# Integration of 6G Signal Processing, Communication, and Computing based on Information Timeliness-aware Digital Twin

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***Abstract*—6G has emerged as a feasible solution to enable intelligent electric vehicle (EV) energy management. It can be further combined with digital twin (DT) to optimize resource management under unobservable information. However, the lack of reliable information timeliness guarantee increases DT inconsistency and undermines resource management optimality. To address this challenge, we investigate DT-empowered resource management from the perspective of age of information (AoI) optimization. We utilize AoI as an effective information timeliness metric to measure DT consistency, and construct an AoI-optimal DT (AoIo-DT) to assist resource management by providing more accurate state estimates. A joint optimization algorithm of signal processing, communication, and computing integration based on AoI-aware deep actor critic (DAC) with DT assistance is proposed to achieve balanced tradeoff between DT consistency and precision improvement of EV energy management. It further improves learning convergence and optimality of DAC by enforcing training with data samples of smaller AoI. Numerical results verify its performance gain in AoI minimization and EV energy management optimization.**

***Index Terms*—EV energy management, digital twin, resource management, information timeliness, 6G.**

## I. Introduction

Electric vehicle (EV) energy management plays an important role in constructing a smart, low-carbon, and sustainable city [1]. It explores the dual roles of EV as load and storage to promote renewable energy accommodation and reduce carbon emission [2], [3]. The core of EV management is to train a model to intelligently manage EV charging/discharging in accordance with dynamic changes of energy demand and supply [4], [5]. Model training requires real-time pre-processing, transmission, and computation of massive data samples of distributed photovoltaic (PV) output, user load variation, and grid operation state [6], [7]. As a result, EV management optimality is closely coupled with resource management of communication network, which imposes new requirements on joint optimization of signal processing, communication, and computing.

6G with integrated artificial intelligence (AI) and communication has emerged as a feasible solution. 6G can be further enhanced by digital twin (DT) to realize network resource management of signal processing, communication, and computing integration [8]. Particularly, DT facilitates network state estimation and optimization guidance for resource management by building a consistent digital representation of physical infrastructures [9]–[12]. The accuracy of state estimates relies on information timeliness, which is fundamentally different from delay. While delay emphasizes the transmission time of individual packets, information timeliness covers the full life cycle of information processing, transmission, computation, and utilization [13]. Among various information timeliness metrics, age of information (AoI) provides effective measurement of DT consistency. Specifically, large AoI causes DT state to severely deviate from actual physical counterpart, which deteriorates resource management performance as well as model training precision for EV management. Therefore, how to optimize AoI for DT to achieve resource management with integration of 6G signal processing, communication, and computing has become a key scientific research problem. Key research challenges are elaborated below.

First, AoI minimization is not always beneficial for model training. AoI is optimized by allocating more resources for state data uploading to shorten uploading interval. Fewer resources are left for uploading data sample of model training, thereby undermining EV energy management. Second, AoI has an unignorable impact on AI-based resource management of 6G. The utilization of data sample with large AoI and inaccurate state estimates caused by DT inconsistency significantly reduces learning performance of AI in 6G. How to incorporate AoI awareness into AI-based resource management of 6G remains an open issue. Last but not least, long-term AoI guarantee is intertwined with the short-term joint optimization of signal processing, communication, and computing. As DT is not expected to foresee future state transition, resource management optimization without thorough understanding of AoI's evolution over time is short sighted.

Several studies are devoted to DT empowered model train-

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ing. In [11], Lu *et al.* designed a DT-based model training framework to improve reliability and security for computing in wireless networks. A DT-empowered model training framework was developed for 5G integrated distribution network to simultaneously optimize training precision and delay [14]. In [15], Van Huynh *et al.* jointly optimized offloading policies and computing resources to achieve fairness-aware latency minimization in DT aided edge computing network. In [16], Sun *et al.* proposed a lightweight DT empowered 6G air-ground network to balance the energy consumption of unmanned aerial vehicles and the accuracy of local model and global model. In [17], Lu *et al.* investigated DT-assisted 6G mobile networks to reduce real-time data processing burden and privacy rises on edge servers. In [18], Do-Duy *et al.* studied a mobile edge computing architecture with the assistance of DT to minimize latency and highlighted the impact of the miss-match of digital twin modeling. In [19], DT was utilized to model the computing capacity of edge servers and optimize the resource allocation. However, these studies utilize all resources for loss function reduction, while the paradox between AoI minimization and model training precision improvement are not considered. Several recent studies investigate AoI reduction based on resource management. In [20], a contract-theoretic caching framework was proposed to jointly minimize the weighted sum of AoI and delay. In [21], Zhu *et al.* addressed the AoI minimization problem for air-ground integration by jointly optimizing bandwidth allocation, trajectory planning and data scheduling. The limitation of aforementioned studies lies in the ignorance of joint optimization of model training and AoI. Moreover, the negative impact of AoI unawareness on AI-based resource management optimization has not been considered.

Deep actor-critic (DAC) network as a model-free learning approach of AI has been widely utilized for handling large-dimensional optimization problem in 6G [22], [23]. In [24], Wu *et al.* employed DAC to optimize unloading strategy and network management for multi-server networks. A DAC-enabled dynamic multi-channel access optimization policy was proposed to maximize the expected number of successful transmissions [25]. However, traditional DAC suffers from poor learning accuracy when using inaccurate state estimates and data samples with large AoI. It is important to alleviate the adverse impact of large AoI on deep neural network training.

To address the above mentioned challenges, a network resource management framework of 6G signal processing, communication, and computing integration is developed based on AoI-optimal DT (AoIo-DT). First, we model DT consistency from the perspective of AoI. The optimization objective is to jointly minimize AoI and global loss function through the optimization of device scheduling, channel allocation, data compression ratio selection, and computation resource allocation. Then, the long-term constraints of AoI guarantee and energy consumption are separated from short-term optimization based on telescoping sum and virtual queue theory. A joint optimization algorithm of signal processing, communication, and computing based on AoI-aware DAC with DT assistance is finally proposed as a solution. Contributions of this paper are presented below.

- *Joint Optimization of AoI and Global Loss Function:* The weighted sum of AoI and global loss function is minimized under a long-term AoI guarantee constraint. The uploading of state data and model training data sample is intelligently optimized to balance AoI reduction and model training performance.
- *AoIo-DT-assisted Resource Management of 6G Signal Processing, Communication, and Computing Integration:* Compared with normal DT, Aolo-DT possesses higher consistency with physical networks due to improved AoI optimality and reliability. It provides more accurate approximation of unobservable sate information such as channel gain and electromagnetic interference (EMI) for resource management optimization.
- *AoI-aware Learning:* DAC is enforced to use samples with smaller AoI for deep neural network training. Both learning convergence and optimality are improved by alleviating the adverse impact of AoI on DAC training. Moreover, AoI guarantee constraints are converted into virtual AoI deficit queues and incorporated into optimization objective. Large AoI deficit closes the loop on resource management to discourage violation of constraints on long-term AoI guarantees.

The remaining part is organized as follows. Section II describes system model. Section III presents problem formulation of model training. The proposed algorithm is given in Section IV. Numerical results are given in Section V. The conclusion is present in Section VI.

## II. System Model

Fig. 1 shows the proposed network resource management framework of 6G signal processing, communication, and computing integration based on information timeliness-aware DT. The objective is to train an EV energy management model based on the collaboration among device layer, edge layer, DT layer, and EV energy management layer. The device layer consists of parked EVs, controllable load, and various infrastructures including charging pile and distributed PV. Communication devices are deployed in the device layer to collect data of operation state and EV energy management [26]. Devices connected with 6G base stations and power line communication (PLC) gateways upload collected data samples to the edge layer. 6G performs well in ultra-high transmission rate and low latency while PLC possesses incomparable advantages in low cost and on-demand coverage. In the edge layer, a local model of EV energy management is trained by each edge server. Edge servers also construct the DT layer by establishing a DT for each device within its service range. In the EV energy management layer, local models are aggregated by the controller for global model training of EV energy management. The global model supports applications of EV energy management such as demand response, carbon footprint monitoring, vehicle-to-grid/grid-to-vehicle (V2G/G2V) control, and flexible load/PV control. The objective is to achieve a balanced minimization between AoI and loss function through network resource management of signal processing, communication and computing integration.

