binary Optimization (QUBO) [13] is used to maximize the utilities of EVs and BSs.

A. Related Works

The potential of BSs to supply energy is analyzed in [2]. Also, the batteries of BSs are recommended to create a distributed storage and flexible power supply system in [14]. Furthermore, a bidirectional energy exchange between a BS and solar-powered grid is formulated in [3]. However, the capability of BSs to fulfill demands of EVs is not yet explored. Meanwhile, the exploitation of V2G is widely suggested in literature. The utilities of EVs buying or selling energy is maximized through Stackelberg game in [1]. Usually, optimization techniques are used for energy management in EVs. In [4], an optimization algorithm reduces grid cost and avails surplus energy from EVs. In [15], Gale-Shapley (GS) algorithm is used to match buying and selling EVs with optimum utilities and social welfare of the system. Social welfare of the system involving charging stations and EVs is also maximized in [7] through contract theory and Deep-Q learning network, where EVs perform edge computing tasks during charging. Although it is considered that EVs can generally supply energy to any consumer, the specific potential of energy exchange from EVs to BSs and vice-versa is not investigated.

Several optimization techniques exploiting quantum theory are proposed for 6G networks. A quantum-inspired real time genetic algorithm is presented in [10] for resource allocation in 6G communications. Additionally, vehicle routing problems are also solved by QUBO in [16] - [17]. However, utilizing quantum theory to optimize T2G, T2V and V2G energy exchange and vehicular edge computing is a novel solution.

B. Contributions and Organization

The main contributions of the paper are as follows

- We formulate V2G, T2G and T2V energy exchange system integrated with vehicular edge computing.
- We optimize the energy exchange and vehicular edge computing using a quantum approach, QUBO, and compare it with GS matching algorithm. QUBO results in less CO_2 emissions than GS algorithm.
- We derive the bounds of time consumed in completing an edge computing task.

The rest of the paper is organized as follows. Section II defines system model. Section III describes problem formulation and its optimization. Performance evaluation and conclusion are presented in Section IV and V respectively.

II. System Architecture and Modeling

A. System Architecture

As shown in Fig. 1, the proposed system includes a 6G-enabled cloud aggregator, grid producing energy from renewable resources, N_{BS} number of BSs and N_{EV} number of EVs acting as edge computing nodes. It incorporates both energy and information exchange among entities in a 6G-enabled Vehicle-to-Everything (V2X) network exploiting bidirectional V2G, T2G and T2V technologies. All EVs, BSs and grid have battery storage systems and can either buy or sell energy. An aggregator receives the amount of energy demanded or available energy to be sold from all entities and optimally matches buyers with sellers resulting in maximum social welfare, SW, of the system. The EVs and BSs are divided into two sets where $\mathcal{I}\,\epsilon\,\{1,2,....,I\}$ is the set of buyers each with energy demand e_i and $\mathcal{J}\,\epsilon\,\{1,2,....,J\}$ is the set of sellers each with surplus energy e_j selling at the price p_j. The optimization solution matches optimal buyers and sellers. If an optimal BS-EV pair is made, the EV performs edge computing task for BS while being charged or discharged and earns incentive. If a BS is not matched with an EV, then the energy exchange takes place with the grid at a price p_G, where $p_G > p_j$ to reduce burden on the grid.

B. Base Stations Model

Assume a 6G cellular BS consisting of two main parts, i.e., a radio equipment known as Remote Radio Unit (RRU) and a Base-Band Unit (BBU) [18]. We consider energy-efficient BSs which go in sleep mode with reduced power consumption at zero load [19] - [20]. The energy consumed by a BS for time t is $e_{BS} = P_{BS}t$, where P_{BS} denotes BS power defined as

$$P_{BS} = \begin{cases} P_{RRU} + P_{BBU}, & 0 < P_{out} < P_{max}, \\ P_{sleep}, & P_{out} = 0, \end{cases} \quad (1)$$

where P_{out} is the output power of antenna upper-bounded by P_{max}, P_{sleep} is the power consumed in sleep mode, P_{RRU} and P_{BBU} are the power consumed by RRU and BBU respectively. $P_{RRU} = \frac{P_{out}}{\eta} + P_{RF}$, where η is the efficiency of power amplifier and P_{RF} is the power of radio circuits. $P_{BBU} = N_{BBU}(P_{BBU}^{min} + (P_{BBU}^{max} - P_{BBU}^{min})\tau_{BBU} f_{BBU}^{\beta})$, where N_{BBU} is the number of active cores in the CPU of BBU, P_{BBU}^{min} and P_{BBU}^{max} is the minimum and maximum power of each core respectively, τ_{BBU} is the percentage of CPU load, f_{BBU} is the CPU frequency and β is its exponential coefficient. $\tau_{BBU} =$

$\frac{I(r)}{N_{BBU} f_{BBU}}$, where $I(r)$ is the instructions per unit time at data rate r.

