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Smart (V2G) Power Transfer on Scenario Based Strategies Trained Through Artificial Neural Networks for Maximum Tariff Saving and Energy Management in MATLAB Simulink

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Abstract – Although numerous amounts of research have been done to find alternate sources of energy consumption and its applications. But in times of energy crisis and global warming urgency, it is needed to pace towards methods of less dependency on fossil fuels in the meantime fulfilling the on-grid demand. With increasing improvements in the EV sector, it is to be noted the effect they will have on Distributed Grids (DG) to cope with such high demand and as a consumer the relative effect of electricity tariff. In this paper, we will design a smart algorithm for V2G implementation such that the user will bear the minimum cost of charging and benefit from reselling at a higher price. It will work with different situational based cases to best decide upon multiple factors which include the SoC of the battery, User profile, and Tariff profile for multiple DISCO. As not much data is present to fully understand the user and system behavior, this paper uses Artificial Neural Networks (ANN) to develop and train scenarios for cases mentioned. Strategy used in this paper is flexible to modify after implementation in an EV and after a sufficient amount of data is collected. It will reprogram for better accuracies and energy management. Simulations are conducted in Simulink environment.

Keywords – Electric Vehicles, Artificial Neural Network (ANN), Tariff, Energy management, MATLAB, Reinforcement Learning

I. Introduction

According to IEA annual report 2022 [1] there was an increase of 6% in renewable systems across the world. even though numerous researches have been carried out in order to look for alternate sources of energy consumption and its applications but now in times of energy crisis and global warming urgency, it is needed to pace towards methods of less dependency over fossil fuels for energy generation to compete the demand. To accomplish this, leading sources which helped are 'Solar Energy', 'Wind Energy', 'Hydro-Electric Energy' and 'Nuclear Energy' to cut down domination of fossil fuel significantly. Moving towards the normalization phase after pandemic there is a greater possibility of rise in air pollution with mass commute. As most of the people go to work by their cars which will bring a dense amount of CO_2 emissions and in case of EVs, surge in demand of electricity during charging. Grid will be unable to compete in supplying enough energy to the end user which may result in blackouts and frequency losses which can affect the whole transmission system and at the least transmission and distribution losses will significantly rise. this paper we will discuss to convert this issue into an opportunity to utilize excess power in electric vehicles to operate buildings and homes or supply back to the grid at peak hours which will decrease demand factor and also notably impact an electricity bill to save cost.

Vehicle-to-Grid (V2G) is a promising future principle where its algorithm and engineering allow EVs to discharge some of their stored energy back to the grid in order to alleviate the stress from power grid stations and distribution sectors which are already constrained by increasing demand. It also increases penetration of an intermittent sustainable renewable sources of electricity such as wind and solar to impact more worthily. In this paper we have discussed the effect of development of an algorithm where fleets of cars and trucks could lead to a sustainable backup supply to support Low Voltage or Medium Voltage grid.

From customers point of view cost is a big part of management for them. EVs initially cost more than conventional combustion engine vehicles but daily usage can save bucks in fuel cost. With energy crisis and big brands moving completely towards EVs will bring stress on the grid which may cause rise in energy prices per KWHs. For this purpose, V2G can also bring an option for user to sell their stored energy when prices are higher and support the grid in the meantime. Also charge their vehicles at times of the cheapest possibility in tariff. But problem arises with different users and their styles. We know that scenarios won't always be same. Sometimes a car will drive to the work place and get back home but also sometimes it might stay home. There is also a possibility of infrastructure difference. Each case will vary the backup supply. So, to understand the case easily this paper considers three cases mentioned in section II.3 assuming flat city roads.

