Smart Control of the Bidirectional Energy Exchange of Electric Vehicles With the Electrical Network.

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Abstract: *The democratization of plug-in hybrid vehicles as well as purely electric vehicles implies a surplus of demand on the distribution networks. Vehicle-to-Grid aims to meet this increased demand by using vehicles no longer as simple loads for the electricity network but as players carrying out two-way energy exchanges. The work presented in this article proposes a real-time "Grid-to-Vehicle/Vehicle-to-Grid" control algorithm for an electrical distribution system. The results show that the system makes it possible to achieve energy gains shared between the actors while efficiently recharging the participating vehicles.*

Keywords*: Electric vehicles; Distribution networks; Smart Grids; Vehicle-to-Grid; Smart control.*

1. Introduction

In the current context, the automobile is essential and occupies the daily universe of our society [1]. Indeed, noise pollution and greenhouse gases as well as a constantly increasing dependence on fuel are leading to a new interest in renewable energies and their uses, in particular as an alternative solution to thermal vehicles [2-4]. The electric vehicle (EV) is a solution put forward by car manufacturers to gradually replace conventional vehicles [5]. This transport solution is dedicated in particular to travel in urban areas as well as to the distribution of goods in the last kilometers [6-8].

On the other hand, the energy need for electricity is constantly growing [9], despite efforts to increase the energy efficiency of the various electrical appliances. Producing a sufficient but not excessive quantity of this resource to adapt supply to demand in real time and ensure continuity of service with a stable electricity network represents an ongoing challenge. It is indeed difficult and costly for electricity producers and distributors to store surpluses produced or in transit on the network and return them when demand exceeds production. These mechanisms require heavy infrastructures distributed throughout the network and generate significant energy losses [10-12]. The idea behind the Smart Grid is to deport some of these control mechanisms to consumer agents, by integrating their modest infrastructures into the process of stabilizing the network and also by modifying consumption behavior [13-16]. We will deal with part of this smart grid problem by focusing on what can be done with a common good, the car, in order to ensure the efficiency of EV charging systems and guarantee energy stability in electrical networks [17,18]. This technical concept, called G2V/V2G (Grid to Vehicle / Vehicle to Grid) [19], is based on the idea of using the batteries of parked electric cars in both directions and with flexibility to [20-22]:

- absorb and store the electricity produced in excess on the network;
- constitute a reserve of electricity to feed the large network or a domestic network if necessary.

In [23,24], a centralized G2V/V2G control algorithms have been proposed. The limit of the centralized approach is its infeasibility with high penetration of plug- in electric vehicles (PEV). Furthermore, its implementation is expensive and sometimes even intractable because it requires large bandwidth (throughput) and extensive two-way communication. In this regard, it is interesting to adopt a decentralized G2V/V2G strategy to improve the performance of high penetration scenarios of PEVs. In [25], a decentralized control algorithm was proposed, the authors considered a time-invariant energy pricing system throughout the PEV recharge scheduling period. This is unrealistic as electricity prices fluctuate during the day depending on energy demand and the availability of electricity. In [26], a decentralized G2V/V2G control algorithm iteratively solves the optimal control problem even with an asynchronous estimation. However, this document did not consider PEVs to be a distributed storage resource. In [27], the authors proposed a concept of PEV charging selection that maximizes driver convenience levels by selecting a specific subset of connected PEVs. However, the document did not consider the concept of V2G or the uncertainties of renewable energy sources.

The proposed algorithm, Real-Time Decentralized Vehicle/Grid (RT-DVG), is based on advisory signals sent by the Low Voltage Distribution Network (LVDN) controller. The latter produces advisory signals that predict the state of the total network energy demand (on-peak, mid-peak, or off-peak) based on the demand of the previous days. This sequence of signals, which is always updated in real time, presents the state of the network during the time interval which starts from the time of arrival of the PEVs until the time of departure of the PEV. Each advisory signal is defined using values below or above an average reference value calculated from the data of the last few days.

2. Optimization problem formulation:

Our objective function of G2V/V2G scheduling aims to reduce the peak power demand and smooth the power curve variation for 24 hours by using the advisory signals sent to the energy management system (EMS). With the yellow signal (*mid-peak*) the reduction of the peak is done by postponing the recharging of the PEVs. However, with the red (*on-peak*) signal, all PEVs in the LVDN try to reduce the disproportion between the reference average demand $P_{avg,onpeak}$ and the average energy demand per hour in the LVDN (See Table 1).