1) Edge Computing Tasks by BSs: BSs also have to perform various computing operations in a 6G network, for example, resource allocation. In the proposed approach, a BS offloads its task to EV to perform during energy exchange. A BS divides the edge computing task into N_s chunks of size s_{EV} and assigns a single chunk to an EV. It may either wait for up to K EVs to complete a task or compute some chunks itself. Also, if an energy exchange between BS and EV is completed before the EV has completed its task, it is likely that the EV will leave and a BS will have to complete the rest of task itself. Then, the time required by a BS in edge computing is

$$t_{BS}^{comp} = max\Big(t_{task}^{comp} - \sum_{EV=1}^{K} t_{EV}^{comp}, 0\Big) + t_{BS}^{add}, \qquad (2)$$

where t_{task}^{comp} is the computation time required to complete whole task, t_{EV}^{comp} is the time required by an EV to complete a chunk and t_{BS}^{add} is the time required to add all computed chunks. Theorem 1 defines the bounds of t_{task}^{comp}.

Theorem 1:

$$\sqrt{(t_{BS}^{comp})^2 - 2t_{BS}^{add} \sum_{EV=1}^{K} t_{EV}^{comp}} - \sum_{EV=1}^{K} t_{EV}^{comp} \leq t_{task}^{comp} \leq t_{BS}^{add} + \sum_{EV=1}^{K} t_{EV}^{comp}.$$

Proof: See Appendix A. □

The utility of a BS in vehicular edge computing is

$$U_{BS}^{comp} = \alpha log\Big(1 + s_{EV}\Big) - \lambda_{BS} T_{EV} - p_{BS}^{task}(t_{BS}^{comp} + t_{BS}^{add}), \qquad (3)$$

where α is the reward coefficient, λ_{BS} is the reward paid by BS to EV, T_{EV} is the time invested by EV and p_{BS}^{task} is the computation and addition cost for BS. The utility definition incorporates log function as it is asymptotically optimal [21].

C. Electric Vehicles Model

The time T_{EV} that an EV invests in energy exchange and edge computing is

$$T_{EV} = t_{EV}^{trv} + max(t_{EV}^{chg}, t_{EV}^{comp}), \qquad (4)$$

where t_{EV}^{trv} is the time required by an EV to travel to BS, t_{EV}^{chg} and t_{EV}^{comp} is the charging and computing time respectively. $t_{EV}^{chg} = \frac{e_i}{P_{chg}}$, where e_i is the energy required by either EV or BS to charge its battery and P_{chg} is the charging power. $t_{EV}^{comp} = t_{EV}^{chg}$ if an EV does not stay to complete the task when an energy exchange is finished. Otherwise, $t_{EV}^{comp} = \frac{s_{EV} C_{EV}}{f_{EV}}$, where C_{EV} is the expected number of CPU cycles for computation of a task per unit its size and f_{EV} is the computational capability of an EV in cycles/second. The energy consumed by EV while traveling is defined in [7] as

$$e_{EV}^{trv} = \frac{d_{EV}}{v} = \frac{f_g \cdot m \cdot g \cdot v}{3,600} + \frac{f_a \cdot \phi \cdot v^3}{76,140}, \qquad (5)$$

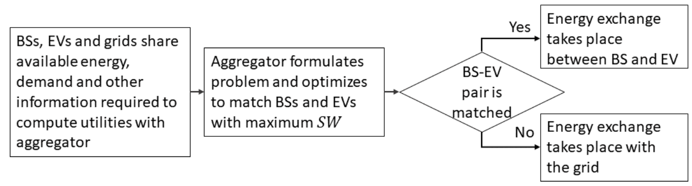


Fig. 2: Problem Optimization Flow.

where d_{EV} is the distance traveled, f_g, m , g, f_a, and ϕ are the ground friction coefficient, mass of EV, gravitational acceleration, air resistance, and windward area respectively. The utility of an EV for performing an edge computing task is

$$U_{EV}^{comp} = \lambda_{BS} T_{EV} - p_{EV}^{batt} e_{EV}^{trv} - p_{EV}^{cpu} s_{EV}^2, \qquad (6)$$

where p_{EV}^{batt} and p_{EV}^{cpu} are the unit costs of energy consumption including battery degradation and computation respectively.

