IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 31 July 2024, accepted 23 August 2024, date of publication 28 August 2024, date of current version 10 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3451186

RESEARCH ARTICLE

A Novel Prosumer-Centric Smart Contract Based Approach for Blockchain-Enabled Energy Scheduling Using Electric Vehicles

IMRAN HUSSAIN[1], HAFIZ ASHIQ HUSSAIN[1], (Member, IEEE), NASIM ULLAH[2], (Member, IEEE), AND STANISLAV MISAK[3]

[1]Department of Electrical and Computer Engineering, Air University, Islamabad 44230, Pakistan
[2]Department of Electrical Engineering, College of Engineering, Taif University, Taif 11099, Saudi Arabia
[3]ENET Center, VSB—Technical University of Ostrava, 70800 Ostrava, Czech Republic

Corresponding author: Nasim Ullah (nasimullah@tu.edu.sa)

This research work was supported by Taif University, Saudi Arabia under Project: TU-DSPP-2024-25.

ABSTRACT Conventional centralized optimization and management approaches may not work well in an emerging and distributed energy system with a high penetration of electric vehicles and green energy sources. The usage of blockchain technology is growing as a strong competitor as it can provide this kind of market with a transparent, secure, and efficient transactional platform. Nevertheless, most energy systems usually depend on complex mathematical optimization, which is poorly incorporated into blockchain applications. Moreover, time-sensitive message dissemination requirements, resource-intensiveness, high computational load, and communication overhead of the traditional blockchain consensus mechanisms make it difficult to connect with real-time vehicular networks. Here, we employ Proof of Intelligence (PoI), a novel prosumer-centric blockchain consensus mechanism to develop a comprehensive model of trust based on commitments of supply and demand through the application of peer-to-peer energy exchange with effective and dynamic integration of renewable sources and electric vehicles both in the day ahead and real-time energy trading platforms. Additionally, the PoI smart contract is developed to seamlessly incorporate mathematical optimization with an increased level of security, scalability, throughput, and low confirmation latency of transactions achieved through the reduced effort involved in finding and confirming the optimal solution in comparison with conventional blockchain consensus mechanisms.

INDEX TERMS Blockchain-enabled energy scheduling, consensus mechanism, distributed energy resource, distributed ledger technology, energy trading, proof of intelligence, smart contract.

NOMENCLATURE

$\alpha^{\text{EV,SE}}_{\text{kd}\omega}$	Factor employed for modelling of final state of batteries of EVs.
$\alpha^{\text{EV,SI}}_{\text{kd}\omega}$	Factor employed for modelling of initial state of batteries of EVs.
η^{EV}	Charging/ discharging efficiency of EVs.
ω	Scenario index, Ω: Scenario array.
π_ω	Probability of occurence of a typical scenario ω.
$\theta^{B}_{\text{bt}\omega}$	Voltage angle at an identified bus during specific time interval in balancing market.
θ^{D}_{bt}	Voltage angle at an identified bus during specific time interval in day ahead market.
A^{D}_{gtd}	Availability factor of renewable source during specific time interval in day ahead market.

The associate editor coordinating the review of this manuscript and approving it for publication was Inam Nutkani.

b	Bus index, B: b's array.
C^{UD}	Price of unfulfilled demand.
$c_{\mathrm{gt}}^{G,\mathrm{D}}$	Cost offered by the generating entity in day-ahead market.
$c_{\mathrm{gt}}^{G,\mathrm{RCD}}$	Low backup price of generating entity g for specific time interval.
$c_{\mathrm{gt}}^{G,\mathrm{RCU}}$	High backup price of generating entity g for specific time interval.
$c_{\mathrm{gt}}^{G,\mathrm{SD}}$	Generation entity's shutdown cost.
$c_{\mathrm{gt}}^{G,\mathrm{SU}}$	Generation entity's startup cost.
$C_{\mathrm{kbt}}^{EV,\mathrm{CD}}$	Bidding cost of EV group k charging in the day ahead marketplace connected to a typical bus during specific time interval.
$C_{\mathrm{kbt}}^{EV,\mathrm{DD}}$	Bidding cost of EV group k discharging in the day ahead marketplace connected to a typical bus during specific time interval.
$C_{\mathrm{kbt}}^{EV,\mathrm{RCD}}$	Cost of low backup provided by EVs group k connected to bus b during specific time interval.
$C_{\mathrm{kbt}}^{EV,\mathrm{RCU}}$	Cost of high backup provided by EVs group k connected to bus b during specific time interval.
$e_{\mathrm{kbt}\omega}^{\mathrm{EV}}$	Stored energy of EVs batteries in specific environment.
$E_{\mathrm{max,k}}^{\mathrm{EV}}$	Maximum capacity of batteries of EVs group.
$F(l)$	Line l destination bus.
g	Generating entity index, G: g's array.
G^{D}	Dispatchable generating entities array.
G^{I}	Intermittent generating entities array.
G_{b}	Generating units array connected with bus b.
k	Index of EVs groups, K: $k's$ array.
l	Transmission line index, L: $l's$ array.
L_{b}^{F}	Transmission lines array connected to terminating bus b.
L_{b}^{O}	Transmission lines array connected to starting bus b.
$N_{\mathrm{kb}}^{\mathrm{EV}}$	Number of EVs in a group connected to bus b.
$O(l)$	Line l origin.
$p_{\mathrm{bt}\omega}^{\mathrm{UD,B}}$	Unfulfilled demand in the run time market.
$P_{\mathrm{bt}}^{\mathrm{D,D}}$	Demand of power in the day ahead trading zone.
$P_{\mathrm{DW,g}}^{\mathrm{G}}$	Low ramp factor of generating entity.
$p_{\mathrm{gt}\omega}^{G,\mathrm{B}}$	Power harnessed through the generating entity in the run time marketplace.
$p_{\mathrm{gt}}^{G,\mathrm{D}}$	Energy planned by generating entity in day ahead marketplace.
$p_{\mathrm{kbt}\omega}^{EV,\mathrm{BC}}$	Power charging of EVs array in a typical situation.
$p_{\mathrm{kbt}\omega}^{EV,\mathrm{BD}}$	Power discharging of EVs array in a typical situation.
$p_{\mathrm{kbt}}^{EV,\mathrm{CD}}$	Charging energy of EVs planned in the day ahead marketplace.
$p_{\mathrm{kbt}}^{EV,\mathrm{DD}}$	Discharging energy of EVs planned in the day ahead marketplace.
$p_{\mathrm{lt}\omega}^{L,\mathrm{B}}$	Power flowing through the transmission line l in run time marketplace.
$p_{\mathrm{lt}\omega}^{L,\mathrm{D}}$	Power passing through the transmission line l in day ahead marketplace.
$P_{\mathrm{max,g}}^{\mathrm{G}}$	Upper bound of generating entities.
$P_{\mathrm{max,k}}^{\mathrm{EV}}$	Highest rate of charging and discharging of electrical vehicles in a single group.
$P_{\mathrm{max,l}}^{\mathrm{L}}$	Transmission line active power carrying capacity.
$P_{\mathrm{min,g}}^{\mathrm{G}}$	Lower bound of generating entities.
$P_{\mathrm{UP,g}}^{\mathrm{G}}$	Upper ramp factor of generating entity.
$r_{\mathrm{gt}\omega}^{\mathrm{G,DD}}$	Deployment of low backup by the generating entity.
$r_{\mathrm{gt}\omega}^{\mathrm{G,DU}}$	Deployment of high backup by the generating entity.
$r_{\mathrm{gt}}^{G,\mathrm{CD}}$	Low backup planned by generating entity g for specific time interval.
$r_{\mathrm{gt}}^{G,\mathrm{CU}}$	High backup planned by generating entity g for specific time interval.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUD}}$	Deployment of high backup from discharging of group of EVs.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}}$	Deployment of low backup achieved through the charging of EVs array.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDD}}$	Deployment of low backup achieved through discharging of EVs array.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DD}}$	Deployment of low backup planned by EVs group.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUC}}$	Deployment of high backup from the charging of EVs array.
$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DU}}$	Deployment of high backup of EVs array.
$r_{\mathrm{kbt}}^{\mathrm{EV,CD}}$	Low backup planned by EVs group.
$r_{\mathrm{kbt}}^{\mathrm{EV,CU}}$	High backup planned by EVs group.

I. INTRODUCTION

An energy system is an assemblage of discrete networks, sources, sinks, corresponding accountable stakeholders, relevant information, and physical fluxes [1]. The information is obtained from observing both individual actors' decisions and physical processes. Interfaces for information sharing are how data is transferred between various accountable stakeholders [2], [3]. Energy networks are expected to become more complex as information volumes and the variety of controllable components rise. It will require additional information to be handled at already-existing interfaces or result in the construction of new ones when combined with the decentralization of duties [4]. One instance of this in the context of electrical networks is the potential conversion of Great Britain's (GB) distribution network operators (DNOs) to distribution system operators (DSOs). DNOs would be tasked with more specialized balancing duties as part of the shift [5], [6], [7]. As a result, more intricate agreements would be needed at interfaces i.e. between two distribution systems or a distribution system and a transmission system, as neighboring stakeholders would be increasingly dependent on the predictable actions of neighboring networks. It begs the question of what- if any, uniform regulations at the interfaces between accountable stakeholders could improve the security and economy of energy system planning and operation [8], [9], [10]. One such upcoming decentralized distributed ledger system is blockchain. In P2P networks, blockchain enables reliable transaction execution, synchronized information exchange, and secure data storage. Blockchain offers a decentralized platform that eliminates the need for a central middleman to record and validate energy transactions [11]. Moreover, blockchain makes it possible to create smart contracts, which have the ability to automate energy trade and encourage EV owners to take part in energy management procedures. The intrinsic qualities of the blockchain offer tremendous promise for peer-to-peer energy trade to strengthen power grid resilience.

The consensus mechanism, which is the foundational technology of blockchain technology, is essential to the efficient and safe operation of blockchain-based resilient power grids. Nonetheless, classic consensus or enhanced variants built upon these traditional processes make up most consensus mechanisms applicable to peer-to-peer energy trading. However, these consensus processes need a significant amount of computer power and enhanced connectivity, reducing their applicability in real-world Internet of Things (IoT) applications like energy trading. Grid resilience can only be improved by facilitating the practical deployment of peer-to-peer energy trading once this fundamental problem has been resolved [12].

