Energy Cost Optimization of Residential Consumer Considering Real-Time Energy Pricing with Plug-in Electric Vehicles

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF FLOW CHARTS

ABSTRACT

The global perspective has been strongly leaning towards non-pollutive infrastructure, chief among them are electric vehicles. The advent towards integrating electric vehicles into society brings with it tremendous opportunities. This project utilizes one such opportunity and proposes the idea of reducing the energy cost burden for residential consumers by taking advantage of an auxiliary source in the form of Plug-in Electric Vehicle. The EV decides on a charging or discharging course of action grid by observing the variable half-hourly grid price and the cost of stored energy in battery hereby referred to as Energy Price Tag or EPT. The proposed algorithm makes use of a meta-heuristic technique known as Particle Swarm optimization to calculate the real-time pricing of charging and discharging of PEV and compare it with half-hourly grid price and thus supply the demand accordingly to reduce the energy cost burden.

This will help reduce the energy cost burden for residential customers as well as on the grid, thus reducing our dependence on the conventional power systems. The proposed charging strategy powered by Particle Swarm Optimization algorithm has been implemented in MATLAB software. This project also shows how the PSO charging algorithm shifts the load from peak to non-peak hours, thus reducing burden on the grid. Finally, simulation results indicated that the PSO based charging strategy can help residential EV owners reduce their monthly energy consumption costs.

Keywords: Plug-in Electric Vehicle, Particle Swarm Optimization, Energy Price Tag (EPT), Charging strategy, Real time pricing, State of Charge.

CHAPTER -1

INTRODUCTION

1.1 PROBLEM DESCRIPTION:

With the constantly evolving development of new loads, that have complex power requirements and the ever-increasing demand for electricity leads to an increased energy cost burden on the residential customer. Thus, it has become crucial to find an effective method to reduce the cost of electricity for customers and use the electricity in an efficient way. One of the ways is to use Plug-in Electric Vehicle as a dynamic load and potential source of stored energy which can be charged by plugging it to the grid during off-peak demand.

This can be implemented using the Particle Swarm Optimization algorithm which calculates the Energy Price Tag of PEV and prioritizes the charging strategy by comparing the EPT with the Real Time Pricing of the grid i.e. half-hourly grid price to 1supply the demand.

1.2 AIM:

This study aims to look out for new techniques for determining the average energy price stored in the Plug-in Electric Vehicle hereafter termed as EPT (energy price tag). EPT helps to prioritize the charging/discharging sequence based on the half-hourly grid price.

1.3 OBJECTIVE:

The main objective of the study is to find the exact time and priority order between the energy exchange from PEV considering the EPT, energy imported from grid and exported back to grid to reduce the household electricity cost. Hence, reducing the energy consumption cost by implementing Real Time Electricity Allocation strategy through Particle Swarm optimization Algorithm.

1.4 SCOPE OF WORK

1. In this project an optimisation algorithm as part of a smart charging infrastructure is implemented to decide the priority order between PEV, household load and grid to reduce the average cost of electricity purchased from grid and improve the utilization efficiency.

2. A real time distributed electricity allocation is proposed for grid connected residential micro-grid with vehicle to grid capability.

3. Dynamic Pricing policy of electricity grid is exploited for optimal charging of PEV to minimise the supply-demand mismatch.

4. Exact cost of PEV battery stored energy (EPT) should be monitored when dealing with PEV in future energy transactions.

5.The optimization algorithm opted here is PSO Particle Swarm Optimization which uses the multiple iteration of a swarm of particles while considering the personal best (pbest) and global best (gbest) to find the optimized solution.

1.5 CHAPTER OUTLINE

Chapter 2: Brief introduction about Energy Price Tag and Real Time pricing.

Chapter 3: Formulation of optimization problem, energy cost function and constraints.

Chapter 4: Introduction to Particle Swarm Optimization, its working procedure with the particle's individual vector, fitness of each individual and flow chart.

Chapter 5: The working of the proposed algorithm and the simulation results obtained in the process.

CHAPTER -2

ENERGY PRICE TAG (EPT) AND PRICING

2.1 ELECTRIC VEHICLE EPT

In today's world of electricity marketplace, the information about the real time price of energy storage devices is an accepted norm. A Smart home requires the real time pricing of storage devices to schedule them according to the peak and off-peak demand and thus reduce energy consumption cost. One such device is the Plug-in Electric Vehicle. Plug-in Electric Vehicle is used in a smart charging network via its Vehicle to Grid i.e. V2G function to reduce the energy costs. As per the real time price of electricity and location of charging, the PEV owner pays a certain rate for charging their vehicle. To successfully develop a charging strategy, a comparative metric is necessary to decide the PEV charge/discharge operating mode. This metric serves as a connection between the energy market and the vehicle owner. Hence, in this project a term known as Energy Price Tag (EPT) is introduced. EPT is an indicator of the average price of the energy stored (c/kwhr) in the PEV battery. EPT is defined as the tariff that allows more realistic exchange of energy among storage devices. [1]In a smart home system, with the knowledge of EPT, the energy flow can be optimized between the various constituents to achieve energy cost minimization; thus, reducing the final cost of energy being stored in the PEV battery.

The EPT for PEV at time step (h) is calculated with the knowledge of the EPT and the total energy available in the previous time step (h-1), and the grid price and amount of energy exchanged during that time step: [1]

$$\textbf{EPT(h)} = \begin{cases} \frac{EPT(h-1)*Energy(h-1)+\Delta Energy(h)*C(h)}{Energy(h-1)+\Delta Energy} & Charging \\ EPT(h-1) & Discharging \end{cases} \quad \textbf{..........(1)}$$

Where,

- EPT(h−1) is the average energy price for time step (h−1),
- Energy(h−1) is the total available energy in time step (h−1),
- Δ Energy is the net change in energy during time step (h),
- C(h) is the price of energy that was exchanged during time step (h)

2.2 REAL-TIME PRICING

Real-time pricing is the electricity tariff charges for the energy delivered to the consumer that vary for a fixed time period usually every hour or every half hour and are usually determined from the wholesale power market prices by a methodology decided by the state or country's electricity regulatory commission. In basic terms, constant evaluation gives purchasers, data about the genuine expense of power at some random time. Power costs change from hour to hour, yet most consumers are compelled to follow through on a similar cost regardless of when they use power. Continuous valuing lets buyers change their power use appropriately; for instance, booking use during times of low demand to pay less expensive rates.

Constant power estimating requires the establishment of a power savvy meter that can send and get data about power expenses and give buyers more data about their own utilization. Smart meters are significant gadgets to guarantee the viable execution of on-going estimating. Smart Meters are the electronic estimation gadget utilized by vitality organizations to record the utilization of power and convey data to their charging division and to clients. The blend of the hardware meters with two way correspondences innovation for data, observing and control is ordinarily known as Advanced Metering Infrastructure (AMI). Smart Meters permit the clients to follow their own vitality use on the Internet or with outsider PC programs.

The input data under consideration as part of this project is collected from ComEd-Commonwealth Edison, the largest electric utility company operating in the state of Illinois, USA. ComEd offers real-time pricing programs in Illinois for a small charge along with the installation of Smart meters. The real-time pricing scenario in India is still in the nascent stages but the Ministry of Power has announced to make the program a reality by 2021. Electric utilities often sell their own demand side management software to the consumers. Instead of this purchase, it is easy to manage by using simple codes such as the one presented in this report.

CHAPTER- 3

OPTIMIZATION PROBLEM

3.1 ENERGY COST FUNCTION

The energy cost function is defined in such a way that the total energy purchase cost from the grid is minimized, while at the same time the PEV is charged with the most inexpensive energy available. The total cost would be the sum of hourly cost of purchasing energy from the grid over a 24-hour time slot and the cost of charging/discharging the PEV and supplying load during this period as defined below:

$$\textbf{Energy cost} = \sum[\mathbf{Egrid(h)} * \mathbf{Cgrid(h)} + \frac{|\mathbf{Cgrid(h)} - \mathbf{EPTpev(h)}|}{\mathbf{Cgrid(h)} - \mathbf{EPTpev(h)}} * \boldsymbol{Epev} * \boldsymbol{EPTpev(h-1)} \quad \text{.........(2)}$$

Where,

$C_{grid}(h)$ is the forecasted price of the grid in (c|kWh) for an hour (h).