Table 1: Definition of Advisory Signals.

Signal	Limit	Required action
Green	Request ≤ $P_{avg,offpeak}$	The system is *off-peak*. The *G2V* (charging PEVs) is encouraged
Yellow	$P_{avg,offpeak}$ < Request ≤ $P_{avg,onpeak}$	The system is *mid-peak*. Energy demand is not high but postponing PEV charging (if possible) is preferred.
Red	Request > $P_{avg,onpeak}$	The system is *on-peak*. Delaying the recharge can help stabilize the system, while respecting the departure time and the SOC of the PEV. *V2G* is necessary.

The average energy demand per hour in the LVDN D_{avg}^{h} is calculated by adding the base load energy demand D_{base}^{h} and the energy demand of the PEVs for each node D_{PEV}^{h}, then averaging over the total number of nodes in the network:

$$D_{avg}^{h} = \frac{\sum_{k=1}^{M} D_{k}^{h}}{M}, \quad for\ h = 1....24 \qquad (1)$$

$$D_{avg}^{h} = \frac{\sum_{k=1}^{M} D_{base,k}^{h} + D_{PEV,k}^{h}}{M}, \quad for\ h = 1....24 \qquad (2)$$

The objective function of the G2V/V2G scheduling of all LVDN PEVs is given by:

$$Schedule = \min_{D_{PEV}} \left(D_{avg}^{h} - P_{avg,onpeak}\right)^{2}, \quad for\ h = 1....24 \qquad (3)$$

$$Schedule = \min_{D_{PEV}} \left(\frac{\sum_{k=1}^{M} D_{base,k}^{h} + D_{PEV,k}^{h}}{M} - P_{avg,onpeak} \right)^{2}, \qquad (4)$$
$$for\ h = 1....24$$

$$s.t. \begin{cases} 20\% < SOC_{k} < 100\%, & \forall k \in M \\ -R_{\max} \le D_{PEV,k}^{h} \le R_{\max} \\ \sum_{k=1}^{M} D_{k}^{h} \quad \Delta t \quad \varphi_{k} = C_{battery} \\ \varphi_{k} \in \{0,1\}, \end{cases} \qquad (5)$$

Whith M is the group of nodes that contains PEVs in the network, $C_{battery}$ is the maximum charge capacity of the battery, and Δt represents the time increment knowing that the unit of time in our work is the hour. The constraints considered are given in Eq (5). The constraint purpose of the state of charge (SOC) is to optimize the life of the battery. $R_{\max}$ is the maximum battery recharge rate. The third constraint is added to indicate that the battery must be fully charged before the deadline. The boolean variable φ_{k} indicates if the PEV is hooked up or not.

Constraints imposed by the LVDN controller:

At the controller, the voltage deviation V_{k} at each node should not exceed 5% of the rated voltage, otherwise the node will be turned off.

$$V_{k,h+1} - V_{k,h} \le 5\%, \quad \forall h, \quad \forall k \in M \qquad (6)$$

To avoid cases of overload due to the arrival of some PEVs together, the controller defines a constraint (7) on the maximum energy demand to limit the consumption of electricity at every interval of 1 hour:

$$\sum_{k=1}^{M} P_{k,h} \le \begin{cases} D_{\max,g}^{h} & \forall \text{ time period with green signal} \\ D_{\max,y}^{h} & \forall \text{ time period with yellow signa} \\ D_{\max,r}^{h} & \forall \text{ time period with red signa} \end{cases} \qquad (7)$$

$$\text{Where } D_{\max,g}^{h} > D_{\max,y}^{h} > D_{\max,r}^{h} \qquad (8)$$

$D^h_{\max,g}$, $D^h_{\max,y}$ and $D^h_{\max,r}$ are all reference variables that control the energy demand profile and can be configured by the operator to meet his specific needs.

3. The algorithm of the proposed approach

The steps of our proposed RT-DVG algorithm are shown in Figure 1. Each PEV arrives at t_{arival} and sends its identifier information to the LVDN controller to request the triggering of the G2V/V2G.