Utility Grids can benefit from aggregated EVs' large-scale battery storage and load frequency control capabilities [13]. The unpredictable nature of electric vehicle (EV) charging and routing presents another challenge for utilities and distribution operators managing EV demand [14]. While EV nodes are quite mobile, the majority of energy trading nodes are immobile. Nevertheless, most existing consensus techniques for blockchains do not allow for the dynamic addition and deletion of nodes [15], [16], [17]. Therefore, we employ a novel consensus technique known as Proof of Intelligence (PoI) to address the challenges associated with vehicular energy trade, enhance the resilience of a renewable energy-integrated power grid, and achieve security, decentralization, and unlimited scalability. This paper has made the following contributions:

- We consider two strategies, one for low traffic volume (group of EVs-k1) and the other for large traffic volume (group of EVs-k2), based on the number of EVs participating in energy trade.
- We go beyond the conventional consensus framework and use the sharding technique based on the characteristics of EVs and the internet of EVs (IoEV) to achieve limitless scalability.
- We disprove the security, unlimited scalability, and decentralization impossibilities of blockchain technology in the context of energy trade.
- The cross-shard trading commit mechanism is suggested for the frequent mobility of electric vehicles. For EV leader election, the PoI consensus mechanism provides unlimited scalability without compromising security. To further increase the transaction speed, we leverage the Hashgraph within each shard as a replacement for conventional consensus techniques.

The advent of smart contract platforms, which are commonly referred to as distributed ledger or blockchain technologies, provides a chance to safely automate numerous interface-related processes and perhaps reduce overall system costs [18]. The notion of smart contracts, which are self-executing agreements in the form of executable software codes, was first introduced by Szabo in 1994 and offers a way to establish highly trustworthy negotiation and self-enforcing settlement processes [19]. These smart contracts developed through blockchain technology can be verified, secured, and replicated. "If A occurs, credit B to account C" can be a basic rule to develop a smart contract [20], [21]. The self-executing aspect of the "credit" statement is an important innovation. The digitally encoded event in the example, "X," is a result of a sensor reading. Therefore, the reliability of sensors, information encoding, and information transfer ultimately determine the reliability of any smart contract method. Furthermore, there is currently discussion and investigation to determine how smart contracts fit into the current legal frameworks. When decision-makers are dispersed around many organizations or between divisions of one larger organization, a smart contract is an excellent tool for enacting agreements for cooperative management of energy exchange procedures [22], [23].

In electrical networks, shared energy transfer operations include the control of components like transformer tap changers, switches, and converters while creating a DC link. DC-links provide the ability to precisely regulate the flow of energy between electrical circuits and provide a clear means of assigning accountability for the management and operation of individual electrical network segments [24]. It is commonly known that DC links can lower network costs by controlling the set points for active and reactive power. Additionally, DC links can disconnect networks, which would make it obvious who is in charge of the system's frequency and, consequently, the stability of the power grid. Hence, the use of smart contracts may be able to reduce unexpectedly complicated control interactions amongst energy systems [25]. Furthermore, agreed norms for shared control can be instantiated in a fashion that is less vulnerable to manipulation and less dependent on conventional techniques for the prosecution of infractions because smart contracts are self-enforcing. Options that are susceptible to manipulation by one or more participants include one-sided authority via a distribution management network or control that is only based on sensor measurements [26].

The goal of this effort is to define the best way for system operators and other stakeholders to think about using smart contracts in energy systems. In doing so, it is necessary to take into account the shared features that smart contracts have in addition to how players engage with them [27], [28], [29]. In general, the dilemma of which controlling factor should be chosen in any given circumstance arises when multiple energy networks, each with several accountable parties, are linked by the same regulated procedure [30], [31], [32]. Here, we describe a generic smart contract type that may be used at any size of power network that has effective surveillance and command to enable shared control over energy transfer procedures. The six steps of the general form of the smart contract include deposit, preference setting, negotiation, procedure instruction, settlement, and withdrawal. We demonstrate the application of smart contracts to control directives between respective parties through the use of an emulated smart contract platform. The comparative performance evaluation metrics of different optimization architectures employed in peer-to-peer energy trading market are shown in Table 1.

TABLE 1. Comparative performance evaluation of optimization techniques.

Description	Centralized	Hierarchical	Blockchain as facilitator	PoI
Computational time (s)	12	77	618	19
Expense growth due to dishonesty (%)	15.3	15.3	0	0
Examples	ref [33]	ref [34]	ref [28]	This article

II. SMART CONTRACT FOR COOPERATIVE MANAGEMENT

Fig. 1 illustrates the overall form of a smart contract that is suggested for use in negotiations and settlements involving controllable processes between two or more concerned stakeholders. We classify information flows within the accountable stakeholders into three layers: decision support, data processing, and decision making [35]. The interface between physical apparatus including metering and protocols of maintenance schedules is the data processing layer dealing with data gathering, compression, and storage. After the available data has been analyzed, information is presented to decision-makers as part of the decision support layer. Cost-minimizing optimization is one instance of the decision support layer [36]. Moreover, the decisions about a controllable process are made at the decision-making layer. The places where a decision maker from one stakeholder must reach a consensus with a decision maker from another stakeholder are known as agreement interfaces [4], [37], [38].

The interoperability defined by the Smart Grid Architecture Model (SGAM) is expanded here by the conceptual framework. According to the SGAM, interoperability is the ability of multiple networks to exchange information to work together to accomplish a common goal [39]. In our approach, a smart contract gives instructions for an actual procedure to integrate the information exchange and control function. To carry out the shared control function, a generic form of smart contract is defined in the suggested architecture, which classifies the data gathering and processing processes.

Particularly, distributed green energy sources like photovoltaic panels, wind turbines, and other decentralized energy-producing entities are the focus of the energy side. The consumers cover a wide spectrum of stakeholders who actively participate in energy trading and consumption, such as users of electric vehicles, microgrids, businesses, and industries. The grid-connected photovoltaic system's worldwide total capacity of 843.09 GW is currently considered the fastest-growing renewable energy technology [40]. The stakeholders in this blockchain-based renewable energy trading platform can conduct a variety of business interactions with one another. Customers can exchange energy with other users or give the grid their excess renewable energy when they participate in distributed energy services between grids and customers. Furthermore, grids and customers work together to maintain equipment, guaranteeing the dependable and effective operation of renewable energy systems. Another facet of the business connection is energy efficiency testing, which enables clients to verify and enhance their patterns of energy usage. Additionally, grids and consumers can represent themselves in commerce, serving as middlemen in energy transactions and assisting in negotiations between buyers and sellers. Another big commercial possibility is data trading, which makes it possible to exchange energy-related data including output estimates, consumption trends, and grid demand. In the ecosystem of renewable energy, this data exchange promotes transparency and allows for well-informed decision-making. This renewable energy trading mechanism is built on top of blockchain technology, which has built-in benefits including immutability, security, and transparency. Blockchain technology can be employed to create a decentralized ledger that transparently and auditably records and verifies all energy transactions. This makes peer-to-peer energy trading easier, fosters trust among participants and does away with the need for middlemen.

III. DAY-AHEAD AND BALANCING ENERGY MARKETS

In this study, we primarily address how the daily electricity market functions in the light of widespread use of electric vehicles. The day-ahead market and the run-time operations are represented as a two-stage mixed-integer problem. Energy and corresponding backup capacity are set aside in the day-ahead marketplace for the whole 24 hours of the next day [41], [42], [43]. This problem is unique in that when EVs are linked to the network, they can offer backup services in addition to dispatchable generating entities. The decision-making process and the problem's unknown parameters including power consumption, battery level of EVs at the start of the charging time, and the fluctuation of intermittent renewable generation sources are represented using stochastic programming [44]. A set of scenarios is created to show the range of possible

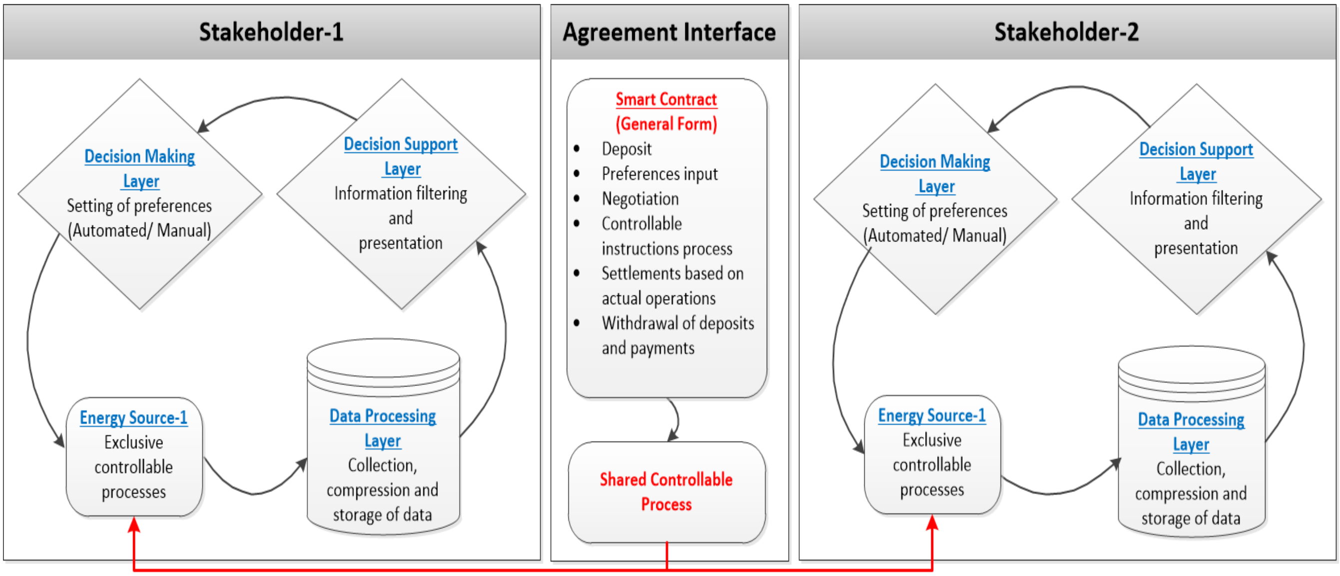

FIGURE 1. Smart contract architecture for cooperative management of an energy transfer procedure. Stakeholders must demonstrate that they have enough money to cover the outcome of the negotiations during the deposit stage. In the event that one stakeholder doesn't, the other regains control of the shared process. Communicating the degree of desire for each operational point is part of the preference establishing process. Subsequently, during the discussion phase, the contract establishes a predetermined set of guidelines about preferences and provides a designated operational point. It is employed to provide instructions to the actual hardware throughout the procedure. Peer-to-peer payments are calculated in the 'settlement' point of the contract according to a set of guidelines based on the negotiation and real-world operations. Lastly, if specified in the regulations, a way to withdraw the deposit and any peer-to-peer payouts is also provided in the smart contract.

