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Digital Twin based Reinforcement Learning for Energy Exchange among Electric Vehicles and Base Stations in a Disaster-affected Region

Ferheen Ayaz, Maziar Nekovee, Zhengguo Sheng, Nagham Saeed

***Abstract*—The cellular base stations (BSs) have backup batteries to maintain uninterrupted power supply. Recent studies have shown that a backup battery may have some spare energy to act as a flexible resource in the power system. Similarly, electric vehicles (EVs) are also capable to give surplus energy stored in their batteries to other consumers or back to the grid. Therefore, both BSs and EVs can also effectively share energy among themselves through Telecom-to-Vehicle (T2V) and Vehicle-to-Telecom (V2T) exchange. However, it is difficult for BSs and EVs to exchange their energies in a disaster-affected region as they may encounter challenges such as connectivity failures, power disruption and damaged routes. This paper proposes an energy exchange solution among BSs and EVs in a post disaster situation. We propose a digital-twin (DT) based solution which utilizes Artificial Intelligence (AI) algorithms to estimate energy consumption of BSs and EVs and identifies their role as energy buyers or sellers. It also models power disruption and disaster-affected blocked routes as Markov processes with parameters derived from real historic data of floods. Then, a reinforcement learning (RL) algorithm is proposed to match BSs and EVs which can feasibly take part in either T2V or V2T exchange. Performance of the proposed solution is compared with independent RL without DT and assisted by federated learning. Simulations show that the DT-based RL results in averagely twice the amount of energy being exchanged as compared to the only RL algorithm run by EVs.**

***Index Terms*—EV, base station, backup batteries, disaster.**

I. Introduction

THE frequency of disaster occurrence is globally increasing because of unprecedented environmental challenges [1]. These disasters often bring destruction to power supply, roads and communication systems due to which rescue operations become extremely difficult. Information and Communication Technology (ICT) have proposed promising solutions to environmental, social and economic challenges of the world including natural disasters. Recent 5G-empowered Internet-of-Things (IoT) and Internet-of-Vehicles (IoV) networks are particularly useful in disaster management [2] - [3]. They can help in providing seamless connectivity for both pre-disaster warnings and post-disaster rescue operations [4]- [5].

Recent advancements in ICT also aim to contribute towards environmental sustainability. For example, dispatchable capacity of 5G base stations (BSs) is now being considered promising to achieve net-zero goal. It is based on the concept that the backup battery of BS is under-utilized and should be used as an energy supply for other consumers and power systems, thereby balancing high demands [9]. The deployment of 6G is set to bring significant advancements and increased infrastructure density, including the installation of a vast number of BSs throughout various regions. The global transition is already underway. Looking ahead, the roadmap includes expanding network coverage and initiating 6G commercialization by 2030, with standardization efforts beginning in 2025. By that year, the number of BSs in only China is expected to reach 8.28 million, consisting of backup batteries with total capacity over 121.06 GWh [6] - [7]. The trial to utilize backup batteries of 200 BSs in Finland as virtual power plants has already been successful and more than 20,000 tons of CO_2 reductions is expected to achieve if the framework is implemented for the entire network of BSs in the country [8]. The mobile consumer, i.e., electric vehicle (EV) can potentially benefit from this situation by reaching towards a BS and undergoing a Telecom-to-Vehicle (T2V) energy exchange. However, a T2V energy exchange may not always be possible, particularly in case of a disaster. If a disaster results in power disruption, the backup battery is required to provide uninterrupted power supply to a BS itself. Also, an extreme power outage situation may lead to complete exhaustion of a backup battery of BS and ultimately communication loss. On the other hand, if there is no power failure, a BS can be effective to supply energy to demanding EVs which cannot reach a charging station.

The use of EV on road is rapidly increasing due to its positive contributions towards global net-zero goals. Furthermore, mobile energy storage feature of EVs makes it useful to carry out post-disaster rescue operations [10]. The utilization of EVs for post-disaster rescue operations has been discussed extensively in existing literature [10]. Since EVs have battery storage systems, they can also be used to implement Vehicle-to-Telecom (V2T) energy exchange which refers to supplying energy from an EV to a BS, which may be required for reliable connectivity during a disaster. In a disaster-affected region, it is important to consider that an EV has sufficient energy and an unobstructed route, so it can reach a BS and travel back. Utilizing surplus energy of EVs to power other

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TABLE I: Opportunities in related works as motivation of solutions proposed in this paper

Related Works	Opportunity	Motivation
Energy sharing by backup batteries of BS [6], [9], [19] - [26]	Potential approach to support grid	Optimization and AI algorithms will maximize utilization of EVs and BS backup batteries
Post-disaster energy management by EV and BS [10], [27] - [31]	Backup batteries of EVs and BS enhance resilience	
RL for energy management of EVs [15], [34] - [32]	Recommended approach	Suitable for T2V and V2T energy management
DT based route and energy management [16], [18], [36] - [47]	Suitable for real-time situation awareness	Appropriate for monitoring and prediction in a disaster situation

consumers or supplying back to the grid via Vehicle-to-Grid (V2G) exchange has already been widely studied [11] - [12]. However, research gap lies in analyzing feasibility, suitable situations and optimization for V2T and T2V energy exchange.

With prevalence of Artificial Intelligence (AI) in road transportation [13] - [14], adaptive optimization algorithms, such as, Reinforcement Learning (RL) are formulated to effectively manage energy sharing by EVs [15]. Recently, digital twin (DT) systems are also proposed for efficient energy management of EVs and V2G exchanges [16]. A DT is an emerging technology to model physical IoT networks in a virtual setting. A DT based virtual model of a physical network synchronizes activities of all physical entities and analyzes their attributes and operational dynamics with regular real-time data interaction. For IoV networks, a DT can simulate traffic environment for all vehicles centrally, analyze the state of vehicles and make more reliable decisions than the decisions made by physical vehicles individually [17]. Therefore, DTs are promising solutions for optimum energy management of EVs and decisions related to energy trading between EVs and other consumers [18].

