Optimization of The Energy Efficiency in Smart Internet of Vehicles Assisted By MEC

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Optimization of the energy efficiency in Smart Internet of Vehicles assisted by MEC

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Abstract
Smart Internet of Vehicles (IoV) as a promising application in Internet of Things (IoT) emerges with the development of the fifth generation mobile communication (5G). Nevertheless, the heterogeneous requirements of sufficient battery capacity, powerful computing ability and energy efficiency for electric vehicles face great challenges due to the explosive data growth in 5G and the sixth generation of mobile communication (6G) networks. In order to alleviate the deficiencies mentioned above, this paper proposes a mobile edge computing (MEC) enabled IoV system, in which electric vehicle nodes (eVNs) upload and download data through an anchor node (AN) which is integrated with a MEC server. Meanwhile, the anchor node transmitters radio signal to electric vehicles with simultaneous wireless information and power transfer (SWIPT) technology so as to compensate the battery limitation of electric vehicles. Moreover, the anchor node equips with full-duplex (FD) and multi-input and multi-output (MIMO) technologies for further improve the spectrum efficiency. Taking into account the issues above, we maximize the average energy efficiency of electric vehicles by jointly optimize the CPU frequency, vehicle transmitting power, computing tasks and uplink rate. In order to solve this nonconvex problem, we propose a novel alternate interior-point iterative scheme (AIIS) under the constraints of computing tasks, energy consumption and time latency. Numerical simulations demonstrate the effectiveness of the proposed scheme comparing with the benchmark schemes.

Keywords: 5G; 6G; Smart Internet of Vehicle; Mobile edge computing; Simultaneous wireless information and power transfer; Full-duplex; Multi-input and multi-output

1 Introduction
1.1 Background and related work
Recently, with the evolution from the fifth generation mobile communication (5G) [1] to the sixth generation mobile communication (6G), some novel technologies, such as mobile edge computing (MEC) [2, 3], satellite communication [4] and spatial multiplexing [5], have been proposed to promote the development of wireless sensor network (WSN) [6], IoT [7] and other novel applications [8,9], so as to meet a whole connected world and realize global coverage. IoV as a special application of IoT attracts extensive attention in terms of road safety, smart transportation and information service [10]. However, since a large number of data traffic connected to the intelligent transportation, the demand of computing resources and battery capacity for these delay-sensitive and computing-intensive applications becomes more and more urgent [11–13]. Hence, mobile edge computing is proposed to mitigate...
the computing burden of electric vehicles [14]. Meanwhile, full-duplex and multi-input and multi-output technologies are proposed to further improve the spectrum efficiency [15]. Besides, the energy consumption of data processing will increase significantly due to the vast number of data traffic. Therefore, SWIPT is supposed to be a meaningful method which provides sufficient energy for electric vehicles to complete their intensive computing tasks.

The last decade, mobile cloud computing (MCC) [16] as a promising method proposed by researchers to cope with the computing resources limitation of vehicles [17]. Even if the vast resources available in the clouds can be leveraged to support resource-constrained vehicles by deliver elastic computing power, the service at the network edge tends to be uncovered [18, 19]. Besides, as the inherent limitation of MCC, long propagation between vehicles and the remote cloud center causes significant long latency [20]. In consideration of the computation-intensive and latency-critical tasks, mobile edge computing (MEC) [21, 22] as a new paradigm proposed to afford massive amount of computation power and storage space distributed at the network edges [23]. Hence, the author in [24] investigated the collaboration between cloud computing and edge computing, where terminals are permitted to offload their computing tasks to the MEC server for mitigating heavy computations as well as reducing time latency, while Yu Liu, et al, propose a novel mobile edge mechanism with a vehicle-mounted edge deployed aiming at maximizing completed task of vehicle-mounted edge with sensitive deadline [25]. Besides, [26] designed a cost-efficient cloud assisted mobile edge computing framework in order to guarantee the minimal system cost through optimizing the computation capacity and dynamically adjust the cloud tenancy strategy.