Algorithm 1 Implementation of Smart Contract

function `init()`:
- **Input**: u, IK_u, $gNumb_u$
- $\{Cert_u, GD_u, qD_u, loc_u\} \leftarrow \text{record}(ID_u, gNumb_u)$

end

function `create()`:
- **Input**: z_u, sub_q, π_u, z_u, $time(t)$, $gCost$, $timestamp(ts)$, sub_u
- confirm(sub_q);
- confirm($sub_u \geq \pi_u$);

end

function `invoke()`:
- **Input**: w_q, w_u
- confirm($t \geq time(t)$);
- $surcharge_q \leftarrow \text{surcharge}(z_u, w_q, w_u, gCost)$;
- forward($surcharge_q + u$, $sub_u - \pi_u$);
- forward(q, $sub_q + \pi_u - surcharge_q$);

end

outcomes for these factors considered during different time intervals.

A power network's operation is a complicated problem that can be divided into multiple phases. First, a process known as "market clearing" is carried out on an hourly basis [45]. The market clearing is often a day-ahead marketplace which is realized a day before the real-world energy provisioning. Determining the energy harnessed through each source, the energy utilized by each load, and the pricing needed to clear the marketplace for each hour of the following day is the goal of the market-clearing mechanism [46]. Moreover, to satisfy the technological prerequisites of the generating entities, electric loads, and transmission lines while adjusting generation to the true requirements for consumption in each time instant, short-time markets which can last anywhere from a few minutes to several hours as an adaptation and marketplaces for supplementary services, are cleared. Power systems with many uncertain production entities and loads are highly sought after by these markets. It is pertinent to mention here that the day ahead marketplace is where the maximum energy trading is negotiated [47], [48].

The power harnessing through wind and photovoltaic panels as well as power demand whether customary or related to EV charging are the primary sources of unpredictability that need to be considered when scheduling the power system. Stochastic processes segregated into a set of scenarios are used to describe these unknown parameters. Such numerical traits are deduced from the historical information [49]. The uncertainty relates to the amount of time the electric vehicles are plugged into the power grid and the initial state of charge (SOC) of their batteries, which establishes the total amount of energy they require and limits the amount of energy they can supply. It is assumed that the users require the batteries of their electric vehicles to be fully charged after the charging slots [50], [51].

The following details highlight the degree of uncertainty surrounding the batteries' initial level of charge [51], [52]:

- Keeping in view historical data, a probability distribution is identified that describes the daily distance driven by electric vehicles. A limited number of scenarios comprise the discretized probability distribution. Every

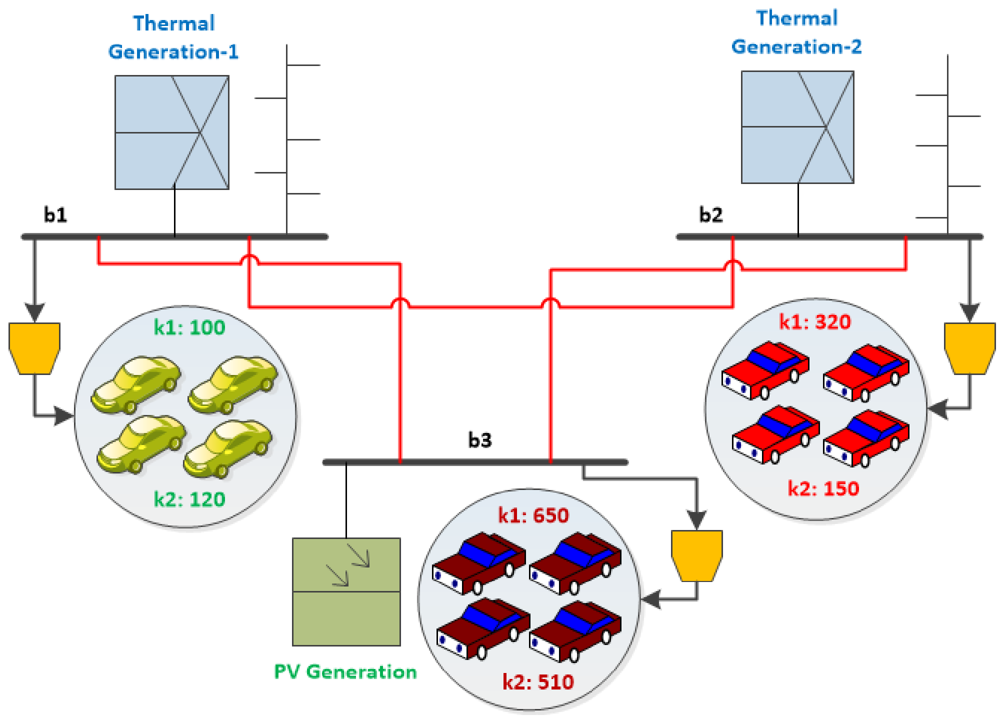

FIGURE 2. Schema of day-ahead scheduling network. Thermal power is produced through generating entities 1 and 2, while renewable power is harnessed through the generation entity 3. The electric vehicles are divided into two types based on how long it takes to charge them.The EVs in group-1 are plugged in during 2^{nd} and 3^{rd} periods while group-2 EVs are only plugged in during the final period.

scenario has a likelihood of occurrence based on the information linked with the daily distance driven by electric vehicles.

- The daily energy usage of every kind of electric vehicle is calculated under different circumstances, taking into account the average electricity consumption per driven kilometer as well as the daily driven distance. This data is used to calculate the batteries' original state of charge (SOC) at the start of the charging cycle.

Additionally, electric vehicles are divided into several categories $k \in K$ such that EVs with similar trends of usage are treated as the same category. The mileage driven each day and the times when EVs are accessible for charging define the EV type. In this sense, it is believed that the original battery state of charge and connecting durations of all EVs of the same type will be similar.

The methodology for day-ahead market clearing ascertains the following:

- The day-ahead generated power $p_{gt}^{G,D}$ and the high and low backup capacities $r_{gt}^{G,CU}$ and $r_{gt}^{G,CD}$ for generating entity g and time interval t.
- The energy sale and purchase in the day-ahead marketplace $p_{kbt}^{EV,DD}$ and $p_{kbt}^{EV,CD}$ as well as the high and low backup capacities $r_{kbt}^{EV,CU}$ and $r_{kbt}^{EV,CD}$ for respective vehicle group connected with a typical bus during a specific time slot.

The highest amount of energy that generation entities and electric vehicles are compelled for deployment if the electric load or the generation of green energy varies from their anticipated output during run time operation is represented by the scheduled up and down backup capacity. Consequently, this capacity is set aside for the deployment of the operating backup, which is utilized to track hourly variations in intermittent demand and production [53].

The procedure of market clearance is expressed as a dual-phase stochastic programming problem, where the first phase is the day ahead marketplace in which various market actors are assigned distinct schedules for energy and backup capacity. The second step of the run-time market operation is characterized by the determination of backup deployment for multiple realizations of the indeterminate parameters. Energy and backup capacity can be co-optimized in the day-ahead marketplace to give the system the flexibility to handle sporadic renewable electricity and potential deviations in the predicted demand [54], [55], [56].

IV. MATHEMATICAL MODELING OF ENERGY TRADING

The problem previously explained is fully formulated mathematically in this part [57]. The following presumptions have been taken into account:

- It is assumed that the goal of the System Operator (SO), whose perspective is taken into account, is to minimize the estimated production cost [58].
- It is believed that the demand is not elastic. Consequently, it is also believed that EV owners want to charge

Algorithm 2 Consensus Mechanism for Energy Scheduling

Input : Delegation A
Step 1: First delegate (x) in delegation (A) is taken as the leader p;
if $x = d$ **then**
  Step 2: Determine solution (z^*) and share it with all other stakeholders in the market;
end
if $x \neq d$ **then**
  if $(z^*)_{d,x_1,x_2,\ldots,x_k}$ *is received before time duration* T *and* $z^* \not\subseteq C_{x,r}$ **then**
    if z^* *is considered as an optimal solution* **then**
      Step 3: $C_{x,r} \leftarrow C_{x,r} \cup \{z^*\}$;
      share $(z^*)_{d,x_1,x_2,\ldots,x_k}$ with all other delegates except $d, x_1, x_2, \ldots, x_k$;
    end
  end
  if $|C_{x,r}| > 0$ **then**
    Step 4: Sharing $(z^*)_d$ with all other stakeholders in the market;
    moving d in the last of A;
  end
  else
    Step 5: $C_{x,b} \leftarrow C_{x,b} \cup \{d\}$;
    remove p from A;
    Step 6: go to step-1 (first delegate (x) in delegation (A) is taken as the leader d);
    Step 7: intelligent selection of delegate as a leader of the delegation;
    $x_i = d$;
    if *(miner x_i's previously mined blocks > blocks mined by other delegates)* **then**
      if *(miner x_i's erroneous mined blocks < erroneous blocks mining by other delegates)* **then**
        if *(miner x_i's time taken to mine block < time taken by other delegates to mine blocks)* **then**
          if *(miner x_i's age in network > average age of other delegates)* **then**
            $x_i = d$;
          end
        end
      end
    end
  end
end
Output: Solution z^*

their cars to a certain extent regardless of the cost of electricity.

- The inclusion of unit commitment variables for thermal entities enables the description of their minimum power output as well as the costs incurred for starting up and shutting down [59].
- It is assumed that the generation-side offer curves are linear.
- Only dispatchable thermal entities, not intermittent renewable entities can supply backup capacity. Because of the flexibility offered by the batteries, EVs can also offer power backup when they are plugged into the network [60].
- The endogenous computation of backup capacity needs is based on the situations under consideration. As a result, limitations on determining minimum backup requirements are ignored [60].
- A DC formulation is employed to depict the transmission system [47].