D. Incentives Model

The utility of a buyer i is

$$U_i = \begin{cases} Q_i - p_j e_i + U_x^{comp}, & \text{Seller is BS or EV,} \\ Q_i - p_G e_i - p_{EV}^{batt} e_{EV}^{trv}, & \text{Seller is grid,} \end{cases} \qquad (7)$$

where U_x^{comp} is the utility of BS or EV for an edge computing task defined in (3) and (6) respectively, $e_{EV}^{trv} = 0$ if buyer is BS and Q_i is the satisfaction factor defined as $Q_i = \frac{\gamma}{SoC_i} log(1 + d_{i,j}^{Social} + e_i)$, where γ is the adjustment coefficient, SoC_i is the State of Charge (SoC) of buyer i at the beginning of charging and $d_{i,j}^{Social}$ is the social distance between buyer i and seller j. $d_{i,j}^{Social} = \sum_l^L \zeta_l d_{i,j,l}^{Social}$, where $d_{i,j,l}^{Social}$ is the social attribute and ζ_l is the weight of each attribute corresponding its value. $d_{i,j,l}^{Social}$ represents social factors, for example, personal interest to perform a task or altruism according to sustainability ranking of energy [1]. The utility of a seller j is

$$U_j = \begin{cases} p_j e_i - Cost(e_i) + U_x^{Comp}, & \text{Buyer is BS or EV,} \\ p_j e_i - Cost(e_i) - p_{EV}^{batt} e_{EV}^{trv}, & \text{Buyer is grid,} \end{cases} \qquad (8)$$

where $Cost(e_i) = ae_i^2 + be_i$ is the cost of acquiring e_i and $a > 0$ and $b > 0$ are the cost factors. The Social Welfare of the system is defined as $W = \sum_{i=1}^{I} U_i + \sum_{j=1}^{J} U_j$.

III. Problem Formulation and Optimization

A. Problem Formulation

The aggregator maximizes SW of the system by optimally matching buyers and sellers. After receiving information from all buyers and sellers, the problem is formulated as

$$\begin{aligned} \max_{U_i, U_j} \quad & SW, \forall i \,\epsilon\, \mathcal{I},\, j \,\epsilon\, \mathcal{J}, \\ \text{s.t.} \quad & \text{C1:} \quad U_i \geq 0 \,\forall i \,\epsilon\, \mathcal{I}, \\ & \text{C2:} \quad U_j \geq 0 \,\forall j \,\epsilon\, \mathcal{J}, \\ & \text{C3:} \quad e_{EV}^{trv} \leq SOC_i \,\forall \text{EV}i, \\ & \text{C4:} \quad e_i \leq SOC_j - RE_j \,\forall i \,\epsilon\, \mathcal{I},\, j \,\epsilon\, \mathcal{J} \\ & \text{C5:} \quad RE_j \geq e_{EV}^{trv} \,\forall \text{EV}j, \end{aligned} \qquad (9)$$

TABLE I: Constraint Penalty Pairs

Constraint	Equivalent Penalty
$U_i \geq 0$	$\mathcal{P}(-z_1)^2$
$U_j \geq 0$	$\mathcal{P}(-z_2)^2$
$e_{EV}^{trv} \leq SOC_i$	$\mathcal{P}(-z_7 + z_8 - z_7 z_8)^2$
$e_i \leq SOC_j - RE_j$	$\mathcal{P}(-z_9 + z_{10} - z_9 z_{10})^2$
$RE_j \geq e_{EV}^{trv}$	$\mathcal{P}(-z_{11})^2$