Taking account of the energy limitation of electric vehicles, several practical methods are employed to extend their battery lifetime, such as energy harvesting (EH) [34], wireless power transfer (WPT) [35] and simultaneous wireless information and power transfer (SWIPT) [36, 37]. However, energy harvesting may suffer from the uncertain environment resulting in obtain unreliable energy sources, while wireless power transfer (WPT) is able to realize more controllable and reliable energy supply from radio frequency (RF). Futher considering that not only energy but also information contained in RF signal, SWIPT is widely used to achieve energy harvesting and information decoding (ID) by power-splitting (PS) and time-switching (TS) [38]. Meanwhile, full-duplex (FD) [39] and multi-input and multi-output (MIMO) [40] are proposed to further improve the spectrum efficiency and reduce the time latency [41].

Although considerable research has been devoted to improve performance of vehicular network with MEC-assisted technologies, such as [42] modeled the data redundancy and collaborative task computing scheme to efficiently reduce the redundant data and utilize the idle resources in nearby MEC servers by allocating the computing tasks so as to achieve the minimal cost of the vehicular system. The author in [43] developed a software defined network (SDN)-enabled heterogeneous vehicular network to improve the scalability of the network as well as provide high reliability and low-latency communication. K. Zhang, et al. [44] proposed a task offloading scheme by jointly consider the data transmission and server selection with deep Q-learning technique. In [45], an adaptive offloading strategy is proposed to
optimize the resource utilization of edge servers based on a multiobjective evolutionary algorithm. Rather less attention has been paid to improve energy efficiency of electric vehicles in IoV considering computing tasks, time latency and spectrum efficiency.

1.2 Contributions
In this paper, we propose an IoV system assisted by MEC which is used for cross-layer offloading to provide ultra-low latency and abundant computation resources. Meanwhile, SWIPT technology is used to afford energy for electric vehicles, and the FD and MIMO technologies are used to further improve the spectrum efficiency. On the premise of computation requirement, time latency and energy constraint of electric vehicles, we maximize the average energy efficiency of electric vehicles. Since the problem is nonconvex, we decouple it into two subproblems at first. According to the previous research [46], we obtain a closed-form solution of the central processing unit (CPU) frequency from the first subproblem. For the second one, we continue to decompose it into three subproblems after substituting the former closed-form solution into the second subproblem. Finally, an alternate interior-point iterative scheme is proposed to address these subproblems. Numerical simulations are executed to demonstrate the superior performance of our scheme comparing with the benchmark schemes. The main contributions of our study can be summarized as follows:

- We come up an IoV system by comprehensively using the MEC, the FD and the SWIPT technologies, so as to achieve low-latency, abundant computation resources and lower energy consumption by jointly optimizing the CPU frequency, power transfer of electric vehicles, the uplink rate and the offloading tasks.
- Under the same computation task, energy consumption and time latency constraints, the proposed scheme can yield high energy efficiency, lower time transmission and is able to tackle more computing tasks comparing with the benchmark schemes.
- MIMO and FD technologies deployed at anchor node are used to further improve the spectrum efficiency and the time latency. Meanwhile, we analysis the energy efficiency fairness of the electric vehicles as well.

The rest of this paper is organized as follows. Section 2 presents the system model. In Section 3, we formulate the mathematical problem and solve it by alternate iterative scheme. Numerical simulations are provided in Section 4. Finally, we conclude this paper in Section 5.

2 Methods
2.1 System model
As shown in Fig. 1, we consider an IoV system assisted by MEC, in which a MEC server is deployed at anchor node (AN) and the electric vehicle as a cognitive node connected with AN. Hence, computing tasks will be offloaded partially from electric vehicle nodes (eVNs) to MEC server. Moreover, we assume that the AN works in full-duplex mode which can simultaneously transmit and receive signals at the same time and frequency so as to utilize SWIPT technology to fulfill energy of eVNs as
well as receive the offloading computing tasks from the other eVNs at the same time. Besides, the eVN is equipped with a PS receiver, which can operate in both energy harvesting state and information decoding state according to the energy conversion factor $\beta$, where $0 \leq \beta \leq 1$.