Algorithm 3 Optimal Smart Contract and Energy Scheduling

Input : λ_s, $Numb_s$, Θ_s, Θ, ω
for $\Theta_s \in \Theta$ **do**
  initiate $z_s^* = \bar{z}_s^* = \underset{z_s \in \omega}{\operatorname{argmax}}\ \lambda_s$;
end
while z_s^* *is an infeasible solution* **do**
  find an infeasible subsequence $\{\bar{z}_n^*, \bar{z}_{n+1}^*, \ldots, \bar{z}_m^*\}$;
  assign the optimal demand as
  $z_l^* = \operatorname{argmax} \sum_{s=n}^{m} \lambda_s(z), \forall l = n, n+1, \ldots, m$;
end
for $\Theta_s \in \Theta$ **do**
  assignment of optimal cost Ω_s^*;
end
if $E_{bkp} < \sum_{s=1}^{S} Numb_s \Theta_s z_s^*$ **then**
  make adjustments to optimal contract;
end
Output: optimal contract $\phi = \{(\tilde{z}_s, \tilde{\Omega}_s) | \forall \Theta_s \in \Theta\}$

Eq. 1 expresses the objective function to be minimized. Because of this inelastic system demand, minimizing the predicted operation cost is the same as maximizing the expected social welfare. This means that objective function consists of the following: (i) the costs associated with generating entities in the day ahead marketplace for starting up, shutting down, planned energy, and high and low backup capacity (ii) the energy stored and released to EVs planned in the day ahead marketplace along with high and low backup capacity to be provided (iii) the anticipated expenses of deploying high and low backup by generating entities and EVs in the run time market and (iv) the anticipated expenses of the involuntary unserved load.

$$
\begin{aligned}
&\text{Minimize}_{\theta} \\
&\sum_{t \in T} \sum_{g \in G} \Big(c_{\mathrm{gt}}^{G,\mathrm{SU}} + c_{\mathrm{gt}}^{G,\mathrm{SD}} + c_{\mathrm{gt}}^{G,D} . p_{\mathrm{gt}}^{G,D} + c_{\mathrm{gt}}^{G,\mathrm{RCU}} . r_{\mathrm{gt}}^{G,\mathrm{CU}} \\
&+ c_{\mathrm{gt}}^{G,\mathrm{RCD}} . r_{\mathrm{gt}}^{G,\mathrm{CD}} \Big) \\
&+ \sum_{t \in T} \sum_{b \in B} \sum_{k \in K} \Big(C_{\mathrm{kbt}}^{\mathrm{EV,DD}} . p_{\mathrm{kbt}}^{\mathrm{EV,DD}} - C_{\mathrm{kbt}}^{\mathrm{EV,CD}} . p_{\mathrm{kbt}}^{\mathrm{EV,CD}} \\
&+ C_{\mathrm{kbt}}^{\mathrm{EV,RCU}} . r_{\mathrm{kbt}}^{\mathrm{EV,CU}} + C_{\mathrm{kbt}}^{\mathrm{EV,RCD}} . r_{\mathrm{kbt}}^{\mathrm{EV,CD}} \Big) \\
&+ \sum_{t \in T} \sum_{\omega \in \Omega} \pi_{\omega} \Big[\sum_{g \in G^D} \Big(C_{\mathrm{gt}\omega}^{G,\mathrm{RDU}} . r_{\mathrm{gt}\omega}^{G,\mathrm{DU}} - C_{\mathrm{gt}\omega}^{G,\mathrm{RDD}} . r_{\mathrm{gt}\omega}^{G,\mathrm{DD}} \Big) \\
&+ \sum_{b \in B} \sum_{k \in K} \Big(C_{\mathrm{kbt}\omega}^{\mathrm{EV,RDU}} . r_{\mathrm{kbt}\omega}^{\mathrm{EV,DU}} - C_{\mathrm{kbt}\omega}^{\mathrm{EV,RDD}} . r_{\mathrm{kbt}\omega}^{\mathrm{EV,DD}} \Big) \\
&+ \sum_{b \in B} C^{\mathrm{UD}} . p_{\mathrm{bt}\omega}^{\mathrm{UD},B} \Big]
\end{aligned} \tag{1}
$$

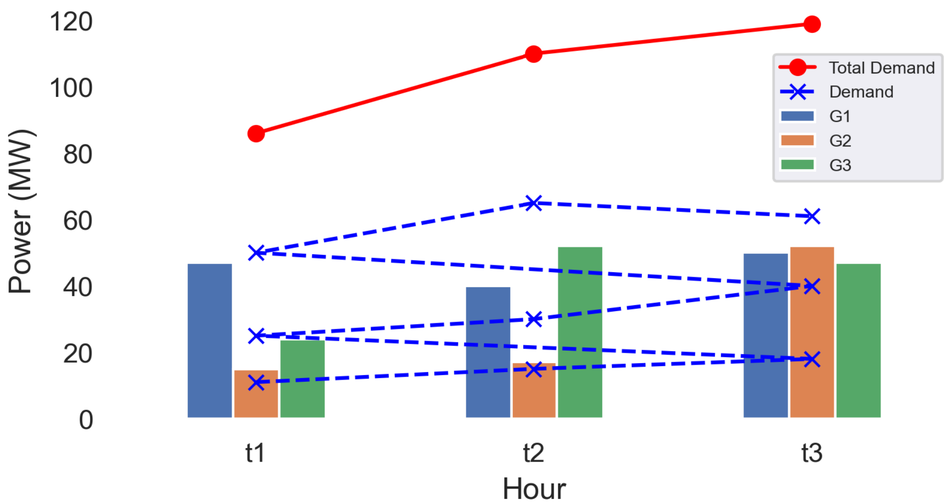

FIGURE 3. Day ahead energy scheduling. The demand power for each network bus and hour, energy scheduled by producing entities and overall demand is depicted.

where, set of optimization variables is given as, $\Theta = \{c_{\mathrm{gt}}^{G,\mathrm{SU}}, c_{\mathrm{gt}}^{G,\mathrm{SD}}, p_{\mathrm{gt}}^{G,D}, r_{\mathrm{gt}}^{G,\mathrm{CD}}, r_{\mathrm{gt}}^{G,\mathrm{CU}}; p_{\mathrm{gt}\omega}^{G,B}, p_{\mathrm{gt}\omega}^{G,\mathrm{BS}}, r_{\mathrm{gt}\omega}^{G,\mathrm{DD}}, r_{\mathrm{gt}\omega}^{G,\mathrm{DU}}; p_{\mathrm{kbt}}^{\mathrm{EV,CD}}, p_{\mathrm{kbt}}^{\mathrm{EV,DD}}, r_{\mathrm{kbt}}^{\mathrm{EV,CD}}, r_{\mathrm{kbt}}^{\mathrm{EV,CU}}, e_{\mathrm{kbt}\omega}^{\mathrm{EV}}, p_{\mathrm{kbt}\omega}^{\mathrm{EV,BC}}, p_{\mathrm{kbt}\omega}^{\mathrm{EV,BD}}, r_{\mathrm{kbt}\omega}^{\mathrm{EV,DD}}; r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}}, r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDD}}, r_{\mathrm{kbt}\omega}^{\mathrm{EV,DU}}, r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUC}}, r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUD}}; p_{\mathrm{lt}\omega}^{L,D}, p_{\mathrm{lt}\omega}^{L,B}; \theta_{\mathrm{bt}}^{D}, p_{\mathrm{bt}\omega}^{\mathrm{UD},B}, \theta_{\mathrm{bt}\omega}^{B}; \forall g \in G, \forall t \in T, \forall \omega \in \Omega, \forall k \in K, \forall b \in B, \forall l \in L\}$.

A. DAY-AHEAD MARKET

The ensuing collection of day-ahead marketplace constraints applies to the objective function. The energy balance is enforced in each bus and time slot by the power balance constraint (see Eq. 2).

$$\sum_{g\in G_b} p_{\mathrm{gt}}^{G,D} + \sum_{k\in K}\left(p_{\mathrm{kbt}}^{\mathrm{EV,DD}} - p_{\mathrm{kbt}}^{\mathrm{EV,CD}}\right) - \sum_{l\in L_b^O} p_{\mathrm{lt}}^{L,D} + \sum_{l\in L_b^F} p_{\mathrm{lt}}^{L,D} = P_{\mathrm{bt}}^{D,D}, \quad \forall b \in B, \forall t \in T \tag{2}$$

Constraints (3a-3g) explain how generating entities work technically. Constraint (3a) sets the lowest and highest limits of power output for dispatchable entities based on the unit-commitment paradigm. Constraints (3b) and (3c) enforce the dispatchable entities' ramping limits, both upward and downward. Constraint (3d) restricts the power production of sporadic renewable entities based on the renewable resource's availability factor considered for each hour. The startup and shutdown prices are defined by constraints (3e-3g), taking into account whether the generating entity switches between on and off from one period to the next.

$$u_{\mathrm{gt}}.P_{\mathrm{min},g}^{G} \le P_{\mathrm{gt}}^{G,D} \le u_{\mathrm{gt}}.P_{\mathrm{max},g}^{G} \tag{3a}$$
$$P_{\mathrm{gt}}^{G,D} - P_{\mathrm{gt}-1}^{G,D} \le P_{\mathrm{UP},g}^{G} \tag{3b}$$
$$P_{\mathrm{gt}-1}^{G,D} - P_{\mathrm{gt}}^{G,D} \le P_{\mathrm{DW},g}^{G} \tag{3c}$$
$$0 \le P_{\mathrm{gt}}^{G,D} \le A_{\mathrm{gtd}}^{D}.P_{\mathrm{max},g}^{G} \tag{3d}$$
$$c_{\mathrm{gt}}^{G,\mathrm{SU}} = C_{g}^{G,\mathrm{SU}} u_{\mathrm{gt}} - u_{g,t-1} \tag{3e}$$
$$c_{\mathrm{gt}}^{G,\mathrm{SD}} = C_{g}^{G,\mathrm{SD}} u_{g,t-1} - u_{\mathrm{gt}} \tag{3f}$$
$$c_{\mathrm{gt}}^{G,\mathrm{SU}}, c_{\mathrm{gt}}^{G,\mathrm{SD}} \ge 0; \quad \forall g \in G^{D}, G^{I}, \forall t \in T \tag{3g}$$

The power charging and discharging planned in the day ahead marketplace for specific time intervals is limited by technical constraints (see Eqs. 4a and 4b).

$$0 \le P_{\mathrm{kbt}}^{\mathrm{EV,CD}} \le N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\mathrm{max},k}^{\mathrm{EV}} \tag{4a}$$
$$0 \le P_{\mathrm{kbt}}^{\mathrm{EV,DD}} \le N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\mathrm{max},k}^{\mathrm{EV}}; \quad \forall k \in K, \forall b \in B, \forall t \in T \tag{4b}$$