$E_{PEV}(h)$ is the energy used to charge or discharge the PEV during hour (h) in kWh and is considered positive when charging and negative during discharging of the PEV.

$E_{grid}(h)$ is the energy purchased from the grid in kWh at hour (h).

The first half of the objective function reduces the sum of the cost of purchasing energy from the grid. The second half is the sum of PEV charge/discharge cost. The EPT_{PEV} is assumed as the tariff for the proceedings of PEV.

In case of grid(h)<$EPT_{PEV}(h-1)$, when the grid price is lower than the PEV battery EPT, we have $|Cgrid(h)-EPT_{PEV}(h-1)|Cgrid(h)-EPT_{PEV}(h-1)<0$. Since $EPT_{PEV}>0$, positive values of E_{PEV} will minimize the objective function which depicts charging of PEV. Hence, by charging with cheap energy from the grid, the EPT_{PEV} is minimized. For other instances, when $Cgrid(h)>EPT_{PEV}(h-1)$, negative values of E_{PEV} will result in additional minimization of the total cost. In other words, the PEV is discharged during these hours in order to reduce the objective function.

3.2 OPERATIONAL CONSTRAINTS

In the charging strategy of all stages of Smart charging infrastructure, system power balance and the operating constraints of the PEV plus the energy storage should be taken into consideration. At every instant (h), the energy generated must be equal to the amount of energy consumed,

$$\mathbf{P_{grid}(h) = P_l(h) + P_{pev}(h)} \text{.........}\mathbf{(3)}$$

Where,

P_L = Household Load demand
P_{PEV} = PEV energy demand
P_{Grid} = Total Power demand from grid

The PEV power limits can be described by:

$$\mathbf{P_{pev}min \leq P_{pev}(h) \leq P_{pev}max} \quad \text{..........}\mathbf{(4)}$$

Equations show the formula adopted for updating of the state of charge (SoC) of PEV battery. Also taking into, the SoC for both PEV is limited between SoC_{min} and SoC_{max}. These constraints are given below:

$$\mathbf{SOCpev\,(h) = SOCpev\,(h-1) + \frac{[Ppev * \Delta t]}{PEVcap}} \text{.................}\mathbf{(5)}$$

$$\mathbf{SOC_{pev\_min} \leq SOC_{pev}(h) \leq SOC_{pev\_max}} \qquad \text{.................}\mathbf{(6)}$$

Where,

SoC = Battery State of charge
SoC_{Max} = Maximum State of Charge
SoC_{Min} = Minimum State of Charge
$SoC_{Initial}$ = Initial State of Charge
SoC_{Final} = Final State of Charge
PEV_{Cap} = Total Battery capacity

CHAPTER 4

PARTICLE SWARM OPTIMIZATION ALGORITHM

4.1 INTRODUCTION

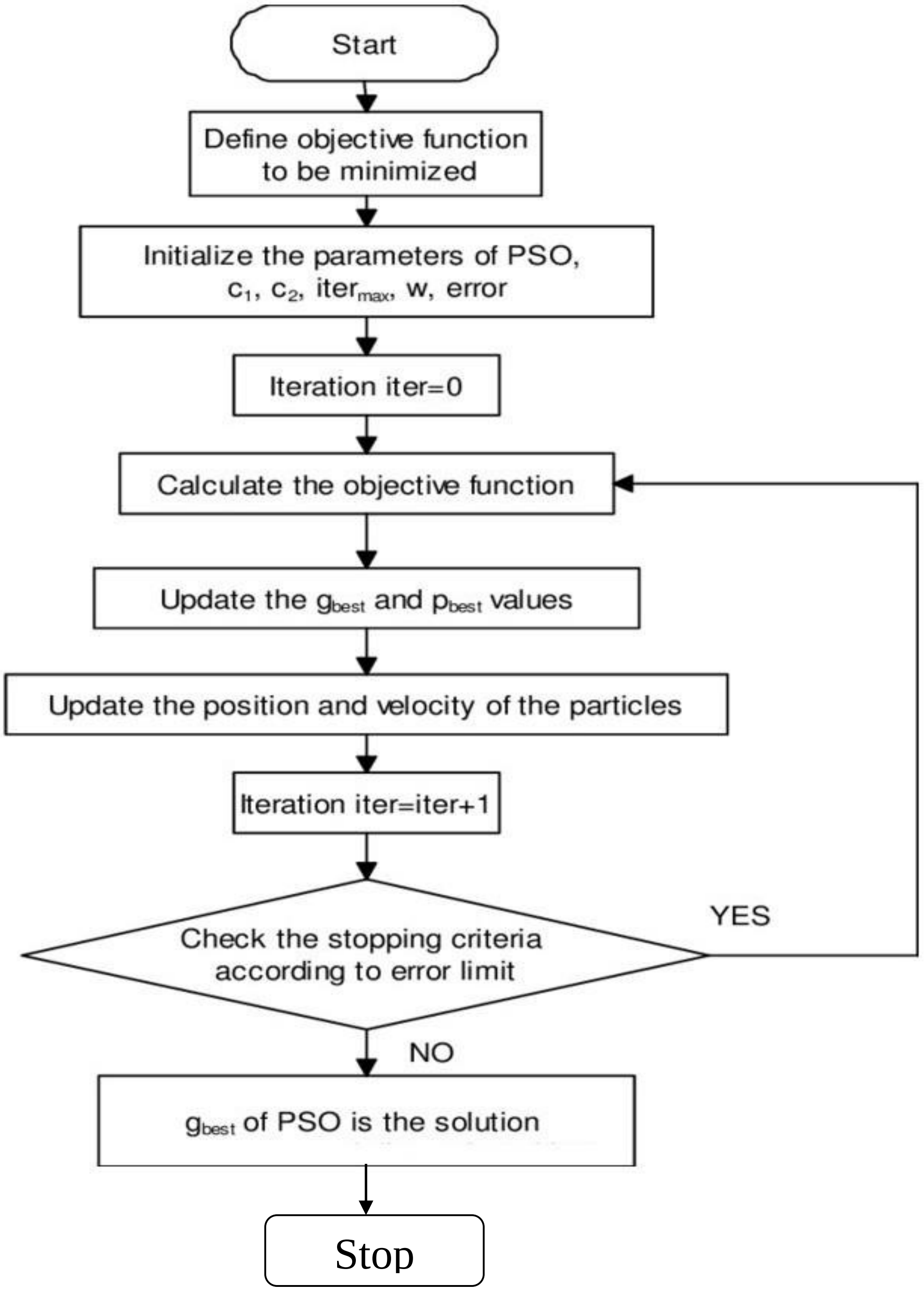
Particle swarm optimization is nature inspired evolutionary and stochastic optimization technique to solve computationally hard optimization problems. PSO is robust technique based on the movement and intelligence of swarm looking for most fertile location. A swarm is an apparently disorganised collection (population)of moving individual tend to cluster together while everyone seems to be moving in a random direction. We can consider the movement of flock of birds in search of food. Bird continuously adjust velocity and update its position depending on feedback from the other bird and based on the its experience.

This searching process can be artificially simulated for solving non-linear optimization problems. PSO uses computing method for optimizing a problem through multiple iteration to improve the solution obtained by the candidate and quality of solution is being improved. Its basic approach to solve a problem is based on the calculation of movement of dubbed particle around in the search space using the mathematical formula over the particle position and velocity. PSO is a metaheuristic as it is based on few or no assumption about the problem being optimized which means PSO does not require that the optimization problem be differentiable as it requires in classic optimization methods such as **Gradient descent** and **Quasi-newton** method. It solves a problem by iteratively trying to improve the particle solution by considering its personal best performance and global best position of particles when compared with each other.

4.2 WORKING OF PSO ALGORITHM

- It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.
- Each particle is treated as a point in a D-dimensional space which adjusts its “flying” according to its own flying experience as well as the flying experience of other particles
- Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that has been achieved so far. This value is called pbest.
- Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighbours of the particle. This value is called gbest.
- The PSO concept consists of changing the velocity (or accelerating) of each particle toward its pbest and the gbest position at each time step.

● Each particle tries to modify its current position and velocity according to the distance between its current position and pbest and the distance between its current position and gbest.