In Fig. 2, each vehicle node $VN_i (i \in \{1, ..., K\})$ offloads partial computing tasks $m_i (0 \leq m_i \leq M_i)$ to the AN within the time duration $\tau_i^u$, where $M_i$ denotes the total computation tasks of $VN_i$ and $K$ is the number of vehicle nodes. Simultaneously, AN transmits the computation tasks $m_j^f (j \in \{1, ..., K\})$ executed by MEC server to $VN_j$ within the time duration $\tau_j^d$, where $m_j^f = \alpha m_j (0 \leq \alpha \leq 1)$, and the parameter $\alpha$ represents the ratio of MEC computation results to offloaded computation tasks. Since the powerful computing ability of MEC server, we ignore the computing time of it [47]. Furthermore, the local computing tasks $m_j^{lo}$, which equals $M_i - m_i$, is completed during the time duration $\tau_j^{lo}$. Besides, we assume that the local computing time slot is less than the uplink time slot, i.e., $0 \leq \tau_i^{lo} \leq \tau_i$. More details will be given in the following subsections.

Notations: In this paper, channel fading model is Rayleigh distribution. The uplink channel and the downlink channel are modeled as uniform distribution~$U(0, 1)$, which are denoted as $h_i^u \in \mathbb{C}^{N \times 1}$ and $h_j^d \in \mathbb{C}^{N \times 1}$, where $N$ is the antenna numbers of AN. Meanwhile, $H_{an}$ represents the self-interference channel of AN. $d_i$ and $d_j \in \mathbb{C}^{N \times 1}$ represent the transmitted signal from vehicle node and AN respectively, where $|d_j| = 1$. In addition, the transmitting power of each vehicle node and AN are denoted as $p_i$ and $p_j$. Besides, $n_{an}$ represents the additive white Gaussian noise (AWGN) of AN with covariance matrix $\sigma_{an}^2 I_M$. Similarly, $n_j$ and $n_{ps}$ are the AWGN of $VN_j$ and PS receiver with covariance $\sigma_j^2$ and $\sigma_{ps}^2$, respectively. Finally, the bandwidth of the system is expressed as $B$.

### 2.1.1 Computation task processing

In uplink transmission, vehicle nodes upload partial computing tasks to the AN in turn. Specifically, $VN_i$ transmits $d_i$ with transmitting power $p_i$ to the AN within the time slot $\tau_i^u$, while the AN transmits $d_j$ with transmitting power $p_j$ at the same time. Therefore, the received signal at AN can be expressed as

$$x_i^u = \sqrt{p_i} h_i^u d_i + H_{an} (\sqrt{p_j} d_j) + n_{an}$$

(1)

where the first component is the desired signal from $VN_i$, the second component is the self-interference at the AN, and the last component is the AWGN at the AN. Meanwhile, the transmitting power of vehicle node should satisfy $p_{\min} \leq p_i \leq p_{\max}$, where $p_{\min}$ and $p_{\max}$ are the minimal and maximal transmitting power of each vehicle node.

According to (1), the power of the received signal and the signal to interference plus noise ratio (SINR) can be derived as

$$P_i = \text{tr}\{x_i (x_i)^H\}$$

$$= p_i \text{tr}\{h_i^u (h_i^u)^H\} + p_j \text{tr}\{H_{an}(H_{an})^H\} + \delta_{an}^2$$

(2)

$$\gamma_i = \frac{p_i \text{tr}\{h_i^u (h_i^u)^H\}}{p_j \text{tr}\{H_{an}(H_{an})^H\} + \delta_{an}^2}$$

(3)
where $(.)^H$, tr{$\cdot$} represent the conjugate and trace of matrix, respectively. According to the equation above, we can obtain the uplink rate which is written as

$$r_i = \text{Blog}(1 + \gamma_i) \quad (4)$$

As we know, if the self-interference can be eliminated completely by self-interference cancelation (SIC), the maximal SINR can be expressed as

$$\gamma_{\text{max}}^i = \frac{p_i \text{tr}\{h_i^u(h_i^u)^H\}}{\delta_{an}^2} \quad (5)$$