The restrictions on the backup capacity scheduled in the day-ahead market are imposed by constraints (5a-5d). Eq. (5a) limits the up backup capacity for the generating entities while accounting for their capacity and the scheduled energy, and (5b) sets the maximum down backup capacity at the same level as the scheduled energy. Constraints (5c) and (5d) impose the non-negativity of the up and down backup capacities on the EVs respectively.

$$0 \le r_{\mathrm{gt}}^{G,\mathrm{CU}} \le u_{\mathrm{gt}}.P_{\mathrm{max},g}^{G} - P_{\mathrm{gt}}^{G,D} \tag{5a}$$
$$0 \le r_{\mathrm{gt}}^{G,\mathrm{CD}} \le P_{\mathrm{gt}}^{G,D} \tag{5b}$$
$$r_{\mathrm{kbt}}^{\mathrm{EV,DU}} \ge 0 \tag{5c}$$
$$r_{\mathrm{kbt}}^{\mathrm{EV,DD}} \ge 0; \quad \forall g \in G^{D}, \forall b \in B, \forall k \in K, \forall t \in T \tag{5d}$$

The power flow across the transmission lines is defined by network power flow constraint (6a) taking into account a DC representation of the network. Constraint (6b) sets a highest and lowest power flow limits for each transmission line, while (6c) states that the voltage angles must be greater than $-\pi$ or less than π rad.

$$p_{\mathrm{lt}}^{L,D}=\frac{\theta_{O(l)t}^{D}-\theta_{F(l)t}^{D}}{X_l} \tag{6a}$$
$$-P_{\max,l}^{L}\leq p_{\mathrm{lt}}^{L,D}\leq p_{\max,l}^{L} \tag{6b}$$
$$-\pi\leq\theta_{\mathrm{bt}}^{D}\leq\pi;\quad\forall b\in B,\forall l\in L,\forall t\in T \tag{6c}$$

B. BALANCING MARKET

The second set of constraints 7-12, is defined to explain the run time functioning of the energy scheduling. The power balance is enforced in each bus, time interval, and scenario (see Eq. 7). The maximum unserved demand is constrained by Eq. 8.

$$\sum_{g\in G_b}p_{\mathrm{gt}\omega}^{G,B}+\sum_{k\in K}\left(p_{\mathrm{kbt}\omega}^{\mathrm{EV,BD}}-p_{\mathrm{kbt}\omega}^{\mathrm{EV,BC}}\right)-\sum_{l\in L_b^O}p_{\mathrm{lt}\omega}^{L,B}+\sum_{l\in L_b^F}p_{\mathrm{lt}\omega}^{L,B}=P_{\mathrm{bt}\omega}^{D,B}-P_{\mathrm{bt}\omega}^{\mathrm{UD},B};\quad\forall b\in B,\forall t\in T \tag{7}$$

$$0\leq p_{\mathrm{dt}\omega}^{\mathrm{UD},B}\leq p_{\mathrm{dt}\omega}^{D,B};\quad\forall d\in D,\forall t\in T \tag{8}$$

The power generated by dispatchable entities in run time operation is defined by constraint (9a), which takes into account the energy planned in the day ahead marketplace and the high and low backup committed in each scenario. Eq. (9b) defines the entity's capacity limits based on the functional state decided in the day ahead marketplace, while Eqs. (9c) and (9d) impose ramping restrictions. Constraints (9e) to (9g) are related to intermittent renewable entities. For example, Eq. (9e) stipulates that the energy provided and the released energy in run time must equal the available potential in respective circumstances. Constraints (9f) and (9g) denote the nonnegativity of the provided and released green power, respectively.

$$p_{\mathrm{gt}\omega}^{G,B}=p_{\mathrm{gt}}^{G,D}+r_{\mathrm{gt}\omega}^{G,\mathrm{DU}}-r_{\mathrm{gt}\omega}^{G,\mathrm{DD}} \tag{9a}$$
$$u_{\mathrm{gt}}.P_{\min,g}^{G}\leq p_{\mathrm{gt}\omega}^{G,B}\leq u_{\mathrm{gt}}.P_{\max,g}^{G} \tag{9b}$$
$$p_{\mathrm{gt}\omega}^{G,B}-p_{\mathrm{gt}-1,\omega}^{G,B}\leq P_{\mathrm{UP},g}^{G} \tag{9c}$$
$$p_{\mathrm{gt}-1,\omega}^{G,B}-p_{\mathrm{gt}\omega}^{G,B}\leq P_{\mathrm{DW},g}^{G} \tag{9d}$$
$$p_{\mathrm{gt}\omega}^{G,B}+p_{\mathrm{gt}\omega}^{G,\mathrm{BS}}=A_{\mathrm{gt}\omega}^{B}.P_{\max,g}^{G} \tag{9e}$$
$$p_{\mathrm{gt}\omega}^{G,B}\geq 0 \tag{9f}$$
$$p_{\mathrm{gt}\omega}^{G,\mathrm{BS}}\geq 0;\quad\forall g\in G^D,G^I,\forall t\in T \tag{9g}$$

The energy level of the electric vehicles in group k is specified by the expression (10a) for the interval before the charging period. Here, the random parameter $\alpha_{\mathrm{k}\omega}^{\mathrm{EV,SI}}$ has a distinct value for every case. The charging state of the EV batteries during run time operation is modeled by Constraints 10b. It is thought that by utilizing the vehicle-to-grid capability, EV energy may also be utilized to add energy to the system. EVs can engage in this process as either producers or consumers of power, based on whether they are charging or discharging. This could occur at the times when EVs represented by set T_k are linked to the network. In this manner, the amount of energy in the specific time slot is equal to the amount in the preceding time slot plus the amount of energy charged in that typical time slot while accounting for charging losses, less the amount of energy released while accounting for process losses.

As indicated by Eq. (10c), the lowest energy level is enforced at the end of the charging session. The final status of the battery is represented in this instance by the parameter $\alpha_{\mathrm{k}\omega}^{\mathrm{EV,SE}}$. The battery's lowest and maximum energy levels throughout the charging time are limited by constraint (10d). The definition of the power that the EVs in group k charge and discharge is given by expressions (10e-10f). In the run time scenario ω, the power charged is equivalent to the power planned in the day ahead marketplace, less the high backup that is committed by decreasing battery charging and the low backup that is deployed by raising battery charging. Conversely, the power discharged is equivalent to the power to be planned in the day ahead marketplace plus the high backup that is committed by increasing battery discharging minus the low backup that is committed by decreasing battery discharging. Constraints (10g-10h) limit the amount of the power that EVs may charge and discharge in real-time. The energy capacity rate of the chargers in group k is indicated by the parameter $P_{\max,k}^{\mathrm{EV}}$.

The total high backup capacity used by electric vehicles in group k, is specified by equation (10i), which includes the up backup used in both the charging and discharging phases. The high backup committed from the charging can not exceed the energy to be charged in the day ahead marketplace, according to constraint (10j). The amount of backup to drain the batteries as indicated by Eq. (10k) required to be less than the group $k's$ entire battery capacity less the energy to be discharged planned in the day ahead marketplace. The down backup committed is equal to the total of the backup deployed when charging and discharging, as stated in Eq. 10l. The down backup used during the charging process is restricted by constraint 10m to the full capacity of the group k batteries less the power planned for charging in the day ahead marketplace. The low backup committed from the discharging can not be greater than the energy to be discharged in the day ahead marketplace, according to constraint (10n).

$$e_{\mathrm{kbt}\omega}^{\mathrm{EV}}=N_{\mathrm{kb}}^{\mathrm{EV}}.\alpha_{\mathrm{k}\omega}^{\mathrm{EV,SI}}.e_{\max,k}^{\mathrm{EV}} \tag{10a}$$
$$e_{\mathrm{kbt}\omega}^{\mathrm{EV}}=e_{\mathrm{kbt}-1\omega}^{\mathrm{EV}}+\eta^{\mathrm{EV}}.p_{\mathrm{kbt}\omega}^{\mathrm{EV,BC}}-\frac{1}{\eta^{\mathrm{EV}}}.p_{\mathrm{kbt}\omega}^{\mathrm{EV,BD}} \tag{10b}$$
$$e_{\mathrm{kbt}\omega}^{\mathrm{EV}}\geq N_{\mathrm{kb}}^{\mathrm{EV}}.\alpha_{\mathrm{k}\omega}^{\mathrm{EV,SE}}.e_{\max,k}^{\mathrm{EV}} \tag{10c}$$
$$N_{\mathrm{kb}}^{\mathrm{EV}}.\alpha_{\mathrm{k}\omega}^{\mathrm{EV,SMIN}}.e_{\max,k}^{\mathrm{EV}}\leq e_{\mathrm{kbt}\omega}^{\mathrm{EV}} \tag{10d}$$
$$p_{\mathrm{kbt}\omega}^{\mathrm{EV,BC}}=p_{\mathrm{kbt}}^{\mathrm{EV,CD}}-r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUC}}+r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}} \tag{10e}$$
$$p_{\mathrm{kbt}\omega}^{\mathrm{EV,BD}}=p_{\mathrm{kbt}}^{\mathrm{EV,DD}}+r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUD}}-r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}} \tag{10f}$$
$$0\leq p_{\mathrm{kbt}\omega}^{\mathrm{EV,BC}}\leq N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\max,k}^{\mathrm{EV}} \tag{10g}$$
$$0\leq p_{\mathrm{kbt}\omega}^{\mathrm{EV,BD}}\leq N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\max,k}^{\mathrm{EV}} \tag{10h}$$
$$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DU}}=r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUC}}+r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUD}} \tag{10i}$$
$$0\leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUC}}\leq p_{\mathrm{kbt}}^{\mathrm{EV,CD}} \tag{10j}$$

$$0 \leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DUD}} \leq N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\max}^{\mathrm{EV}} - p_{\mathrm{kbt}}^{\mathrm{EV,DD}} \tag{10k}$$

$$r_{\mathrm{kbt}\omega}^{\mathrm{EV,DD}} = r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}} + r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDD}} \tag{10l}$$

$$0 \leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDC}} \leq N_{\mathrm{kb}}^{\mathrm{EV}}.P_{\max}^{\mathrm{EV}} - p_{\mathrm{kbt}}^{\mathrm{EV,CD}} \tag{10m}$$

$$0 \leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DDD}} \leq p_{\mathrm{kbt}}^{\mathrm{EV,DD}}; \quad \forall k \in K, \forall b \in B, \forall t \in T \tag{10n}$$