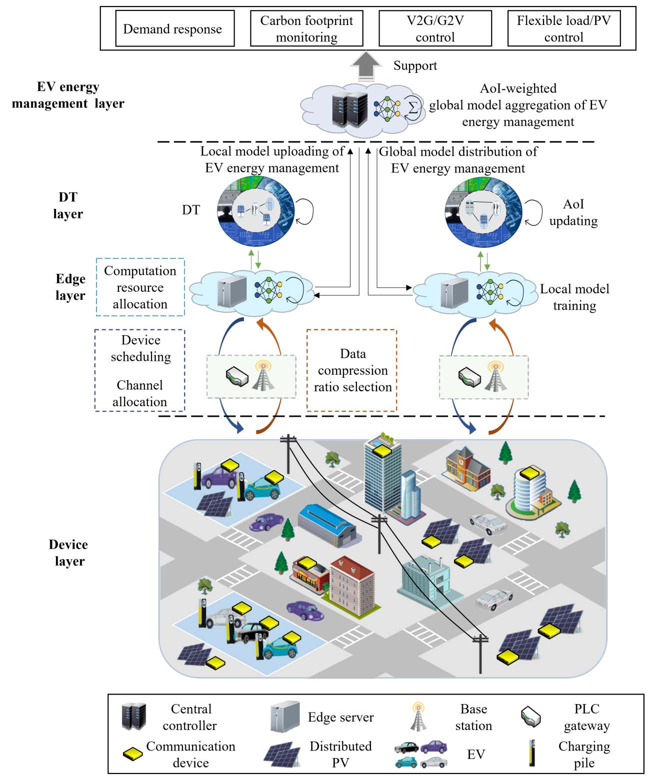



Fig. 1. The network resource management framework of signal processing, communication, and computing integration based on information timeliness-aware DT.

Finally, the global model is used for local model training in the next iteration.

### A. DT Model

Denote the set of $I$ devices as $\mathcal{U} = \{u_1, \cdots, u_i, \cdots, u_I\}$, and the set of $J$ edge servers as $\mathcal{S} = \{s_1, \cdots, s_j, \cdots, s_J\}$. Denote the set of devices available for $s_j$ as $\mathcal{U}_j$. $s_j$ establishes a DT for $u_i$ based on AoI $\rho_i(t)$ (seconds) as

$$DT_i(t) = \Theta(\mathcal{M}_i, \mathcal{F}_i(t), \rho_i(t)), \tag{1}$$

where $t$ is the index of model training iteration. $\mathcal{M}_i$ represents time-invariant operation data, which is commonly utilized during the modeling and initialization phases of DT. $\mathcal{F}_i(t)$ represents time-varying state data. AoI quantifies the experienced duration since the last time when DT is synchronized based on the state data. Larger $\rho_i(t)$ indicates that $\mathcal{F}_i$ of $DT_i$ has not been synchronized for a long time, thereby resulting in higher DT inconsistency. DT is constructed to master the real-time operating status of the physical world which is beneficial for improving resource management adaptability and model training accuracy.

### B. Resource Management Model of 6G Signal Processing, Communication, and Computing Integration

The resource management of signal processing, communication, and computing integration involves the joint optimization of device scheduling, channel allocation, data compression ratio selection, and computation resource allocation.

*1) Device Scheduling:* Edge server $s_j$ dynamically schedules devices within set $\mathcal{U}_j$ to either upload state data or data sample via allocated channels. The state data are utilized to synchronize DT for AoI reduction, while the data samples of EV energy management are exploited for increasing model precision. Define the device scheduling indicator as $a_{i,j}(t) \in \{0, 1\}$. $s_j$ schedules $u_i \in \mathcal{U}_j$ to upload state data when $a_{i,j}(t) = 0$, and to upload data samples when $a_{i,j}(t) = 1$.

*2) Channel Allocation:* Denote the multi-mode channel set of $s_j$ as $\mathcal{C}_j = \{c_1^j, \cdots, c_n^j, \cdots, c_N^j\}$. Define the channel allocation indicator as $x_{i,j,n}(t) \in \{0, 1\}$. When $x_{i,j,n}(t) = 1, n = 1, 2, \cdots, N_1$, $c_n^j$ represents PLC channel allocated to $u_i$. When $x_{i,j,n}(t) = 1, n = N_1 + 1, N_1 + 2, \cdots, N$, $c_n^j$ represents 6G channel allocated to $u_i$. The network transmission rate from $u_i$ to $s_j$ is

$$r_{i,j,n}(t) = x_{i,j,n}(t) B_{j,n} \log\Big(1 + \frac{P_i(t) h_{i,j,n}(t)}{I_{i,j,n}(t) + N_0}\Big), \tag{2}$$

where $B_{j,n}$ denotes the bandwidth. $B_{j,n} \in \{B_{PLC}, B_{6G}\}$, where $B_{PLC}$ and $B_{6G}$ represent the bandwidths of PLC and 6G. $P_i(t)$ and $h_{i,j,n}(t)$ are the power and channel gain of data uploading. $P_i(t) \in \{P_{PLC}, P_{6G}\}$, where $P_{PLC}$ and $P_{6G}$ represent the transmission power for PLC and 6G. $I_{i,j,n}(t)$ and $N_0$ are power of EMI and noise. EMI is caused by the operation of power electronic devices and electrical equipment. The Alpha stable distribution [27] with a thick tail is used to describe EMI power distribution, which is given by

$$E(e^{k\eta I_{i,j,n}}) = \begin{cases} \exp\big(k\mu_{i,j,n}\eta - \varpi_{i,j,n}|\eta|^{\alpha_{i,j,n}}(1 - k\varkappa_{i,j,n} \\ \qquad \operatorname{sgn}(\eta)\tan(\alpha_n\pi/2))\big), \alpha_{i,j,n} \neq 1 \\ \exp\big(k\mu_{i,j,n}\eta - \varpi_{i,j,n}|\eta|1 - k\varkappa_{i,j,n} \\ \qquad \operatorname{sgn}(t)(\ln|\eta|)(2/\pi)\big), \alpha_{i,j,n} = 1, \end{cases} \tag{3}$$

where $k$ represents the imaginary part of the complex number. $\alpha_{i,j,n} \in (0, 2]$ determines the heaviness of distribution tail. The smaller $\alpha_{i,j,n}$ is, the heavier the tail is. $\varkappa_{i,j,n} \in [-1, 1]$, $\varpi_{i,j,n} > 0$, and $\mu_{i,j,n}$ are skewness parameter, scale parameter, and positional parameter, respectively.

*3) Data Compression Ratio Selection:* Denote the data compression ratio indicator of signal processing as $y_i(t) \in \mathcal{Y} = \{y_{min}, \cdots, y_m, \cdots, y_{max}\}$, where $y_{min}$, $y_m$, and $y_{max}$ represent the minimum level, the $n$-th level, and the maximum level of data compression ratios, respectively. $y_i(t) = y_m$ represents that $s_j$ schedules $u_i \in \mathcal{U}_j$ to utilize the $m$-th level ratio for data compression. We consider that the data compression and the transmission of the compressed data are parallel, i.e., data being compressed at the same time as they are transmitted. The data transmission rate depends on the minimum of the compression speed and the channel transmission rate [28]. Since the proposed algorithm dynamically optimizes the network resource allocation by observing the evolution of AoI, the impact of data compression delay on AoI has been naturally taken into data compression ratio account. Denoting $z_{i,m}(t)$ as the data compression speed when the $m$-th level compression ratio is adopted and $\tau_0$ as the uploading duration of data sample, the uploaded number of EV energy management data samples is

$$d_i(t) = \sum_{\forall c_n^j \in \mathcal{C}_j} a_{i,j}(t) \left\lfloor \frac{\min\{z_{i,m}(t), \frac{r_{i,j,n}(t)}{y_i(t)}\}\tau_0}{\psi_i} \right\rfloor, u_i \in \mathcal{U}_j. \tag{4}$$

where $\psi_i$ (bits) represents the original volume of data samples before compression.