4.2.1 Generic Particle Swarm Optimisation Algorithm Flowchart

4.3 FITNESS FUNCTION

The fitness function is a function that maps the values in your particles to a real value that must reward those particles that are close to your optimisation criterion.

4.4 VECTORS OF PARTICULAR INDIVIDUAL

There are many particles which have different status which is represented by the following vector.

- The x-vector records the current position of the particle in search space.
- The p-vector (pbest) records the location of best solution found so far by the particle
- The v-vector contains the gradient (direction) for which particle will travel if undisturbed.

4.5 INITIAL PARAMETERS

It defines the scenario of the several individuals before we start finding the best solution through multiple iteration, such as the starting of flock of birds' movement for search of food.

- Swarm size is the number
- of particles moving in the search space
- Position of particle is the position of particle in the search space
- Velocity of particle is the velocity component that decides the direction of movement of the swarm particle
- Maximum no. of particle is the constraint and part of the decision variable matrix.

4.6 CONTROL PARAMETERS

Optimised solution is controlled and governed by the several parameters called control parameter. Quality of solution is improved by increasing no of iterations.

- Inertial weight: It controls the momentum of particle by verifying contribution of previous velocity to current velocity. It is represented by W.
- Number of iterations
- Acceleration coefficient: Stochastic influencers

C_1 and C_2=acceleration coefficient

❖ Cognitive component: Indicator of the amount of confidence of a particle in itself.

❖ Social Component: Indicator of the amount of confidence a particle has in its neighbours

4.7 VELOCITY VECTOR

V_{t+1}= W*V_t+C_1*rand(0,1) *(pbest-X_1)+C_2*rand(0,1)*(gbest-X_2)   …………….(7)

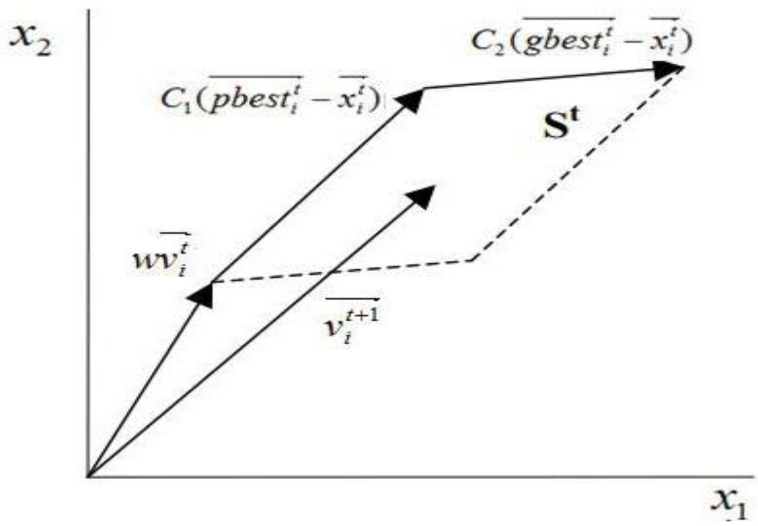


Fig 4.7.1: Velocity Vector

4.7.1 MOMENTUM PART (*W*V_t)*

- It serves as the memory of the previous flight.
- Prevents the particle from changing drastically the direction.
- Based towards previous direction.

4.7.2 COGNITIVE PART (*C_1*rand (0,1) *(pbest-X_1))*

- It quantifies the performance of i^{th} particle relative to its past performance.
- Particles are drawn back to their own best position.
- Nostalgia of the particle.

4.7.3 SOCIAL PART (*C_2*rand (0,*1) *(gbest-*X_2))*

- It quantifies the performance of the i^{th} particle relative to the neighbour.
- Particles are determined by drawn towards the best position determined by the group.
- It resembles the group norm that each particle seeks to attain.

4.8 POSITION VECTOR

$X_{t+1}= X_t+V_{t+1}$ ………….. (9)

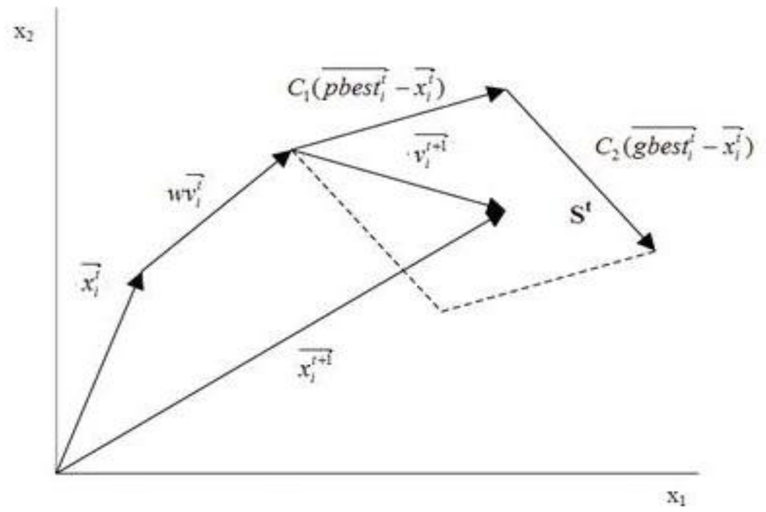


Fig 4.8.1: Position Vector

4.9: SAMPLE PSO WORKING

Let us consider a sphere function with a five-dimensional space and hence a minimum of 10 decision variables. A particle position in the sphere function space has 10 markers of its position and hence 10 decision variables to find best position and the lowest value of function. nVar represents number of decision variables and is equal to 10. The decision variable matrix is formed with this value of nVar. Next, we reduce the search space for the particle position values with constricting the maximum value of decision variable VarMax and minimum value of decision variable VarMin as +10 and -10 respectively. The remaining parameters are set at standard values of inertia weight as 1, damping ratio for consecutive iterations of 99%, cognitive component of 1.5 and social component of 2.0. The function and parameters are as shown below:

```
function z=Sphere(x)

    z=sum(x.^2);

end
```

```
nVar=10;

VarSize=[1 nVar];

VarMin=-10;
VarMax= 10;
```

```
w=1;
wdamp=0.99;
c1=1.5;
c2=2.0;
```

Fig 4.9.1: Sample PSO function and parameters

Initial particle position is randomized, and the velocity is initialized as zero.

6.8033	-8.5849	-2.4242	-4.6366	-6.9416	2.6200	-3.6725	9.1822	-0.0265	4.7722

Fig 4.9.2: Initial random particle position vector

0	0	0	0	0	0	0	0	0	0

Fig 4.9.3 Initial Zero velocity vector

After the first iteration, the velocity is calculated as per equation (8) and then the particle position is updated as per equation (9). The updated vectors are shown below:

4.8033	-6.5849	-2.4257	-2.6366	-4.9416	3.1121	-1.6725	7.1822	-0.1310	2.7722

Fig 4.9.4 Updated particle velocity vector

-2.0000	2.0000	-0.0016	2.0000	2.0000	0.4921	2.0000	-2.0000	-0.1045	-2.0000

Fig 4.9.5: Updated particle position vector

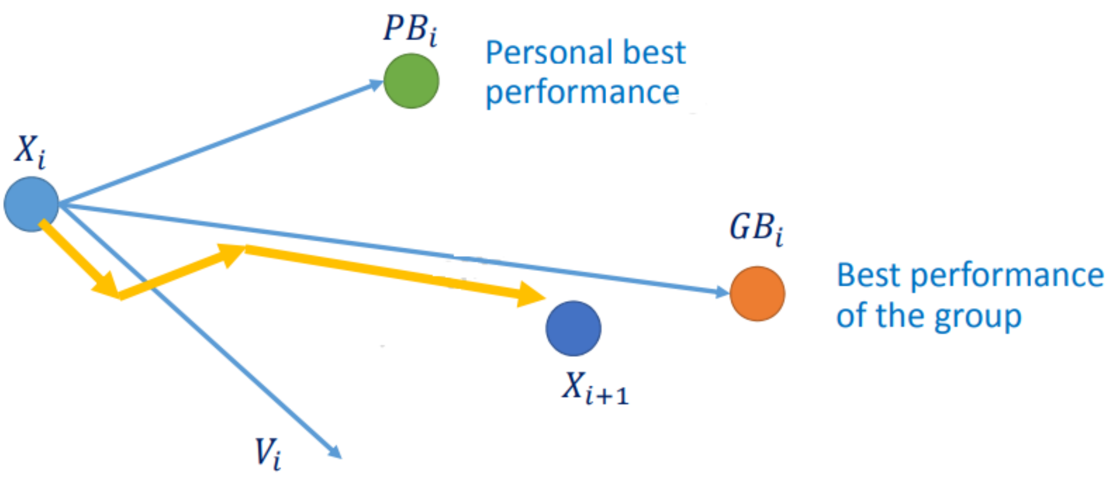


Fig 4.9.6: Particle influence due to Pbest and Gbest after each iteration

CHAPTER-5

MODEL DESCRIPTION

5.1 SMART CHARGING

Charging of Electric Vehicles while maintaining grid reliability and lower monthly electric bills is one of the main challenges for future smart grid. The smart charging system plays an essential role in optimizing electric vehicle energy consumption and thus reducing the consumer energy costs. The Plug-in electric vehicle has inbuilt infrastructure that is connected to a smart meter via the home Wi-Fi network. The smart meter receives the half hourly grid price from the utilities and the PEV charging system along with the household controller schedules the charging and discharging of the vehicle. This makes it possible to shift the PEV load from peak to non-peak hours or reduced load during peak hours. This kind of infrastructure makes it possible for the PEV to be connected to the smart grid, thus enabling several forms of Vehicle to Grid (V2G) transmission which can help the consumer reduce their monthly electric bill.

The PEV under consideration here is the Tesla Model 3 standard range vehicle. The aforementioned vehicle is one of the most popular PEVs in the United States of America and hence has been taken as the typical PEV for this model. The onboard charger of rating 11 Kw is part of the smart charging infrastructure. Although an in-built bidirectional charger isn’t commercially available yet, Tesla Motors has announced that it will be made available before the end of the year; yet another reason for choosing this PEV variant for the project.

The smart charging infrastructure under consideration consists of the half hourly grid prices, daily load demand curve of the household and power limits of the PEV charger. Once the PEV is at home and plugged into the grid for charging, the proposed optimization algorithm is applied to primarily minimize the charging cost.

5.2 PROPOSED ALGORITHM

The algorithm establishes a relation between half hourly grid price, Energy Price Tag of PEV, household load demand, Battery State of Charge and the vehicle charging demand. The algorithm has two modes which decide whether the PEV is to be charged or discharged. The energy price tag of the battery is calculated from previous charging patterns and by comparing this value with the half hourly grid price, the charging decision is finalized. The main constraint while making the decision is the State of Charge of the battery. Despite modern advancements in vehicle battery technology, charging or discharging of the battery to its maximum and minimum limits respectively reduces battery health and efficiency in the long term. Hence, as part of the algorithm, the battery SoC is limited to a minimum and maximum value. Another constraint is the experimental bidirectional charger with set PEV energy limits for charging and discharging procedure.

The inputs considered for this algorithm are as follows:

C_{grid}= Half hourly grid price
P_L = Household Load demand
P_{PEV} = PEV energy demand
$MaxP_{PEV}$++ = Max PEV energy (Charging)
$MinP_{PEV}$-- = Max PEV energy (Discharging)
P_{Grid} = Total Power demand from grid
EPT = Energy Price Tag of PEV Battery
$EPT_{Initial}$ = Initial EPT
SoC = Battery State of charge
SoC_{Max} = Maximum State of Charge
SoC_{Min} = Minimum State of Charge
$SoC_{Initial}$ = Initial State of Charge
SoC_{Final} = Final State of Charge
PEV_{Cap} = Total Battery capacity of PEV

The algorithm works in two simple modes and outputs the PEV charging and discharging limits per half hour along with the total charging cost.

5.2.1 Mode 1:

Charging Procedure due to EPT: When the EPT of the vehicle is greater than the half hourly grid price, the PEV is charged with cheap electricity from the grid.

5.2.2 Mode 2:

Discharging Procedure due to EPT: When the EPT of the vehicle is lower than the half hourly grid price, the load is supplied by cheap electricity from PEV.

5.3 IMPLEMENTATION OF PSO

In this section, we present the simulation of PSO based charging strategy for plug-in electric vehicles which reduces the overall energy consumption cost by comparing the cost of stored energy of PEV battery with grid price, reducing load during peak hours and charging during off peak hours. The first step is defining the objective function, initializing the swarm and adding the suitable charging constraints faced by the infrastructure. The next step is to update the particle velocity and hence the particle position. Once this is done, the cost of the particle is evaluated. Next, the personal best position and personal best cost are compared and updated. Finally, the Global best cost is compared and thus updated. The number of iterations is utilized as the stopping criterion to avoid false positives which might lead to non-updating of particle position.

5.4 OBJECTIVE FUNCTION

As mentioned at the beginning of the thesis, the cost of the energy consumed is considered as the objective function to be optimized. For each half hour, the energy demand from the grid and the EPT of the vehicle is calculated. The summation of grid energy cost and the PEV charging/discharging cost gives the energy consumption of the household for that particular half hour. We consider the first half of equation (2) as the objective equation:

Objective/Cost Function= $\mathbf{Sum(E_{grid}*C_{grid})}$**…………………..(10)**

Once this is done, the State of Charge of the battery is updated to avoid overburdening the battery. The objective function contains the energy demand which is a combination of the load demand and the PEV demand which is one of the important decision criteria in the optimization algorithm. The second half of the initial cost is used to verify the EPT values to cross reference with the output of the PSO charging strategy.

EPT reference cost $= \frac{|\mathbf{Cgrid(h) - EPTpev(h)}|}{\mathbf{Cgrid(h) - EPTpev(h)}} * \boldsymbol{Epev} * \boldsymbol{EPTpev(h-1)}$**…………………...(11)**

5.5 INITIALIZATION OF PSO PARAMETERS

It is assumed that the Plug-in Electric Vehicle reaches home at 6:00 PM and leaves the next day at 8:00 AM. The algorithm operates in a window of 14 hours from 6 PM to AM. This is done so that the battery does not get overheated due to continuous usage and thus reducing battery life. Considering the 12-hr window, the number of decision variables for the PSO is 12*2=24 since the grid price changes every half hour.
As per the Tesla Model 3 normal range specifications, the charging and discharging limits which are represented by the VarMin and VarMax of the PSO decision variable matrix are set at -3.5 Kw and 5.5 Kw respectively.

The remaining parameters are set at standard PSO values, which are:
Inertia weight = 1
Damping ratio = 0.97
Cognitive component = 1.5
Social component = 2.0

5.6 INITIALIZATION OF SWARM PARTICLE

After setting up the empty particle vector, the swarm is initialized randomly and fills the decision variable matrix. The DV matrix consists of the PEV charge and discharge values for the 14-hr period with a 2-hr break to extend battery life and prevent overheating. The initialized matrix is used to calculate the State of Charge matrix. Next, the SoC matrix is limited to the SoC_{max} and SoC_{min} input values. In case the SoC value exceeds the limits, the DV matrix for the particular particle is initialized again until the values are within specified limits. The personal best position of the particle is initialized, and Global best is updated after verifying the SoC matrix. The search space is constricted with the state of charge constraints so that solution is reached at a faster pace.

5.7 PSO VELOCITY CALCULATION

The initial swarm position and velocity are updated for all the particles via a for loop according to the PSO equations as explained above. The state of charge is calculated and verified against the specified limits. In case the limits are exceeded, the velocity is calculated again and thus particle position is updated. In each iteration, the Global best cost is updated and after the specified number of iterations, the best cost is displayed.

The particle velocity is limited to a minimum and maximum value to facilitate a robust search of the DV matrix search space. The particle position is also limited to the maximum and minimum decision variables according to the specifications of the Tesla Model 3 specifications.

5.8 INITIAL CONDITION

Car Model considered for the application of this strategy is the **TESLA MODEL 3 Standard Range** vehicle.