Constraints (11a-11d) restrict the generating entities' and EVs' up-and-down backup to the backup capacity planned for the upcoming day.

$$0 \leq r_{\mathrm{gt}\omega}^{G,\mathrm{DU}} \leq r_{\mathrm{gt}}^{G,\mathrm{CU}} \tag{11a}$$

$$0 \leq r_{\mathrm{gt}\omega}^{G,\mathrm{DD}} \leq r_{\mathrm{gt}}^{G,\mathrm{CD}} \tag{11b}$$

$$0 \leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DU}} \leq r_{\mathrm{kbt}}^{\mathrm{EV,CU}} \tag{11c}$$

$$0 \leq r_{\mathrm{kbt}\omega}^{\mathrm{EV,DD}} \leq r_{\mathrm{kbt}}^{\mathrm{EV,CD}}; \geq 0; \quad \forall g \in G^{D}, \forall b \in B, \forall t \in T \tag{11d}$$

Finally, a set of constraints (12a-12c) specify the run time limits of the power flow through the transmission lines.

$$p_{\mathrm{lt}\omega}^{L,B} = \frac{\theta_{O(l)\mathrm{t}\omega}^{B} - \theta_{F(l)\mathrm{t}\omega}^{B}}{X_l} \tag{12a}$$

$$-p_{\max,l}^{L} \leq p_{\mathrm{lt}\omega}^{L,B} \leq p_{\max,l}^{L} \tag{12b}$$

$$-\pi \leq \theta_{\mathrm{bt}\omega}^{B} \leq \pi; \quad \forall l \in L, \forall b \in B, \forall t \in T \tag{12c}$$

V. CASE STUDY

The problem previously formulated is fully implemented through 'Scientific Python Development Environment (Spyder 5.4.3)' as the basic platform for the development of prosumer-centric distributed ledger smart contracts and 'IBM ILOG CPLEX Optimization Studio' to find the optimized solution of supply and demand through CPLEX solver while effectively incorporating electric vehicles in the peer-to-peer energy trading market. We take a power network consisting of three buses, each with a generating entity and a demand, connected via three transmission lines (see Fig. 2). The generating entities' capacity, minimum power harnessing, high/ low ramp capability, and operating costs, are shown in Table 2. Thermal power production makes up generating entities 1 and 2, while renewable power harnessing is represented by generating entity 3. The shutdown expenses are estimated to be half of the start-up expenses, which are 8,500$ and 11,200$ for generating entities 1 and 2, respectively. The start-up expenses are equivalent to the expenses of operating at full capacity for a single day i.e. 18,300$ and 25,200$ for generating entities 1 and 2, respectively. It is believed that backup services cannot be rendered by intermittent renewable sources. By using generating entities 1 and 2, the cost of scheduling up/down backup services is 3 $/MW and 4 $/MW, respectively. Generating entities 1 and 2 have generation costs of 8 $/MWh and 16 $/MWh for up backup and 6 $/MWh and 12 $/MWh for down backup, respectively.

Three hours are taken into consideration during the planning phase. Every hour, the renewable source's availability factors are 0.3, 0.8, and 0.7, respectively. The unmet demand is attributable to involuntary means 800 $/MWh in costs. The

TABLE 2. Salients of generating entities.

Generating Entity	Capacity (MW)	Ramp Up/Down (MW)	Minimum Power (MW)	Operating Cost ($/MWh)
Thermal Gen-1	50	45	40	14
Thermal Gen-2	70	35	15	23
PV Gen	80	80	0	4

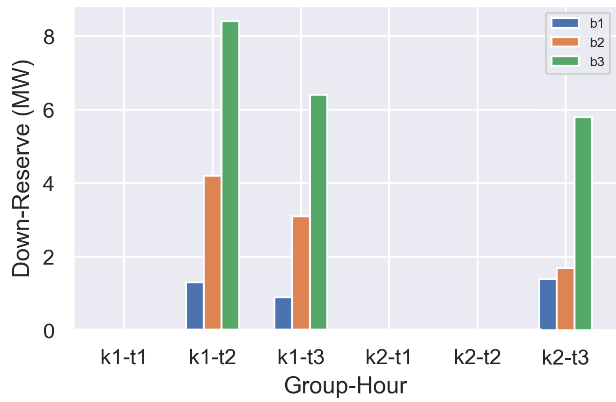

FIGURE 4. Down backup scheduled by electric vehicle groups in the day ahead energy trading marketplace for each time slot.

transmission lines have 180 MW capacity and a 0.0006 Ohms reactance. The electric vehicles are divided into two types based on how long it takes to charge them. Group 2 is only plugged in during the final time slot, while Group 1 is plugged in during the 2^{nd} and 3^{rd} time slots. Each network bus has both of the EV groups. The battery has a 45 kWh capacity and a maximum charging/discharging power of 13 kW. When it comes to EV charging and discharging, the efficiency rate is 0.79. The battery has a minimum energy level of 9 kWh. When the connection time expires, the battery needs to be fully charged. The set points for the execution of the proposed model while using the distributed ledger technology are shown in Table 3.

TABLE 3. Experimental set points.

Experimental Metric	Set Point
Size of energy block	2.0 MB
Size of energy micro block	0.6 MB
Diameter of shard	0 - 3.5 km
Propagation delay of energy micro block	0.6 s
Propagation delay of energy block	0.7 s
Euclidean distance between EVs	10 - 120 m

The only variable under consideration is the battery's initial charging state, which is represented as an unknown quantity using two possible scenarios. In scenario $w1$, the battery state at the start of the charging time slot for each EV ensemble is assumed to be 60 % and 80 %, respectively. Whereas, in scenario $w2$, these are assumed to be 70 % and 90 % for the two groups of EVs. The discharging cost groups 1 and 2 are assumed to be 11 $/MWh and 13 $/MWh, whereas the cost to charge the EVs is none. In the day ahead marketplace, scheduling backup up or down cost is 2 $/MWh. In the run-time operation, deploying down backup costs 7 $/MWh,

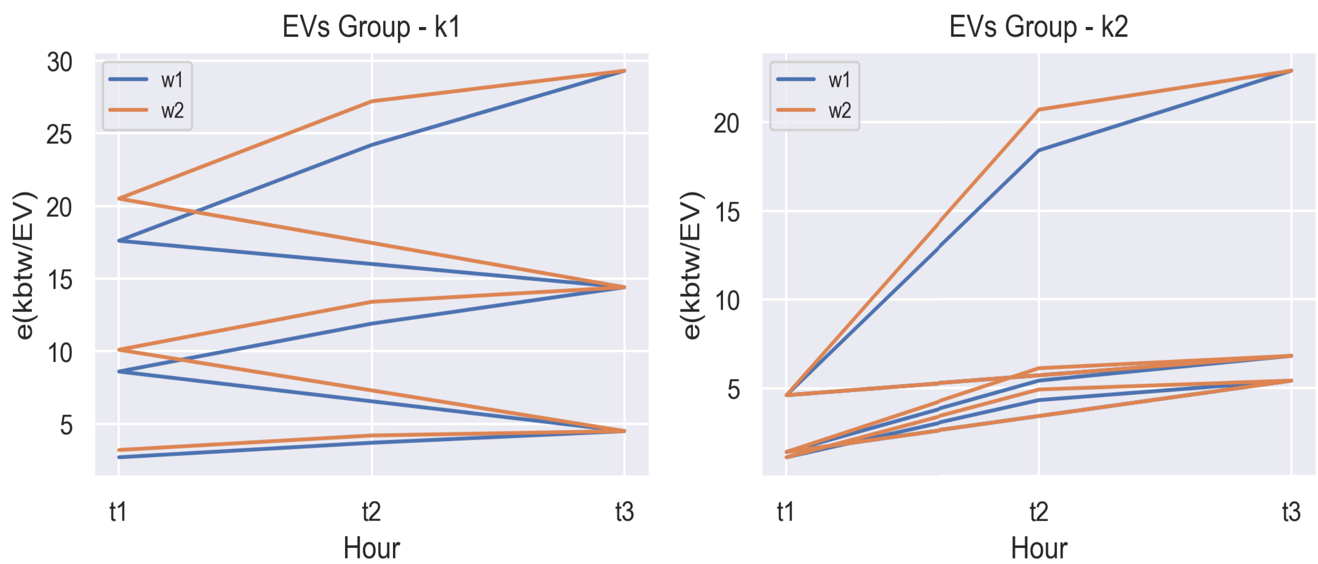

FIGURE 5. Energy stored in the batteries of EVs in the real-time operation.

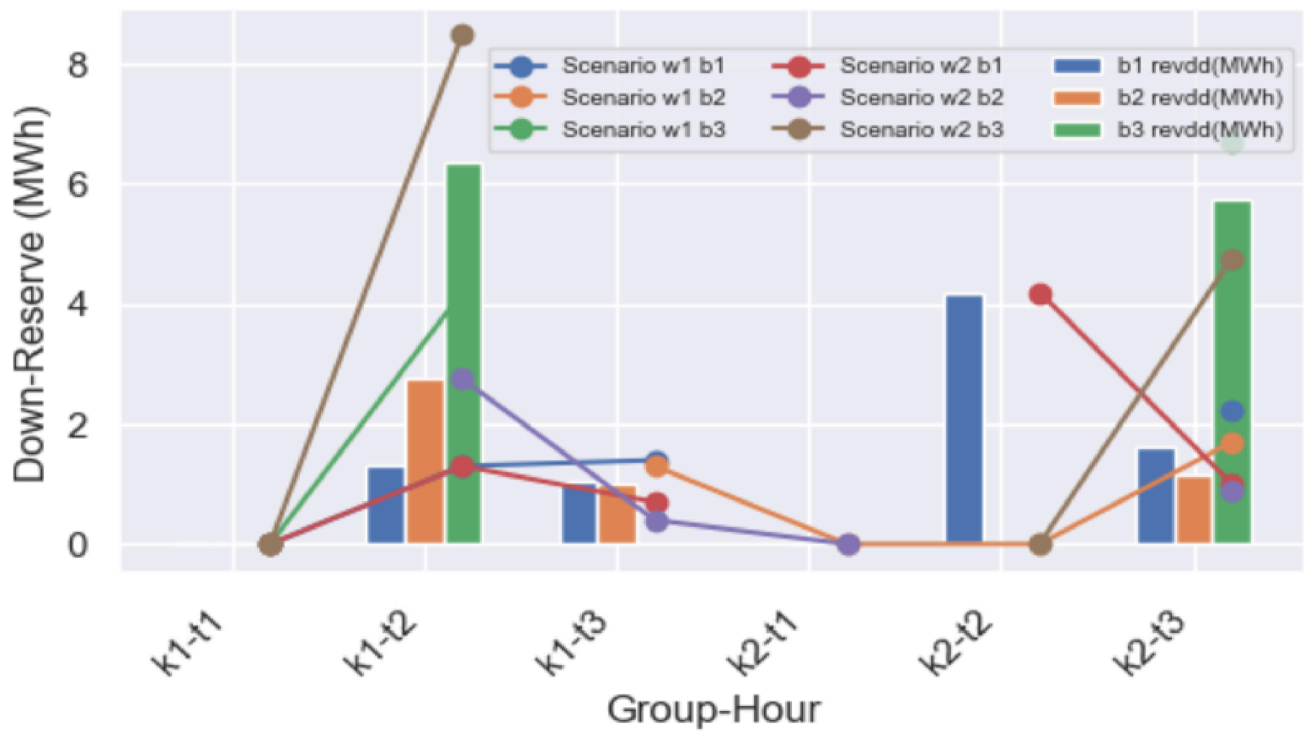

FIGURE 6. Day-ahead scenarios of energy trading.

whereas deploying up backup for EVs group 1 and 2 cost 11 $/MWh and 13 $/MWh, respectively.