TABLE II: Simulation Parameters

Parameter	Value	Parameter	Value
N_{EV}	[100, 200]	N_{BS}	[3, 5]
P_{BBU}^{min}	5 W	P_{BBU}^{max}	20 W
P_{RF}	21.9 W	P_{sleep}	6.45 W
η	31.1%	f_{BBU}	2.5 GHz
m	1000	f_g	0.018
f_a	0.4	ϕ	2 m^2
s_{EV}	20 M	P_{chg}	110 kW
f_{EV}	2 GHz	C_{EV}	2.4381$\times$10^9 cycles/M
p_{EV}^{batt}	0.00028	p_{EV}^{CPU}	0.1
a	0.1	b	0.1
α	500	γ	0.1
λ_{BS}	1	p_{BS}^{task}	500
p_j	18.5	p_G	18.6

where constraints C1 and C2 guarantee that all buyers and sellers can benefit from the optimized matching, C3 ensures that all buyer EVs have enough energy to reach seller, C4 defines the upper threshold of surplus energy provided by a seller considering the amount of remaining energy it wants to keep with itself after selling, i.e., RE_j and C5 ensures that a seller EV must have sufficient surplus energy to reach the buyer. The flow of optimization process is shown in Fig. 2.

B. Gale-Shapley (GS) Optimization

GS optimization is a game theory approach which solves a bipartite matching problem with two-sided preferences [15]. It considers individual rationality as identified by constraints C1 and C2. In GS optimization, a preference list of sellers for each buyer i is formed with the most preferred seller providing highest U_i and vice-versa. A match is finalized resulting in maximum $U_i + U_j$. The algorithm results in optimum number of BSs matched with EVs resulting in maximum SW. The remaining buyers and sellers carry out their energy exchange with grid in return of positive utilities.

Fig. 3: Traffic simulation in SUMO.

C. Quantum Optimization

Since (9) is a combinatorial problem, QUBO is one of the most appropriate quantum approaches to solve it [13]. For QUBO, we need to formulate a problem over binary variables only. Therefore, we begin with the arbitrary connected bipartite graph of y vertices and a binary decision variable $x_{i,j}$ which has a value 1 if there exists an edge (matching pair) between i and j for edge weight $w_{i,j}$ and the value is 0 otherwise [16]. (9) is now transformed into $min_{\{x_{i,j}\} i \rightarrow j \epsilon \{0,1\}} \sum_{i \rightarrow j} w_{i,j} x_{i,j}$, where $w_{i,j} = -U_i - U_j$, i.e, the sum of negatives of utilities because QUBO models a minimization problem. The maximization problem is solved through QUBO by minimizing the negatives of its objective function [22]. QUBO problem can be expressed as $\min_{\mathbf{x}} f_Q(\mathbf{x})$.

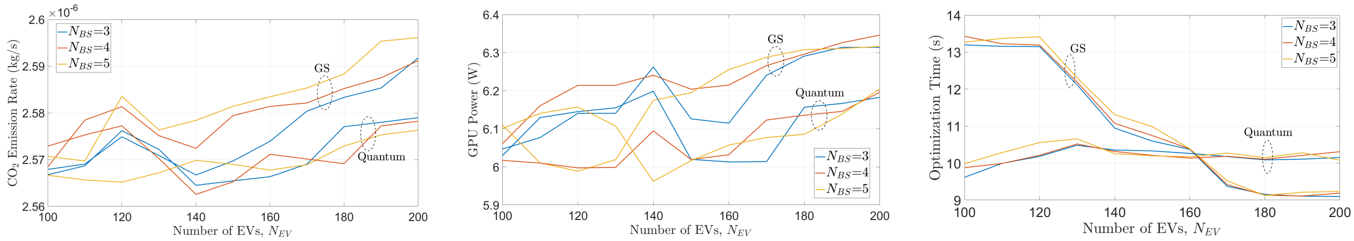
$$f_Q(\mathbf{x}) = \sum_{i,j} \sum_{k,l} Q_{i,j,k,l} x_{i,j} x_{k,l} + \sum_{i,j} g_{i,j} x_{i,j} = \mathbf{x}^\top \mathbf{Q} \mathbf{x} + \mathbf{g} \mathbf{x}, \tag{10}$$

