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A Novel Arithmetic Optimization Technique for Electric Vehicle Charging

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Abstract: With the increased usage of Electric vehicles in recent days, the optimal usage of battery both in terms of electrical and economic perspective is very important. Though several battery optimization techniques are evolving day by day, the method to achieve an efficient control of all parameters like battery current, power and power loss has not yet been achieved. This paper proposes a novel approach of implementing an arithmetic optimization scheme for FTP 75 drive cycle source. In this connect, the details of the arithmetic operators are discussed and their relations with electrical parameters are framed from the fundamental equations. A Pseudo-code has been developed and implemented for identifying the optimum charging point from different search spaces. The simulation results obtained for different electrical parameters with respect to different arithmetic operators, emphasizes the enhanced operation of electric vehicles at optimum charging points.

Keywords: Electric Vehicle, FTP drive cycle, Charging unit, Arithmetic optimization

1. Introduction

The various process of optimizing the charging techniques for electric vehicles using different battery characteristics are proposed in [1-3]. This includes improving battery optimization by circuit design modifications and improving vehicle energy efficiency by partial electrical parameters enhancement. Load compensation is also considered here. Among the various electrical parameters, the power loss is directly related to variable battery voltage and constant current charging levels [4-8]. The electrical optimal parameters are assumed as variables for analysis while the fundamental battery parameters like charging state, intervals and rate are considered as constant. The battery charging feature indirectly reduces charging deprivation and affects the vehicle execution, thereby reflecting on the overall cost [9, 10]. The resource allocation of the electrical parameters adjusts the battery charging to an optimal level suitable for different vehicle-driven circumstances. Though various solutions related to battery structure are proposed in [11, 12], they are found to be incomplete in satisfying the technical and optimal battery charging requirements. Following this, various practical approaches for optimized battery charging connected with system cost, energy management and safety measures are discussed in [13-16].

It is generally found that, the predictable irregularities in battery parameters have a crucial role in determining the vehicle efficiency. New charging modes subjected to different supply arrangement are being examined in [17]. Few of the safety considerations are battery state, initial temperature, and heat level at every cycle for changes in load. The consistency of charging models for different energy transmission groups is enhanced for the usage of Electric Vehicles (EV) in different applications [18]. With increase in demand being the primary objective, the control of energy transmission among the vehicles is much focused. [19] Proposes various smart charging architectural practices implementable at different network stages to improve the security. This is done by establishing communication among different levels such as charging module, vehicle battery state and security components at charging stations. In order to manage the cloud data and the power flow, a new scheduling scheme using linear programming is suggested [20]. This computing technique helps in tracing the energy strategy and optimizing the scheduling process using the data obtained from system variables.

The influence of distributed EV structure centered on the standard derivatives are examined with conventional system parameters in [21]. In this innovative methodology, the energy management is carried out using essential inputs from the directives.

Ganesh et al., [22] suggests that the separation process helps in bearing the impact of fault conditions on EV battery. Also, the proposed battery states help in identifying the fault affected schemes and their impact on practical renewable energy sources. The EV Charging network is designed to include the complete feature, based on diffusing power [23]. With the usage of new model, the capacity of charging unit is enhanced and directly lays down new foundations for distribution network.

The EV related economic constraints like technology for charging, demands, charging time and power transfer are considered as a single factor for analysis [24]. This factor modelled for individual stages, helps in framing a new mathematical equilibrium comprising a circulated network. Automated charging and discharging control of EV is improved through necessary arrangements in charging station, to confront the benchmark [25]. Energy targets are set for different charging locations with a motto to improvise the charging scheme incorporating the renewable energy with grid systems. [26] Proposes new charging techniques for EV that takes care of issues related with load disturbances, voltage variations and power drops.

Ahmad *et al*. [27] have demonstrated a two-stage process for the placement of fast charging stations (FCSs). The charging station owner decision index (CSODI), which takes into account the EV flow index and the land cost index, was introduced in the first stage. In order to maximize EV flow and minimize land cost for FCS deployment, the CSODI was developed. The next step involves formulating an optimization problem that takes into account the distribution system operator's limitations in order to minimize the overall active power loss. Bilal and Rizwan [28] have suggested a new hybrid technique for investigating the optimal location of electric vehicle charging stations.

Along with charging stations, reactive power compensation is also offered to address power outages and maintain the dependability of the distribution network. Furthermore, this article has looked closely at car to grid facilities. The proposed approach is a combination of particle swarm optimization (PSO) and grey wolf optimization (GWO). Vamshi and Jayaram [29] have presented a two-stage approach to mitigate the effects of EVs high power consumption on the distribution network. First, it chooses the best sites for FCS based on projections of node traffic density. It then assigns EVs to these FCSs in order to lower the power demand on the distribution system. The goals are to minimize annual energy loss, optimize load demand, reduce station development costs, and maximize CS income while taking into account limitations such charger number, station capacity, and desired battery SOC. A GWO technique is used to identify the optimal FCS placements.

To reduce the power loss, an optimal charging arrangement is preferred, suitable for uncoordinated and stochastic mode of charging. The energy loss between the grid and vehicle can also be shielded using suitable infrastructure [30]. Plug-in capability is augmented through synchronizing and optimized prediction methods. The methods of modifying the existing charging infrastructure to suit various battery charging patterns are offered. This powering unit is compatible with both renewable sources and transmission suppliers [31-35]. A new set of charging algorithms improves the power quality issues in both EV voltages and current at all the stages. These issues are considered a problem statement in this work, and the novel optimization technique for improving the battery charging only through internal parameters is reported.

2. System description

This section explains the fundamental blocks, parameters, and relationships between the blocks involved in the proposed scheme.

Figure 1 illustrates a process for determining optimal locations for EV charging stations, starting with data collection on EV flow and land costs within a transportation network. Potential sites are identified and ranked using the Location Compatibility Index (LCI) and Electric Vehicle Flow Index (EVFI). Input from the Distribution Network Operator is incorporated, considering objectives like minimizing power loss and constraints related to voltage, current, and power. The AOA is then applied to select the best sites, resulting in optimal and efficient charging station placement while minimizing grid impact.

2.1 Charging Unit Block

According to speed variations, the charging unit is used for direct control of motor drive speed and indirect control of gears of the Permanent Magnet Synchronous Motor (PMSM). Figure2 represents the basic charging unit structure along with an optimization algorithm. The algorithm depends on the reference speed obtained from FTP 75 drive source, discussed in the later sections. The charging level includes the DC voltage source and internal resistor status, which expands the prospect of the charging pattern.