The optimized total cost comes to be 3660.6$. In the day ahead marketplace, costs of the power that production entities schedule equals 3663.6$. Due to the deployment of down backup from EVs, the expenses of the backup planned for the day ahead is 108.7$. The demand power for each network bus and hour, energy scheduled in the day ahead marketplace by producing entities and the overall load is shown in Fig. 3. Given the renewable entity's lower cost compared to the other two dispatchable entities, producing entity 1 meets a significant portion of the energy requirements, reaching peak performance in the final hour. Both the electricity that EVs are scheduled to discharge or charge in the day ahead marketplace and the backup scheduled by generating entities are zero at all times.

The down backup capacity scheduled by EVs for the day ahead marketplace is shown in Fig. 4. The EVs are linked when the down backup capacity is scheduled. There is no scheduled high backup capacity. The SOC (state of charge) and energy discharged (charged and discharged) of the EV batteries are described in Fig. 5 for each real-time operation scenario. For example, in hour 2 and scenario 1, the energy level in group 1's batteries at bus b3 is equivalent to 24.2 MWh, resulting from charging 8.5 MWh in hour 1, which is 17.6 MWh. It is pertinent to mention here that the power being charged is subject to the charging efficiency rate. Lastly, Fig. 6 shows the down backup due to EV batteries being charged in the run time operation.

VI. CONCLUSION

In this paper, we developed a comprehensive blockchain-enabled peer-to-peer prosumer-centric energy exchange model of a power system with an effective and dynamic incorporation of a significant number of electric cars and intermittent green generation sources both in the day ahead and run-time energy trading markets. The proposed framework prevents energy crisis while offering a dynamic grid regulation mechanism and facilitating EV owners with an effective provision of high-pool energy storage systems. Here, we employed a novel PoI consensus mechanism for a two-stage stochastic programming problem representing the hybrid power system and achieved accurate and reliable optimized results through the seamless execution of smart contracts. Blockchain can assist in managing peak shaving by providing incentives for EV drivers to sell energy to the grid. It can also improve EV driver satisfaction by enabling the sale of energy from local communities and private EV charging station owners, hence reducing costs by eliminating middlemen. Various availability levels of renewable intermittent production have been investigated in the case study. The primary findings derived from this numerical analysis include (i) EVs have been observed as not selling their energy in the day ahead energy marketplace. It suggests that EVs are more likely to engage in the reserve market because it is simpler for them to adjust how their batteries are charged and discharged to provide backup services rather than committing to sell energy in the day ahead marketplace, which would require run-time operation in every scenario. (ii) EVs are more likely to participate in down backup than up backup; therefore, it is relatively more advantageous to the power network to charge the EVs' batteries through commitment of low reserve while ensuring the energy balance. (iii) Diesel-generating entities are less expensive than petrol units; on the other hand, renewable generation may be able to lessen the impact of fossil fuel installations on the environment. (iv) Overall running expenses rise in direct proportion to the number of EVs. Nevertheless, it is important to remember that EVs' active involvement in the system contributes to lower overall costs. We plan to expand this study for the development and execution of smart contracts associated with multi-operator competitive market, while analysing the significant impact on the system's overall performance and scalability in the dynamic peer-to-peer energy trading market.

ACKNOWLEDGMENT

This work was partially funded by the European Union through the Operational Programme Just Transition, project TN02000025 National Centre for Energy II, and ExPEDite project, a Research and Innovation action to support the implementation of the Climate Neutral and Smart Cities Mission project under the REFRESH (Research Excellence For Region Sustainability and High-tech Industries) project number CZ.10.03.01/00/22_003/0000048. ExPEDite is supported by the Horizon Mission Programme of the European Union under grant agreement No. 101139527. The authors would also like to express their gratitude to Taif University, Saudi Arabia for funding this research under project number TU-DSPP-2024-25.

REFERENCES

[1] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," *Proc. IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011.

[2] K. Mahmud, G. E. Town, S. Morsalin, and M. J. Hossain, "Integration of electric vehicles and management in the internet of energy," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 4179–4203, Feb. 2018.

[3] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Trans. Power Electron.*, vol. 28, no. 5, pp. 2151–2169, May 2013.

[4] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nature Energy*, vol. 3, no. 2, pp. 94–101, Feb. 2018.

[5] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nature Energy*, vol. 1, no. 4, p. 16032, 2016.

[6] H. Yu, S. Niu, Y. Shang, Z. Shao, Y. Jia, and L. Jian, "Electric vehicles integration and vehicle-to-grid operation in active distribution grids: A comprehensive review on power architectures, grid connection standards and typical applications," *Renew. Sustain. Energy Rev.*, vol. 168, Oct. 2022, Art. no. 112812.

[7] S. Mateen, M. Amir, A. Haque, and F. I. Bakhsh, "Ultra-fast charging of electric vehicles: A review of power electronics converter, grid stability and optimal battery consideration in multi-energy systems," *Sustain. Energy, Grids Netw.*, vol. 35, Sep. 2023, Art. no. 101112.

[8] S. Mohanty, S. Panda, S. M. Parida, P. K. Rout, B. K. Sahu, M. Bajaj, H. M. Zawbaa, N. M. Kumar, and S. Kamel, "Demand side management of electric vehicles in smart grids: A survey on strategies, challenges, modeling, and optimization," *Energy Rep.*, vol. 8, pp. 12466–12490, Nov. 2022.

[9] H. S. Das, M. M. Rahman, S. Li, and C. W. Tan, "Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review," *Renew. Sustain. Energy Rev.*, vol. 120, Mar. 2020, Art. no. 109618.

[10] I. Mahmud, M. B. Medha, and M. Hasanuzzaman, "Global challenges of electric vehicle charging systems and its future prospects: A review," *Res. Transp. Bus. Manage.*, vol. 49, Aug. 2023, Art. no. 101011.

[11] T. AlSkaif, J. L. Crespo-Vazquez, M. Sekuloski, G. van Leeuwen, and J. P. S. Catalão, "Blockchain-based fully peer-to-peer energy trading strategies for residential energy systems," *IEEE Trans. Ind. Informat.*, vol. 18, no. 1, pp. 231–241, Jan. 2022.

[12] I. Park, T. Lee, and J. Jang, "Trade-off in implementation of P2P energy trading over hyperledger blockchain," in *Proc. IEEE Int. Conf. Consum. Electron.-Asia (ICCE-Asia)*, Nov. 2020, pp. 1–4.

[13] A. Azarhooshang, D. Sedighizadeh, and M. Sedighizadeh, "Two-stage stochastic operation considering day-ahead and real-time scheduling of microgrids with high renewable energy sources and electric vehicles based on multi-layer energy management system," *Electr. Power Syst. Res.*, vol. 201, Dec. 2021, Art. no. 107527.