This paper proposes a DT based RL algorithm to implement both T2V and V2T exchange in a disaster-affected region. The motivation of considering post-disaster situation is to assess the resilience of the proposed solution in emergency situations when power disruption, communication loss and road damage are expected. A DT system predicts energy requirements of BSs and EVs considering the likelihood of the damaging effects of a disaster. It also estimates routes availability based on previous data. Then, it utilizes RL to optimize energy exchange. The main contributions of the paper are as follows

- We propose a DT based system to analyze the energy requirements of EVs and BSs and propose T2V and V2T exchange to meet energy demands.
- We design RL algorithm to maximize T2V and V2T energy exchange in a disaster-affected region
- We evaluate the results of DT based RL algorithm and compare them with independently run RL without DT and RL supported by federated learning (FL). Simulations show that the highest energy exchange is achieved by DT.

The rest of the paper is organized as follows. Section II discusses related works. Section III defines system model. Section IV explains DT based solution for energy exchange and RL algorithm. Performance evaluation and conclusion are presented in Section V and VI respectively.

II. Related Works

A. *Energy sharing by backup batteries of BS*

Backup battery utilization in BS is proposed in [19] and the practical extent of utilization, i.e., dispatchable capacity is theoretically analyzed in [9]. Existing literature is focused towards designing optimization algorithms to enhance operational economics. In [20], dispatcahable capacity of BS is analyzed using stochastic modeling and distributed optimization algorithm is used for fully utilizing the backup batteries of BSs. In [21], the investment cost and location of energy storage systems are optimized by leveraging the full potential of BS backup batteries to support power systems. In [22], an incentive model is designed for 5G operators to motivate them for sharing spare capacity of backup battery. Artificial Intelligence (AI) algorithms have also been used for optimization. For example, a deep Q learning algorithm is proposed in [23] to maximize the utilization by managing charging times. K-means++ clustering is used in [24] to cluster 5G BSs on the basis of geographical location and power consumption, and evaluate the dispatchable capacity of each cluster. Recent research has mostly explored the capacity of BSs to support power systems and grids. T2V exchange is proposed utilizing quantum optimization in [25]. Considering the potential, the concept of distributed energy exchange between BSs and EVs to meet demands in post-disaster situation is worth investigating. The generic frameworks of T2V and Telecom-to-Grid (T2G) energy exchange are described in [6]. Besides EV, the backup battery of BS can also be effectively utilized to charge other IoT devices, such as, Uncrewed Aerial Vehicle (UAV) [26].

B. *Energy management*

a) Post-disaster energy management: The resilience and sustainability of power distribution networks is largely affected by disasters. Mobile energy storage systems including EVs are considered as efficient resource to maintain demand-supply balance in such situations [10], [27]- [28]. The backup battery of 5G BS is proposed as power supply in emergency situations in [29]. In [30] and [31], photovoltaic (PV) system is proposed to be integrated with backup battery of BS for post-disaster resilience. However, a PV system largely depends on weather conditions and may not produce sufficient energy during floods and rains. Therefore, EV can be a useful supplier in such case. On the contrary, if a BS has adequate supply produced by PV system, it can also share its energy with the demanding EVs. Hence, a T2V and V2T exchange is a promising research direction in both cases.

b) RL for energy management of EVs: The energy management of EVs is a complex problem with many uncertain variables. For example, EV's energy consumption is dependent on multiple parameters including its motor power, varying speed and route length. Additionally, clean energy sources powering EVs have fluctuating outputs. In such scenarios, Machine Learning (ML) methods produce more efficient energy management solutions than other algorithms. Specifically, RL algorithms have great potential to achieve optimum results without prior knowledge of environment as they dynamically learn to design their action strategy to maximize expected future rewards at each state. In [32], RL is suggested as a promising technique for distributed EV charging systems. In [34], Markov Decision Process (MDP) controls charging and discharging strategy of EVs in a V2G exchange on the basis of federated RL. A deep RL based approach to optimize charging control strategy of EVs by MDP is proposed in [33]. Similarly, peer-to-peer energy exchange involving EVs and other entities including home and grid are controlled via MDP executed by RL in [15]. RL based home energy management systems including EV charging are also proposed in [35].

c) DT based energy systems: The ability of DTs to perform real time analysis of physical world in a virtual setup have immensely supported continuous decision making in various applications. In context of EVs and energy systems, DTs have been employed for distributed energy exchange [36], battery modeling [37] and charging management at stations [16], [18]. In [38], DT is proposed for the situation awareness of modern energy systems including distributed resources and EVs. A coordinated control of distributed energy resources by a centralized DT is proposed in [39]. The combination of DT and RL is recommended for Internet-of-Energy systems in [40]. In [41], DT with RL outperforms DT without RL for energy management and optimization in green cities.

C. DT based route management

The role of DT in evacuation planning after a flood disaster is highlighted in [42], where DT is proposed to identify optimal evacuation routes in real-time. A DT-based flood monitoring system which utilizes combination of real-time data and information of historically blocked routes is also presented in [43]. DT backed by historical data has been used to ensure water safety management and monitor traffic in [44]. The DT of a transportation network is proposed to optimize safe routes for ambulances and first responders in [45]. Apart from flood disaster, DT is also suggested as an effective approach to identify safe routes for rescue operations in other emergencies and incidents [46]. In [47], DT predicts lane traffic by utilizing natural driving data.