*4) Computation Resource Allocation:* Denote the computation resources allocated by $s_j$ for local model training as $f_j(t)$. For local model training, $s_j$ replaces the local model $\boldsymbol{\omega}_j(t)$ with the global model trained in the previous iteration $\boldsymbol{\omega}(t-1)$ as $\boldsymbol{\omega}_j(t) = \boldsymbol{\omega}(t-1)$, and then $s_j$ executes local model training. Define the set of EV energy management data samples from $u_i$ as $\mathcal{D}_i(t) = \{\boldsymbol{\alpha}_1^i, \cdots, \boldsymbol{\alpha}_k^i, \cdots, \boldsymbol{\alpha}_{d_i(t)}^i\}$. The accuracy of local model training depends on both local model parameters and DT model. Denote the loss function of $\boldsymbol{\omega}_j(t)$ on the $k$-th data sample $\boldsymbol{\alpha}_k^i$ as $l_i(\boldsymbol{\omega}_j(t)\boldsymbol{\alpha}_k^i, DT_i)$ [10], which is given by

$$L_j(\boldsymbol{\omega}_j(t), t) = \frac{\sum_{u_i \in \mathcal{U}_j} \sum_{\forall \boldsymbol{\alpha}_k^i \in \mathcal{D}_i(t)} l_i(\boldsymbol{\omega}_j(t), \boldsymbol{\alpha}_k^i, DT_i)}{D_j(t)}. \tag{5}$$

Then, $\boldsymbol{\omega}_j(t)$ is updated based on $L_j(\boldsymbol{\omega}_j(t), t)$, where $D_j(t)$ is the total number of data samples received by $s_j$ in the $t$-th iteration.

The delay of local model training is derived as

$$\tau_j(t) = \frac{\sum_{u_i \in \mathcal{U}_j} \xi(y_i(t)) d_i(t)}{f_j(t)}, \tag{6}$$

where $\xi(y_i(t))$ represents data sample training complexity under the data compression ratio of $\xi(y_i(t))$. The complexity is positively related with data compression ratio.

The energy consumed for local model training is derived as

$$E_j(t) = \sum_{u_i \in \mathcal{U}_j} \xi(y_i(t)) d_i(t) \beta_j f_j^2(t), \forall s_j \in \mathcal{S}, \tag{7}$$

where $\beta_j$ is a constant.

### C. AoI-Weighted Global Model Aggregation of EV Energy Management

The central controller, denoted as $s_0$, has to receive all local models of EV energy management for global model training. Therefore, $\tau_j(t)$ depends on the largest training delay, i.e.,

$$\tau(t) = \max_j \{\tau_j(t)\}, \forall s_j \in \mathcal{S}. \tag{8}$$

The precision of global model is measured based on global loss function. To characterize the influence of DT inconsistency on global loss function, the local models are weighted based on AoI. The local model with a smaller AoI and higher DT consistency, e.g., $\boldsymbol{\omega}_j(t)$, is endowed with a larger weight to improve the global model training performance. The weight of $\boldsymbol{\omega}_j(t)$ is given by

$$\lambda_j(t) = \frac{1/[\bar{\rho}_j(t-1) + \tau_0 + \tau(t)]}{\sum_{j=1}^J 1/[(\bar{\rho}_j(t-1) + \tau_0 + \tau(t)]}, \tag{9}$$

where $\bar{\rho}_j(t-1)$ represents the $(t-1)$-th AoI of DT layer. The derivation of $\bar{\rho}_j(t-1)$ is elaborated in the next subsection.

The AoI-weighted global model aggregation is performed as

$$\boldsymbol{\omega}(t) = \sum_{j=1}^J \frac{\lambda_j(t) D_j(t)}{\sum_{j=1}^J \lambda_j(t) D_j(t)} \boldsymbol{\omega}_j(t). \tag{10}$$

The global loss function is calculated as

$$L(\boldsymbol{\omega}(t), t) = \sum_{j=1}^J \frac{\lambda_j(t) D_j(t)}{\sum_{j=1}^J \lambda_j(t) D_j(t)} L_j(\boldsymbol{\omega}_j(t), t). \tag{11}$$

### D. AoI Updating

After global model aggregation, $s_j$ updates the AoI of $DT_i$ as

$$\rho_i(t) = \begin{cases} \tau(t) + \tau_g, & \sum_{j=1}^J a_{i,j}(t) = 0, \\ \rho_i(t-1) + \tau_0 + \tau(t) + \tau_g, & \sum_{j=1}^J a_{i,j}(t) = 1, \end{cases} \tag{12}$$

where $\tau_g$ represents the global aggregation delay. Here, $\sum_{j=1}^J a_{i,j}(t) = 0$ represents the scenario of state data uploading for DT synchronization. AoI at the end of $t$-th iteration depends on the local training delay and the global aggregation delay. $\sum_{j=1}^J a_{i,j}(t) = 1$ represents the scenario of data sample uploading for local training. Since DT is not synchronized in the $t$-th iteration, both $\rho_i(t-1)$ and $\tau_0$ have to be considered in AoI updating. It is obvious that scheduling devices for data sample uploading inevitably increases AoI.

The AoI of DT layer is defined as

$$\bar{\rho}_j(t) = \frac{1}{|\mathcal{U}_j|} \sum_{u_i \in \mathcal{U}_j} (\rho_i(t))^2. \tag{13}$$

The impact of network resource allocation of signal processing, communication and computing integration on model training delay of EV energy management and AoI evolution is shown in Fig. 2. As shown in Fig. 2(a) and (c), the simultaneous processing of EV energy management data samples uploaded by $u_1$ and $u_2$ causes larger local model training delay. The controller has to wait for the local model of $s_1$, which inevitably leads to large AoI. Fig. 2(b) and (d) demonstrate that if $s_1$ schedules $u_2$ to upload state data, the AoI of $u_2$ is reduced due to DT synchronization. Furthermore, the AoI of $u_1$ is also decreased because all computation resources are allocated to $u_1$ to minimize training delay as well as waiting delay. Last but not least, a larger data compression ratio is selected for $u_3$, which enables $u_3$ to upload more data samples and improve training precision.

## III. Problem Formulation of Model Training based on Signal Processing, Communication and Computing Integration

### A. Problem Formulation

In this paper, we address the model training problem of DT empowered EV energy management through AoI optimization. We aim to achieve balanced minimization between global loss

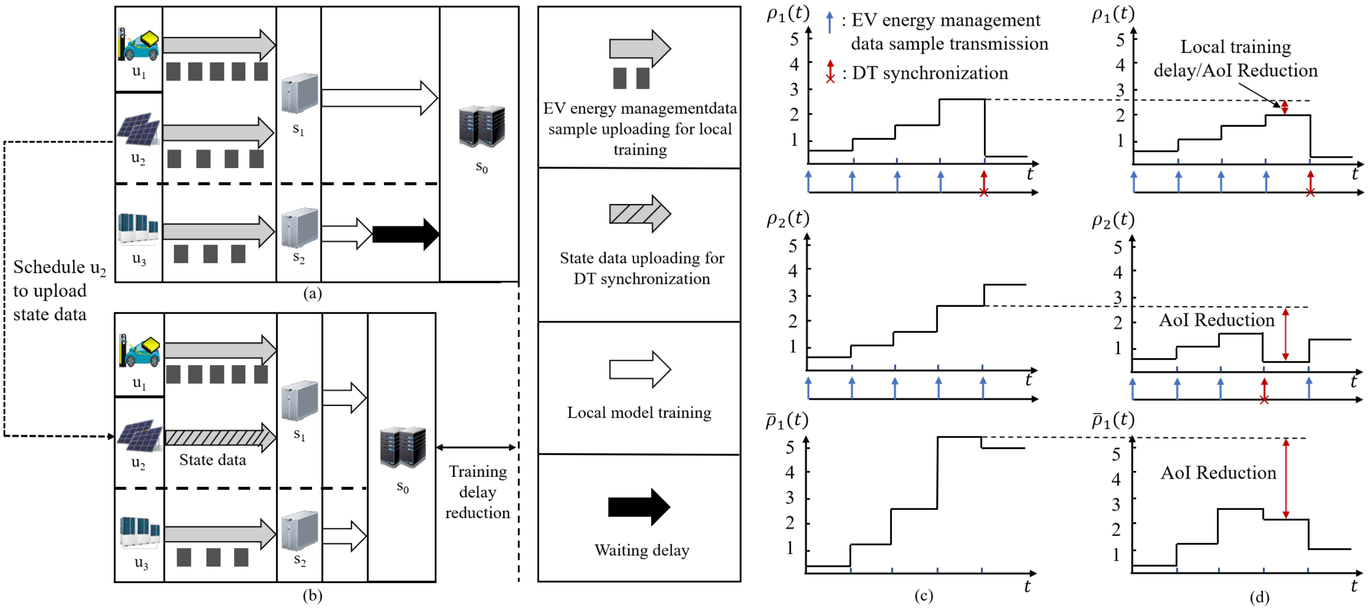



Fig. 2. The relationship among resource management, training delay, and AoI evolution: (a) Model training delay without resource management; (b) Model training delay with resource management of signal processing, communication and computing integration; (c) AoI evolution without resource management; (d) AoI evolution with resource management of signal processing, communication and computing integration.