Table 5.8.1: Initial Conditions for PSO based charging strategy

$EPT_{Initial}$	3 c/kwhr
$MaxP_{PEV}$++	5.5 Kw
$MinP_{PEV}$--	-3.5 Kw
SoC_{Max}	80%

SoC_{Min}	30%
$SoC_{Initial}$	40%
SoC_{Final}	60%
PEV_{CAP}	54 kwhr

The initial values are taken as per the current driving standards and the Tesla Model 3 specifications. The initial EPT value and State of Charge are taken after an exhaustive driving schedule of a standard driving day

5.9 PSEUDO CODE

```
START

Define Objective Function
Initialize PSO Parameters
Set up empty particle vector
Initialize Gbest as inf

For i=1 to swarm size
{
Initialize State of Charge zero matrix
Initialize x=1

While (x==1)
{
    x=0;
Initialize each particle position randomly

For i=1 to decision matrix size
{
Calculate State of Charge matrix
}
End for

    For i=1 to 14
    {
        if(soc<0.3 or soc>0.8)
        {
            x=1;
```

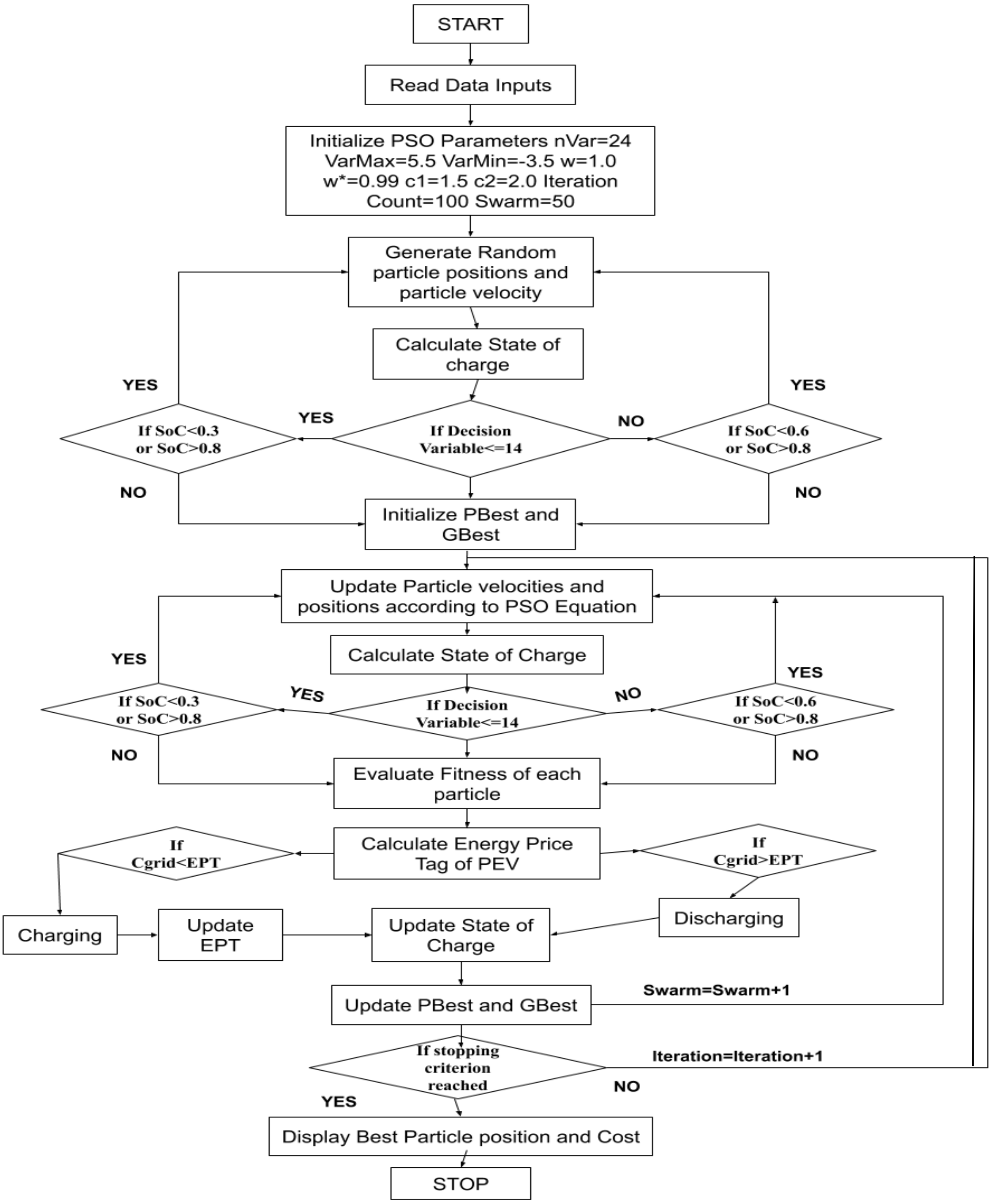
```
            Break;
          }
          End if
      }
      End For

    For i=15 to 24
    {
        if(soc<0.6 or soc>0.8)
        {
            x=1;
            Break;
          }
          End if
      }
      End For
}
End While

Initialize Particle velocity as zero vector
Evaluate Particle cost from objective function

Pbest.Position=Particle(i).Position   %Update Personal Best
Pbest.Cost=Particle(i).Cost

if(Pbest.cost<Gbest.cost)                %Update Global Best
    {
Gbest=Pbest;
    }
    End if
    }
End for


For each particle from i=1 to maximum iteration count
{
For entire swarm from i=1 to swarm size
{
    x=1;
    while (x==1)
    {
```

```
%Update Particle Velocity
Particle velocity= w*(particle velocity)+c1*randomize(DVMatrix)*(pbest position-particle position)+c2*randomize(DV Matrix)*(Gbest position particle position)

Particle position= particle position + particle velocity
Calculate State of Charge for current particle position

     For i=1 to 14
     {
       if(soc<0.3 or soc>0.8)
       {
          x=1;
          Break;
       }
       End if
     }
     End For

     For i=15 to 24
     {
       if(soc<0.6 or soc>0.8)
       {
          x=1;
          Break;
       }
       End if
     }
     End For
}
End While

Evaluate particle cost (fitness)

if(particle cost<Pbest.cost)
{
Update particle Pbest position
Update particle Pbest cost
}
End if

if(Pbest cost<Gbest cost)
{
Gbest=Pbest;
```

```
}
End if
}
End for
}
End for
```

STOP

The Flowchart in fig 5.9.1 explains the optimized charging strategy. The flowchart starts with reading the input parameters for the Plug-in electric vehicle. The PSO parameters along with the decision variable matrix are initialized. Next, the swarm is initialized randomly but with the state of charge constrictions so that the swarm reaches the solution at a faster pace with less number of iterations. Depending on the decision variable number, the state of charge condition changes for the initial randomization as well as the PSO main loop randomization. After initialization of personal best and global best, the main loop of PSO begins. Next, particle velocity is updated as per equation (7) and particle position is updated as per equation (8). The state of charge is checked according to the value of the decision variable and in case the constraint is exceeded, the velocity and position are calculated again. Further, the EPT is calculated and compared with the grid price and the decision to charge or discharge the PEV is taken while the EPT values are calculated. Finally, the Personal best and global best are updated and moves on to the next iteration.



5.9.1 Proposed PSO Based Charging strategy flowchart

5.10 INPUT DATA

The input data considered in this charging strategy is collected from ComEd, Commonwealth Edison, the largest electric utility company is the state of Illinois, USA.

The load demand data is an average Illinois household from the month of March 2017.The real-time pricing is the ComEd's price scheme from the same month of march2017.