[14] K. Y. Yap, H. H. Chin, and J. J. Klemeš, "Solar energy-powered battery electric vehicle charging stations: Current development and future prospect review," *Renew. Sustain. Energy Rev.*, vol. 169, Nov. 2022, Art. no. 112862.
[15] U. Rehman, "A robust vehicle to grid aggregation framework for electric vehicles charging cost minimization and for smart grid regulation," *Int. J. Electr. Power Energy Syst.*, vol. 140, Sep. 2022, Art. no. 108090.
[16] P. Thomas and P. K. Shanmugam, "A review on mathematical models of electric vehicle for energy management and grid integration studies," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105468.
[17] Y. Zheng, S. Niu, Y. Shang, Z. Shao, and L. Jian, "Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation," *Renew. Sustain. Energy Rev.*, vol. 112, pp. 424–439, Sep. 2019.
[18] A. Sheikh, V. Kamuni, A. Urooj, S. Wagh, N. Singh, and D. Patel, "Secured energy trading using Byzantine-based blockchain consensus," *IEEE Access*, vol. 8, pp. 8554–8571, 2020.
[19] Y. Wang, D. Zhang, Y. Li, W. Jiao, G. Wang, J. Zhao, Y. Qiang, and K. Li, "Enhancing power grid resilience with blockchain-enabled vehicle-to-vehicle energy trading in renewable energy integration," *IEEE Trans. Ind. Appl.*, vol. 60, no. 2, pp. 2037–2052, Mar./Apr. 2024.
[20] G. M. Madhu, C. Vyjayanthi, and C. N. Modi, "A novel framework for monitoring solar PV based electric vehicle community charging station and grid frequency regulation using blockchain," in *Proc. 10th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Jul. 2019, pp. 1–7.
[21] Z. Su, Y. Wang, Q. Xu, M. Fei, Y.-C. Tian, and N. Zhang, "A secure charging scheme for electric vehicles with smart communities in energy blockchain," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4601–4613, Jun. 2019.
[22] H. ElHusseini, C. Assi, B. Moussa, R. Attallah, and A. Ghrayeb, "Blockchain, AI and smart grids: The three musketeers to a decentralized EV charging infrastructure," *IEEE Internet Things Mag.*, vol. 3, no. 2, pp. 24–29, Jun. 2020.
[23] M. Baza, A. Sherif, M. M. E. A. Mahmoud, S. Bakiras, W. Alasmary, M. Abdallah, and X. Lin, "Privacy-preserving blockchain-based energy trading schemes for electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9369–9384, Sep. 2021.
[24] D. H. Farrokh Rahimi, S. N. Gupta Gourisetti, and T. Martinez, "IEEE blockchain transactive energy (BCTE),a bridge to a democratized energy marketplace," *IEEE Position Vis. Statement Paper*, vol. 3.0, pp. 1–37, May 2021.
[25] W. Tushar, C. Yuen, T. K. Saha, T. Morstyn, A. C. Chapman, M. J. E. Alam, S. Hanif, and H. V. Poor, "Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116131.
[26] M. K. AlAshery, Z. Yi, D. Shi, X. Lu, C. Xu, Z. Wang, and W. Qiao, "A blockchain-enabled multi-settlement quasi-ideal peer-to-peer trading framework," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 885–896, Jan. 2021.
[27] S. Chen, C. Xu, Z. Yan, X. Guan, and X. Le, "Accommodating strategic players in distributed algorithms for power dispatch problems," *IEEE Trans. Cybern.*, vol. 52, no. 11, pp. 12594–12603, Nov. 2022.
[28] S. Chen, Z. Shen, L. Zhang, Z. Yan, C. Li, N. Zhang, and J. Wu, "A trusted energy trading framework by marrying blockchain and optimization," *Adv. Appl. Energy*, vol. 2, May 2021, Art. no. 100029.
[29] S. Chen, L. Zhang, Z. Yan, and Z. Shen, "A distributed and robust security-constrained economic dispatch algorithm based on blockchain," *IEEE Trans. Power Syst.*, vol. 37, no. 1, pp. 691–700, Jan. 2022.
[30] J. Ping, Z. Yan, S. Chen, L. Yao, and M. Qian, "Coordinating EV charging via blockchain," *J. Mod. Power Syst. Clean Energy*, vol. 8, no. 3, pp. 573–581, May 2020.
[31] J. Ping, Z. Yan, and S. Chen, "A two-stage autonomous EV charging coordination method enabled by blockchain," *J. Mod. Power Syst. Clean Energy*, vol. 9, no. 1, pp. 104–113, Jan. 2021.
[32] R. Domínguez, G. Oggioni, and Y. Smeers, "Reserve procurement and flexibility services in power systems with high renewable capacity: Effects of integration on different market designs," *Int. J. Elect. Power Energy Syst.*, vol. 113, pp. 1014–1034, Dec. 2019.
[33] D. K. Molzahn, F. Dörfler, H. Sandberg, S. H. Low, S. Chakrabarti, R. Baldick, and J. Lavaei, "A survey of distributed optimization and control algorithms for electric power systems," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 2941–2962, Nov. 2017.
[34] J. A. Aguado and V. H. Quintana, "Inter-utilities power-exchange coordination: A market-oriented approach," *IEEE Trans. Power Syst.*, vol. 16, no. 3, pp. 513–519, Aug. 2001.
[35] C. Newton, P. Lang, and S. Terry, "Field trial results of power electronics in low-voltage distribution networks," *CIRED-Open Access Proc. J.*, vol. 2017, no. 1, pp. 184–188, 2017.
[36] L. Thomas, Y. Zhou, C. Long, J. Wu, and N. Jenkins, "A general form of smart contract for decentralized energy systems management," *Nature Energy*, vol. 4, no. 2, pp. 140–149, Jan. 2019.
[37] Y. Mavrocostanti and J. Berry, "Real-time, centralised voltage control in 33 and 11 kv electricity distribution networks," *CIRED-Open Access Proc. J.*, vol. 2017, no. 1, pp. 1406–1409, 2017.
[38] N. U. Sehar, O. Khalid, I. A. Khan, F. Rehman, M. A. B. Fayyaz, A. R. Ansari, and R. Nawaz, "Blockchain enabled data security in vehicular networks," *Sci. Rep.*, vol. 13, no. 1, p. 4412, Mar. 2023.
[39] N. R. Pradhan, A. P. Singh, S. Verma, M. Wozniak, J. Shafi, and M. F. Ijaz, "A blockchain based lightweight peer-to-peer energy trading framework for secured high throughput micro-transactions," *Sci. Rep.*, vol. 12, no. 1, p. 14523, Aug. 2022.
[40] N. M. Manousakis, P. S. Karagiannopoulos, G. J. Tsekouras, and F. D. Kanellos, "Integration of renewable energy and electric vehicles in power systems: A review," *Processes*, vol. 11, no. 5, p. 1544, May 2023.
[41] M. Asensio and J. Contreras, "Stochastic unit commitment in isolated systems with renewable penetration under CVaR assessment," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1356–1367, May 2016.
[42] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*, 2nd ed., Springer, 2011.
[43] M. Carrión, R. Domínguez, M. Cañas-Carretón, and R. Zárate-Miñano, "Scheduling isolated power systems considering electric vehicles and primary frequency response," *Energy*, vol. 168, pp. 1192–1207, Feb. 2019.
[44] J. Donadee and M. D. Ilic, "Stochastic optimization of grid to vehicle frequency regulation capacity bids," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1061–1069, Mar. 2014.
[45] M. Carrión, R. Domínguez, and R. Zárate-Miñano, "Influence of the controllability of electric vehicles on generation and storage capacity expansion decisions," *Energy*, vol. 189, Dec. 2019, Art. no. 116156.
[46] M. Carrión and R. Zárate-Miñano, "Operation of renewable-dominated power systems with a significant penetration of plug-in electric vehicles," *Energy*, vol. 90, pp. 827–835, Oct. 2015.
[47] A. J. Conejo and L. Baringo, *Power System Operations* (Springer Text Book), vol. 14. Springer, 2018.
[48] R. Newell, D. Raimi, and G. Aldana, "Global energy outlook 2019: The next generation of energy," *Resour. Future*, vol. 1, no. 8, pp. 1–46, 2019.
[49] W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," *Transp. Res. D, Transp. Environ.*, vol. 2, no. 3, pp. 157–175, Sep. 1997.
[50] B. Kroposki, B. Johnson, Y. Zhang, V. Gevorgian, P. Denholm, B.-M. Hodge, and B. Hannegan, "Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy," *IEEE Power Energy Mag.*, vol. 15, no. 2, pp. 61–73, Mar. 2017.
[51] B. E. Lebrouhi, Y. Khattari, B. Lamrani, M. Maaroufi, Y. Zeraouli, and T. Kousksou, "Key challenges for a large-scale development of battery electric vehicles: A comprehensive review," *J. Energy Storage*, vol. 44, Dec. 2021, Art. no. 103273.
[52] H. Liu, Z. Hu, Y. Song, and J. Lin, "Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3480–3489, Aug. 2013.
[53] H. Liu, Z. Hu, Y. Song, J. Wang, and X. Xie, "Vehicle-to-grid control for supplementary frequency regulation considering charging demands," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3110–3119, Nov. 2015.
[54] Y. Mu, J. Wu, J. Ekanayake, N. Jenkins, and H. Jia, "Primary frequency response from electric vehicles in the great Britain power system," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 1142–1150, Jun. 2013.
[55] M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez, "Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3506–3515, Sep. 2016.
[56] M. González Vayá and G. Andersson, "Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2375–2385, Sep. 2015.
[57] L. Baringo, M. Carrión, and R. Domínguez, *Electric Vehicles and Renewable Generation: Power System Operation and Planning Under Uncertainty*. Springer, 2023.

[58] S. I. Vagropoulos, D. K. Kyriazidis, and A. G. Bakirtzis, "Real-time charging management framework for electric vehicle aggregators in a market environment," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 948–957, Mar. 2016.
[59] E. Yao, V. W. S. Wong, and R. Schober, "Robust frequency regulation capacity scheduling algorithm for electric vehicles," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 984–997, Mar. 2017.
[60] B. Xu, Y. Wang, Y. Dvorkin, R. Fernández-Blanco, C. A. Silva-Monroy, J.-P. Watson, and D. S. Kirschen, "Scalable planning for energy storage in energy and reserve markets," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4515–4527, Nov. 2017.

IMRAN HUSSAIN received the bachelor's degree in electrical engineering, in 2009, and the master's degree (Hons.) in electrical engineering, in 2021. He is currently pursuing the Ph.D. degree in electrical engineering with the Department of Electrical and Computer Engineering, Air University, Islamabad, Pakistan. He has vast industrial experience with both power and IT sectors, including the design, construction, and operations of high voltage power transmission lines, substations, and large scale data centers hosting various IT services. His research interests include renewable energy harvesting, high power switched-capacitor converters, PV faults detection and mitigation, power system protection, reliability analysis of power converters, grid integration of renewable energy sources and electric vehicles along with their smart charging schemes, electrical energy trading in smart grid architecture, power and cooling infrastructure of data centers, computer networks, and blockchain technology. He was a Gold Medalist in master's degree.

HAFIZ ASHIQ HUSSAIN (Member, IEEE) received the Ph.D. degree in telecom engineering from Beijing University of Posts and Telecommunications, China. He has vast industrial and academic experience. He is currently the Head of the Department of Electrical and Computer Engineering, Air University, Islamabad, Pakistan. He has supervised several master's and Ph.D. students and contributed in many national and international journals and conference proceedings. His research interests include power systems, optical fiber communication, and silicon photonics. He is a Life Member of the Pakistan Engineering Council (PEC).

NASIM ULLAH (Member, IEEE) received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Peshawar, in 2004, and the Ph.D. degree in mechatronics engineering from Beihang University, Beijing, China, in 2013. He is currently a Professor with the Department of Electrical Engineering, Taif University, Saudi Arabia. He has completed several research projects funded by the Deanship of Scientific Research, Taif University; and the Ministry of Education, Saudi Arabia, as a Principal Investigator (PI). He has authored/co-authored more than 200 research articles in peer-review journals and contributed several book chapters. His research interests include renewable energy, microgrid, smart grids, power electronic applications in power systems, smart transformers, robotics, and flight control systems.

STANISLAV MISAK was born in Czech Republic, in 1978. He received the Ing. and Ph.D. degrees from the Department of Electrical Engineering, VSB—Technical University of Ostrava, in 2003 and 2007, respectively. He is currently a Professor and the CEO of the ENET Research Centre and the Centre for Energy and Environmental Technologies, VSB—Technical University of Ostrava. He holds a patent for a fault detector for medium voltage power lines. His current research interests include implementation of smart grid technologies using prediction models and bio-inspired methods.