Hence, the ideal uplink rate can be written as

$$r_{i,\text{max}} = \text{Blog}(1 + \gamma_{\text{max}}^i) \quad (6)$$

However, limited by SIC device, self interference cannot be completely eliminated. Therefore, the uplink rate should not exceed the ideal maximal uplink rate, i.e.,

$$r_i \leq r_{i,\text{max}} \quad (7)$$

Based on the analysis above, we can calculate the uplink time slot $\tau_{i,u}$ and the energy consumption of $VN_i$,

$$\tau_i = \frac{m_i}{r_i} \quad (8)$$

$$e_{i,vn} = p_i \frac{m_i}{r_i} \quad (9)$$

Based on the theory of [47], the local computing time duration and the energy consumption can be derived as

$$\tau_{i,\text{lo}} = \sum_{i=1}^{C(M_i-m_i)} \frac{1}{f_i^n} \quad (10)$$

$$e_{i,\text{lo}} = \sum_{n=1}^{C(M_i-m_i)} \kappa(f_i^n)^2 \quad (11)$$

where $C$ is the required CPU cycles for computing 1-bit of data, $f_i^n$ represents the CPU frequency of $VN_j$ required for n-th CPU cycles. Here, $0 \leq f_i^n \leq f_i^{\text{max}}$, $f_i^{\text{max}}$ is the maximum CPU frequency. And $\kappa$ denotes the efficient capacitance coefficient based on the chip architecture of vehicles.

2.1.2 Energy harvesting

Similarly, in the downlink transmission, $VN_j$ receives signal from the AN including the desired RF signal and the AWGN at $VN_j$, which are expressed as

$$x_j = \sqrt{p_j}(h_j^d)^T d_j + n_j \quad (12)$$
In (12), \( (\cdot)^T \) is the transposition operation. Similar to the uplink transmission, we can obtain the received signal power at \( VN_i \) and the downlink signal to noise (SNR),

\[
P_j = p_j \text{tr}\{ (h^d_j)^T (h^d_j)^{TH} \} + \delta_j^2
\]

\[
\gamma_j = \frac{\beta p_j \text{tr}\{ (h^d_j)^T (h^d_j)^{TH} \}}{\delta_j^2}
\]

Hence, the downlink rate and the time slot can be derived as

\[
r_j = B \log(1 + \gamma_j)
\]

\[
\tau_j = \frac{\alpha m_j}{r_j}
\]

According to the energy harvesting factor \( \beta \) of the PS receiver, the energy harvesting of \( VN_i \) is shown as

\[
e_{i}^{\text{eh}} = \beta p_j \text{tr}\{ (h^d_j)^T (h^d_j)^{TH} \} \tau_j^d
\]

2.1.3 Problem formulation

We assume that the total time duration is \( T \), hence, the time slot of all vehicles in uplink and downlink transmission should no more than \( T \), respectively, i.e.,

\[
0 \leq \sum_{i=1}^{K} \tau_i^u \leq T
\]

\[
0 \leq \sum_{j=1}^{K} \tau_j^d \leq T
\]

Moreover, since vehicle node is not able to transmit and receive signal simultaneously, there should be no overlap between uplink and downlink transmission time of a same vehicle node, i.e.,

\[
\sum_{i=1}^{K} \tau_i^u + \tau_K \leq T
\]

\[
\sum_{i=1}^{K} \tau_i^u \leq T - \sum_{j=K_{\text{tmp}}}^{K} \tau_j^d
\]

where \( K_{\text{tmp}} \in \{1, ..., K\} \).

Meanwhile, the downlink transmission slot is less than the uplink transmission slot, so as to guarantee the computing tasks offloading from the next vehicle node can be processed at the AN without time latency and queuing, i.e.,

\[
\tau_j^d \leq \tau_i^u, j = i - 1
\]
Besides, we assume that each vehicle node has enough energy to complete the computing tasks by harvesting energy from the AN. Meanwhile, the energy harvested from the AN should no more than the total transmitting power from the AN. Hence, the energy consumption of each vehicle should satisfy,

\[ e_i^{vn} + e_i^{lo} \leq e_i^{eh} \]  \hspace{1cm} (23)

\[ e_i^{eh} \leq e_i^{an} \]  \hspace{1cm} (24)

where \( e_i^{an} = p_j r_j \). According to the derivations above, we formulate the following problem \((P1)\) which is aim to maximizing the average energy efficiency of the total vehicle nodes.