The charging unit schematic offers comprehension of charging measurement, the starting point for motor drive functioning and processes, identification of arrangement used. In specific cases, alternate charging patterns could be employed to signify various methods of fulfilling speed limits. Generally, the battery consists of a DC voltage source of 350 V with an internal resistor of 0.002 Ω, connected in series. The sensing unit provides mathematical summation and difference of battery voltage and current measurements.

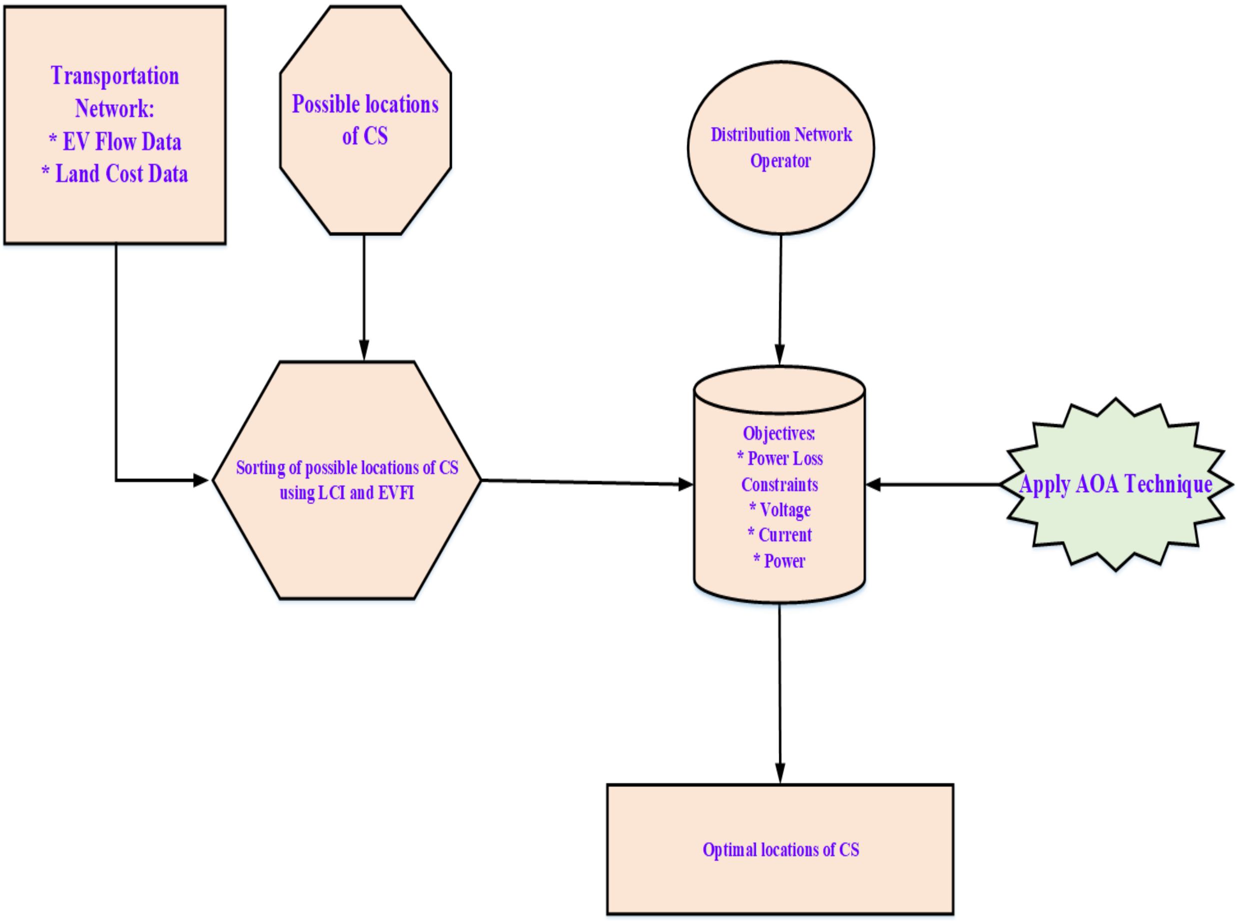

Figure 1. Overview of EV charging

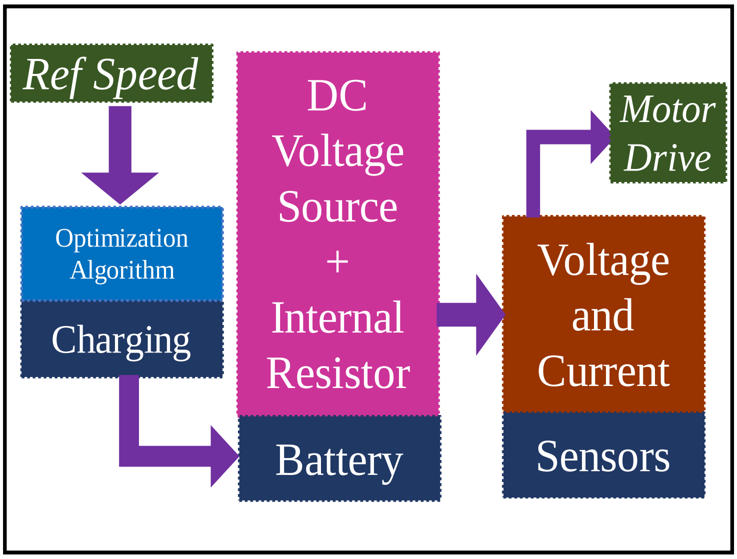

Figure 2. Charging Unit

To show the superiority of the proposed algorithm, the voltage, current, power, and power losses are considered as ensign parameters sensed from this block.

2.2 Motor Drive

In this block, conversion of electrical energy to mechanical energy takes place. The voltage and current from the charging unit drive the Permanent Magnet Synchronous Motor. The torque is decided based on the speed reference derived from the low pass filter ranging between maximum and minimum values. The motor-drive system operates with normal values for maximum torque, power, and torque constant as tabulated in Table 1. The rotor mechanical parameters are attached with a gear ratio in the shaft directly connected to the vehicle axle, as presented in Figure 3. The motion sensor is used to verify the speed for controlling the driver environment and charging pattern.