For implementation there are multiple options to work which includes smart grid connectivity with vehicles and other is on deck support through machine learning or reinforcement learning in an EV. For such cases Bayesian regression models for statistical analysis can be used as discussed by author [2]. Bayesian estimations are faster but restricted with functionality as compared to other methods of deep learning. Artificial Neural Network is one topic which uses a training under set of data and scenarios and after repeated epochs and datasets it becomes standalone to decide upon random cases as discussed in paper [3]. ANN can be used to implement user profiles. After training and receiving results in future it can also be re-trained from new data for more accurate results. This will work on implementation of Vehicle-to-Grid (V2G) in a practical scenario and build case studies to analyses its impact while maximizing the reward for customer and algorithm will control the charging and discharging decisions depending upon conditions of State of Charge (SoC), Tariff and User Profile.

II. Materials and Method

In this paper, scenario-based strategies are built for V2G implementation. For this purpose, three main components were kept in focus:

1. SoC of the battery.
2. Tariff feasibility.
3. User Profile.

1. SoC of the battery: It is vital for strategies in this paper. Unscented Kalman filter (UKF) based strategies were proposed in [4] & [5]. Along with reduced computing time, it also restricts the error within 1.5% from signals noise and create more effective algorithm. Idea proposed in [1] also indicates the use of ANN controller can further improve results by 60% as compared to using conventional methods of EKF and ALS.

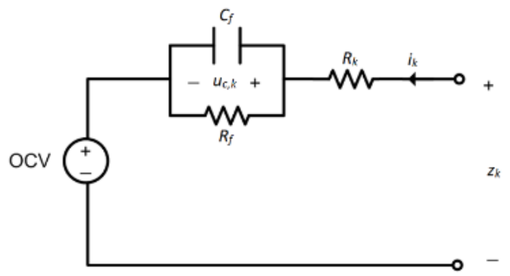

Figure1: RC model of a battery circuit

Considering this RC circuit which constitutes a battery.

$$Zk = OCV\,(SOCk) + Rkik + \mathrm{U}c{,}k \qquad (1)$$

where;

zk = model voltage at some value of k, OCV = open-circuit voltage, $SOCk$ = state-of-charge at instant k, Uc,k is the voltage across the RC network. Rk is the internal resistance. ik is the cell terminal current at instant k (positive when charging and negative when discharging).

$$SoC = \frac{C_k}{C_n}\ X\ 100\% \qquad (2)$$

here,

C_k = Instantaneous Capacity in Ah, C_n = Nominal Capacity in Ah.

For UKF modelling, SoC can be written as the sum of the white signal noise ($\ddot{w}$) and factor of charge $i(\tau)$ and nominal capacity C_n over time period t.

$$x(t) = x(0) + \eta \int_0^t \frac{i(\tau)}{Cn}\,d\tau + \ddot{w} \qquad (3)$$

This is then modeled in MATLAB as an author in [6] defined. Using this method, we developed a method for SoC estimation of a generic battery of 12V at an ambient temperature ranging from 5-40 degrees Celsius to mirror a realistic scenario. To provide the accurate like variation in our ANN trainer, State transition table block is used in Simulink to vary the SoC as per the battery behavior of charging and discharging and kept in limits to avoid battery degradation as discussed in [7]. Simulink model of SoC estimation as shown in figure provides vital information as most cases depends upon the capacity of our battery.

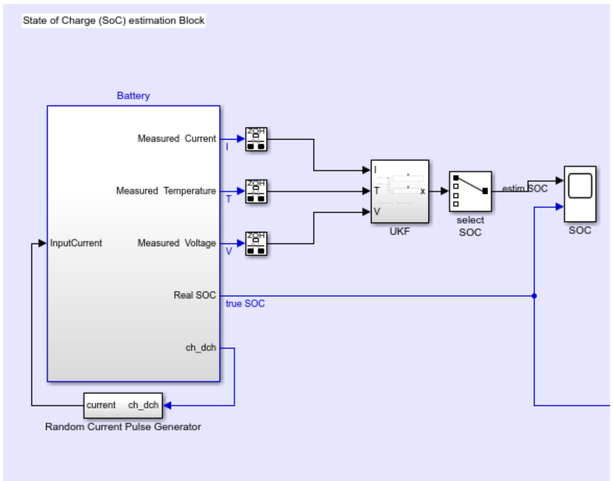

Figure2: SoC estimation block

Results of estimated SoC of a formula is also found to become realistic after $0.4\text{x}10^4$seconds and ranges from 0.3 – 0.9 SoC through its intervals.