\[
(P1) \quad \begin{array}{l}
\max_{f^n, p, m, r} \frac{1}{K} \{ \sum_{i=1}^{K} \frac{r_i}{e_i^{vn} + e_i^{lo}} \} \\
\text{s.t.} \quad C1 : e_i^{vn} + e_i^{lo} \leq e_i^{eh} \\
\quad \quad C2 : e_i^{eh} \leq e_i^{an} \\
\quad \quad C3 : 0 \leq f_i^n \leq f_i^{max} \\
\quad \quad C4 : p_{min} \leq p_i \leq p_{max} \\
\quad \quad C5 : 0 \leq m_i \leq M_i \\
\quad \quad C6 : 0 \leq r_i \leq r_i^{max} \\
\quad \quad C7 : 0 \leq \tau_i^{lo} \leq \tau_i^{an} \\
\quad \quad C8 : \tau_j^d \leq \tau_i^n, j = i - 1 \\
\quad \quad C9 : 0 \leq \sum_{i=1}^{K} \tau_i^n \leq T \\
\quad \quad C10 : 0 \leq \sum_{j=1}^{K} \tau_j^d \leq T \\
\quad \quad C11 : \sum_{i=1}^{K \text{tmp}} \tau_i^n \leq T - \sum_{j=K \text{tmp}}^{K} \tau_j^d
\end{array}
\]  \hspace{1cm} (25)

where \( f^n = [f_1^n, ..., f_K^n]^T \), \( p = [p_1, ..., p_K]^T \), \( m = [m_1, ..., m_K]^T \), \( r = [r_1, ..., r_K]^T \)
represent the CPU frequency, the uplink transmitting power, the offloading computation tasks and the uplink rate of all vehicle nodes, respectively. Moreover, the \( f_i^{max} \) is the maximum CPU frequency.

### 2.2 Solution of problem

In this section, since the cost function and the constraints in problem \((P1)\) are nonlinear and nonconvex, we first divide problem \((P1)\) into two subproblems. For the first one, we obtain a closed-form solution of CPU frequency with fixed variables \( p, m, r \). Substituting the closed-form solution into \((P1)\), the second subproblem is derived. For the second subproblem, we utilize an alternate interior-point iterative scheme after decompose it into three subproblems. Finally, the suboptimal variables \(< f^n, p, m, r >\) are obtained.

#### 2.2.1 Local computing optimization

Inspired by [47], the optimal CPU frequency should satisfy

\[
f_1^1 = f_2^1 = ... = f_i^{C(M_i - m_i)} = \frac{C(M_i - m_i)}{\tau_i^{lo}} = \tilde{f}_i
\]  \hspace{1cm} (26)
where \( \overline{f}_i \) is the average CPU frequency. Based on the derivation above, the original problem (P1) is converted into the problem (P2) as following.

\[
(P2) \quad \min_{\overline{f}} \frac{1}{R} \left( \sum_{i=1}^{K} e_i^{lo} \right) \\
\text{s.t.} \begin{cases} 
C1: e_i^{vn} + e_i^{lo} \leq e_i^{th} \\
C2: 0 \leq \tau_i^{lo} \leq \tau_i^{u} 
\end{cases}
\tag{27}
\]

To further simplify the problem (P2), we obtain the following problem (P3)

\[
(P3) \quad \min_{\overline{f}} \frac{1}{R} \left\{ \sum_{i=1}^{K} \kappa C(M_i - m_i)(\overline{f}_i)^2 \right\} \\
\text{s.t.} \begin{cases} 
C1: e_i^{vn} + \kappa C(M_i - m_i)(\overline{f}_i)^2 \leq e_i^{th} \\
C2: 0 \leq C(M_i - m_i) / \overline{f}_i \leq \tau_i^{u} 
\end{cases}
\tag{28}
\]

where C2 indicates that the lower bound of \( \overline{f}_i \) is \( \frac{C(M_i - m_i)}{\tau_i^{u}} \). We define the lower bound of \( \overline{f}_i \) as the optimal CPU frequency \( f_i^{opt} \).