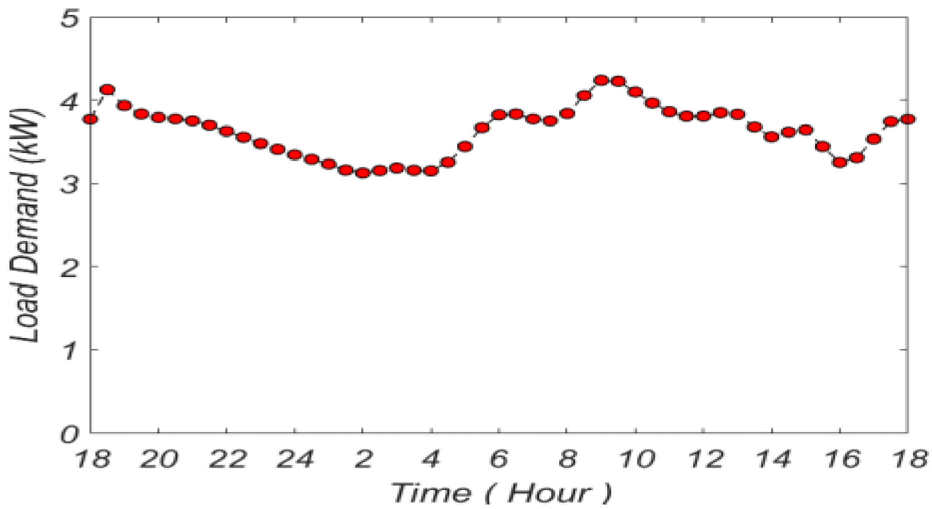


Fig 5.10.1: Load Demand

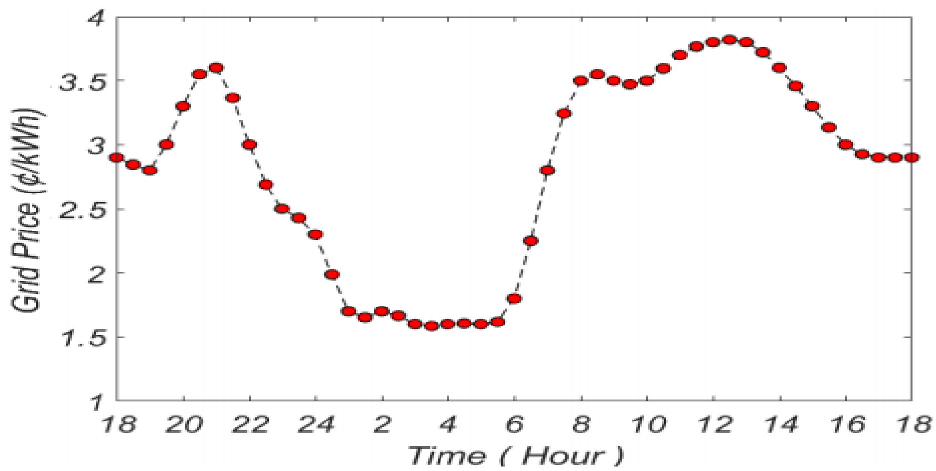


Fig 5.10.2: Half Hourly grid price

Ref for Fig 5.10.1~2: SimaAznavi; PoriaFajri; ArashAsrari "Smart Home Energy Management Considering Real-Time Energy Pricing of Plug-in Electric Vehicles" 2018 IEEE Energy Conversion Congress and Exposition (ECCE)

Table 5.10.1: Load Demand ComEd, a US electric utility company data of average Illinois household, March 2017

S.No	Time (hr)	Demand (Kw)	S.No	Time (hr)	Demand (Kw)
1	18	3.811	26	6	3.811
2	18.5	4.132	27	6.5	3.792
3	19	3.962	28	7	3.906
4	19.5	3.981	29	7.5	4.255
5	20	3.868	30	8	4.113
6	20.5	3.83	31	8.5	4.283
7	21	3.811	32	9	4.245
8	21.5	3.736	33	9.5	4.113
9	22	3.66	34	10	3.981
10	22.5	3.585	35	10.5	3.887
11	23	3.509	36	11	3.849
12	23.5	3.434	37	11.5	3.849
14	0	3.321	39	12.5	3.849
15	0.5	3.264	40	13	3.717
16	1	3.189	41	13.5	3.604
17	1.5	3.151	42	14	3.679
18	2	3.208	43	14.5	3.698
19	2.5	3.226	44	15	3.453
20	3	3.189	45	15.5	3.283
21	3.5	3.208	46	16	3.377
22	4	3.302	47	16.5	3.585
23	4.5	3.491	48	17	3.792
24	5	3.736	49	17.5	3.83
25	5.5	3.868	50	18	3.811

Table 5.10.2: Half hourly Grid Price: ComEd, US electric utility company real-time pricing data, March 2017

S.No	Time (hour)	Price(c/kwh)	S.No	Time (hour)	Price(c/kwh)
1	18	2.946	26	6	2.286
2	18.5	2.865	27	6.5	2.842
4	19.5	3.039	28	7	3.27
5	20	3.34	29	7.5	3.525
6	20.5	3.595	30	8	3.571
7	21	3.629	31	8.5	3.525
8	21.5	3.398	32	9	3.502
9	22	3.015	33	9.5	3.548
10	22.5	2.714	34	10	3.618
11	23	2.517	35	10.5	3.722
12	23.5	2.448	36	11	3.792
13	24	2.309	37	11.5	3.838
14	0	2.008	38	12	3.861
15	0.5	1.718	39	12.5	3.838
16	1	1.683	40	13	3.757
17	1.5	1.718	41	13.5	3.641
18	2	1.683	42	14	3.479
19	2.5	1.637	43	14.5	3.328
20	3	1.614	44	15	3.154
21	3.5	1.625	45	15.5	3.039
22	4	1.625	46	16	2.934
23	4.5	1.614	47	16.5	2.946
24	5	1.637	48	17	2.934
25	5.5	1.822	49	17.5	2.946

Ref for Table 5.10.1~2: SimaAznavi;PoriaFajri; ArashAsrari “Smart Home Energy Management Considering Real-Time Energy Pricing of Plug-in Electric Vehicles” 2018 IEEE Energy Conversion Congress and Exposition (ECCE)

CHAPTER 6

SIMULATIONOF PSO BASED CHARGING

6.1 SIMULATION RESULT

Under this section, we explain the simulation of the PSO based charging strategy implemented for the Plug-in electric vehicle. MATLAB (Matrix Laboratory) 2016a is the software used for this simulation. The code contains two randomization parts; the first part is the randomization for the swarm initialization and second is the dual random factors for the velocity component. Hence, the optimization takes different number of iterations to reach the best cost for every run. In this project, the code has been compiled for 10 times and the average of the optimization curves is displayed in fig 6.1.1. Although, the number of iterations taken is different, the best cost is always in the neighbourhood of 139.85xx cents with the remaining two decimal places undergoing change based on the randomization.

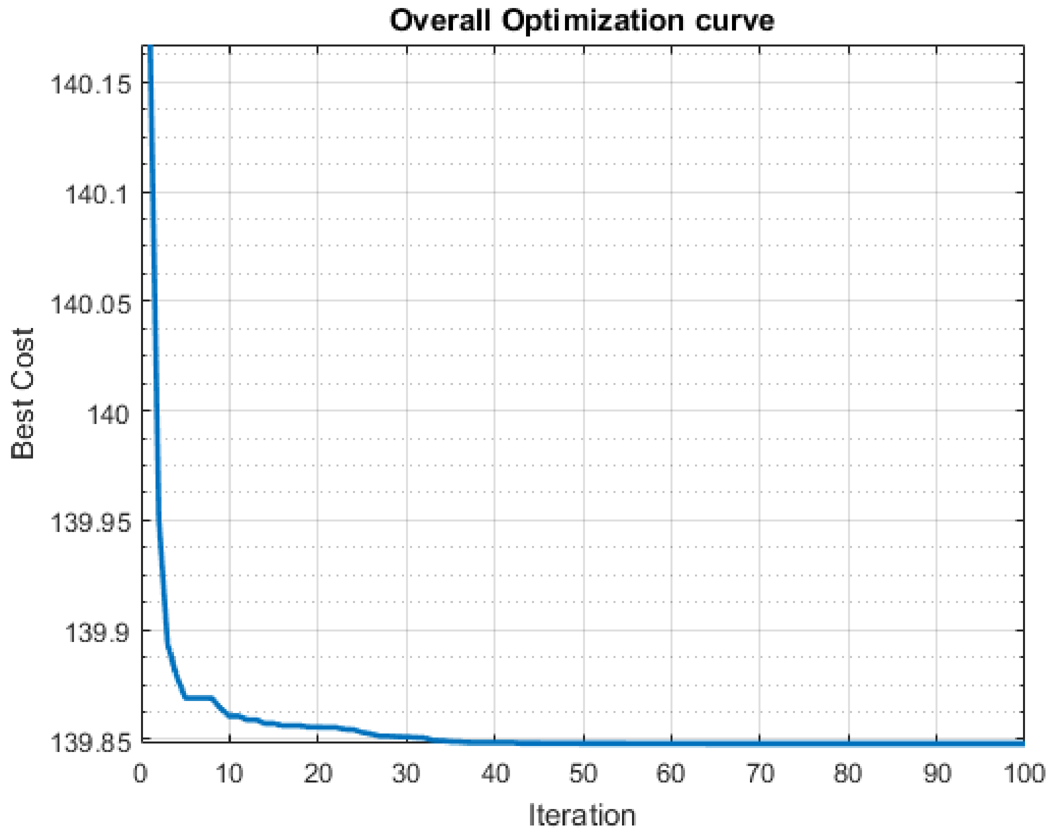


Fig 6.1.1: Average energy cost optimization curve using PSO charging strategy for 10 runs

By compiling the average of all 10 runs, we can plot the mean optimization curve as shown in fig 6.1.1. This figure shows the reduction in energy cost for consecutive iterations. The iteration count was decided such that the optimization is observable without affecting all the swarm particles which is a common issue associated with particle swarm optimization. The best particle position (average of particle position of 10 runs) of the swarm which represents the energy demand of PV for all the time steps is represented in table 6.1.1. The reduced energy cost consumption is 139.85 cents for the 14 hr window from 6 PM to 8 AM.