function and AoI of DT layer through network resource management of signal processing, communication and computing integration. Furthermore, both time-averaged AoI reduction and long-term AoI guarantee are considered to improve AoI optimality and reliability. Therefore, we formulate the problem as

$$\begin{aligned}
&\min_{\{a_{i,j}(t),x_{i,j,n}(t),y_i(t),f_j(t)\}} L(\boldsymbol{\omega}(T),T)+\frac{V_\rho}{T}\sum_{t=1}^{T}\sum_{j=1}^{J}\bar{\rho}_j(t),\\
&\text{s.t. } C_1: a_{i,j}(t)\in\{0,1\},\forall u_i\in\mathcal{U}_j,\forall s_j\in\mathcal{S},\\
&\quad C_2: \sum_{j=1}^{J}\sum_{i=1}^{I}x_{i,j,n}(t)=1,\forall c_n\in\mathcal{C},\\
&\quad C_3: \sum_{j=1}^{J}\sum_{n=1}^{N}x_{i,j,n}(t)=1,\forall u_i\in\mathcal{U}_j,\\
&\quad C_4: 0\le f_j(t)\le f_{j,max}(t),\forall s_j\in\mathcal{S},\\
&\quad C_5: \frac{1}{T}\sum_{t=1}^{T}\bar{\rho}_j(t)\leqslant\bar{\rho}_{j,max},\forall s_j\in\mathcal{S},\\
&\quad C_6: \sum_{t=1}^{T}E_j(t)\le E_{max},\forall s_j\in\mathcal{S},
\end{aligned}\tag{14}$$

where $V_\rho$ is the weight of AoI. $T$ is the total number of iterations. $C_1$, $C_2$ and $C_3$ are the constraints of device scheduling and channel allocation. $C_4$ represents that the resources allocated by $s_j$ should be lower than $f_{j,max}(t)$. $C_5$ represents that the time-averaged AoI of DT layer should be no less $\bar{\rho}_{j,max}$. $C_6$ indicates that the energy consumed over $T$ iterations should be within the energy budget $E_{max}$.

### *B. Problem Decoupling and Transformation based on Telescoping Sum Theorem and Virtual Queue*

It can be noted that several challenges prevent the established problem from being solved directly. Specifically, the formulated problem is NP-hard because $L(\boldsymbol{\omega}(T),T)$ depends on resource management strategies of signal processing, communication and computing integration over $T$ iterations. Moreover, $L(\boldsymbol{\omega}(T),T)$ is also coupled with $C_6$ and $C_7$. To provide a feasible solution, we propose a two-stage problem transformation approach. First, $L(\boldsymbol{\omega}(T),T)$ is decoupled based on the telescoping sum as

$$L(\boldsymbol{\omega}(T),T)=\frac{1}{T}\Big[\sum_{t=1}^{T}L(\boldsymbol{\omega}(t),t)-\sum_{t=1}^{T}L(\boldsymbol{\omega}(t-1),t-1)\Big].\tag{15}$$

Second, the coupling between $L(\boldsymbol{\omega}(T),T)$ and $C_6$, $C_7$ is addressed based on virtual queue [29] without foreseeing future information. Virtual deficit queues of AoI and energy corresponding to $C_6$ and $C_7$ are respectively constructed as

$$G_j(t+1)=\max\Big\{G_j(t)+\bar{\rho}_j(t)-\bar{\rho}_{j,max},0\Big\},\tag{16}$$

$$N_j(t+1)=\max\Big\{N_j(t)+E_j(t)-E_{max},0\Big\}.\tag{17}$$

$C_6$ and $C_7$ hold automatically as long as virtual queues are mean rate stable [30].

Define $\Phi(t)$ as $\Phi(t)=\frac{1}{T}\Big[L(\boldsymbol{\omega}(t),t)+V_\rho\sum_{m=1}^{t}\sum_{j=1}^{J}\bar{\rho}_j(m)\Big]$. Lyapunov drift-plus-penalty is defined as

$$\triangle_V K(\boldsymbol{G}(t))=V\mathbb{E}[\Phi(t)|\boldsymbol{G}(t)]+\frac{1}{2}\sum_{j=1}^{J}\left[G_j^2(t+1)-G_j^2(t)\right]$$

$$+\frac{1}{2}\sum_{j=1}^{J}\left[N_j^2(t+1)-N_j^2(t)\right]. \tag{18}$$

$V$ is a weight to trade off queue fluctuation and minimization of $\Phi(t)$.

Therefore, (14) is converted to minimize the upper bound of $\triangle_V K(\boldsymbol{G}(t))$, i.e.,

$$\begin{aligned}\min_{\boldsymbol{a}_j(t),\boldsymbol{x}_j(t),\boldsymbol{y}_j(t),f_j(t)} \Pi_j(t) = V\Big[\frac{1}{T}L_j(\boldsymbol{\omega_j}(t),t) \\ + V_\rho\bar{\rho}_j(t)\Big] + G_j(t)\bar{\rho}_j(t) + N_j(t)E_j(t),\end{aligned}$$

$$\text{s.t. } C_1 \sim C_5, \tag{19}$$

where $\boldsymbol{a}_j(t)=\{a_{i,j}(t)|u_i\in\mathcal{U}_j\}$, $\boldsymbol{x}_j(t)=\{x_{i,j,n}(t)|u_i\in\mathcal{U}_j, c_n^j\in\mathcal{C}_j\}$, and $\boldsymbol{y}_j(t)=\{y_{i,m}(t)|u_i\in\mathcal{U}_j\}$.

## IV. Joint Optimization Algorithm of Signal Processing, Communication, and Computing Integration based on AoI-aware DAC with DT Assistance

We propose a feasible solution to (19), which realizes integrated signal processing, communication and computing for resource management.

### A. Markov Decision Process Model

We model (19) as a Markov decision process (MDP).

*1) State Space Construction With DT Assistance:* The state space is constructed as $\boldsymbol{S}_j(t)=\{G_j(t),N_j(t),\bar{\rho}_{j,max},\boldsymbol{\rho}_j(t-1),\boldsymbol{d}_j(t-1),\boldsymbol{h}'_j(t),\boldsymbol{I}'_j(t)\}$, which contains both observable and unobservable information. The observable information includes $G_j(t)$, $N_j(t)$, $\bar{\rho}_{j,max}$, $\boldsymbol{\rho}_j(t-1)=\{\rho_i(t-1)\}$, $\boldsymbol{d}_j(t-1)=\{d_i(t-1)\}$, $\forall u_i\in\mathcal{U}_j$. Channel gain $\boldsymbol{h}'_j(t)=\{h'_{i,j,n}(t)\}$ and EMI power $\boldsymbol{I}'_j(t)=\{I'_{i,j,n}(t)\}$ are unobservable owing to the limitation of device processing ability and the concern of signaling overhead [31]. Therefore, they are approximated by AoIo-DT.

*2) Action Space Discretization:* The action space of resource management of signal processing, communication, and computing integration $\boldsymbol{A}_j(t)$, is constructed as the combination of $\boldsymbol{a}_j(t)$, $\boldsymbol{x}_j(t)$, $\boldsymbol{y}_i(t)$, and $f_j(t)$. We discretize $f_j(t)$ into $H$ levels, $H\in\mathbb{N}^+$.

*3) Cost Function:* We construct the cost function as $\Pi_j(t)$, which is consistent with the optimization problem (19).