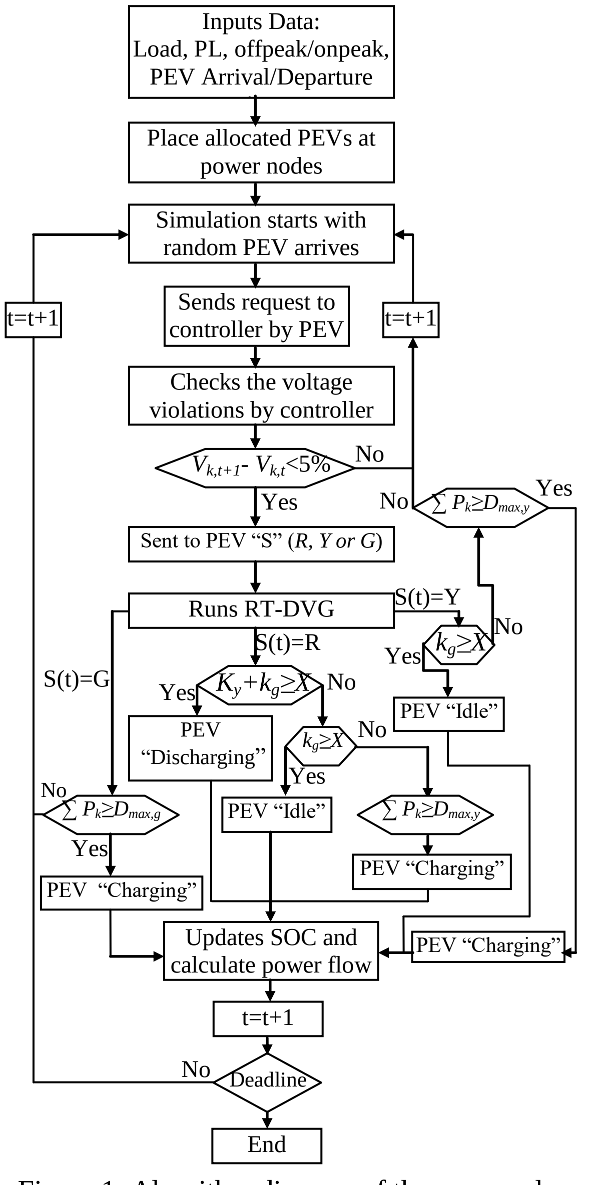


Figure 1: Algorithm diagram of the proposed approach.

To avoid voltage violation, the controller verify all nodes and disables the node that violates the constraints. If there isn't any of violation, it returns a response packet S which presents the distribution of the advisory signals over the interval of time between the arrival and the departure of the PEV. The PEV receives this packet and then executes the proposed algorithm in order the optimal action to do: G2V (if green signal), V2G (if red signal), or idle (if yellow signal). The red signal indicates that the power demand of the system is high (on-peak) and that V2G is necessary. The yellow signal indicates that the system demand is average (mid-peak) and that it is preferable to recharge the PEV later if necessary. The green signal is displayed when the system demand is not high (off-peak) (Table 1). In this case, it is encouraged to postpone recharging the PEV and store the extra energy for use when the signal turns red.
The recharging of the PEV is postponed only when the number of green signals in S is greater than the hours of recharging required X (Figure 1). For the discharge (V2G) of the PEV, the number of green and yellow signals must be equal to the sum of X and the number of hours necessary to recover the hours of the V2G. By running the RT-DVG, each PEV establishes its real-time G2V/V2G scheduling. As a result, the SOC is actualized and the OpenDSS is called upon to perform the system power flow analyses. This process repeats each time at the start of the next time interval (next hour) until the PEV start time is reached. Thus, the PEV becomes disconnected.

4. Test system

Figure 2 represents the electricity distribution network considered. Indeed, we have modified the model of the electricity distribution network described in [28] by adding nodes representing the controllers of the LVDNs. This network consists of 9 LVDNs from which 9 nodes will play the role of 9 controllers of these LVDNs. Once the PEV initiates the action of the G2V/V2G during the simulation, OMNET++ sends a request to request the energy from the OpenDSS. We also used the communication infrastructure of Figure 3.