D. Limitations and Motivation

The backup battery of BS is recently studied as a useful resource to supply energy and support grid in generic situations only. Meanwhile, significant increase in disasters and resulting damage on main grid and infrastructure is a serious concern, which is usually tackled by utilizing the readily available energy sources [48]. Therefore, we explore the opportunity to avail dispatchable capacity of BS in post-disaster situation. Furthermore, RL, DT and their combination are recommended approaches for energy management. However, their applications in BS backup battery utilization are not yet studied. Additionally, DT has been suggested as an effective approach for both energy and route management, Therefore, its maximum utilization can be attained by using it simultaneously for both purposes. Keeping in view the feasibility analysis of dispatchable capacity of BSs, suitability of RL for distributed energy exchange and DT for continuous monitoring and situation awareness in both energy systems and disaster management, this paper combines all the approaches to implement successful T2V and V2T energy exchange after a disaster has occurred. Table I summarizes the related works into four broad approaches, lists the potential opportunities and novel research directions arising from related works which are exploited by the solutions proposed in this paper.

TABLE II: List of Key Notations

Notation	Definition
I	Number of buyers
J	Number of sellers
K	Number of EVs (per km^2)
L	Number of BSs (per km^2)
SoC	State of Charge (%) in a battery
X	State space
λ_d	Blocking rate of route d
μ_d	Opening rate of route d
λ_{power}	Power disruption rate
μ_{power}	Power availability rate
ϕ^d_{route}	Set of routes
δ^k_w	Working set for EV k reach
δ^k_f	Failure set for EV k reach
$\mathbf{A}^k_{agg}$	Transition probability density matrix for EV k
$\mathbf{P}^k_{agg}(t)$	Probability matrix at time t for EV k
$\mathbf{p}^k(t)$	Probability vector at time t for EV k
T_k	Time for an EV k to reach BS (s)
α_i	Lower SoC threshold for buyer i (%)
α_j	Upper SoC threshold for seller j (%)
R_i	Reward of buyer i
R_j	Reward of seller j
SW	Social Welfare
e_i	Energy received by buyer i (kWh)
c_i	Cost of e_i
e_d	Energy used in traveling through route d (kWh)
c_d	Cost of e_d
ρ	Battery degradation cost (/kWh)
γ	Adjustment coefficient
$\mathbf{S}(t)$	State vector at time t for RL
$\mathbf{Acc}$	Action set
a	Action

III. System Model

Consider a 5G vehicle-to-everything (V2X) network where $\mathcal{K} = \{1, 2, ..., K\}$ EVs and $\mathcal{L} = \{1, 2, ..., L\}$ BSs are randomly distributed within a finite two-dimensional area. In this system, there are some BSs and EVs with energy demands while some others have capacity to provide a portion of energy from their batteries. Therefore, the BSs and EVs are also divided into two groups, i.e., $\mathcal{I} = \{1, 2, ..., I\}$ buyers and $\mathcal{J} = \{1, 2, ..., J\}$ sellers, depending on their demands and surplus supplies. As shown in Fig. 1, we consider the following conditions which can occur due to a disaster

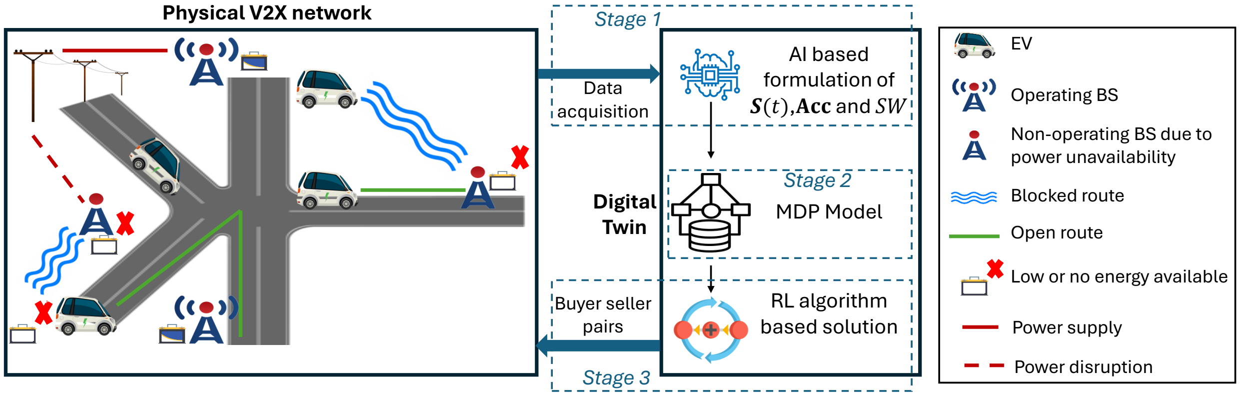

Fig. 1: The proposed DT based solution for energy exchange among BSs and EVs in a disaster-affected region.

- The routes from an EV to BS can be opened or blocked. In case of a blocked route, an EV may reach a BS through an alternate route.
- If communications with any BS is lost, it is assumed that the BS has run out of power.

Table II defines the key notations used in the paper.

A. Ability of EVs to reach BS

The ability of an EV to reach a BS depends upon its route and the State of Charge (SoC). It is defined as the remaining charge available in its battery in relation to the total battery capacity. $SoC = 100\%$ implies a full battery state and $SoC = 0\%$ refers to an empty state [49] .

Markov model has been thoroughly used to model road damage due to various factors including flood in existing literature [51]. The route d between BS and EV is represented as a continuous-time Markov model [50]. Any route d can be blocked due to a disaster. Let λ_d and μ_d respectively represent the number of times a route d is blocked or opened in a data record. The Markov model is defined as follows.