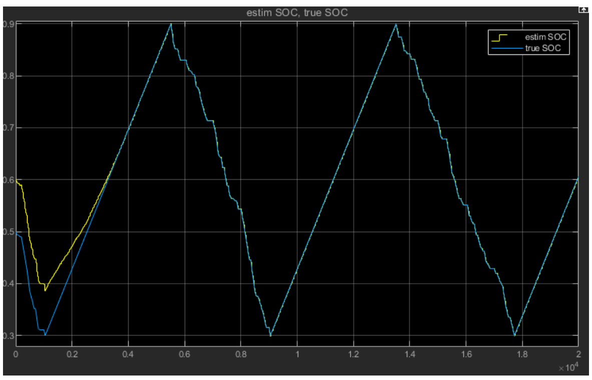

Figure 3: SoC graph

2. Tariff Feasibility: With inflation in charge, cost became one of the highest priorities of a customer. To gain the advantage of a maximum magnitude, this paper provides algorithm which not only looked up for the best time to sell but also through different DISCOS in different areas which usually have different price backets. For our training of ANN, we developed a chart of prices per company as shown in table 1.

Time	Provider 1	Provider 2
00:00-6:00	4 TL	3 TL
6:00-10:00	6 TL	5 TL
10:00-15:00	9 TL	9 TL
15:00-19:00	6 TL	5 TL
19:00-0:00	10 TL	12 TL

Table 1: Time and Tariff comparison

This paper creates a smart algorithm which identifies suitable time for V2G power sharing as well as the best price to sell such that the customer benefits from it.

3. User Profile: Going through content analysis methods, user profile is further defined in multiple cases depending upon the usage of the car, stationary timings and routes. Cases in consideration are defined as following:

a. Home-Work-Home: EV goes to work and travels back to home. Figure 1 shows the flow of our program. Here SoC has to be above CS1 with 5% failsafe of traffic battery to return to home. CS1 defines the change in charging status since it started moving from home.

$$Uo = 1 \quad @\, SoC > (\Delta CS1 + 5\%) \tag{4}$$

$$Uo = 0 \quad @\, SoC < (\Delta CS1 + 5\%) \tag{5}$$

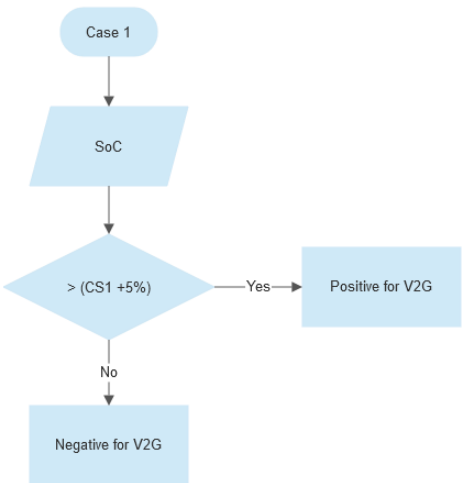

Figure 4: Flow of user profile H-W-H

EV always goes in V2G mode when state of charge is more than the capacity of used capacity and reserve.

b. Stays Home: This case always allows V2G to initiate considering all other conditions are met.

$$Uo = 1$$

c. Random Mode: This is a highly uncertain mode of usage which require detailed analysis, route mapping and traffic scenarios with time. This can be modified with new data collected from ANN to be trained accordingly. In order to train our neural network and ease of complexities, we will consider it as a case of non-operational for V2G.

$$Uo = 0$$

With this, our data inputs for an Artificial Neural Network are satisfied. Simulink then send the processed data to MATLAB command window to start ANN training.