### B. Algorithm Implementation

Fig. 3. shows the detailed algorithm framework. Each edge server respectively constructs a set of deep neural networks for resource management optimization. The set of $s_j$ consists of a main actor network $\boldsymbol{\nu}_j^{main}$, a target actor network $\boldsymbol{\nu}_j^{target}$, a main critic network $\boldsymbol{\theta}_j^{main}$, a target critic network $\boldsymbol{\theta}_j^{target}$, and an experience replay pool $\boldsymbol{\mathcal{R}}_j(t)$. Compared with conventional DAC, the detrimental effect of AoI on DT-assisted information estimation of channel gain and EMI power is taken into account by the proposed algorithm to improve the learning performance. Particularly, the proposed algorithm defines the probability of extracting training samples and loss function of $\boldsymbol{\theta}_j^{main}$ based on $\bar{\rho}_j(t)$. It achieves resource management of signal processing, communication, and computing integration by continuously learning the mapping among the optimal action, state estimates, and AoI evolution.

**Algorithm 1** Joint optimization algorithm of signal processing, communication, and computing integration based on AoI-aware DAC with DT assistance

**Initialize** $G_j(t)=0$, $N_j(t)=0$, $\boldsymbol{a}_j(t)=0$, $\boldsymbol{x}_j(t)=0$, $\boldsymbol{y}_i(t)$, and $f_j(t)=0$.
**For** $t=1,\cdots,T$ **do**
  Set $\boldsymbol{\omega}_j(t)=\boldsymbol{\omega}(t-1)$.
  Obtain resource management strategy $\tilde{\boldsymbol{A}}_j(t)$ according to $\boldsymbol{\pi}(\boldsymbol{S}_j(t)|\boldsymbol{\nu}_j^{main})$.
  $\forall u_i\in\mathcal{U}_j$ uploads EV energy management data samples or state data according to $\tilde{\boldsymbol{A}}_j(t)$.
  $\forall s_j\in\mathcal{S}$ trains $\boldsymbol{\omega}_j(t)$.
  Train the global model as (10).
  Calculate $\bar{\rho}_j(t)$, $G_j(t+1)$, $N_j(t+1)$ based on (13), (16), and (17).
  Derive $\Pi_j(t)$ based on (19).
  Transfer $\boldsymbol{S}_j(t)$ to $\boldsymbol{S}_j(t+1)$ and update the experience pool.
  Calculate TD error $\delta_j^{t-e}(t)$ based on (20).
  Update $p_j^e(t)$ as (21) based on $\bar{\rho}_j(t-e-1)$ and $\delta_j^{t-e}(t)$.
  Extract $\tilde{\boldsymbol{\mathcal{R}}}_j(t)$ from the experience pool.
  Update $\Gamma_j(t)$ according to (22).
  Calculate $\boldsymbol{\nu}_j^{main}$ and $\boldsymbol{\theta}_j^{main}$ as (23) and (24).
  Update $\boldsymbol{\theta}_j^{target}=\boldsymbol{\theta}_j^{main}$ and $\boldsymbol{\nu}_j^{target}=\boldsymbol{\nu}_j^{main}$ every $T_0$ iterations.
**end for**

The proposed algorithm is implemented in three stages in Algorithm 1, i.e., initialization, AoIo-DT-assisted resource management, and AoI-aware learning.

*1) Initialization:* Set $G_j(t)$, $N_j(t)$, $\boldsymbol{a}_j(t)$, $\boldsymbol{x}_j(t)$, $\boldsymbol{y}_i(t)$, and $f_j(t)$ as zero.

*2) AoIo-DT-Assisted Resource Management:* $s_j$ sets local model of EV energy management as $\boldsymbol{\omega}_j(t)=\boldsymbol{\omega}(t-1)$, and obtains resource management strategy $\tilde{\boldsymbol{A}}_j(t)$ based on $\boldsymbol{\pi}(\boldsymbol{S}_j(t)|\boldsymbol{\nu}_j^{main})$.

Then, $\forall u_i\in\mathcal{U}_j$ uploads data samples of EV energy management or state data according to the derived strategy. Each edge server trains local model $\boldsymbol{\omega}_j(t)$. After local model training, the global model is aggregated according to (10).

*3) AoI-Aware Learning:* After global aggregation, the central controller feeds back a timestamp to edge server. Then, the AoI of DT, and virtual deficit queues are updated according to (13), (16) and (17). $\Pi_j(t)$ is also updated based on (19). Next, the state $\boldsymbol{S}_j(t)$ is transferred into $\boldsymbol{S}_j(t+1)$, and a sample of network $\vartheta_j(t)$ is constructed and used to replace most stale network sample. The TD error corresponding to the $e$-th network sample is given by

$$\begin{aligned}\delta_j^{t-e}(t) = \Pi_j^{t-e}(t) + \gamma\boldsymbol{Q}_j(\boldsymbol{S}_j^{t-e}(t+1),\tilde{\boldsymbol{A}}_j^{t-e}(t+1),\boldsymbol{\theta}_j^{target}) \\ - \boldsymbol{Q}_j(\boldsymbol{S}_j^{t-e}(t),\tilde{\boldsymbol{A}}_j^{t-e}(t),\boldsymbol{\theta}_j^{main}),\end{aligned} \tag{20}$$

where $\gamma$ represents the discounting coefficient.

Considering the adverse influence of AoI on state estimates and TD error on network learning, the probability of extracting

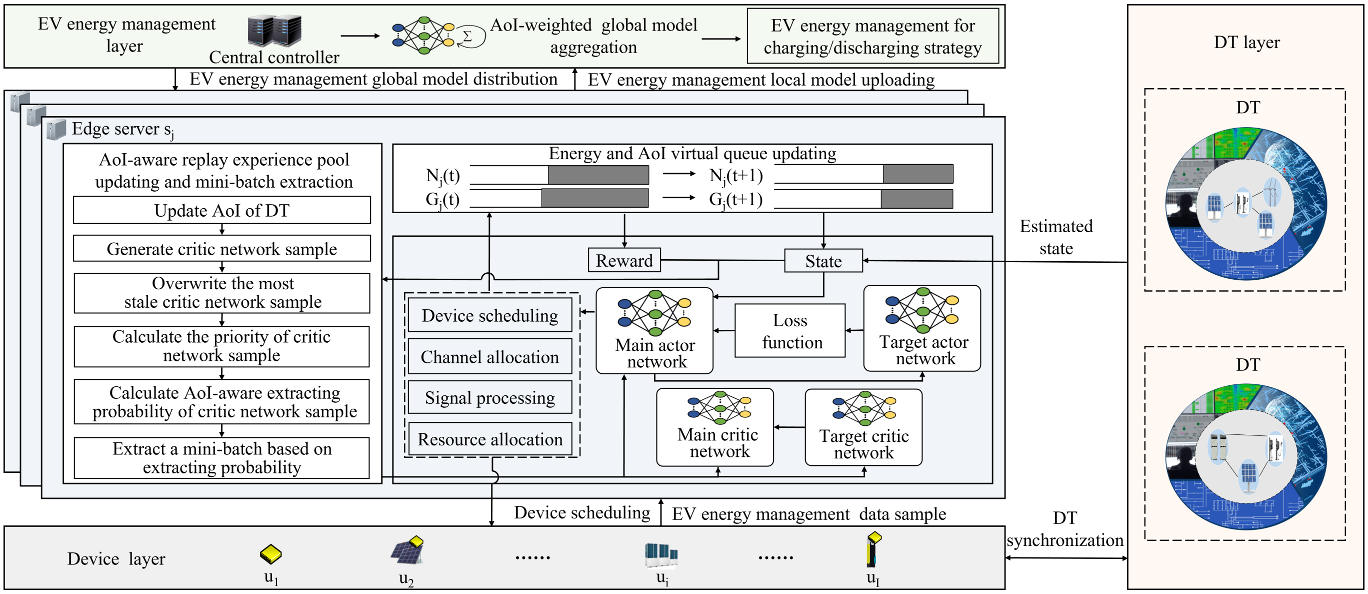



Fig. 3. The proposed algorithm based on AoI-aware DAC with DT assistance.

network sample $\vartheta_j(t-e)$ is jointly determined by $\bar{\rho}_j(t-e-1)$ and $\delta_j^{t-e}(t)$, which is derived as

$$p_j^e(t) = \frac{\frac{|\delta_j^{t-e}(t)|}{\bar{\rho}_j(t-e-1)}}{\sum_{m=1}^{E} \frac{|\delta_j^{t-e}(t)|}{\bar{\rho}_j(t-m-1)}}. \quad (21)$$

$p_j^e(t)$ also represents the priority of $\vartheta_j(t-e)$, i.e., higher priority network samples are given larger extracting probabilities.