Table 1. Motor Drive Specifications

Specifications	Value
Maximum Torque	360 Nm
Maximum Power	150 kW
Torque Constant	0.02 seconds
Rotor Inertia	3.93 ×10-4 kgm2
Rotor Damping	1 ×10-5 Nm/rad/sec
Initial Rotor speed	0 rpm
Gear Ratio	0.4286

PMSM drive integrates electrical and mechanical parts of the EV system, separating the overall system into extremely dissociated small stages. The block diagram of drive helps one envisage the motor as a powerful cooperating battery and shaft torque that can be theorized and established autonomously. This structural design makes the system achieve superior speed tractability and empowers the mechanical system to multiply and advance more effortlessly to adjust with altering charging level and torque variation. Controlling of drive axle position using the training procedure is crucial for assembling gear and motion sensor system, to perform in analogy with electrical and mechanical part. The gear part demonstrates the high-altitude viewpoint of the charging patterns, combining battery and sensors. The motion sensors lay multiple levels of emphasis towards individual orientation for better analysis.

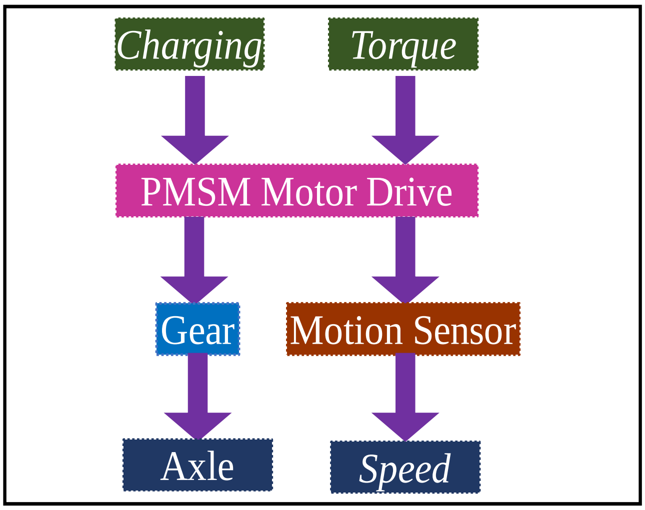

Figure 3. PMSM Motor Drive

2.3 Longitudinal Vehicle

Different inputs are considered for operating the one-dimensional vehicle as to the PMSM shaft and axle through gear arrangement. The Road Grade and Brake Force are also considered as additional inputs to better the optimization. These inputs are deemed to be inactive for our analysis, as shown in Figure 4.

The vehicle outputs such as gravitation force G, driving cycle variation, and charging are taken as vehicle speed references for other blocks. Table 2 lists the specification of the vehicle used.

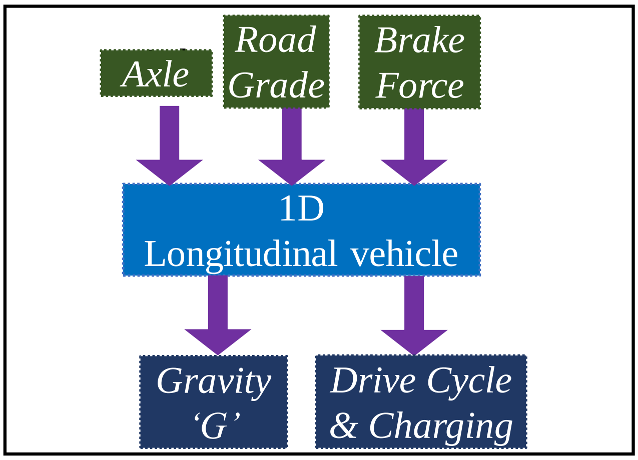

Figure 4. Longitudinal Vehicle

Table 2. Longitudinal vehicle Specifications

Specifications	Value
Vehicle Effective Mass	1600 Kg
Tire rolling radius	30 cm
Road Load coefficient A	100 N
Road Load coefficient B	0 N/kmph
Road Load coefficient C	0.0350 N/kmph2
Brake Force	NA
Road Grade	NA

2.4 Drive Cycle Block

Here FTP 75, prescribed by the US agency, is selected as a driving cycle that measures emission and testing for the electric vehicle. In the block shown in Figure 5, the speed variations are converted to Motor drive torque.

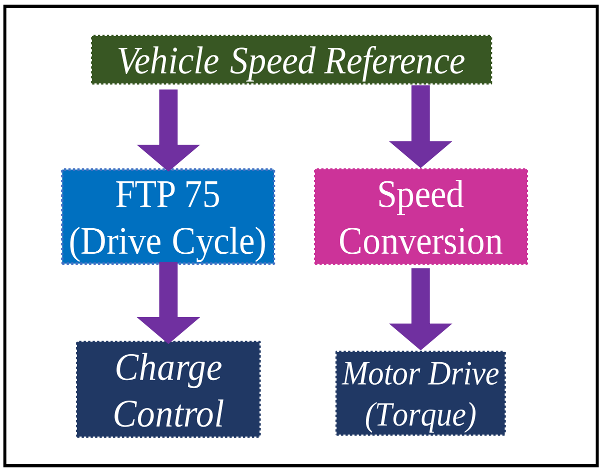

Figure 5. Drive Cycle

3. Proposed arithmetic optimization algorithm for electric vehicle battery charging

From figure 1-4, the various vehicle parameters are modelled as arithmetic operations such as battery voltage, current, power, power loss, and electric efficiency, as shown in Table 3.

Table 3. Arithmetic Operators And Vehicle Parameters

Arithmetic Operators	Vehicle Parameters
Addition 'A'	Battery Voltage and Current
Subtraction 'S'	Battery Voltage and Current
Multiplication 'M'	Battery Power
Division 'D'	Battery Power Loss

In this optimization technique, the selection of electric parameters is assumed for different random vehicle situations. The optimal value for speed variation is analyzed for the conditions mentioned in Tables I to III. As 'FTP 75' is taken as a search space in the vehicle parameters perspective, it helps in providing a comprehensive solution of speed variation from the drive cycle. This drive cycle selection avoids unwanted or undesired solutions, thereby reducing the complexity. The drive cycle's reference speed is initially considered an optimum solution, as shown in Figure 6.