2.2.2 Communication optimization

Substituting the optimal CPU frequency \( f_i^{opt} \) into the original problem (P1), it can be rewritten as problem (P4).

\[
(P4) \quad \max_{p, m, \overline{f}} \frac{1}{R} \left\{ \sum_{i=1}^{K} \frac{r_i}{e_i^{vn} + e_i^{lo}} \right\} \\
\text{s.t.} \begin{cases} 
C1: e_i^{vn} + e_i^{lo} \leq e_i^{th} \\
C2: e_i^{vh} \leq e_i^{sh} \\
C3: p_{min} \leq p_i \leq p_{max} \\
C4: 0 \leq m_i \leq M_i \\
C5: 0 \leq \tau_i \leq \tau_i^{max} \\
C6: \tau_j^{d} \leq \tau_j^{u}, j = i - 1 \\
C7: 0 \leq \sum_{j=1}^{K} \tau_j^{u} \leq T \\
C8: 0 \leq \sum_{j=1}^{K} \tau_j^{d} \leq T \\
C9: \sum_{i=1}^{K} \tau_i^{u} \leq T - \sum_{j=K_{imp}}^{K} \tau_j^{d} 
\end{cases}
\tag{29}
\]

Since the problem (P4) is still a NP-hard problem, we continue to decompose it into three subproblems, which are denoted as (P4.1) ~ (P4.3), respectively.

\[
(P4.1) \quad \max_{p} \frac{1}{R} \left( \sum_{i=1}^{K} \frac{r_i}{e_i^{vn} + e_i^{lo}} \right) \\
\text{s.t.} \begin{cases}
C1: e_i^{vn} + e_i^{lo} \leq e_i^{th} \\
C2: e_i^{vh} \leq e_i^{sh} \\
C3: p_{min} \leq p_i \leq p_{max} \\
C4: \tau_j^{d} \leq \tau_j^{u}, j = i - 1 \\
C5: 0 \leq \sum_{j=1}^{K} \tau_j^{u} \leq T \\
C6: 0 \leq \sum_{j=1}^{K} \tau_j^{d} \leq T \\
C7: \sum_{i=1}^{K} \tau_i^{u} \leq T - \sum_{j=K_{imp}}^{K} \tau_j^{d} 
\end{cases}
\tag{30}
\]

The problem (P4.1) is only related to \( p \), which can solved by classical interior-point algorithm.
\[ (P4.2) \quad \max \frac{1}{\kappa} \left\{ \sum_{i=1}^{K} \frac{r_i}{e_i^v + e_i^w} \right\} \]
\[ s.t. \]
\[ C1: e_i^v + e_i^w \leq e_i^h \]
\[ C2: e_i^h \leq e_i^{an} \]
\[ C3: 0 \leq m_i \leq M_i \]
\[ C4: \tau_j^d \leq \tau_i^u, \quad j = i - 1 \]
\[ C5: 0 \leq \sum_{j=1}^{K} \tau_j^u \leq T \]
\[ C6: 0 \leq \sum_{j=1}^{K} \tau_j^d \leq T \]
\[ C7: \sum_{i=1}^{K_{tmp}} \tau_i^u \leq T - \sum_{j=1}^{K_{tmp}} \tau_j^d \]

As same as the problem (P4.1), interior-point algorithm is used to address the problem (P4.2) to achieve the optimal \( \mathbf{m} \).

\[ (P4.3) \quad \max \frac{1}{\kappa} \left\{ \sum_{i=1}^{K} \frac{r_i}{e_i^v + e_i^w} \right\} \]
\[ s.t. \]
\[ C1: e_i^v + e_i^w \leq e_i^h \]
\[ C2: e_i^h \leq e_i^{an} \]
\[ C3: 0 \leq r_i \leq r_i^{max} \]
\[ C4: \tau_j^d \leq \tau_i^u, \quad j = i - 1 \]
\[ C5: 0 \leq \sum_{j=1}^{K} \tau_j^u \leq T \]
\[ C6: 0 \leq \sum_{j=1}^{K} \tau_j^d \leq T \]
\[ C7: \sum_{i=1}^{K_{tmp}} \tau_i^u \leq T - \sum_{j=1}^{K_{tmp}} \tau_j^d \]

Similarly, the optimal variable \( \mathbf{r} \) is obtained by solving the problem (P4.3) using the interior-point algorithm.

Each subproblem of (P4.1) ∼ (P4.3) is regarded as an approximate convex problem of the corresponding variable, while the other variable are fixed. In order to solve the problem (P4), each subproblem is addressed by classical interior-point algorithm. After that, the whole problem is solved by alternate iterative scheme, which is denoted as Algorithm 1.