Definition 1: State of route d is modeled as a continuous-time Markov process $\{X^d_{route}(t), t > 0\}$. The state space is defined as

$$X^d_{route}(t) = \begin{cases} 0, & \text{route } d \text{ is blocked at time } t, \\ 1, & \text{route } d \text{ is open at time } t. \end{cases} \quad (1)$$

The Markov process is homogeneous with blocking rate λ_d and opening rate μ_d. In case of an open route, an EV must have sufficient SoC to travel through it.

Definition 2: The ability of an EV k to reach BS l is modeled as a continuous stochastic process $\{X^k_{reach}(t), t > 0\}$. The state space is defined as

$$X^k_{reach}(t) = \begin{cases} 0, & \text{EV cannot reach BS,} \\ 1, & \text{EV can reach BS.} \end{cases} \quad (2)$$

Considering Definition 1 and 2, if $X^k_{reach}(t) = 1$, there is at least one route d open at time t for EV to travel to a BS. Let ϕ^d_{route} be the set of routes which connect an EV to a BS. We aggregate the Markov process of routes in ϕ^d_{route} to form a new Markov process.

Definition 3: The Markov process $\{X^k_{agg}(t), t > 0\}$ is the aggregation of Markov processes of routes in ϕ^d_{route}. The state space can defined as the binary code $x_1 x_2 ... x_{|\phi^d_{route}|}$, and the d^{th} bit represents the state of d^{th} route in ϕ^d_{route} at time t.

The state space of $X^k_{agg}(t)$ is divided into two sets: the working set δ^k_w and the failure set δ^k_f. For every state of $X^k_{agg}(t)$, we check whether the EV k is reachable or not via open route in ϕ^d_{route}. If EV k is reachable, it is included in δ^k_w, otherwise in δ^k_f. The transition probability density matrix $\mathbf{A}^k_{agg}$ of $X^k_{agg}(t)$ can be constructed as [9]

- $\mathbf{A}^k_{agg}(m, n) = \lambda_d (m \neq n)$: if the binary codes of states m and n are equal except of the d^{th} bit. The d^{th} bit of state m and n is 1 and 0 respectively.
- $\mathbf{A}^k_{agg}(m, n) = \mu_d (m \neq n)$: if the binary codes of states m and n are equal except of the d^{th} bit. The d^{th} bit of state m and n is 0 and 1 respectively.
- $\mathbf{A}^k_{agg}(m, n) = 0 (m \neq n)$: Other situations.
- $\mathbf{A}^k_{agg}(m, m) = -\sum_{m \neq n} \mathbf{A}^k_{agg}(m, n)$.

The transition probability matrix $\mathbf{P}^k_{agg}(t)$ and the probability vector $\mathbf{p}^k(t)$ of $X^k_{agg}(t)$ are defined as

$$\mathbf{P}^k_{agg}(t)(m, n) = Prob(X^k_{agg}(t) = n | X^k_{agg}(0) = m), \quad (3)$$

$$\mathbf{p}^k(t) = Prob(X^k_{agg}(t) = m). \quad (4)$$

$X^k_{reach}(t) = 1$ if and only if $X^k_{agg}(t)$ is in the working state, i.e.,

$$Prob(X^k_{reach}(t) = 1) = \sum_{m \epsilon \delta^k_w} \mathbf{p}^k(t)(m). \quad (5)$$

B. Possibility for T2V or V2T exchange

A T2V or V2T exchange takes place when the energy buyer has low SoC and the seller is left with at least a threshold amount of energy that it wants to keep for itself after the energy exchange. For instance, an EV must have some energy left to travel in unforeseen circumstances which may occur due to a disaster. Also, a BS is originally powered by a power distribution network. In case of a failure in distribution network, its backup battery provides energy to a BS. Each BS is equipped with a backup battery module. The power distribution network failure affects the availability of energy in a backup battery of BS, since the BS would prioritize to power itself from the backup battery instead of providing it to an EV. Therefore, the energy available to be exchanged is represented as two-state model.

Definition 4: State of power distribution network is a continuous time Markov process $\{X_{power}(t), t \geq 0\}$. The state space is defined as

$$X_{power}(t) = \begin{cases} 0, & \text{Power disruption state at time } t, \\ 1, & \text{Power availability state at time } t. \end{cases} \tag{6}$$

The Markov process is homogeneous with disruption rate λ_{power} and availability rate μ_{power} [9].

Each BS and EV available for energy exchange have one of the two possible states, i.e., buyer (state 0) or seller (state 0). Therefore, available EVs and BSs are also represented as two-state models.

Definition 5: State of available BS l is defined as

$$X^l_{BS}(t) = \begin{cases} 0, & SoC_l(t+T_k) \leq \alpha_i \text{ and } X_{power}(t) = 0, \\ 1, & SoC_l(t+T_k) \geq \alpha_j \text{ and } X_{power}(t) = 1, \end{cases} \tag{7}$$

where α_i and α_j respectively denote the lower and upper threshold levels of SoC which categorize a BS as a buyer or seller and T_k is the time required by EV k to reach a BS.

Definition 6: State of available EV k is defined as

$$X^k_{EV}(t) = \begin{cases} 0, & SoC_k(t+T_k) \leq \alpha_i, \\ 1, & SoC_k(t+T_k) \geq \alpha_j. \end{cases} \tag{8}$$

α_i and α_j are considered as the safe limits to optimize lifespan of a battery. For EVs, they also incorporate the energy required to travel towards a BS. Their optimum values are defined in [52].