For different time variations, it is mathematically represented as in Equation 1,

$$N(t) = \begin{bmatrix} N_1 & N_2 & \cdots & N_i \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ \vdots \\ t_i \end{bmatrix} \tag{1}$$

The next step is to explore the solutions for different electrical parameters mentioned in Table III, using the search space. As given by Equation 2, the optimization of battery charging is decided by optimum voltage and current values. With the initial values listed by Table 1, iteration is started. The convergence is decided by the maximum and minimum charging level and other battery parameters like the State of Charge (SOC), cycle life, and constant operating temperature.

$$P(t_i) = v(t_i) \times i(t_i) \tag{2}$$

The last step is to select the optimal solution for electrical power and power loss using Equation 3. From the search space, the optimization parameters are

$$P_{loss} = \sum_{j=1}^{\max} \sum_{i=1}^{\max} \frac{f(T(t_i) \times N(t_i)) - f(v(t_i) \times i(t_i))}{T_{ij}} \tag{3}$$

Based on the inference from Table III, two multiplication operators (M) are used in Equation 3, which are Vehicle Power (Torque x Speed) and Motor Power (Voltage x Current). Also, the division operator (D) used in the same Equation provides the details about the distribution of power losses instantly. The optimum solution of the speed variations is obtained based on the convergence of the relationship between the three operators (S, M, and D) in the same function.

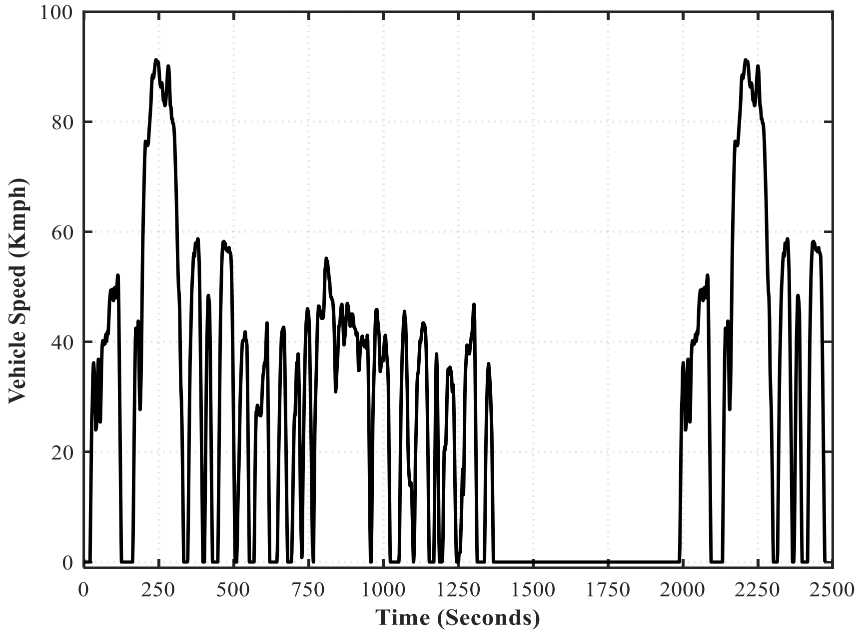

Figure 6. FTP75 driving cycle used for Simulation

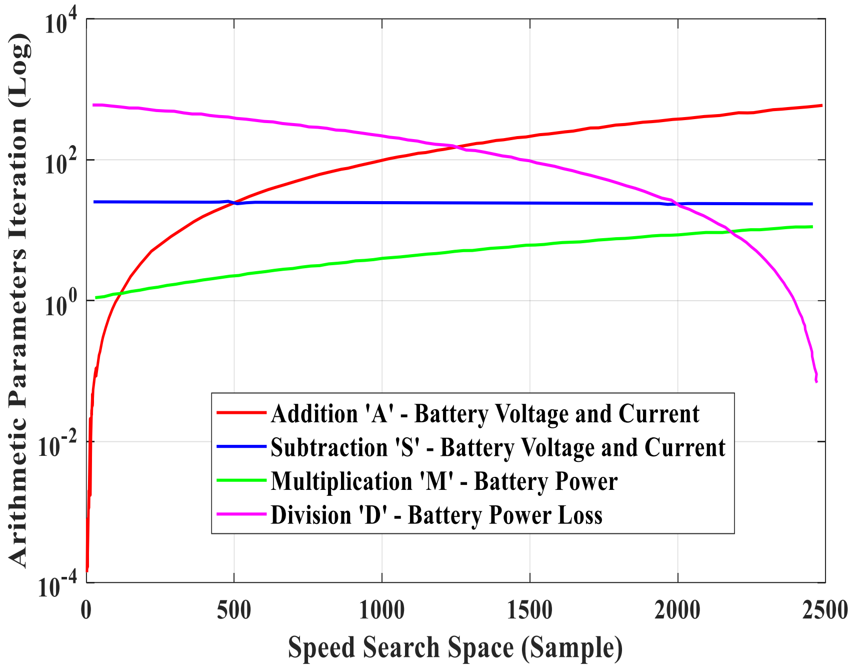

Figure 7. Relationship between Optimization Operators and Parameters for Search Space

Initialize the Motor - Vehicle specification as Table 1 and 2
Initialize the speed values as 'FTP cycle from time domain'.
while ($N_{motor} < N_{vehicle}$) do
Calculate the electrical efficiency (FF) for the given speeds
Find the best solution.
Update the Power value (P) using Eq. (2).
Update the Power loss value (P_{loss}) using Eq. (3).
for (i=1 to Solutions) do
for (j=1 to Positions) do
Generate a random value between [N_{min}, N_{max}]
if Voltage > Power then
Exploration phase
if Current > Power loss then
(1) Optimize Charging according to power loss (D " ÷ ").
Optimize the i^{th} solutions' positions using the first rule in Eq. (3).
else
(2) Optimize Charging according to power (M " × ").
Update the j^{th} solutions' positions in Eq. (3).
end if
else
Exploitation phase
if Power > P_{loss} then
(1) Apply the Subtraction math operator (S " − ").
Update the i^{th} solutions' positions using the first rule in Eq. (4).
else
(2) Apply the Addition math operator (A " + ").
Update the i^{th} solutions' positions using the second rule in Eq. (4).
end if
end if
end for
end for
$N_{new}=N_{initial}+N_i$
end while
Return the best solution (N).

Figure 8. Pseudo-code of proposed arithmetic optimization for battery charging

The resultant solution search must involve an exploration search that detects the near-optimal solution, which may be deduced after several endeavors (iterations). In addition, the exploration operators (D and M) were operated at this stage of optimization to aid the exploitation stage in the search process through improved communication between them. In the final process of selecting the optimal solution, Equation (1) – (3) offers a correlation between all the parameters except power (P). The optimization addition (A) parameter is not included in the search space for a better solution. The electrical efficiency and power loss specified in terms of addition arithmetic operator are given in Equation 4.

$$P(t_i) = P_{in}(t_i) \times \left(1 - \frac{P_{out}(t_i)}{P_{out}(t_i) + P_{loss}(t_i)}\right) \quad (4)$$

Thus, all the parameters and arithmetic operators are in their distributed relationship, thereby providing a search space, as illustrated in Figure 7.