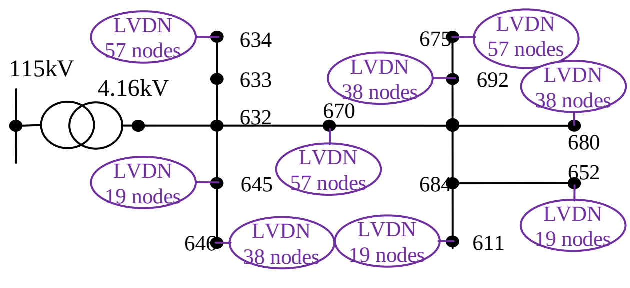


Figure 2: Single-line diagram of the power distribution network.

An Ethernet passive optical network (EPON) of 9 nodes "one optical network unit (UNO) per LVDN" is evenly distributed over the entire network of 9 LVDNs. We used one mesh portal point (MPP) per LVDN to connect each controller to its group of PEVs [29].

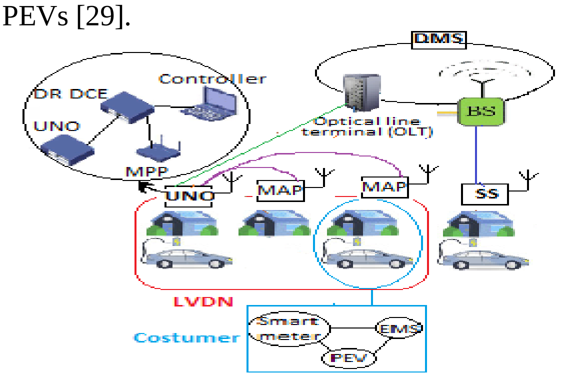
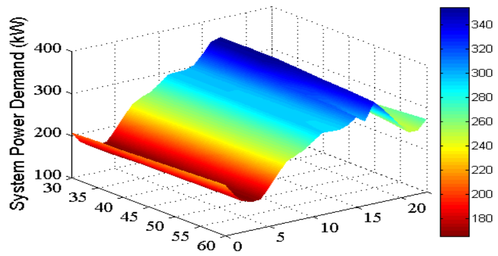


Figure 3: The Fiber-Wireless (WiFi) communications infrastructure.

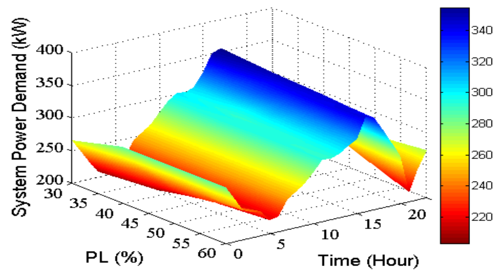
5. Simulation results

5.1 Performance in terms of power

Figures 4 to 6, shows the results of the RT_DVG method for various penetration levels (PLs) of VEPs compared with the scenario of random charging. For a PL of 30%, the maximum reduction in peak energy demand reaches 10%. For higher PLs, the reduction in peak energy demand becomes more significant and increases to the maximum value (PL = 60%).



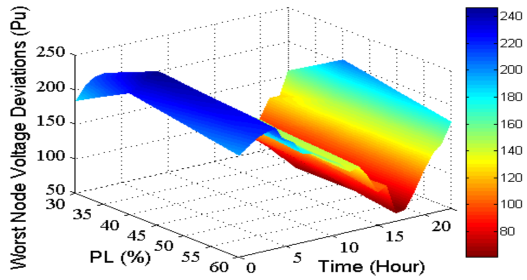
(a)



(b)

Figure 4: System power demand in terms of different penetration levels (PLs) of the PEVs: a) Random charging scenario, b) RT-DVG scenario.