Afterwards, a mini-batch $\tilde{\mathcal{R}}_j(t)$ is extracted based on AoI-aware probability distribution $\boldsymbol{p}_j(t) = \{p_j^e(t)\}$ to derive the loss function as

$$\Gamma_j(t) = \frac{1}{M} \sum_{\vartheta_j(t-e)\in\tilde{\mathcal{R}}_j(t)} p_j^e(t)\left(\delta_j^{t-e}(t)\right)^2, \quad (22)$$

where $M$ is the number of network samples.

$s_j$ updates $\boldsymbol{\nu}_j^{main}$ and $\boldsymbol{\theta}_j^{main}$ based on the gradient descent method as

$$\boldsymbol{\nu}_j^{main} = \boldsymbol{\nu}_j^{main} - \psi_\nu \sqrt{\Gamma_j(t)} \nabla_{\boldsymbol{\nu}_j^{main}} \log \boldsymbol{\pi}(\boldsymbol{S}_j(t)|\boldsymbol{\nu}_j^{main}), \quad (23)$$

$$\boldsymbol{\theta}_j^{main} = \boldsymbol{\theta}_j^{main} - \psi_\theta \nabla_{\boldsymbol{\nu}_j^{main}} \Gamma_j(t), \quad (24)$$

where $\psi_\nu$ and $\psi_\theta$ are the learning steps of actor network and critic network. $\boldsymbol{\nu}_j^{target}$ and $\boldsymbol{\theta}_j^{target}$ are updated every $T_0 > 1$ iterations as $\boldsymbol{\nu}_j^{target} = \boldsymbol{\nu}_j^{main}$ and $\boldsymbol{\theta}_j^{target} = \boldsymbol{\theta}_j^{main}$.

Afterwards, the trained EV energy management model is leveraged to generate EV energy management strategies based on various inputs such as EV charging load, PV output, and load variation. Grid companies or third-party aggregators perform EV energy management to achieve better energy demand-supply balance, promote clean energy utilization, and reduce carbon emission.

Compared with the conventional DAC algorithm, the proposed algorithm additionally calculates the probability of extracting network samples with a complexity of $O(E)$, which renders it more practical.

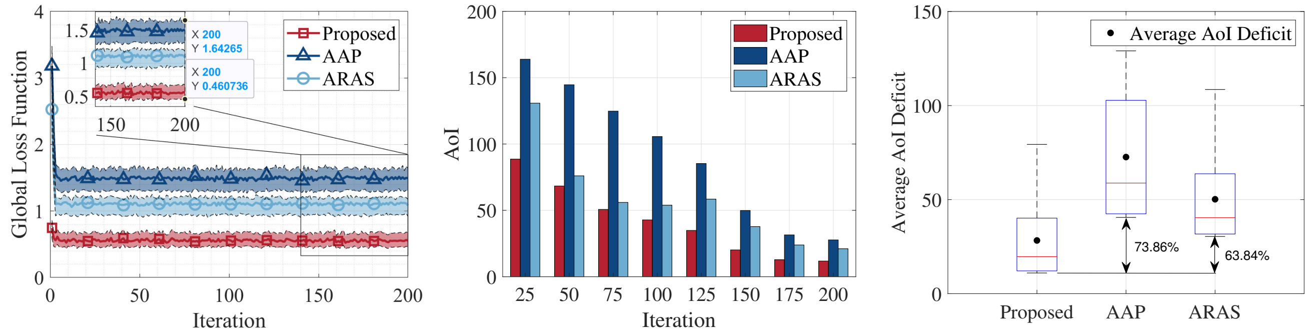
TABLE I
SIMULATION PARAMETERS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $T$ | 200 | $I$, $J$ | 40, 4 |
| $H$ | 3 | $N_1, N$ | 5, 10 |
| $\xi$ | $10^6$ cycles | $N_0$ | $-114$ dBm |
| $B_{PLC}, B_{6G}$ | 0.1, 0.2 MHz | $P_{PLC}$ | 0.2 W |
| $P_{5G}$ | 0.4 W | $y_{i,m}(t)$ | 5, 7, 9 |
| $\tau_g$ | 10 ms | $f_{j,max}$ | [4, 10] GHz |
| $\tau_0$ | 0.1 s | $\gamma$ | 0.99 |
| $V, V_\rho$ | 10, 30 | $\psi$ | 0.001 |

## V. Numerical Results

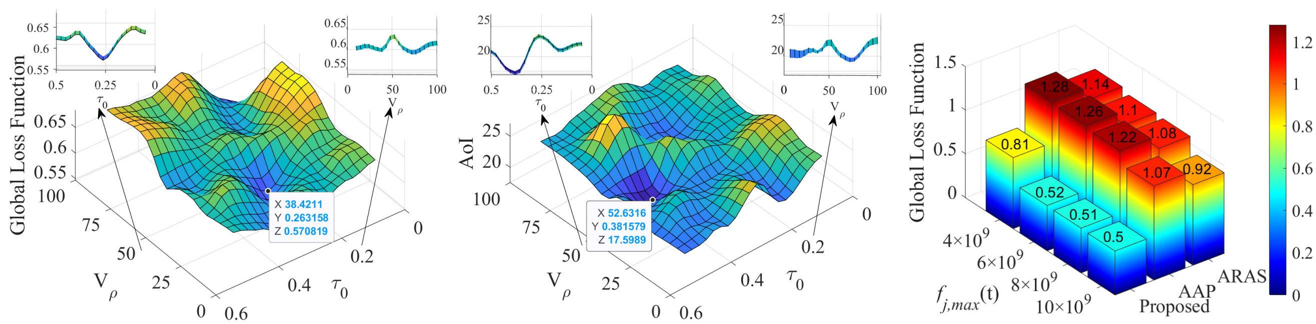
We consider a resource management scenario for model training of EV energy management. Two state-of-art algorithms i.e., age-aware policy algorithm (AAP) [32] and age-aware resource allocation strategy (ARAS) [33], are compared with the proposed algorithm. AAP minimizes AoI by optimizing device scheduling, but cannot jointly optimize data compression ratio selection, channel allocation and computation resource allocation. ARAS jointly minimizes AoI and global loss function by optimizing device scheduling and channel allocation based on alternate iterative optimization under the long-term training delay constraints, but data compression ratio selection and computation resource allocation are not optimized. However, neither AAP nor ARAS considers the constraint of AoI guarantee. The local dataset is constructed based on the ImageNet dataset [14]. Table I shows simulation parameters [3], [18].

Fig. 4(a) shows global loss function performance. The global loss function decreases initially and eventually becomes stable after $t = 20$. When $t = 200$, the global loss function of the proposed algorithm is reduced by 61.61% and 47.79% compared to AAP and ARAS, respectively. The reason is that data sample uploading of EV energy management is dynamically scheduled for global loss function reduction.




(a) (b) (c)

Fig. 4. Comparison with AAP and ARAS: (a) Global loss function; (b) AoI; (c) AoI deficit.




(a) (b) (c)

Fig. 5. Influence of key parameters: (a) Impact of $\tau_0$ and $V_\rho$ on global loss function; (b) Impact of $\tau_0$ and $V_\rho$ on AoI. (c) Impact of $f_{j,\max}(t)$ on global loss function.

ARAS is addicted to reducing training delay, resulting in inadequate training of global model. AAP neglects the severe influence of large AoI on global loss function which causes the decrease of global model training precision.

Figs. 4(b) and (c) show AoI versus iterations and the box plots of AoI deficit. Compared with AAP and ARAS, the proposed algorithm reduces AoI by $57.45\%$ and $44.04\%$, the average AoI deficit by $61.06\%$ and $43.64\%$, and the minimum average AoI deficit by $73.86\%$ and $63.84\%$. Neither AAP nor ARAS is capable of realizing long-term AoI guarantee.

Fig. 5(a) and (b) demonstrate the influence of uploading duration of data sample and weight of AoI. The global loss function decreases initially and then grows, while AoI continuously decreases due to the paradox between model training and DT synchronization. A large $\tau_0$ helps to reduce global loss function by uploading more data samples, but increases model training delay and AoI.