The speed of the search space is observed to be gradually increasing for the addition arithmetic operator up to 750 samples and in the order of 10^2 to 10^3 for the following 1750 samples. The Division arithmetic operator possesses the inverse characteristics of the addition operation. The first 2000 samples take an iteration between 10^3 to $10^{2,}$ and the last 500 samples exhibit a sudden decrease in the iteration from 10^2 to 10^1. Thus, it implies that, with an increased number of samples, the division operator requires more computations. For subtraction and multiplication operators, up to 2000 samples have the breadth of 103 to 102 iterations, but for the last 500 samples, it takes 103 iterations between addition and division operators. Finally, the iterative search detects a rapid optimal speed calculated from the individual operators at each step. The exploration seems to be improved with Equation 4 compared to Equation 3 and 2. The investigation begins with Equation 4 and reports to Eq- 2 for speed adaptation at each search stage. At last, the scheme updates the speed details from Equation 3 and 2 and reverts to Equation 4. The Pseudo-code developed for the proposed arithmetic-based battery charging optimization is shown in Figure 8.

4. Results and Discussion

The previous section provides the mode of implementing the proposed optimization techniques for chosen specifications. The battery charge analyzed for the different arithmetic operators and the solutions identified are illustrated in Figure 9.

From the results, all the answers uphold the logic of arithmetic operators. The charge optimization forms the Addition, An operator from battery voltage and current rather than battery power and power loss. At the same time, the batter's power capability seems to be improved for the Division, D operator as mentioned in Equation 4. Also, from Figure 10, the division operator seems to display the dominant behaviour among all the operators. Over an entire operating time, the battery current is dominating for the division arithmetic operator. It can also be seen that the subtraction operator advances the division operator with the shift of 5 to 10 seconds, owing to fewer computational attempts with the same number of samples. With Addition and Multiplication operators, the peak of the battery current is reduced by 1 to 5% compared to the division operator. For an intermediate time, the value is reduced by 5 to 8%. Figure 11 indicates that subtraction has an additional impact on power and power losses too. While the battery power computed for division operator spans for full operating time, the multiplication operator outlines them by 1 to 5%. For the same operating time, with the addition and subtraction operators, the battery power is reduced by 1 to 3 W. Figure 12 depicts the power loss variation of the battery for different arithmetic operations. The amount of battery power loss computed for the division arithmetic operator is very high for the entire running period. The behavior of the Subtraction operator lies with the division operator but is decreased by 0.01 W. For Addition and Multiplication operators, the battery power loss is lessened by 0.02 W to 0.05 W than the division operator for an entire operating interval.