From Figure 4, a similar behavior of power demand is observed for PLs of 40% and 60% between 11 PM and 2 AM. We conclude that for PLs that exceed 40 %, a few PEVs have not received authorization for recharging because the maximum authorized power $D_{\max}$ has been reached. Therefore, it is advisable in this case for these PEVs to do the V2G, if possible, and to help the network by returning energy to it. This allows PEVs to gain in the price of electricity since this price increases when there is a high demand for energy (on-peak periods). We also note that the energy demand during the period between 6 AM and 11 AM (mid-peak) is kept unchanged for all the PLs. The scenarios of Random Charging present two challenges. In first, large peaks appear on the power demand curve (Figure 4(a)). Second, they show remarkable voltage deviations (Figure 5(a)) and power losses (Figure 6(a)) that increase with PL. Figure 4(b) shows that, for a PL of 60%, the maximum decrease in peak demand for RT-DVG exceeds that of Random Charging by a percentage of 20%. Also, our RT-DVG shows less voltage deviations than Random Charging for different PLs, as shown in Figure 5(b). The proposed method results shown in Figure 6(b) indicate a significant improvement in reducing power losses in on-peak periods. For a PL of 60%, the total power losses at 6 PM are are diminished from 33 [kW] to 20 [kW] with the RT_DVG, which is equivalent to a reduction of 40%.



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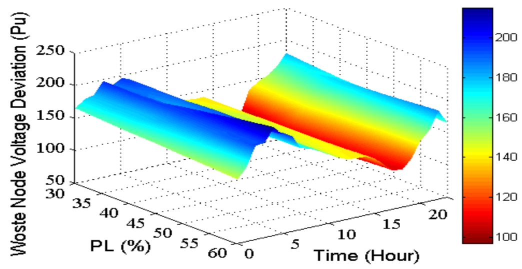
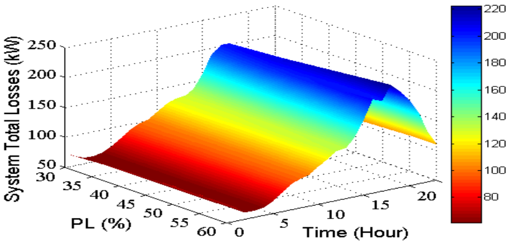


(b)

Figure 5: Voltage deviations in terms of different penetration levels (PLs) of the PEVs: a) Random charging scenario, b) RT-DVG scenario.



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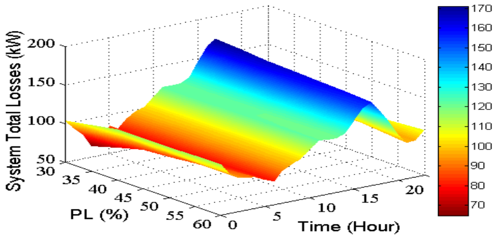


(b)

Figure 6: Total power losses in terms of different penetration levels (PLs) of the PEVs: a) Random charging scenario, b) RT-DVG scenario.

Comparing between the RT-DVG and the centralized algorithm IntVGR [30] (Figure 7), we observe that the peaks of the power demand during the whole day decrease using these two algorithms, but the curve of the energy demand of the RT-DVG is more attenuated than that of the IntVGR. It should also be noted that in the case of G2V/V2G control algorithms for a centralized electrical distribution system, the distribution management system (DMS) requires a global knowledge of all the parameters of the PEVs to solve the optimization function while respecting the needs of each PEV. While the decentralized RT-DVG algorithm is implemented locally in each PEV and only considers advisory signals indicating the status of the system in terms of energy demand.

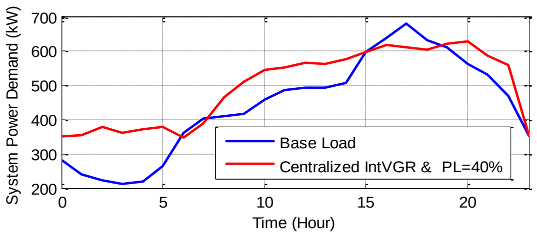
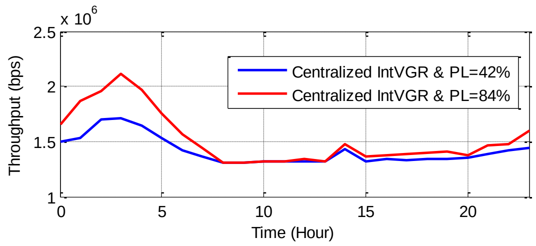


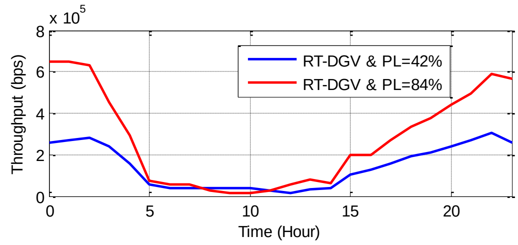
Figure 7: System power demand for centralized IntVGR with 40% of PL.