Fig. 5(c) shows the impact of $f_{j,max}(t)$, which has a negative impact on global loss functions improvement. When computation resources are sufficient, more devices can be scheduled to upload data samples to reduce global loss function. When $f_{j,max}(t) = 10$ GHz, the proposed algorithm outperforms AAP and ARAS by $53.27\%$ and $45.65\%$ due to the well exploitation of computation resources.

We consider a scenario of EV energy management with $1000$ EVs and distributed PV generators in distribution grid. The rated capacity of EV storage battery is $45$ kWh, and the upper and lower bounds of state of charge (SoC) are set as $0.95$ and $0.3$. The maximum and minimum charging and discharging power are $4$ kW and 1kW. Fig. 6 and Fig. 7 show the average EV charging demand, original daily load curve, PV output, and time-of-use (TOU) price in practical scenarios [34]. EVs provide ancillary services of peak shaving and valley filling to obtain revenue from the grid. The EV charging cost is defined as the difference between charging fee and obtained revenue. EV energy management aims to minimize load fluctuation and EV charging cost by jointly optimizing EV charging and discharging [35]. In practical scenarios, EV energy management model is trained based on the data samples collected from devices, which include daily loads, TOU prices, PV outputs, EV SoC, EV charging demands, and timestamps.

Fig. 8 shows the EV energy management performance. EVs charge during the off-peak load period, i.e., 0:00-8:00, to meet their own charging demands and fill load valley. The reasons are twofolds. First, the lower electricity price of off-peak period reduces charging cost. Second, EVs earn additional revenue by providing valley-filling service. On the other hand, EVs discharge during the peak load period, i.e., 11:00-13:00, and 19:00-21:00, to shave load peak when PV output falls far behind load demand. EVs obtain more revenue by providing peak-shaving service due to the peak load tariff imposed by the TOU pricing mechanism.

Fig. 9 shows actual load curve with EV energy management

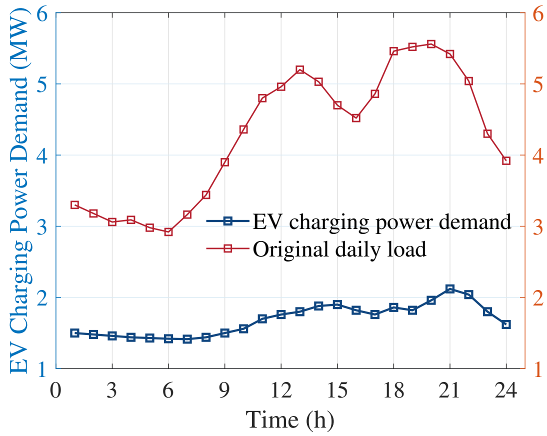



Fig. 6. EV charging demand and load curve without EV energy management.

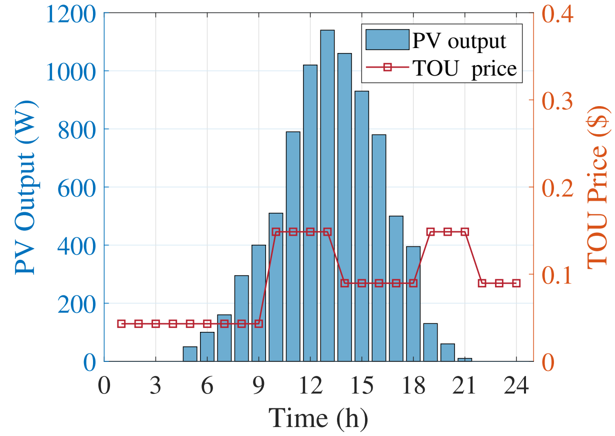



Fig. 7. PV output and TOU price.

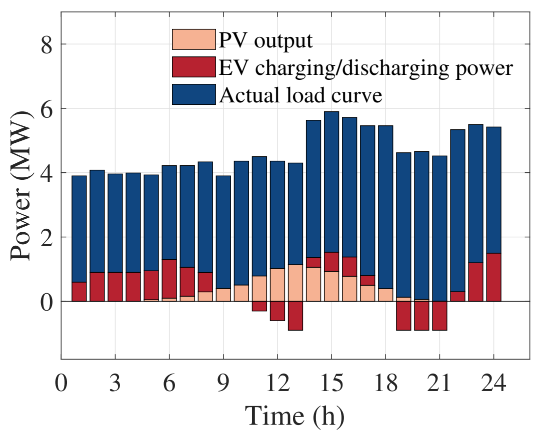



Fig. 8. EV energy management performance.

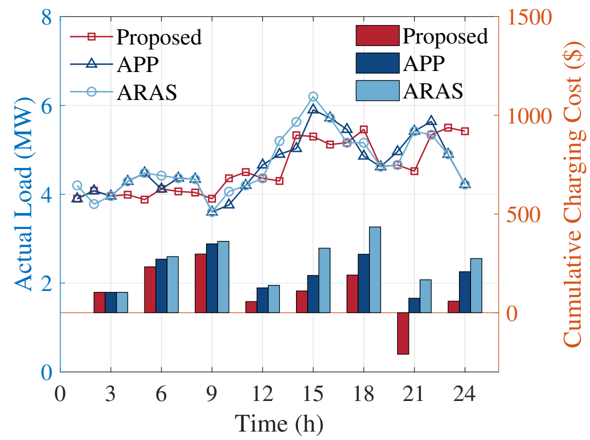



Fig. 9. Actual load curve with EV energy management and cumulative charging cost.

and cumulative charing cost. Compared with APP and ARAS, the proposed algorithm reduces load curve fluctuation by $17.02\%$ and $21.77\%$, and reduces cumulative charging cost by $71.92\%$ and $78.74\%$, respectively. The model training precision of EV management is improved from three perspectives. First, AoI-weighted global model aggregation is leveraged to alleviate the adverse impact of AoI on global model training. Second, AoIo-DT is employed to provide more accurate state estimates to reduce global loss function through coordinated resource management. Third, AoI-aware learning encourages DAC training to use samples with lower AoI to achieve better learning convergence and optimality performance.

## VI. Conclusion

In this paper, the model training problem of DT empowered EV energy management is addressed from the perspective of AoI optimization. The proposed algorithm achieves network resource management of 6G signal processing, communication, and computing integration through AoIo-DT assistance and AoI-aware learning. Compared with AAP and ARAS, the global loss function is improved by $61.61\%$ and $47.79\%$ and the AoI is reduced by $57.45\%$ and $44.04\%$. The proposed algorithm was further validated in a more complex scenario of EV energy management with 1000 EVs and distributed PV generators. Under dynamic load, PV output, and TOU price, the proposed algorithm outperforms APP and ARAS by $17.02\%$ and $21.77\%$ in load curve fluctuation reduction, and $71.92\%$ and $78.74\%$ in cumulative charging cost saving. We conclude that the great potentials of EVs are better exploited through joint optimization of signal processing, communication, and computing. In [36], a novel fashion to model task caching strategies was proposed, which provided a solution for the improvement of system model. In the future, we will further investigate the impact of caching issues in DT model.

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## References

[1] S. A. Khowaja, P. Khuwaja, K. Dev *et al.*, "A secure data sharing scheme in community segmented vehicular social networks for 6G," *IEEE Trans. Ind. Informat.*, vol. 19, no. 1, pp. 890–899, Jan. 2023.

[2] Z. Zhou, B. Wang, Y. Guo, and Y. Zhang, “Blockchain and computational intelligence inspired incentive-compatible demand response in internet of electric vehicles,” *IEEE Trans. Emerging Top. Comput. Intell.*, vol. 3, no. 3, pp. 205–216, Jun. 2019.

[3] Z. Zhou, B. Wang, M. Dong, and K. Ota, “Secure and efficient vehicle-to-grid energy trading in cyber physical systems: Integration of blockchain and edge computing,” *IEEE Trans. Syst. Man Cybern.: Syst.*, vol. 50, no. 1, pp. 43–57, Jan. 2020.

[4] M. Kamal, G. Srivastava, and M. Tariq, “Blockchain-based lightweight and secured V2V communication in the internet of vehicles,” *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 3997–4004, Jul. 2021.