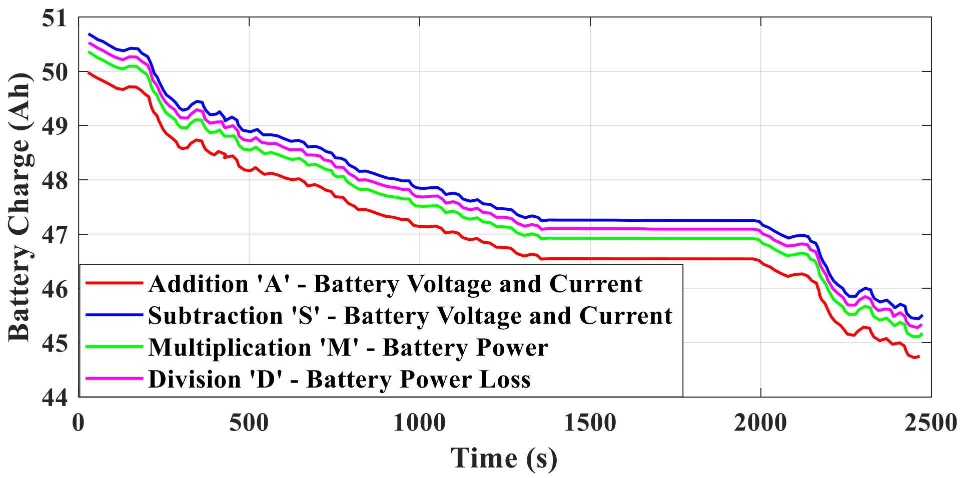

Figure 9. Simulation of Battery Charge for different speed variations

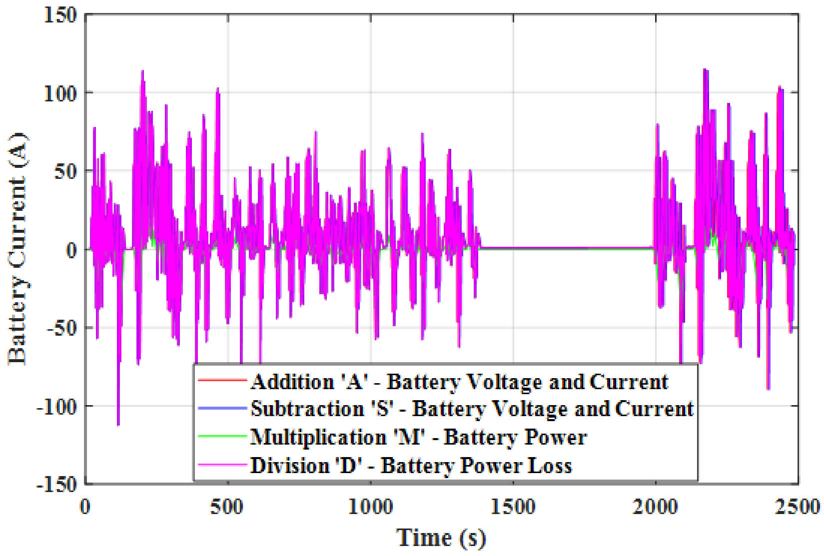

Figure 10. Comparison of Battery Current for different speed variations

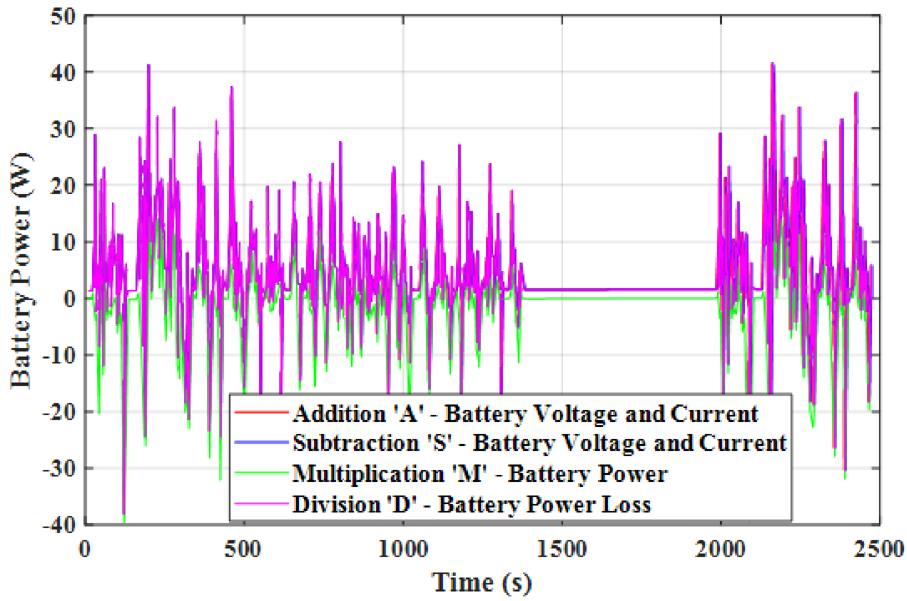

Figure 11. Comparison of Battery Current for different speed variations

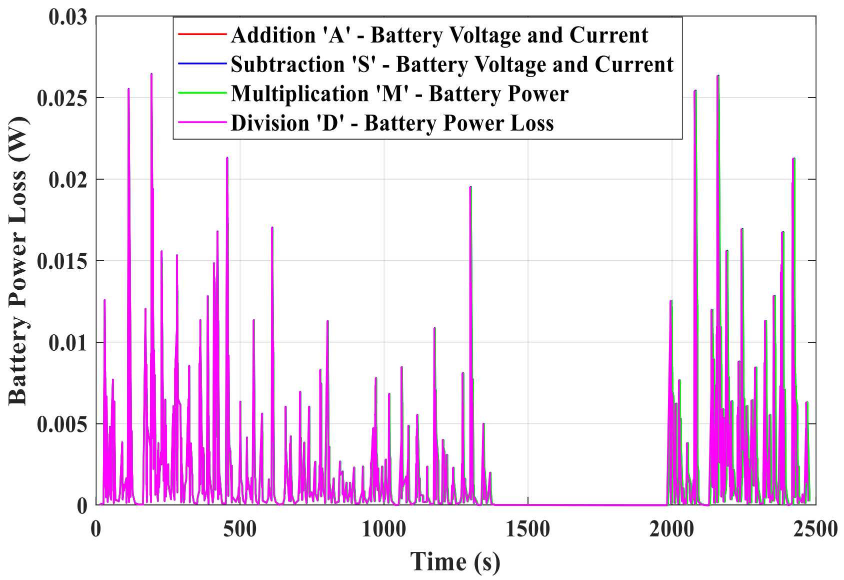

Figure 12. Comparison of Battery Power Loss for different speed variations

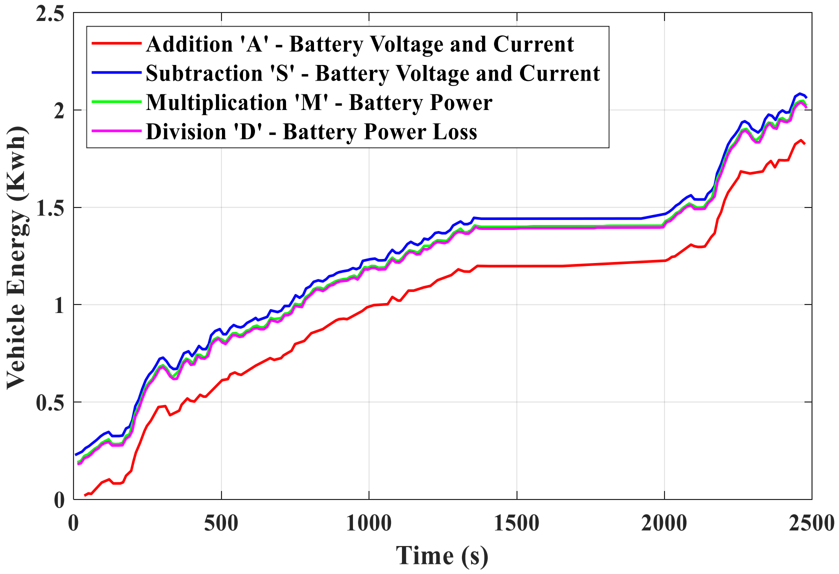

Figure 13. Comparison of Vehicle Energy for running period

Table 4. Comparison Of Power Loss With Proposed And Existing Literatures

Methods	Power loss (kW)
Ahmad *et al*. [27]	198.92
Bilal and Rizwan [28]	191.49
Vamshi and Jayaram [29]	182.63
AOA (proposed)	163.24

Table 5. Comparison Of Computation Time With Proposed And Existing Literatures

Methods	Computation Time (s)
Ahmad *et al*. [27]	0.61
Bilal and Rizwan [28]	0.54
Vamshi and Jayaram [29]	0.42
AOA (proposed)	0.38

Figure 13 represents the EV energy variation over a running period for different arithmetic operations. The energy seems to be gradually increasing for all arithmetic operators in the entire running duration. The addition arithmetic operator demonstrates the low energy transfer with the peak of 1.8 kWh at the end of the running period. Next to the addition operator, the division operator confirms an energy transfer of about 0.3 kWh. Similarly, the multiplication and division operator provide higher energy transfer than the addition operator by 0.8 kWh and 1.7 kWh.

The result analysis reflects the nature of power variation and the dominance of the 'D' operator. The influence of vehicle energy determined for different optimization mirrors the battery charging characteristics and the merit of the proposed optimization techniques. Though the addition, an operator does not create an impact on vehicle energy, the other parameters reflect almost the exact amount of energy characteristics. The Subtraction S exhibits the most optimal characteristics among all the parameters. Thus, the priority of selecting the battery optimization is decided on the order of power, power loss, voltage, and current.