5.2. Performance in terms of communication

To examine the performance of the communication infrastructure of Figure 3, we examined the throughput and the transmission delay between the PEVs and the DMS for the following values of PLs: 42% and 84%.



(a)

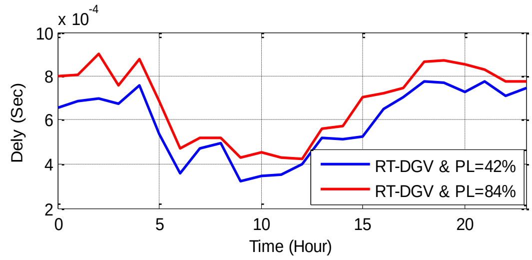


(b)

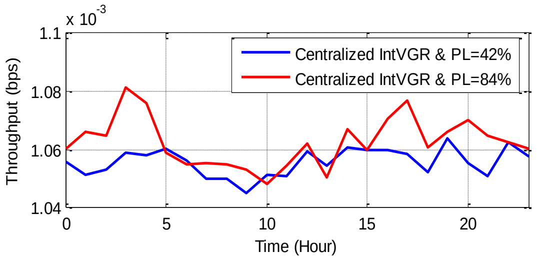
Figure 8: Throughput measured between the PEVs and the LVDN controller.

A comparison of study is carried between our decentralized algorithm and the centralized algorithm IntVGR to assess improvement of the performance in terms of communication. In Figure 8(a), the throughput measured between the PEVs and the LVDN controller starts to increase at the expected arrival time of the PEVs ((5 PM - 6 PM) and reaches its maximum value around 8 PM. Then it stays almost constant until the time of departure of the PEVs (6 AM - 7 AM). It is because of with the fact that the the VEPs come in the afternoon and begin to exchange demand requests energy with the LVDN controller every hour to plan their G2V/V2G schedules. From Figure 8(a), using the RT-DVG algorithm, the throughput reaches a maximum of value (0.65 [Mbps]), so that using the centralized IntVGR method, the throughput reaches a maximum value of 2.1 [Mbps] (Figure 8 (b)). This increase in throughput with the centralized algorithm is due to the excessive exchange of notification packets (every second). While with the decentralized algorithm, the information exchanged between the LVDN controller and PEVs are limited to control messages (every hour).

Figure 9 presents the delay variations of the data transferred between the LVDN controller and the PEVs. The transmission delay with the proposed approach varies from 0.35 [ms] to 0.8 [ms], while the Int-VGR measures a delay almost equal to 1 [ms] (Fig. 9 (b)). This delay reduction with the RT-DVG algorithm is explained by the fact that this algorithm uses fewer packet types between the PEVs and the LVDN controller.



(a)



(b)

Figure 9: Transmission delay measured between the PEVs and the DMS.

6. Conclusion

In this article, we proposed a real-time G2V/V2G control algorithm for a decentralized electrical distribution system in LVDNs where each PEV defines its own G2V/V2G schedule based on advisory signals sent by the controller. of the LVDN. The simulation results show a significant improvement in the performance in terms of communication of the decentralized RT-DVG algorithm compared to the centralized IntVGR algorithm. Indeed, RT-DVG requires less bandwidth and less delay (throughput of 0.65 [Mbps] and delay of below than 0.8 [ms]) than InIVGR (throughput of 2.1 [Mbps] and delay of 1.074 [ms]). On the other hand, the simulation results in terms of power proved the efficiency of proposed RT-DVG algorithm in reducing the peak power demand while minimizing the power losses. We can finally conclude that the RT-DVG can be considered effective and meets the requirements of PEV drivers.

7. Future Scope

This work gives new directions for future perspectives. Each of the discussed approaches: centralized and decentralized has its pros and cons. An interesting next step may be to find an intermediate solution that develops an adaptive approach by combining the centralized mode and the decentralized mode.