where $\mathbf{Q}$ is a quadratic coefficient and $\mathbf{g}$ is a linear coefficient representing information about relationships between variables in $\mathbf{x}$. $x_{i,j}$ decides the allocation of qubits, i.e., a logical qubit i is assigned to hardware qubit j when $x_{i,j} = 1$ [24]. Also, (9) is a constrained problem which is converted into a QUBO problem by reformulating the constraints using penalties [22]. The inequality constraints in (9) are transformed into equivalent penalties as defined in Table I, where $\mathcal{P}$ is a user-defined penalty coefficient and z is equivalent binary variable [23]. We then form the Ising Hamiltonian of the problem as $H = H_A + \sum_{p=1}^{5} H_p$, where H_A represents the QUBO problem and H_p represents each of the equivalent penalty constraints defined in Table I. The quadratic coefficient $\mathbf{Q}$ in (10) can be found in the QUBO formulations of H using quadratic optimization tools [25].

IV. Performance Evaluation

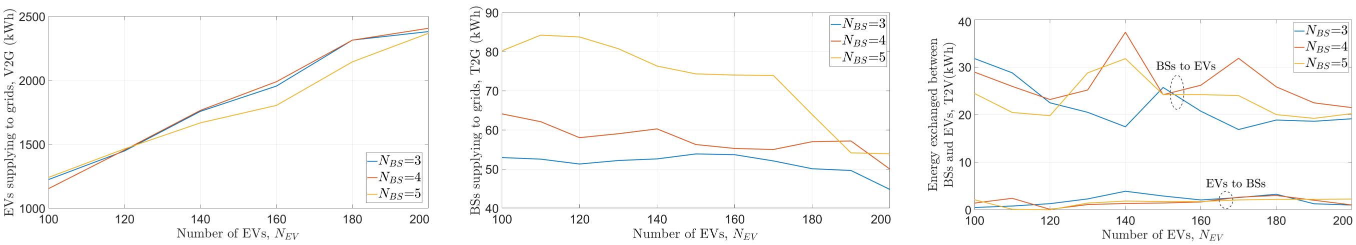
We analyze the performance of the proposed solution using Python. Table II lists the simulation parameters which align with other related research [7], [18]. As shown in Fig. 3, the vehicular traffic is simulated in a 2.5 $\times$ 2.5 km area of Central London using Simulation of Urban Mobility (SUMO) where BSs are uniformly distributed. The speed of EVs is received from SUMO simulation and its SoC is considered as a uniform random variable with range [10,100]. The SoC of BSs is extracted at a random time from open-source dataset provided in [26]. RE_j for each seller is computed as an energy consumption for an hour according to the models defined in Section II. The results are averaged over 100 simulation runs.

Fig. 4 compares the performance of optimization algorithms using emissions tracker feature of the Python library codecarbon [27]. As shown in Fig. 4 (a), the CO_2 emission rate significantly rises in GS algorithm with increase in N_{EV}. The reason of high CO_2 emission rate is the rising GPU power as shown in Fig. 4 (b). Therefore, quantum optimization is an environment-friendly option. The trade-off is shown in Fig. 4 (c), where the quantum optimization consumes more



(a) CO_2 Emission Rate (b) GPU Power (c) Optimization Time

Fig. 4: Comparison of Gale-Shapley and Quantum Optimization.



(a) V2G (b) T2G (c) T2V

Fig. 5: Energy supplied by BSs and EVs.

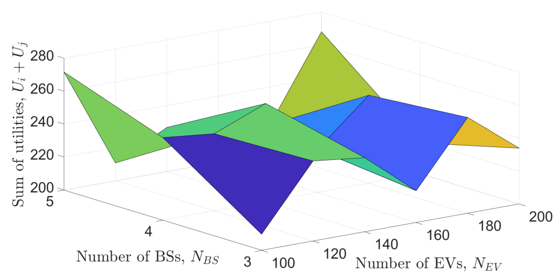


Fig. 6: Average sum of utilities after optimization.

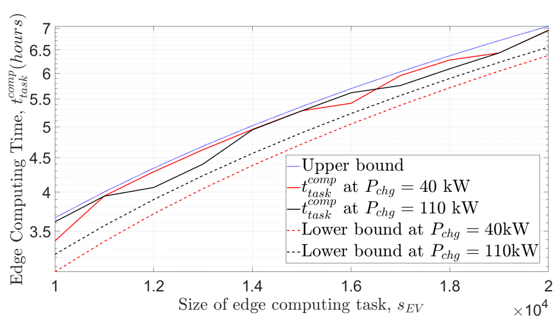


Fig. 7: Time consumption in edge computing.

time than GS with the increase in N_{EV}. However, keeping in view the net-zero goal, a few seconds delay in exchange of less CO_2 emissions can be tolerated in this case.