Table 4 illustrates a comparison of power loss across various methods employed in electric vehicle charging optimization, highlighting the effectiveness of the proposed AOA. The data reveals that the AOA technique significantly reduces power loss to 163.24 kW, which is the lowest among the evaluated methods. In comparison, the method introduced by Vamshi and Jayaram [29] results in a power loss of 182.63 kW, while. Bilal and Rizwan [28] and Ahmad et al. [27] report losses of 191.49 kW and 198.92 kW, respectively. The substantial reduction in power loss achieved by the AOA underscores its potential for enhancing efficiency in electric vehicle charging systems. Table 5 presents a comparison of computation times for different approaches used in electric vehicle charging optimization, including the proposed AOA and existing methods from the literature. The proposed AOA technique demonstrates the lowest computation time of 0.38 seconds, outperforming other methods such as those by Vamshi and Jayaram [29] (0.42 s), Bilal and Rizwan [28] (0.54 s), and Ahmad et al. [27] (0.61 s). This reduction in computation time highlights the efficiency of the AOA technique, making it a more suitable choice for fast and effective electric vehicle charging optimization.

4.1 Discussion

The results demonstrate the significant advantages of the proposed AOA in the context of electric vehicle charging optimization. The AOA achieves the lowest power loss of 163.24 kW, outperforming existing methodologies by substantial margins: 182.63 kW for Vamshi and Jayaram [29], 191.49 kW for Bilal and Rizwan [28], and 198.92 kW for Ahmad et al. [27]. This dual improvement in both power loss and computational efficiency, with a computation time of just 0.38 seconds, highlights the AOA's effectiveness, suggesting that it can enhance the overall performance of electric vehicle charging systems. Consequently, the AOA stands out as a promising approach for future research and application in optimizing electric vehicle charging processes, potentially contributing to more sustainable and efficient energy management solutions.

5. Conclusion

A novel optimization technique is proposed for battery optimization in the electric vehicle through arithmetic operators for identifying better solutions. The search space from the FTP 75 drive cycle is taken as a reference for framing the arithmetic operators' boundaries. The fundamental equations relating to the electrical parameters and arithmetic operators are considered for generating the pseudo-code. The algorithm is implemented to determine the optimum speed variation for better charging and is validated through the simulation results. In the future, these new optimization techniques can be extended for different road grades and brake forces as well.

References

[1] S. Jeong, Y. J. Jang, D. Kum, M.S. Lee, Charging Automation for Electric Vehicles: Is a Smaller Battery Good for the Wireless Charging Electric Vehicles. IEEE Transactions on Automation Science and Engineering, 16(1), (2019) 486–497. https://doi.org/10.1109/TASE.2018.2827954

[2] A. Delgado, D. Schoenberger, J.Á. Oliver, P. Alou, J. A. Cobos, Design Guidelines of Inductive Coils Using a Polymer Bonded Magnetic Composite for Inductive Power Transfer Systems in Electric Vehicles. Power Electronics IEEE Transactions on, 35(8), (2020) 7884-7893. https://doi.org/10.1109/TPEL.2020.2965219

[3] P. Darvish, S. Mekhilef, A.B.I. Hazlee, A Novel S S–LCLCC Compensation for Three-Coil WPT to Improve Misalignment and Energy Efficiency Stiffness of Wireless Charging System. Power Electronics IEEE Transactions on, 36(2), (2021) 1341-1355. https://doi.org/10.1109/TPEL.2020.3007832

[4] J. Ahn, B.K. Lee, High-Efficiency Adaptive-Current Charging Strategy for Electric Vehicles Considering Variation of Internal Resistance of Lithium-Ion Battery. IEEE Trans. Power Electron, 34(4), (2019) 3041–3052. https://doi.org/10.1109/TPEL.2018.2848550

[5] A. Relan, V. Gupta, R. Kumar, S. Vyas, B.K. Panigrahi, (2020) Optimal Siting of Electric Vehicle Battery Swapping Stations with Centralized Charging. 2020 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), IEEE, India. https://doi.org/10.1109/PEDES49360.2020.9379513

[6] K. Tahara, K. Ishikawa, M. Ishigaki, (2020) Battery as a Service for Electric Vehicles: Design and Optimization of Partially Swappable and Shareable Battery System. 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), IEEE, Greece. https://doi.org/10.1109/ITSC45102.2020.9294582

[7] F.L.D. Silva, C.E.H. Nishida, D. M. Roijers, A.H.R. Costa, (2020) Coordination of Electric Vehicle Charging Through Multi-agent Reinforcement Learning. IEEE Transactions on Smart Grid, 11(3), 2347–2356. https://doi.org/10.1109/TSG.2019.2952331

[8] A. Mirheli, L. Hajibabai, (2020) Charging Infrastructure and Pricing Strategy: How to Accommodate Different Perspectives?. 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), IEEE, Greece. https://doi.org/10.1109/ITSC45102.2020.9294508

[9] S.B. Fahmy, S.E. Guirguis, O.M. Shehata, E.I. Morgan, (2020) Investigation of an Optimal Charging/Discharging Policy for Electric Vehicles Parking Station in a Smart Grid Environment. 2020 8th International Conference on Control, Mechatronics and Automation (ICCMA), IEEE, Russia. https://doi.org/10.1109/ICCMA51325.2020.9301484

[10] P. Makeen, H.A. Ghali, S. Memon, Experimental and Theoretical Analysis of the Fast Charging Polymer Lithium-Ion Battery Based on Cuckoo Optimization Algorithm (COA). IEEE Access, 8, (2020) 140486–140496. https://doi.org/10.1109/ACCESS.2020.3012913

[11] Z. Wei, Y. Li, L. Cai, Electric Vehicle Charging Scheme for a Park-and-Charge System Considering Battery Degradation Costs. IEEE Transactions on Intelligent Vehicles, 3(3), (2018) 361–373. https://doi.org/10.1109/TIV.2018.2843126

[12] R. Xiong, J. Cao, Q. Yu, H. He, F. Sun, Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles. IEEE Access, 6, (2018) 1832–1843. https://doi.org/10.1109/ACCESS.2017.2780258

[13] Y.H. Jia, Y. Mei, M. Zhang, A Bilevel Ant Colony Optimization Algorithm for Capacitated Electric Vehicle Routing Problem. IEEE Transactions on Cybernetics, 52(10), (2022) 10855 – 10868. https://doi.org/10.1109/TCYB.2021.3069942

[14] N. Mhaisen, N. Fetais, A. Massoud, (2020) Real-Time Scheduling for Electric Vehicles Charging/Discharging Using Reinforcement Learning. 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), IEEE, Qatar. https://doi.org/10.1109/ICIoT48696.2020.9089471