Without Optimization: Total Electricity Price = 202.84 cents

With Optimization: Total Electricity Price = 139.85 cents

The optimization algorithm helps the residential consumer save around (202.84-139.85=) 62.99 cents which translates to roughly $0.63 and a monthly saving of minimum $18.9. The savings can be increased by letting the PEV stay connected to the grid over the weekend when it doesn’t need to be driven around.

Minimum Monthly Total Savings= $18.9= Rs. 1417.5

Minimum Yearly Savings= $226.8= Rs. 17,010

Fig 6.1.2 shows the Energy Price tag of the PEV with and without the optimization algorithm. It can be clearly observed that the EPT without any optimization is extremely high at 3.16 c/kWh whereas the EPT with the implementation of the optimization algorithm is highly minimized at 1.0918 c/kWh. Although, the change in EPT for charging without PSO strategy is minimal, the cost associated with this is extremely high.

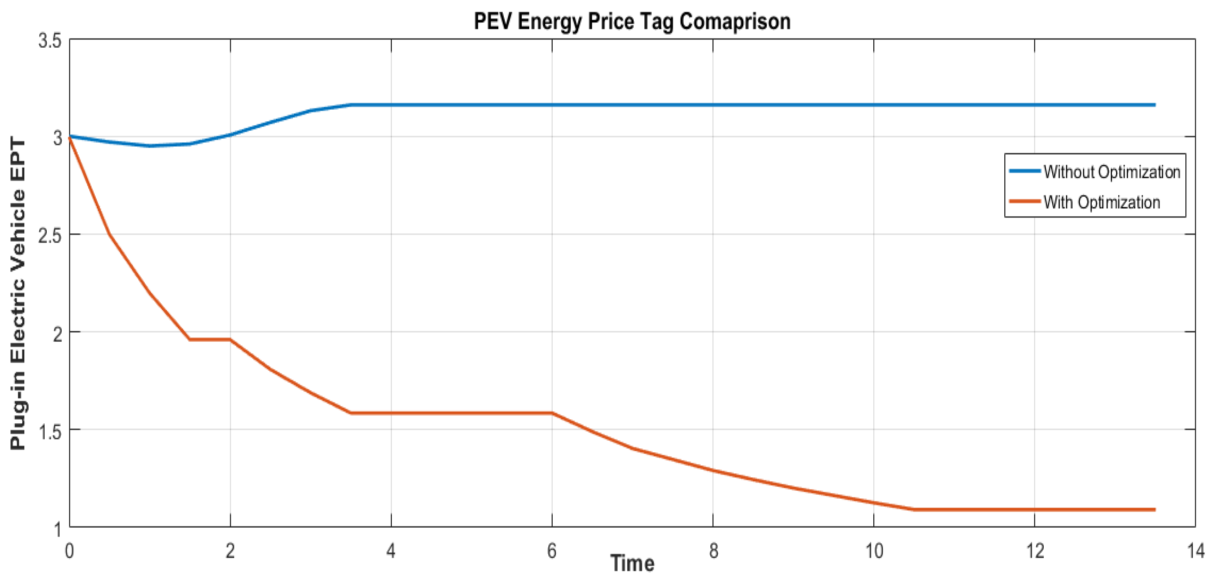


Fig 6.1.2: Comparison of Energy Price of Plug-in Electric vehicle with and without PSO based charging strategy.

This essentially means that the electric vehicle is being charged with cheap power from the grid via PSO based strategy and with expensive power from the grid in the direct scenario without optimization. The above figure clearly shows the low price of charging the Electric Vehicle with PSO based charging optimization. There is a nearly 65.45% decrease in the cost of charging apart from the obvious savings in the electric bill. During the peak hours of 6PM to 10PM the EPT continuously reduces with selective charging and then discharges the PEV to remain constant. In the late night slot, the PEV charges properly to ensure minimum SoC for next day driving but still the EPT reduces because of the low grid price during the 10PM to 6AM slot. Next, considering the next peak time slot of 6:30 AM to 10 AM, the EPT remains constant and discharges to further reduce costs.

Fig 6.1.3 shows the half hourly energy demand of the household. With the implementation of the optimization algorithm, it is observed that the demand at peak hours is reduced and shifted to non-peak hours. This means that the demands during the two peak hour periods of late evening and standard morning are reduced and the non-peak hours demand when grid price is low are increased. It is observed that the peak hour period time slots are 6-10PM at night and 6:30-8AM in the morning. In these time slots, the non-PSO demand curve is above the PSO optimized demand curve and hence it's expensive due to high grid prices during peak hours.

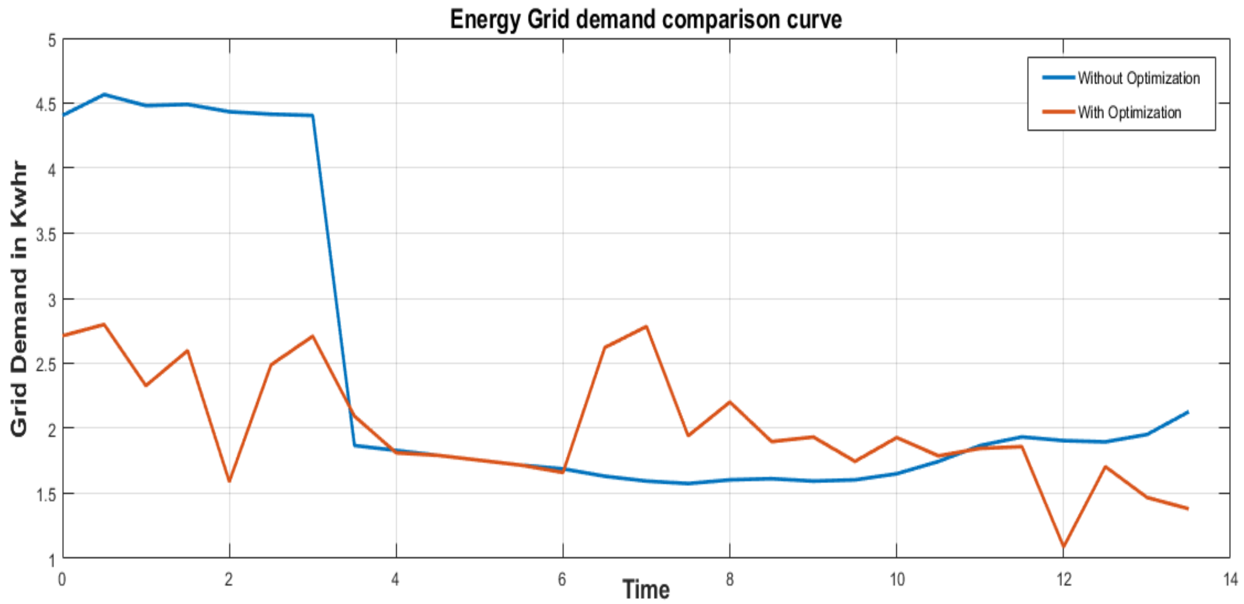


Fig 6.1.3: Comparison of Energy Demand of household with and without PSO based charging strategy

This graph depicts that the PSO based charging strategy helps in reducing the peak demand as well. Thus it leads to additional savings for locations where consumers have to pay surcharge for peak demand conditions. During the first peak slot of 6PM to 10PM, there is a large difference between the two curves, this is because the vehicle has just reached home and is in a condition to charge and discharge to the extreme limits, plus the high demand in standard condition is because the PEV is plugged in to charge normally. But it is noticeable in the second peak slot of 6:30AM to 8AM that the curves are close; this is because of the additional constraint to maintain a state of charge of at least 60% to be available for next day's driving requirements.