8. References

[1] Abid, M., Tabaa, M., Chakir, A., & Hachimi, H. (2022). Routing and charging of Electric Vehicles: Literature Review. *Energy Reports*, *8*, 556–578. https://doi.org/10.1016/j.egyr.2022.07.089

[2] Mastoi, M. S., Zhuang, S., Munir, H. M., Haris, M., Hassan, M., Usman, M., Bukhari, S. S., & Ro, J.-S. (2022). An in-depth analysis of Electric Vehicle Charging Station Infrastructure, policy implications, and future trends. *Energy Reports*, *8*, 11504–11529. https://doi.org/10.1016/j.egyr.2022.09.011

[3] Hagman, J., & Stier, J. J. (2022). Selling electric vehicles: Experiences from vehicle salespeople in Sweden. *Research in Transportation Business & Management*, 100882. https://doi.org/10.1016/j.rtbm.2022.100882

[4] Yin, W. J., & Qin, X. (2022). Cooperative optimization strategy for large-scale electric vehicle charging and discharging. *Energy*, *258*, 124969. https://doi.org/10.1016/j.energy.2022.124969

[5] Lee, M. (2020). An analysis of the effects of artificial intelligence on electric vehicle technology innovation using patent data. *World Patent Information*, *63*, 102002. https://doi.org/10.1016/j.wpi.2020.102002

[6] Marmiroli, B., Venditti, M., Dotelli, G., & Spessa, E. (2020). The transport of goods in the urban environment: A comparative life cycle assessment of electric, compressed natural gas and diesel light-duty vehicles. *Applied Energy*, *260*, 114236. https://doi.org/10.1016/j.apenergy.2019.114236

[7] Li, Y., Lim, M. K., Tan, Y., Lee, S. Y., & Tseng, M.-L. (2020). Sharing economy to improve routing for urban logistics distribution using Electric Vehicles. *Resources, Conservation and Recycling*, *153*, 104585. https://doi.org/10.1016/j.resconrec.2019.104585

[8] Ghaebi Panah, P., Hooshmand, R.-A., Gholipour, M., & Bornapour, M. (2020). Urban microgrid ancillary service provision using Plugin Electric Vehicle and waste-to-energy CHP. *Journal of Energy Storage*, *29*, 101413. https://doi.org/10.1016/j.est.2020.101413

[9] Ouyang, P., Xu, Y.-P., Qi, L.-Y., & Jafari, H. (2022). An improved version of Search and Rescue Algorithm for electrical power energy production and the demand of China. *Energy Reports*, *8*, 3395–3405. https://doi.org/10.1016/j.egyr.2022.02.154

[10] Zahedmanesh, A., Muttaqi, K., & Sutanto, D. (2021). A cooperative energy management in a virtual energy hub of an electric transportation system powered by PV generation and Energy Storage. *IEEE Transactions on Transportation*

Electrification, *7*(3), 1123–1133. https://doi.org/ 10.1109/ tte. 2021. 3055218

[11] Singaravelan, A., M., K., Ram, J. P., B., G., & Kim, Y.-J. (2021). Application of two-phase simplex method (TPSM) for an efficient home energy management system to reduce peak demand and consumer consumption cost. *IEEE Access*, *9*, 63591–63601. https://doi.org/10.1109/access.2021.3072683

[12] Jahangir, M. H., & Ghanbari Motlagh, S. (2022). Feasibility Study of Ceto Wave Energy Converter in Iranian coastal areas to meet electrical demands (a case study). *Energy for Sustainable Development*, *70*, 272–289. https://doi.org/10.1016/j.esd.2022.07.0 17

[13] Zhang, N., Lu, Y., Chen, J., & Hwang, B.-G. (2022). An agent-based diffusion model for residential photovoltaic deployment in Singapore: Perspective of consumers' behaviour. *Journal of Cleaner Production*, *367*, 132793. https://doi.org/10.1016/ j.jclepro.2022.132793

[14] Zhang, H., Yue, D., Dou, C., Li, K., & Xie, X. (2021). Event-triggered multiagent optimization for two-layered model of hybrid energy system with price bidding-based demand response. *IEEE Transactions on Cybernetics*, *51*(4), 2068–2079. https://doi.org/10.1109/tcyb.2019.2931706

[15] Algarvio, H., & Lopes, F. (2022). Agent-based retail competition and portfolio optimization in liberalized electricity markets: A study involving real-world consumers. *International Journal of Electrical Power & Energy Systems*, *137*, 107687. https://doi.org/10.1016/j.ijepes.2021.107687

[16] Haggi, H., & Sun, W. (2021). Multi-round double auction-enabled peer-to-peer energy exchange in active distribution networks. *IEEE Transactions on Smart Grid*, *12*(5), 4403–4414. https://doi.org/10.1109/tsg.2021.3088309

[17] Alfaverh, F., Denai, M., & Sun, Y. (2020). Demand response strategy based on reinforcement learning and fuzzy reasoning for Home Energy Management. *IEEE Access*, *8*, 39310–39321.