C. Reward and Social Welfare

Considering bidirectional energy exchange, the role of buyer and seller is interchangeable between BS and EV. The reward functions of both buyer and seller are formulated to make sure T2V or V2T energy exchange is profitable for both EV user and BS operator. The utilities of buyers and sellers are termed as rewards for formulating a reward based RL algorithm. A buyer i pays c_i to a seller j for e_i amount of energy attained. For a fixed c_i, the reward of a buyer depends upon its SoC at the time of energy exchange. If the buyer is EV, its reward also varies with the energy consumed in traveling towards a seller BS. The reward of buyer i when it buys e_i amount of energy is

$$R_i = \frac{\gamma}{SoC_i} log(1+e_i) - c_i e_i - \rho e_i - c_d e_d, \tag{9}$$

where $\gamma > 0$ is the adjustment coefficient, c_i is the unit cost of e_i paid by buyer i, ρ is the unit battery degradation cost representing the loss of battery capacity over time and eventual replacement , e_d is the energy consumed by an EV while traveling on a route d to reach BS and c_d is the unit traveling cost. Natural logarithmic function is used in (9) to express the relationship between energy demand and buyer's satisfaction and to model R_i as a concave non-decreasing term [53].

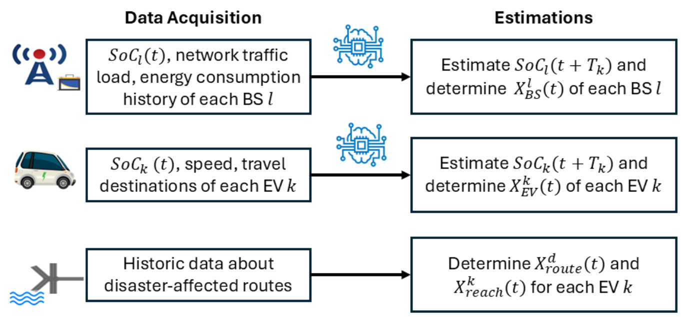

Fig. 2: Data acquisition and estimation by DT.

The reward of seller j is

$$R_j = c_i e_i - c_j e_i - c_d e_d, \tag{10}$$

where c_j is the unit cost of previously acquiring e_i. $c_d = e_d = 0$, when the buyer or seller is BS in (9) and (10) respectively.

The social welfare of the system is

$$SW = \sum_{i=1}^{I} R_i + \sum_{j=1}^{J} R_j, \tag{11}$$

SW is used to map numeric individual rewards to collective welfare. The motivation behind adopting SW in the system is its approximation as the unanimity in a decision. It is considered as the closest profile where all individuals agree [54]. Its real-world application is presented in [55], where SW is defined as a metric to reflect incentives of all individuals involved in streamlining urbanization for flood management. An alternative societal metric is Pareto-optimality, which is a state when it is impossible to make any individual better off without making someone else worse off. However, unlike SW, it does not represent fairness of a situation.

IV. The Proposed Digital Twin Based T2V and V2T Energy Exchange Solution

The proposed DT based solution is illustrated in Fig. 1. It formulates an energy maximization problem and solves it through three stages explained below.

A. Energy exchange maximization problem

Our main objective is to maximize SW of the system by optimally matching buyers and sellers and determining open routes for EVs. We have the optimization problem as follows

P1:

$$\begin{aligned} \max_{e_i, e_d} \quad & \sum_{i=1}^{I} R_i + \sum_{j=1}^{J} R_j, \\ \text{s.t.} \quad & \text{C1: } e_i + e_d \leq e^{th}_j \,\forall\, s \,\epsilon\, \{1,2,3,....,J\}, \\ & \text{C2: } R_i \geq 0 \,\forall\, i \,\epsilon\, \{1,2,3,....,I\}, \\ & \text{C3: } R_j \geq 0 \,\forall\, j \,\epsilon\, \{1,2,3,....,J\}, \end{aligned}$$

where constraint C1 limits the energy exchange by an upper bound e^{th}_j, and C2 and C3 guarantee the positive reward of both buyer and seller.

B. Stage 1: Data Acquisition and Estimation

As shown in Fig. 2, the DT of the V2X network regularly acquires data from real BSs and EVs including SoC_l and SoC_k, network traffic load, energy consumption history, speed and travel destinations of EVs to estimate their hourly energy requirements and surplus supplies. An ML regression model XGB is used to predict network load of a BS, followed by a Deep Neural Network (DNN) to estimate $SoC_l(t+T_k)$. Compared with other mathematical and regression models, DNN achieves better accuracy [56]. $SoC_k(t+T_k)$ is predicted by kinematic calculations defined in [57], where the speed of an EV k is determined by ML regression model CatBoost due to its better computing efficiency and less training times [12]. Disaster related historic data of the region is used to statistically model blocked or open routes and power disruption or availability, as defined in Section III. It is noted that temporal modeling of blocked routes in a road network is out of the scope of this paper but can be carried out through various methods other than estimation through historical data, such as utilizing LiDAR data to analyze road inundation [58] or employing UAVs for surveying disaster-affected region [59]. The data acquisition and estimation is used to model the system defined in Section III.

C. Stage 2: Markov Decision Process (MDP) Model

In this subsection, we convert Problem P1 into an MDP model with state space, action space and reward function defined as follows.

1) State Space: The state space of K EVs and L BSs available for energy exchange is realized according to the buying or selling state of each EV and BS and the ability of an EV to reach BS. Hence the state vector $\mathbf{S}(t)$ at time t can be represented as

$$\begin{array}{l}
[X^1_{reach}(t), X^1_{EV}(t), X^1_{BS}(t), ..., X^1_{reach}(t), X^1_{EV}(t), X^L_{BS}(t),\\
X^2_{reach}(t), X^2_{EV}(t), X^1_{BS}(t), ..., X^2_{reach}(t), X^2_{EV}(t), X^L_{BS}(t),\\
.\\
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X^K_{reach}(t), X^K_{EV}(t), X^1_{BS}(t), ..., X^K_{reach}(t), X^K_{EV}(t), X^L_{BS}(t)].
\end{array} \tag{12}$$

The state of buying or selling EV and BS depends on their corresponding SoC and the state transition probability of X^k_{reach} defined in Section II.