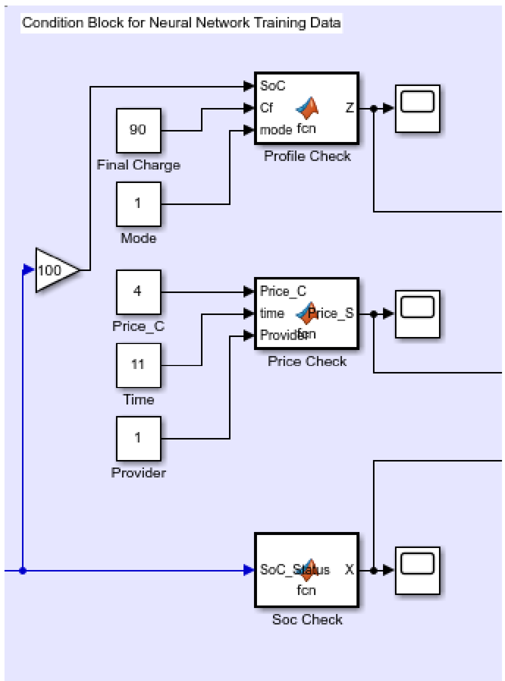

Figure 5: ANN training cases simulation model

For ANN training, this paper used Levenberg-Marquardt Backpropagation (trainlm) method. This method is significantly faster as author in [8] discussed in experiments conducted with minimum epochs being desired by trainlm method. Furthermore, ANN in this paper shapes up with neurons as shown in the figure 7.

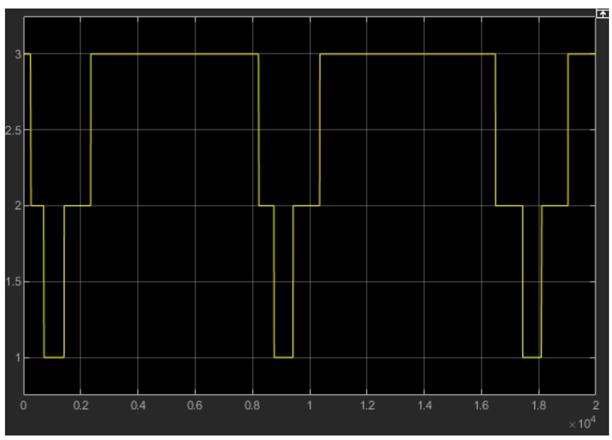

Figure 6: Final Simulation result

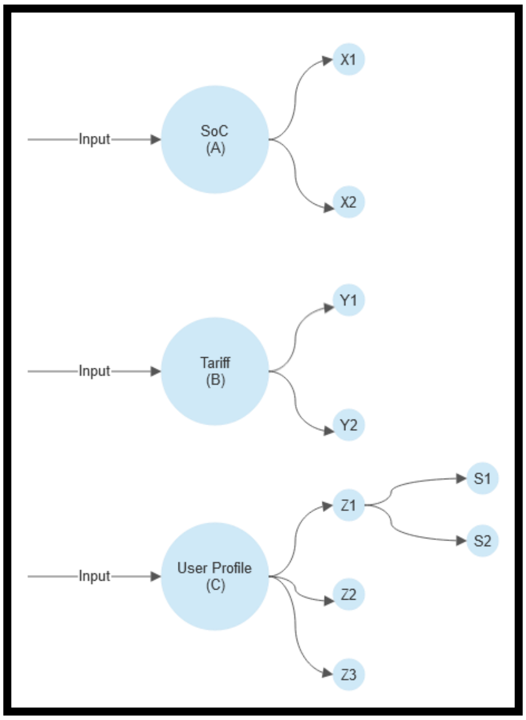

Figure 7: node diagram for an ANN Network

In figure 7: X1 and X2 are the states of SoC through which the V2G power transfer authorization is decided. If the state being X1 which means state is true and process further in this algorithm.

Y1 and Y2 decides upon Tariff as being true or false respectively.

Z1, Z2 and Z3 decides cases of user profile with three cases defined in this paper in section 3. While Z1 goes into sub-neural network which decides if condition is true with enough SoC to get back to home or state is false.