[18] Alqahtani, M., Scott, M. J., & Hu, M. (2022). Dynamic Energy Scheduling and routing of a large fleet of electric vehicles using multi-agent reinforcement learning. *Computers & Industrial Engineering*, *169*, 108180. https://doi.org/10.1016/j.cie.2022.108180

[19] Das, S., Acharjee, P., & Bhattacharya, A. (2021). Charging scheduling of electric vehicle incorporating grid-to-vehicle and vehicle-to-grid technology considering in smart grid. *IEEE Transactions on Industry Applications*, *57*(2), 1688–1702. https://doi.org/10.1109/tia.2020.3041808

[20] Khalid, H. M., & Peng, J. C.-H. (2020). Bidirectional charging in V2G systems: An in-cell variation analysis of vehicle batteries. *IEEE Systems Journal*, *14*(3), 3665–3675. https://doi.org/10.1109/jsyst.2019 . 2958967

[21] Liu, S., Xin, D., Yang, L., Li, J., & Wang, L. (2020). A hierarchical V2G/G2V energy management system for electric-drive-reconstructed onboard converter. *IEEE Access*, *8*, 198201–198213. https://doi.org/10.1109/access.2020.3034968

[22] Wang, H., Shi, M., Xie, P., Dong, Q., & Jia, Y. (2022). Optimal operating regime of an electric vehicle aggregator considering reserve provision. *Energy Reports*, *8*, 353–362. https://doi.org/10.1016/j.egyr.2022.02.163

[23] Shang, Y., Liu, M., Shao, Z., & Jian, L. (2020). A centralized vehicle-to-grid scheme with distributed computing capacity engaging internet of smart charging points: Case study. International Journal of Energy Research, 45(1), 841–863.

[24] Chen, N., Tan, C. W., & Quek, T. Q. (2014). Electric vehicle charging in smart grid: Optimality and Valley-filling algorithms. IEEE Journal of Selected Topics in Signal Processing, 8(6), 1073–1083.

[25] Gan, L., Topcu, U., & Low, S. H. (2013). Optimal Decentralized Protocol for Electric Vehicle Charging. IEEE Transactions on Power Systems, 28(2), 940–951.

[26] Wen, C.-K., Chen, J.-C., Teng, J.-H., & Ting, P. (2012). Decentralized plug-in electric vehicle charging selection algorithm in Power Systems. IEEE Transactions on Smart Grid, 3(4), 1779–1789.

[27] CAI, J., CHEN, C., LIU, P., & DUAN, S. (2015). Centralized control of parallel connected power conditioning system in electric vehicle charge–discharge and Storage Integration Station. Journal of Modern Power Systems and Clean Energy, 3(2), 269–276.

[28] Rodríguez Paz, M. C., Ferraz, R. G., Bretas, A. S., & Leborgne, R. C. (2010). System unbalance and fault impedance effect on faulted distribution networks. *Computers & Mathematics with Applications*, *60*(4), 1105–1114. https://doi.org/10.1016/j.camwa.2010.03.067

[29] Bhattarai, B. P., Levesque, M., Maier, M., Bak-Jensen, B., & Radhakrishna Pillai, J. (2015). Optimizing Electric Vehicle Coordination over a heterogeneous mesh network in a scaled-down Smart Grid testbed. *IEEE Transactions on Smart Grid*, *6*(2), 784–794. https://doi.org/10.1109/tsg.2014.2384202

[30] Solanke, T. U., Ramachandaramurthy, V. K., Yong, J. Y., Pasupuleti, J., Kasinathan, P., & Rajagopalan, A. (2020). A review of strategic charging–discharging control of grid-connected electric vehicles. *Journal of Energy Storage*, *28*, 101193. https://doi.org/10.1016/j.est.2020.101193.