Fig. 5 shows the amount of energy supplied by EVs and BSs. Fig. 5 (a) indicates that EVs contribute significantly in V2G exchange. The contribution slightly reduces as N_{BS} rises. It is because larger N_{BS} leads to more BS-EV pairs resulting in increased EV to BS energy transfer with some reduction in V2G energy exchange. Similarly, Fig. 5 (b) shows that the T2G energy transfer from BS to grid decreases with rising N_{EV} because it leads to increased demands of EVs which are fulfilled by BSs. The amount of energy transferred from BSs to EVs is significantly higher than that from EVs to BS via T2V exchange, as shown in Fig. 5 (c). The energy transferred from BSs to EVs shows the promising potential of utilization of BSs as energy suppliers when the demand increases in a road transportation network.

Fig. 6 shows the average sum of utilities of buyers and sellers resulted after optimization, which is at its peak when N_{BS} is large. The minimum value is observed at lowest N_{BS} and N_{EV}. When the density of EVs and BSs is high, it is more likely that they are located closer to each other and an EV has to travel less to reach to a BS, which ultimately results in a greater $U_i + U_j$. It shows that the proposed model is suitable for 6G networks with high densities of BSs and EVs.

Fig. 7 shows the time required to complete an edge computing task. t_{task}^{comp} increases with s_{EV} and lies within the bounds defined in Theorem 1. When P_{chg} is higher, it is more likely that an EV completes the energy exchange before an edge computing task. Since $f_{BBU} > f_{EV}$, the BS can finish the task faster than an EV. Therefore, the average t_{task}^{comp} at $P_{chg} = 40\,$kW is 137 s higher than t_{task}^{comp} at $P_{chg} = 110\,$kW. However, edge computing by EV saves the power and computing resources of a BS. The bounds of t_{task}^{comp} can assist a BS to decide if it can wait for EVs or needs to complete a task itself in time-critical applications.

V. Conclusion

This paper presents a bidirectional V2G, T2G and T2V energy exchange orchestrated by a 6G-enabled aggregator. Additionally, a simultaneous edge-computing task offloading from BSs to EVs is proposed for efficient utilization of computing resources and charging or discharging times of EVs. The optimization problem is formulated aiming to maximize SW of the system which comprises of individual utilities of BSs and EVs. GS and quantum optimization algorithm are utilized to match BS-EV pairs resulting in highest SW. Simulation results show that quantum optimization produces less emissions as compared to GS. The proposed optimization shows the potential of BSs to trade energy with grid and EVs.

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APPENDIX A: PROOF OF THEOREM 1

Taking squares on both sides of (2) and using $(max(a-b,0)+c)^2 \leq a^2+b^2+c^2-2a(c-b)$, for any $a,b,c \geq 0$, we get

$$\begin{aligned}(t_{BS}^{comp})^2 \leq &(t_{task}^{comp})^2 + \Big(\sum_{EV=1}^{K} t_{EV}^{comp}\Big)^2 \\ &+ \Big(t_{BS}^{add}\Big)^2 - 2t_{task}^{comp}(t_{BS}^{add} - \sum_{EV=1}^{K} t_{EV}^{comp}\Big),\end{aligned} \tag{11}$$

which is a quadratic equation over t_{task}^{comp} whose solution leads to

$$t_{task}^{comp} \geq t_{BS}^{add} - \sum_{EV=1}^{K} t_{EV}^{comp} + \sqrt{(t_{BS}^{comp})^2 - 2t_{BS}^{add}\sum_{EV=1}^{K} t_{EV}^{comp}}. \tag{12}$$

Considering $t_{BS}^{add} \approx 0$,

$$t_{task}^{comp} \geq \sqrt{(t_{BS}^{comp})^2 - 2t_{BS}^{add}\sum_{EV=1}^{K} t_{EV}^{comp}} - \sum_{EV=1}^{K} t_{EV}^{comp}. \tag{13}$$

If a BS does not have to compute itself and waits for all EVs to perform edge computing then, $t_{task}^{comp} \leq t_{BS}^{add} + \sum_{EV=1}^{K} t_{EV}^{comp}$.

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