**Algorithm 1 Alternate interior-point iterative scheme (AII)\)**

**Input:** \( \mathbf{h}_v, \mathbf{h}_u, \mathbf{H}_m, \mathbf{p}_0, \mathbf{m}_0, \mathbf{r}_0, \mathbf{d}, d_i, K, N, B, T, C, \kappa, \alpha, \beta, \gamma, \delta, \sigma, \rho, \delta_m, \rho_{min}, \rho_{max}, M, p_j \),
where \( \{i, j\} \in \{1, ..., K\} \), \( \mathbf{p}_0 \), \( \mathbf{m}_0 \), and \( \mathbf{r}_0 \) represent the initial offloading computation tasks, the uplink transmission power and rate of the vehicle nodes, respectively.

1: According to (P3), \( f_i^{opt} = C(M_i - m_i) / (2 \tau_i^u) \), \( e_i^v = \tau_i^u \), and \( e_i^w = C(M_i - m_i)^2 / (2 \tau_i^u \tau_i^d) \).
2: Convert (P3) into (P4) by substituting \( f_i^{opt} = C(M_i - m_i) / (2 \tau_i^u) \), \( \tau_i^d = \tau_i^u \), and \( e_i^w = C(M_i - m_i)^2 / (2 \tau_i^u \tau_i^d) \).
3: Set the initial value \( p_{ini} = p_i(0), m_{ini} = m_i(0), r_{ini} = r_i(0), \) and iteration number \( k = 1 \).
4: repeat
5: Solve problem (P4.1) with fixed \( m_{(k-1)}, r_{(k-1)} \), while \( p_{ini} = p_i(k-1) \), to achieve the optimal \( \mathbf{p}_1 \);
6: Solve problem (P4.2) with fixed \( p_{(k-1)}, r_{(k-1)} \), while \( m_{ini} = m_i(k-1) \), to achieve the optimal \( \mathbf{m}_1 \);
7: Solve problem (P4.3) with fixed \( p_{(k-1)}, m_{(k-1)} \), while \( r_{ini} = r_i(k-1) \), to achieve the optimal \( \mathbf{r}_1 \);
8: Set \( k = k + 1 \);
9: until the objective function of problem (P4) converges.

**Output:** \( f^{(opt)}_1, p^{(opt)}_i, m^{(opt)}_{(k-1)}, r^{(opt)}_i \)
4 Results and discussion

In this section, according to the numerical simulations, we discuss the performance of the proposed scheme in this paper comparing with the two benchmark schemes. Three offloading strategies are denoted as below and the simulation parameters are listed in Table 1.

- FVS: all variables are fixed.
- FOS: computing tasks completely offload to the AN which indicates the local computing task is zero.
- AIIS: computing tasks are offloaded arbitrarily based on the maximum average energy efficiency of total vehicle nodes.

In Fig. 3, we find that the average energy efficiency of the total vehicles decreases as computing tasks increase. However, the proposed AIIS scheme still has the maximum average energy efficiency comparing with the benchmark schemes. Fig. 4 investigates the influence of antenna numbers on system performance. Here, we assume that the number of vehicles equals 10 and the antenna numbers are \{6,8,10\}. As shown in figure, with the number of antennas increasing, the average energy efficiency for each scheme is improved. However, the average energy efficiency of the proposed scheme is higher than that of the comparing schemes with the same antenna numbers.

Fig. 5 studies the system performance with different numbers of vehicle nodes from 1 to 10, where we can find that the number of vehicles make no difference to the average energy efficiency for each scheme due to the total energy efficiency of all vehicles are averaged. Nevertheless, the proposed scheme is superior to the comparing scheme under the same number of vehicles. Fig. 6 studies the effect of the downlink transmitting power from the AN. Similarly, the transmitting power seems to have no effect on the average energy efficiency. Hence we may achieve lower energy consumption with higher energy efficiency. Besides, the system performance of the proposed scheme is better than that of the other two schemes as well.

Under the same conditions, Fig. 7 shows that the transmission time of three schemes increases with the number of computation tasks increasing. However, the proposed scheme has the lower transmission time compared to the other schemes.