2) Action Space: We use $\mathbf{Acc} = \{1, 2, ..., L\}$ to represent the set of possible actions. The action is that an EV k can be associated with one BS l from available L BSs.

3) Reward Function: The reward function is the objective function of problem P1, which denote the social welfare of the system. The gain of the reward is determined by the actions of EVs. If one or more EVs gain equal optimal SW with the same BS or vice-versa, the algorithm decides the optimal buyer and seller match according to maximum amount of energy being exchanged.

Algorithm 1 RL based MDP for SW Maximization.

procedure RL BASED MDP.
  Obtain SoC of BSs and EVs.
  For any stage t, acquire $\mathbf{S}(t)$.
  while $k \leq K$ **do**
    while $a \leq L$ **do**
      For every state $\mathbf{s} \,\epsilon\, \mathbf{S}$ compute state transitional probability and SW as defined in (3) and (11) respectively.
      Find optimal $a^*(k)$ according to maximum SW.
      $q = k - 1$
      while $q > 0$ **do**
        if $a^*(k) == a^*(q)$ **then** Change $a^*(k)$ or $a^*(q)$ according to higher e_i.
        end if
        $q \leftarrow q - 1$.
      end while
    end while
  end while
  return a^* for every EV k.
end procedure

D. Stage 3: Reinforcement Learning (RL) Algorithm

RL algorithm is adopted to solve the proposed MDP model. It analyzes all possible combinations of BSs and EVs to match buyers and sellers for either T2V or V2T energy exchange resulting in optimal SW.

1) RL with DT: In RL with DT, the state space, action space and rewards are regularly updated through real time data acquisition and estimations as shown in Fig. 2. Then, the RL algorithm finds an optimal solution for all EVs and BSs in a centralized manner. Each buyer and seller pair formulated by RL algorithm is unique so that two or more EVs do not travel towards the same BS for energy exchange. Algorithm 1 defines the RL algorithm supported by DT. The EVs regularly receive updated algorithm from DT so that they are able to process the energy exchange after the disaster even if they lose communication with the DT. In case of disaster, if communication is not broken, DT acquires real-time status of BSs and updates the RL algorithm accordingly for all EVs.

2) RL without DT: In subsequent section, performance of the proposed solution is compared with RL without DT utilizing two approaches described as follows. In both approaches, individual EVs execute their own RL algorithm in a distributed manner. In RL without DT, it is possible that two or more EVs are matched with the same BS. In this case, the energy exchange takes place on first come first serve basis. When an energy exchange of an EV is completed with a certain BS, other EVs are notified via vehicle-to-vehicle (V2V) communication so that they change the state of that BS and update their algorithm.

a) RL with Federated Learning (FL): In this scenario, Stage 1 is performed through FL. The BSs and EVs develop their local models utilizing their private data to estimate $SoC_l(t+T_k)$ and $SoC_k(t+T_k)$ respectively. Instead of sharing data with DT, They upload local models to a central cloud

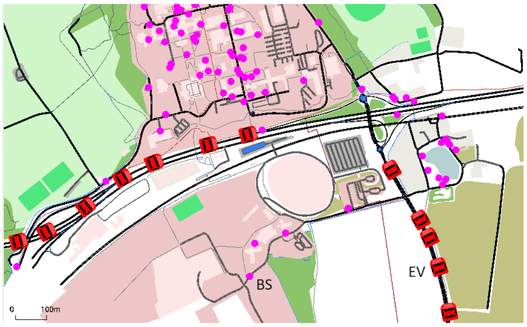


Fig. 3: Simulation Map.

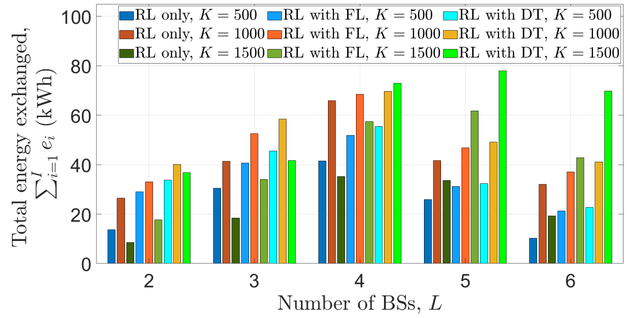


Fig. 4: Energy exchanged.

TABLE III: Simulation Parameters

Parameter	Value	Parameter	Value
Area	20 km^2	RL Iterations	300
BS battery capacity	30 kWh	BS battery capacity	50 kWh
K	[500, 1500] /km^2	L	[2, 6] /km^2
c_i	100	c_j	80
c_d	20	e_j^{th}	10 kWh
α_i	30%	α_j	50%
ρ	0.01	γ	1

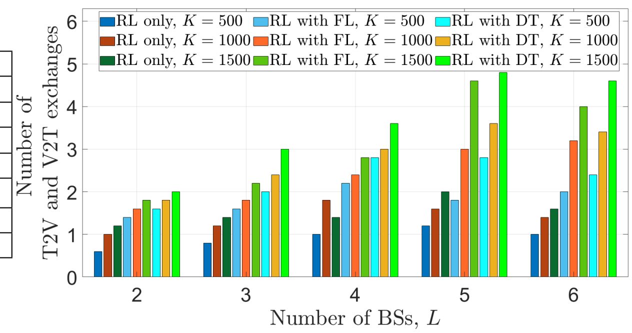


Fig. 5: Number of exchanges.

which creates aggregated global models [60]. All EVs utilize global models to create the state space, action space and rewards for running RL algorithm.

b) RL only: In this setup, the EVs assume $SoC_l(t+T_k)$ of BS as a random variable following lognormal distribution in case of communication loss [12]. They utilize their local data and AI estimation of $SoC_k(t+T_k)$ instead of prediction by global model.