Table 6.1.1: Total Demand and PEV Demand with and without PSO based charging strategy

Time (hrs)	Demand (kw) Without Optimization	PEV Demand (kw) Without Optimization	Total Demand (kw) Without Optimization	PEV Demand (kw) With Optimization	Total Demand (kw) With Optimization
18	3.811	5.5	9.311	1.6116	5.4226
18.5	4.132	5.5	9.632	1.4644	5.5964
19	3.962	5.5	9.462	0.6938	4.6558
19.5	3.981	5.5	9.481	1.2138	5.1948
20	3.868	5.5	8.068	-0.6882	3.1798
20.5	3.83	5.5	9.368	1.1458	4.9758
21	3.811	5.5	9.311	1.6060	5.4170
21.5	3.736	5.5	9.236	0.4514	4.1874
22	3.66	5.5	9.16	-0.0362	3.6238
22.5	3.585	0	3.585	0	3.5850
23	3.509	0	3.509	0	3.5090
23.5	3.434	0	3.434	0	3.4340
0	3.321	0	3.321	0	3.3210
0.5	3.264	0	3.264	1.9776	5.2416
1	3.189	0	3.189	2.3772	5.5662
1.5	3.151	0	3.151	0.7346	3.8856
2	3.208	0	3.208	1.1964	4.4044
2.5	3.226	0	3.226	0.5706	3.7966
3	3.189	0	3.989	0.6776	4.6656
3.5	3.208	0	3.208	0.2844	3.4924
4	3.302	0	3.302	0.5562	3.8582

4.5	3.491	0	3.491	0.0860	3.577
5	3.736	0	3.736	-0.0442	3.6918
5.5	3.868	0	3.868	-0.1496	3.7184
6	3.811	0	3.811	-1.6334	2.1776
6.5	4.132	0	4.132	-0.3804	3.7516
7	3.962	0	3.962	-0.9692	2.9928
7.5	3.981	0	3.981	-1.4922	2.4888

Table 6.1.1 depicts the total demand as well as the PEV demand with and without optimization. The difference in PEV charging is clearly noticeable with the non-optimization scenario increasing the demand drastically, thus increasing the peak; whereas the scenario with PSO based charging optimization strategy charges and discharges to a lower setting while reducing the peak demand and charging to higher setting in the off peak hours.

CHAPTER 7

CONCLUSIONS

The concept of employing real time pricing of electricity to optimally manage the charging strategy of plug-in electric vehicles and thus reducing the energy cost consumption of residential consumers was proposed in this report. The cost of storing energy in PEV battery was proposed which allowed a pragmatic energy exchange as part of the smart charging infrastructure.

This report uses a robust metaheuristic technique- Particle Swarm Optimization to determine the optimal charging strategy to reduce the household energy consumption cost. MATLAB software was used to model the charging strategy. The simulation results confirm the significant reduction in energy consumption cost by implementing the proposed algorithm. For a typical household in the United States using the Tesla Model 3 normal range PEV, the energy cost was reduced from 202.84 cents to 139.85 cents for a 14 hour period via the PSO based charging strategy. The report thus successfully depicts the potential of the proposed PSO based charging strategy to significantly improve energy cost savings.

FUTURE SCOPE AND TRENDS

Electric vehicles are safeguards for the future. With current global opinion shifting away from fossil fuels and moving towards cleaner energy, EV sales are predicted to witness a mammoth increase. This will create a need for smart charging infrastructure to be installed in the EV as well as at charging stations and EV owner households. There will definitely be a need for robust optimization and charging algorithms to deal with this increase in EVs. A few issues that could be addressed are:

- Reducing strain on grid during mass EV charging
- Optimal scheduling of multiple EVs at a charging station
- Robust V2G transmission schemes to further reduce EV ownership costs
- Route mapping of EVs to charging stations in conjunction with smart grid

Apart from the software perspective, the future also holds multiple challenges for improving EV hardware. From charging stations to EV battery, the possibilities are limitless.

REFERENCES

1. Aznavi, S., Fajri, P. and Asrari, A., 2018, September. Smart Home Energy Management Considering Real-Time Energy Pricing of Plug-in Electric Vehicles. In *2018 IEEE Energy Conversion Congress and Exposition (ECCE)* (pp. 67-72). IEEE.

2. Zhou, Y., Cao, S., Hensen, J.L. and Lund, P.D., 2019. Energy integration and interaction between buildings and vehicles: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, *114*, p.109337.

3. Wu, X., Hu, X., Moura, S., Yin, X. and Pickert, V., 2016. Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array. *Journal of Power Sources*, *333*, pp.203-212.

4. T. Gnann, T.S. Stephens, Z. Lin, P. Plötz, C. Liu, J. Brokate, "What drives the market for plug-in electric vehicles? - A review of international PEV market diffusion models", Renewable and Sustainable Energy Reviews, vol. 93, pp. 158-164, 2018

5. Yousefi, M., Kianpoor, N., Hajizadeh, A. and Soltani, M., 2019, June. Smart Energy Management System for Residential Homes Regarding Uncertainties of Photovoltaic Array and Plug-in Electric Vehicle. In *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)* (pp. 2201-2206). IEEE.

6. Hajforoosh, S., Masoum, M.A. and Islam, S.M., 2015. Real-time charging coordination of plug-in electric vehicles based on hybrid fuzzy discrete particle swarm optimization. *Electric Power Systems Research*, *128*, pp.19-29.

7. Jin, C., Sheng, X. and Ghosh, P., 2013, July. Energy efficient algorithms for electric vehicle charging with intermittent renewable energy sources. In *2013 IEEE Power & Energy Society General Meeting* (pp. 1-5). IEEE.

8. Xing, H., Fu, M., Lin, Z. and Mou, Y., 2015. Decentralized optimal scheduling for charging and discharging of plug-in electric vehicles in smart grids. *IEEE Transactions on Power Systems*, *31*(5), pp.4118-4127.

9. Banvait, H., Lin, X., Anwar, S. and Chen, Y., 2009. Plug-in hybrid electric vehicle energy management system using particle swarm optimization. *World Electric Vehicle Journal*, *3*(3), pp.618-628.

10. Yang, J., He, L. and Fu, S., 2014. An improved PSO-based charging strategy of electric vehicles in electrical distribution grid. *Applied Energy*, *128*, pp.82-92.

11. Wu, X., Cao, B., Wen, J. and Bian, Y., 2008, September. Particle swarm optimization for plug-in hybrid electric vehicle control strategy parameter. In *2008 IEEE Vehicle Power and Propulsion Conference* (pp. 1-5). IEEE.

12. Chen, Z., Xiong, R., Wang, K. and Jiao, B., 2015. Optimal energy management strategy of a plug-in hybrid electric vehicle based on a particle swarm optimization algorithm. *Energies*, *8*(5), pp.3661-3678.

13. Ebbesen, S., Kiwitz, P. and Guzzella, L., 2012, June. A generic particle swarm optimization Matlab function. In *2012 American Control Conference (ACC)* (pp. 1519-1524). IEEE.

14. Elloumi, W. and Alimi, A.M., 2010, May. A more efficient MOPSO for optimization. In *ACS/IEEE International Conference on Computer Systems and Applications-AICCSA 2010* (pp. 1-7). IEEE.

15. Shi, Y., 2004. Particle swarm optimization. *IEEE connections*, *2*(1), pp.8-13.

16. Trelea, I.C., 2003. The particle swarm optimization algorithm: convergence analysis and parameter selection. *Information processing letters*, *85*(6), pp.317-325.

17. Jiang, Y., Hu, T., Huang, C. and Wu, X., 2007. An improved particle swarm optimization algorithm. *Applied Mathematics and Computation*, *193*(1), pp.231-239.

18. Chen, C.Y. and Ye, F., 2012, May. Particle swarm optimization algorithm and its application to clustering analysis. In *2012 Proceedings of 17th Conference on Electrical Power Distribution* (pp. 789-794). IEEE.