Formula for this system becomes:

$$Output = A(X) + B(Y) + C\,\{Z1(S1) + Z1(S2) + Z2 + Z3\} \quad (6)$$

For any case where output becomes 3 which shows all the three cases are true i.e., SoC is in range, Tariff is feasible for profit and user profile allows to transfer power, this control algorithm sends signal to initiate Vehicle to Grid power transfer.

This data is saved in MATLAB and feed-forwarded to our ANN for training. Following code initiates the training:

```
I=out.Input;
T=out.Output;
I=I';
T=T';
net=newff(minmax(I),[3,5,1],{'logsig','tansig','purelin'},'trainlm');
net = init(net);
net.trainParam.show =1;
net.trainParam.epochs = 1000;
net.trainParam.goal =1e-12;
net=train(net,I,T);
```

III. RESULTS

Results should be clear and concise. The most important features and trends in the results should be described but should not interpreted in detail.

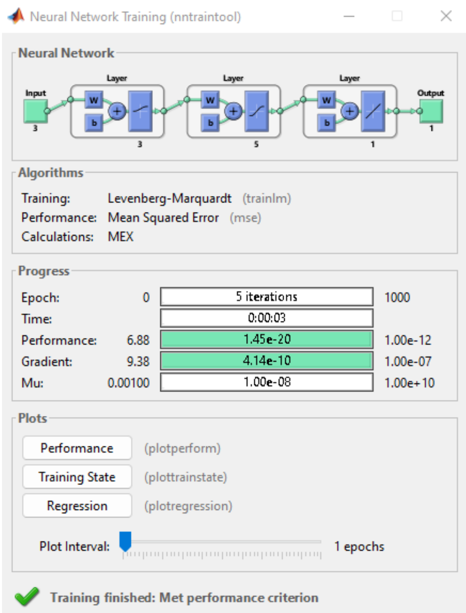

Figure 8: ANN Training

This algorithm was successfully completed in five epochs shown in figure 8. With line of regression satisfying at unity as shown in figure 9.

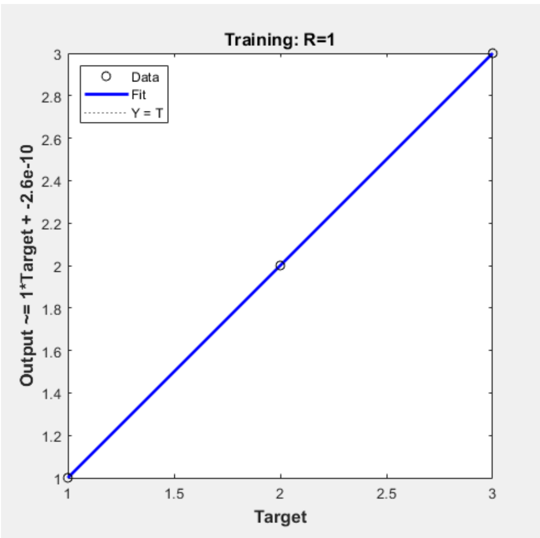

Figure 9: Line of regression

In figure 9 it is observed that with three cases becoming true our output also produces a signal of magnitude 3 which was initially desired and discussed in section II and equation (6).

IV. CONCLUSION

This paper studies the algorithm for efficient V2G power transfer. It defines the scope of true cases for which maximum savings can be done while supporting the power grid. User profile and tariff decision process is also proposed through reinforcement learning and ANN are used to construct this system. ANN capability to be reprogrammed after collecting necessary data makes it viable cost effective. It also provides an idea in current scenario where not much data is available due to lack of infrastructure for V2G in practical world. Results indicated the successful behavior as expected with only initiating V2G transfer when batteries SoC is under desired limitations, authentication of user profile validity and best tariff for users benefit.

ABBREVIATIONS

The following abbreviations are used in this paper:

EV	Electric Vehicle
DG	Distributed Generation
V2G	Vehicle to Grid
SoC	State of Charge
DISCO	Distribution Companies
EKF	Extended Kalman Filter
ALS	Auto-covariance Lease Squares
UKF	Unscented Kalman Filter

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