V. Performance Evaluation

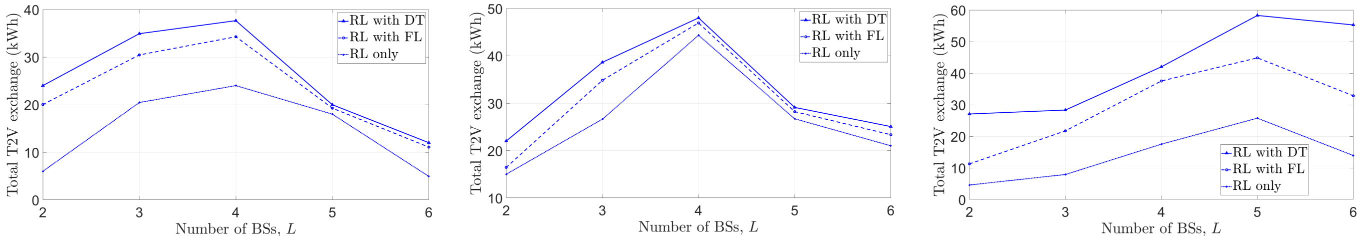
A. Simulation Settings

In this section, we discuss simulation results of the proposed solution. The DT based RL algorithm is implemented in Python and integrated with OMNeT++, which is used to realize V2X communications [61]. The open-source dataset of flooding and water rescue incidents in East Sussex is used to model the working and failure rates of Markov processes according to number successful rescue operations in the routes [62]. The motivation of simulating East Sussex area is due to high vulnerability to flood damages. Existing literature also demonstrate IoV-based flood rescue systems in this region [4]. The road traffic is simulated on the map of East Sussex, as shown in Fig. 3. EV density represents light, medium and heavy traffic scenarios [63]. The number of BSs are aligned with deployment scenarios of 5G networks in existing literature [64] . Simulation parameters are listed in Table III. Evaluation results are averaged over 100 simulation runs and time for each simulation is 2000 s.

B. Energy Exchange

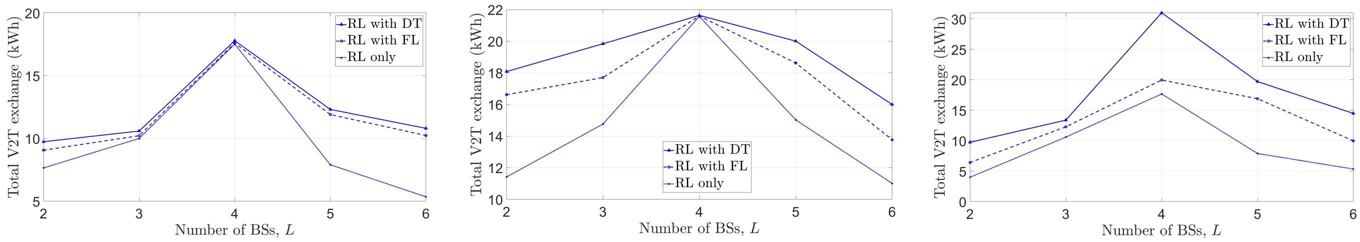
Fig. 4 shows that total amount of energy exchanged with the RL algorithm. The energy exchange of RL with DT is significantly higher than RL with FL and RL only. On an average, the total energy exchanged by RL with DT is twice as that exchanged by RL only. RL with FL results in higher energy exchange than RL only due to better estimations of SoC by global models but a centralized RL algorithm formed by DT outperforms FL. Furthermore, the energy exchange with DT significantly rises when number of EVs and BSs increase, unlike the trend observed in RL without DT, which performs optimally with 1000 EVs and results in the larger energy exchange than the same solution performed with 500 or 1500 EVs. It shows the scalability limitation of RL without DT. It is because a decentralized energy management approach is not suitable for number of EVs larger than 1000. On the contrary, the proposed DT based solution is scalable and particularly suitable for heavy traffic. With the 5G roll-out and global inclination towards environment sustainability, both the number of BSs and EVs are expected to increase. Therefore, it is important to find solutions particularly important for high density of BSs and EVs. The performance of the proposed solution in heavy traffic is further demonstrated in Fig. 5, which shows the number of exchanges, i.e., number of buyers and sellers pair. The average number of exchanges is highest with 1500 EVs per km^2.

Fig. 6 and 7 show the total energy transferred via T2V and V2T exchange respectively. Since DT based RL centrally considers the amount of energy being exchanged while optimally matching all buyers and sellers, it results in larger amount of energy transferred than RL without DT, where the energy exchange takes place whenever first EV reaches a BS. The energy exchanged through RL with FL is closer to RL with DT in Fig. 6 (a) and Fig. 7 (a), when EV traffic is low. However, the performances of both approaches do not match in heavy traffic, as seen in Fig. 6 (c) and Fig. 7 (c), which particularly shows the suitability of the proposed solution in dense urban