[15] R.M. Elavarasan, G.M. Shafiullah, S. Padmanaban, N.M. Kumar, A. Annam, A.M. Vetrichelvan, L. Mihet-Popa, J.B. Holm-Nielsen, A Comprehensive Review on Renewable Energy Development, Challenges, and Policies of Leading Indian States with an International Perspective. IEEE Access, 8, (2020) 74432–74457. https://doi.org/10.1109/ACCESS.2020.2988011

[16] M. Mathankumar, K. Tamilarasu Viswanathan, K. Balachander, S. Suryaprakash, Design and implementation of improved sliding mode control for electric vehicle voltage stabilization. Materials Today: Proceedings, 45, (2021) 1747-1749. https://doi.org/10.1016/j.matpr.2020.08.622

[17] J. linru, Z. Yuanxing, L. taoyong, D. Xiaohong, Z. Jing, Analysis on Charging Safety and Optimization of Electric Vehicles. IEEE 6th International Conference on Computer and Communications (ICCC), (2020) 2382-2385. https://doi.org/10.1109/ICCC51575.2020.9344906

[18] H.C. Güldorum, İ. Şengör, O. Erdinç, (2020) Charging Management System for Electric Vehicles considering Vehicle-to-Vehicle (V2V) Concept. 12th International Conference on Electrical and Electronics Engineering (ELECO), IEEE, Turkey.

[19] C. Liu, J. Wang, J. Xu, X. Yu, L. Tian, J. Wang, J. Xu, X. Yu, L. Tian, J. Wang, L. Zhou, D. Zhang, (2020) Key security challenges for electric vehicle charging system. In 2020 2nd International Conference on Artificial Intelligence and Advanced Manufacture (AIAM), IEEE, United Kingdom. https://doi.org/10.1109/AIAM50918.2020.00061

[20] J. Zhang, Q. Jiang, A. Pan, T. Li, Z. Liu, Y. Zhang, L. Jiang, X. Zhan, (2021) An optimal dispatching strategy for charging and discharging of electric vehicles based on cloud-edge collaboration. In 2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES), IEEE, China. https://doi.org/10.1109/AEEES51875.2021.9403163

[21] M. Oliinyk, J. Džmura, D. Pál, (2020) The impact of an electric vehicle charging on the distribution system. International Scientific Conference on Electric Power Engineering (EPE), IEEE, Czech Republic. https://doi.org/10.1109/EPE51172.2020.9269213

[22] V. Ganesh, V.M. Ajay Krishna, R.R. Ajit Ram, (2021) Safety Feature in Electric Vehicle at Public Charging Station. 7th International Conference on Electrical Energy Systems (ICEES), IEEE, India. https://doi.org/10.1109/ICEES51510.2021.9383722

[23] Y. Zhang, Z. Chen, P. Li, H. Liu, Z. Zhou, L. Yang, (2020) Radiation Influence Model of Electric Vehicle Charging Station. 4th Conference on Energy Internet and Energy Systems Integration (EI2), IEEE, IEEE, China. https://doi.org/10.1109/EI250167.2020.9347238

[24] Z. Chen, D. Yu, M. Pan, J. Zhang, R. Yuan, X. Liu, S. Zhao, (2021) Distributed charging control of electric vehicles considering cooperative factor in photovoltaic charging station. In 2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES), IEEE, China. https://doi.org/10.1109/AEEES51875.2021.9403153

[25] D. Patil, R. N. Dubey, C. Kulkarni, F. Nadaf, D. Nair, G. B. Ramesh, (2020) Utilization of Solar Power for Automated Automotive and Locomotive Charging. International Conference for Emerging Technology (INCET), IEEE, India. https://doi.org/10.1109/INCET49848.2020.9154114

[26] T. Ninković, M. Ćalasan, S. Mujović, (2020) Coordination of electric vehicles charging in the distribution system. 19th International Symposium Infoteh-Jahorina (Infoteh), IEEE, Bosnia and Herzegovina. https://doi.org/10.1109/INFOTEH48170.2020.9066303

[27] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, I. Khan, Placement of electric vehicle fast charging stations in distribution network considering power

loss, land cost, and electric vehicle population. Energy Sources A Recovery Util. Environ. Effects, 44(1), (2022) 1693–1709. https://doi.org/10.1080/15567036.2022.2055233

[28] M. Bilal, M. Rizwan, Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility. Energy sources, part a: recovery, utilization, and environmental effects, (2021) 1-30. https://doi.org/10.1080/15567036.2021.1923870

[29] A. Vamshi, N. Jayaram, An approach for minimizing annual energy loss by electric vehicle scheduling to optimal fast charging stations. Energy Sources A Recovery Util. Environ. Effects, 46(1), (2024) 11744–11770. https://doi.org/10.1080/15567036.2024.2389226

[30] S. Deb, A. K. Goswami, R. L. Chetri, R. Roy, (2020) Distribution System Congestion Management by Charging Coordination of Plug-in Electric Vehicle. 3rd International Conference on Energy, Power and Environment: Towards Clean Energy Technologies, IEEE, India. https://doi.org/10.1109/ICEPE50861.2021.9404380

[31] K. Vijayakumar, (2021) Solar Charging Infrastructure for E-vehicles - A Review. International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE, India. https://doi.org/10.1109/ICACITE51222.2021.9404557

[32] S.A. Lupu, A.A. Dinu, C.M. Gheorghe, (2021) System for Managing the Electric Vehicle Charging Stations. An Educational Platform. 12th International Symposium on Advanced Topics in Electrical Engineering (ATEE), IEEE, Romania. https://doi.org/10.1109/ATEE52255.2021.9425080

[33] S. N. Hewalekar, S.Y. Gadgune, (2020) Progression of Smart Metering Infrastructure for Electric Vehicle Charging Stations. Third International Conference on Smart Systems and Inventive Technology (ICSSIT), IEEE, India. https://doi.org/10.1109/ICSSIT48917.2020.9214248

[34] K. Kumar, S. Gupta, S. Nema, (2021) A review of dynamic charging of electric vehicles. 7th International Conference on Electrical Energy Systems (ICEES), IEEE, India. https://doi.org/10.1109/ICEES51510.2021.9383634

[35] L. Caro, G. Ramos, D. Montenegro, D. Celeita, (2020) Variable Harmonic Distortion in Electric Vehicle Charging Stations. IEEE Industry Applications Society Annual Meeting, IEEE, USA. https://doi.org/10.1109/IAS44978.2020.9334798

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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