[5] J. Zhou, D. Tian, Y. Wang *et al.*, “Reliability-optimal cooperative communication and computing in connected vehicle systems,” *IEEE Trans. Mob. Comput.*, vol. 19, no. 5, pp. 1216–1232, May 2020.

[6] M. Kamal, M. Tariq, G. Srivastava, and L. Malina, “Optimized security algorithms for intelligent and autonomous vehicular transportation systems,” *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 2038–2044, Feb. 2023.

[7] Y. Shu, Z. Wang, H. Liao *et al.*, “Age-of-information-aware digital twin assisted resource management for distributed energy scheduling,” in *Proc. IEEE Global Communications Conference (IEEE GLOBECOM)*, Rio de Janeiro, Brazil, Dec. 2022, pp. 5705–5710.

[8] M. Adhikari, A. Hazra, V. G. Menon, B. K. Chaurasia, and S. Mumtaz, “A roadmap of next-generation wireless technology for 6G-enabled vehicular networks,” *IEEE Internet Things Mag.*, vol. 4, no. 4, pp. 79–85, Dec. 2021.

[9] S. Zhang, H. Gu, K. Chi *et al.*, “DRL-based partial offloading for maximizing sum computation rate of wireless powered mobile edge computing network,” *IEEE Trans. Wireless Commun.*, vol. 21, no. 12, pp. 10 934–10 948, Dec. 2022.

[10] W. Sun, S. Lei, L. Wang, Z. Liu, and Y. Zhang, “Adaptive federated learning and digital twin for industrial internet of things,” *IEEE Trans. Ind. Informat.*, vol. 17, no. 8, pp. 5605–5614, Aug. 2021.

[11] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, “Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks,” *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5098–5107, Jul. 2021.

[12] F. Wang, D. Jiang, Z. Wang, and S. Mumtaz, “Service continuity based data delivery optimization in satellite-terrestrial networks,” *IEEE Trans. Veh. Technol.*, vol. 72, no. 10, pp. 13 604–13 617, Oct. 2023.

[13] J. Choi, V. Marojevic, C. B. Dietrich, and S. Ahn, “DSRC-enabled train safety communication system at unmanned crossings,” *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 18 210–18 223, Oct. 2022.

[14] Z. Zhou, Z. Jia, H. Liao *et al.*, “Secure and latency-aware digital twin assisted resource scheduling for 5G edge computing-empowered distribution grids,” *IEEE Trans. Ind. Informat.*, vol. 18, no. 7, pp. 4933–4943, Jul. 2022.

[15] D. Van Huynh, V.-D. Nguyen, S. R. Khosravirad, G. K. Karagiannidis, and T. Q. Duong, “Distributed communication and computation resource management for digital twin-aided edge computing with short-packet communications,” *IEEE J. Sel. Areas Commun.*, vol. 41, no. 10, pp. 3008–3021, Oct. 2023.

[16] W. Sun, S. Lian, H. Zhang, and Y. Zhang, “Lightweight digital twin and federated learning with distributed incentive in air-ground 6G networks,” *IEEE Trans. Network Sci. Eng.*, vol. 10, no. 3, pp. 1214–1227, Oct. 2022.

[17] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, “Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks,” *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5098–5107, Aug. 2020.

[18] T. Do-Duy, D. Van Huynh, O. A. Dobre, B. Canberk, and T. Q. Duong, “Digital twin-aided intelligent offloading with edge selection in mobile edge computing,” *IEEE Wireless Commun. Lett.*, vol. 11, no. 4, pp. 806–810, Jan. 2022.

[19] D. Van Huynh, V.-D. Nguyen, S. R. Khosravirad *et al.*, “URLLC edge networks with joint optimal user association, task offloading and resource allocation: A digital twin approach,” *IEEE Trans. Commun.*, vol. 70, no. 11, pp. 7669–7682, Nov. 2022.

[20] W. Y. B. Lim, Z. Xiong, J. Kang *et al.*, “When information freshness meets service latency in federated learning: A task-aware incentive scheme for smart industries,” *IEEE Trans. Ind. Informat.*, vol. 18, no. 1, pp. 457–466, Jan. 2022.

[21] Z. Zhu, S. Wan, P. Fan, and K. B. Letaief, “An edge federated MARL approach for timeliness maintenance in MEC collaboration,” in *Proc. IEEE International Conference on Communications Workshops (ICC Workshops)*, Montreal, QC, Canada, Jun. 2021, pp. 1–6.

[22] S. B. Prathiba, G. Raja, K. Dev, N. Kumar, and M. Guizani, “A hybrid deep reinforcement learning for autonomous vehicles smart-platooning,” *IEEE Trans. Veh. Technol.*, vol. 70, no. 12, pp. 13 340–13 350, Dec. 2021.

[23] Y. Cao, S.-Y. Lien, and Y.-C. Liang, “Deep reinforcement learning for multi-user access control in non-terrestrial networks,” *IEEE Trans. Commun.*, vol. 69, no. 3, pp. 1605–1619, Mar. 2021.

[24] Y.-C. Wu, T. Q. Dinh, Y. Fu, C. Lin, and T. Q. S. Quek, “A hybrid DQN and optimization approach for strategy and resource allocation in MEC networks,” *IEEE Trans. Wireless Commun.*, vol. 20, no. 7, pp. 4282–4295, Jul. 2021.

[25] S. Wang, H. Liu, P. H. Gomes, and B. Krishnamachari, “Deep reinforcement learning for dynamic multichannel access in wireless networks,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 2, pp. 257–265, Jun. 2018.

[26] J. Lopez, J. E. Rubio, and C. Alcaraz, “A resilient architecture for the smart grid,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 8, pp. 3745–3753, Aug. 2018.

[27] H. Chen and S. Ye, “Modeling and optimization of EMI filter by using artificial neural network,” *IEEE Trans. Electromagn. Compat.*, vol. 61, no. 6, pp. 1979–1987, Dec. 2019.

[28] C. Luo, Y. Cui, and S. Lin, “Container migration method based on bandwidth prediction and adaptive compression,” *Computer Engineering*, vol. 48, no. 5, pp. 200–207, May 2022.

[29] H. Liao, X. Chen, Z. Zhou, N. Liu, and B. Ai, “Licensed and unlicensed spectrum management for cognitive M2M: A context-aware learning approach,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 3, pp. 915–925, Sep. 2020.

[30] M. J. Neely, *Stochastic Network Optimization With Application to Communication and Queueing Systems*. San Rafael, CA, USA: Morgan and Claypool, 2010.

[31] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, “Deep reinforcement learning for stochastic computation offloading in digital twin networks,” *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 4968–4977, Jul. 2021.

[32] X. Liu, X. Qin, H. Chen *et al.*, “Age-aware communication strategy in federated learning with energy harvesting devices,” in *Proc. IEEE International Conference on Communications in China (IEEE ICCC)*, Xiamen, China, Nov. 2021, pp. 358–363.

[33] J. Sun, L. Wang, Z. Jiang, S. Zhou, and Z. Niu, “Age-optimal scheduling for heterogeneous traffic with timely throughput constraints,” *IEEE J. Sel. Areas Commun.*, vol. 39, no. 5, pp. 1485–1498, May 2021.

[34] Y. Wang, Y. Zheng, H. Xue, and Y. Mi, “Optimal dispatch of mobile energy storage for peak load shifting based on enhanced firework algorithm,” *Autom. Elect. Power Syst.*, vol. 45, no. 5, pp. 48–56, Mar. 2021.

[35] M. J. E. Alam, K. M. Muttaqi, and D. Sutanto, “Effective utilization of available PEV battery capacity for mitigation of solar PV impact and grid support with integrated V2G functionality,” *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1562–1571, May 2016.

[36] D. Van Huynh, S. R. Khosravirad, A. Masaracchia, O. A. Dobre, and T. Q. Duong, “Edge intelligence-based ultra-reliable and low-latency communications for digital twin-enabled metaverse,” *IEEE Wireless Commun. Lett.*, vol. 11, no. 8, pp. 1733–1737, Aug. 2022.

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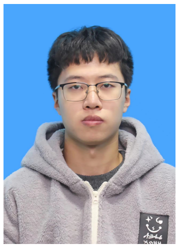

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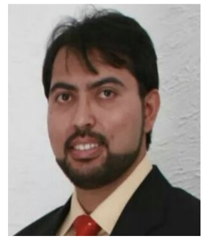

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