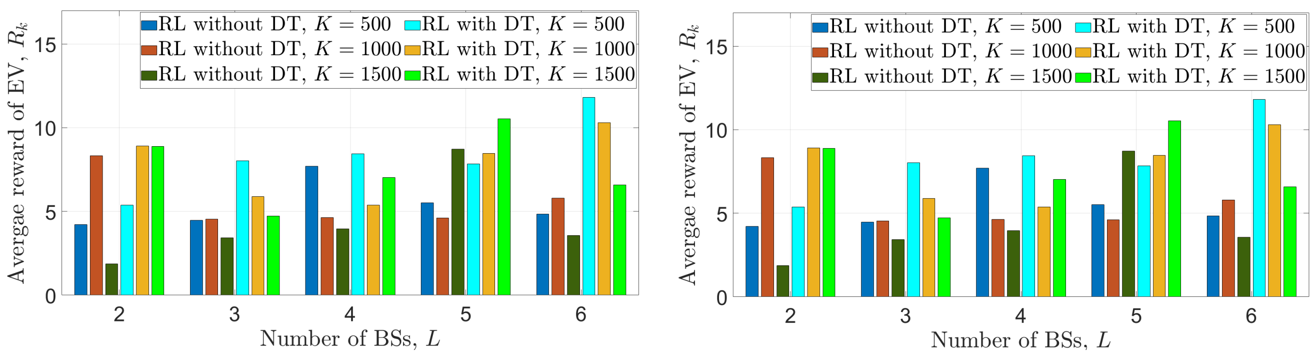
(a) $K = 500$ (b) $K = 1000$ (c) $K = 1500$

Fig. 6: Total T2V energy exchanged.



(a) $K = 500$ (b) $K = 1000$ (c) $K = 1500$

Fig. 7: Total V2T energy exchanged.



(a) BS (b) EV

Fig. 8: Reward of BSs and EVs.

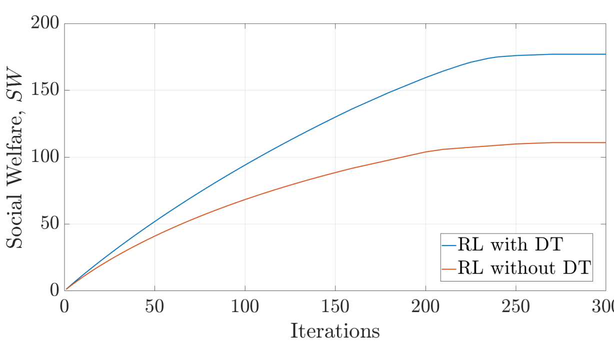


Fig. 9: SW per iteration.

scenarios. Furthermore, in both T2V and V2T exchange, there is an optimum pair of number of BS which results in the highest energy exchange. It is because with fewer BSs, there are not many feasible buyer-seller pairs resulting in a profitable T2V or V2T exchange. One the contrary, with highly dense BS setup, there are not enough EVs to trade significant amount of energy with each BS. The energy exchanged via T2V is approximately doubled as compared to V2T. This is because BSs do not have to consume energy while traveling and pay the travel cost and therefore have higher potential to become a seller.

C. Reward and Social Welfare

Since rewards and SW are RL dependent parameters, they are only affected by DT and not FL. The average reward of a BS and EV are shown in Fig. 8. Since the rewards depend upon energy costs, the number of BSs and EVs do not have significant impact upon the individual rewards. However, there is a notable difference between rewards attained with and without DT. On an average, both BS and EV rewards are 1.7 times higher with DT. Also, in both cases, the BS rewards are 1.5 times higher than EV rewards because BS do not have to pay traveling cost for an energy exchange.

Fig. 9 shows the SW of system. The SW of RL with DT is averagely higher as compared to RL without DT. This is because a DT optimally performs the algorithm for all EVs

TABLE IV: Asymptotic complexities of RL solutions

Approach	Communication	Computation
RL with DT	$\mathcal{O}(K^2+L)$	$\mathcal{O}(KL^2)$
RL with FL	$\mathcal{O}(K^2+L)$	$\mathcal{O}(K^2L)$
RL only	$\mathcal{O}(KL)$	$\mathcal{O}(KL)$

and BSs. Without DT, the EVs aim to maximize their own reward and BS reward for maximizing SW and do not have knowledge about the reward of other EVs. Also, when multiple EVs are matched with the same BS, the energy exchange in RL without DT takes place as soon as the first EV reaches the BS which may result in a lower SW as compared to the EV which could arrive later.

D. Asymptotic Complexities and Scalability

Table IV lists asymptotic communication and computation complexities of all approaches. RL with DT regularly acquires data from BSs and EVs and shares only RL algorithm to EVs only. The communication complexity is equivalent RL with FL, where BSs and EVs upload local model. The global models of both EVs and BSs are shared with EVs only. In RL only, the communication cost with central server is eliminated. EVs only communicate with reachable BSs to get information about their SoC and update other EVs only when the energy exchange takes place. RL with DT trades off communication and computation cost for a larger amount of energy exchange.

For evaluating computation complexity, we consider that each available EV calculates the SW by matching itself with each BS, as shown in Algorithm 1. Specifically in RL with DT, the algorithm additionally checks if a BS selected by EV for energy exchange has already been matched with another EV, as shown in line 8 to line 13 of Algorithm 1. In RL with FL, each BS and EV computes a local model and each EV computes RL algorithm also. Considering $K > L$, the computation complexity of RL with FL is the highest and RL only has least computation complexity.

In a predefined region, the number of BSs and EVs cannot increase beyond a certain extent. For better scalability, a large transportation network can be divided into a number of clusters, each with its own DT.

VI. Conclusion

This paper proposes to utilize surplus energy stored in batteries of BSs and EVs to meet the energy demands in case of a disaster. A bidirectional energy exchange is considered where both BSs and EVs can either sell or buy energy to and from each other. A DT based RL solution is formulated to optimize the energy exchange in a 5G V2X network. Simulation results show that BSs are able to sell larger amount of energy and earn greater reward because they do not have to consume energy for traveling and bear related costs. Furthermore, both energy exchange and reward are reduced to half when RL solution is performed individually by EVs. It concludes that DT is effective for centrally managing the energy exchange for all EVs by real-time data acquisition for better decision-making. However, there is an increase in communication and computation complexity of DT is employed.

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