To further study the fairness of each vehicle, we obtain the Fig. 8 and Fig. 9. For the former, variance of energy efficiency of all vehicles are given to prove that the proposed scheme AIIS has the best energy efficiency fairness between the same vehicle numbers compared to the other schemes, which indicates that the quality of service of different vehicles can be guaranteed. For the latter, the proposed scheme has the lower variance of transmission time consumptions between all vehicles with the same computation tasks comparing with the benchmark schemes, which indicates that the time-latency fairness between the different vehicles of AIIS is superior to that of the comparing schemes.

5 Conclusion

In this paper, we propose an IoV system assisted by MEC server which is deployed at anchor node. Electric vehicle as a cognitive node uploads their intensive computing tasks to the AN as well as harvests energy from the RF signal transmitted by the AN with SWIPT technology, so as to alleviate the heavy computing tasks, reduce the
time latency and compensate the limited battery capacity of vehicle node. Besides, FD and MIMO are proposed to further improve the spectrum efficiency. Finally, an alternate interior-point iterative scheme (AIIS) is proposed to solve a nonlinear and nonconvex problem which is aim to maximize the average energy efficiency of vehicles by jointly optimize the computing and communication resources. Numerical simulations demonstrate that the performance of the proposed scheme is superior to other comparison schemes, which is beneficial for the future IoV system service.

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References


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Abbreviations
IoV: Internet of Vehicle; IoT: Internet of Things; 5G: the fifth generation mobile communications; 6G: the sixth generation of mobile communications; MEC: mobile edge computing; eVNs: electric vehicle nodes; AN: anchor node; SWIPT: simultaneous wireless information and power transfer; FD: full-duplex; MIMO: multi-input and multi-output; WSN: wireless sensor network; MCC: mobile cloud computing; EH: energy harvesting; WPT: wireless power transfer; ID: information decoding; PS: power-splitting; TS: timeswitching; SDN: software defined network; CPU: central processing unit; SNIR: interference plus noise ratio; SIC: self-interference cancelation; RF: radio frequency; SNR: signal to noise.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
Jiafei Fu proposes an alternate interior-point iterative scheme (AIIS) to optimize the energy efficiency of electric vehicles in a smart IoV system and she is the major contributor in writing the manuscript. All authors read and approved the final manuscript.

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References

Figures

Tables
Figure 1 System model

Figure 2 Time slot

Table 1 Simulation parameters

<table>
<thead>
<tr>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_i, h_j$</td>
<td>Modeled as Random uniform distribution $\sim U(0.5, 1)$</td>
</tr>
<tr>
<td>$H_0$</td>
<td>Modeled as Random Rayleigh Fading channel $\sim CN(0, 0.1)$</td>
</tr>
<tr>
<td>$N$</td>
<td>6, 8, 10</td>
</tr>
<tr>
<td>$K$</td>
<td>1 $\sim$ 10</td>
</tr>
<tr>
<td>$B$</td>
<td>2MHz</td>
</tr>
<tr>
<td>$C$</td>
<td>$10^3$ cycles/bit</td>
</tr>
<tr>
<td>$T$</td>
<td>0.5</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.2</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>$10^{-23}$</td>
</tr>
<tr>
<td>$p_j$</td>
<td>$10W \sim 30W$</td>
</tr>
<tr>
<td>$p_{\min}$</td>
<td>1W</td>
</tr>
<tr>
<td>$p_{\max}$</td>
<td>5W</td>
</tr>
<tr>
<td>$\delta^2_{\text{a}, \text{b}, \text{c}, \text{d}}$</td>
<td>$10^{-7}W$</td>
</tr>
</tbody>
</table>
Figure 3 The average energy efficiency of vehicles versus the computation task M

Figure 4 The average energy efficiency of vehicle nodes (VNs) versus the computation task M under different antenna numbers N
Figure 5 The average energy efficiency of vehicle nodes (VNs) versus the different number of VNs.

Figure 6 The average energy efficiency of vehicle nodes (VNs) versus the different transmitting power of AN.
Figure 7 The transmission time consumption of vehicle nodes (VNs) versus the computation task $M$.

Figure 8 The variance of energy efficiency between all vehicle nodes (VNs) under different antenna numbers $N$. 
Figure 9 The variance of transmission time consumption of vehicle nodes (VNs) under different computation task M.