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Bounds for Optimal Control of a Regional Plug-In Electric Vehicle Charging Station System

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ABSTRACT: In order to support the increasing penetration of plug-in electric vehicle (PEV) users, a novel regional PEV charging station system with DC level 3 fast charging is proposed in this project. To promote sustainable development, the proposed system is designed to be equipped with a distributed energy storage system charged by wind generation, solar PV generation, and electricity from the power grid, which can simultaneously charge multiple PEVs. The objective of the proposed system is to minimize operational cost. In practical, power grid is in the need of storage system that must charge/discharge the power during stochastic period of grid. While incorporating the batteries into the power grid, it is required to maintain the best charging coordinates or otherwise it will rise tradeoff between the cost and power delivery. This project is proposed for the purpose of introducing the vehicle battery cost model for the micro grid system to deliver an optimum unit commitment. In this work, the vehicle battery cost model is designed and optimum battery charging/discharging coordinates are effectively done with the help of well-known technique called 'simulated annealing' algorithm. With this intelligent control method, it is possible to achieve minimum vehicle battery operating cost and also possible to manage the load variability. The proposed work is implemented on MATLAB R2014a software with the real time data collected for solar and wind power systems. The results are showing the effectiveness of the proposed simulated annealing based battery cost optimization technique.

I. INTRODUCTION

Plug-in electric vehicles (PEVs) are now being rolled out to consumers throughout the United States. General Motors Company is producing the Chevrolet Volt, a plug-in hybrid. Ford Motor Company is producing the Ford Electric Focus and Nissan Motors is manufacturing the Leaf, both of which are all-electric vehicles. And a number of startup companies are producing specialty PEVs, the most prominent being Tesla Motors, producer of the all-electric Tesla Roadster.

The Smart Grid will have the infrastructure needed to enable the efficient use of this new generation of PEVs. PEVs can drastically reduce our dependence on oil, and they emit no air pollutants when running in all-electric modes. However, they do rely on power plants to charge their batteries, and conventional fossil-fueled power plants emit pollution. To run a PEV as cleanly as possible, it needs to be charged in the wee hours of the morning, when power demand is at its lowest and when wind power is typically at its peak. Smart Grid technologies will help to meet this goal by interacting with the PEV to charge it at the most optimal time. But sophisticated software will assure that your PEV is still fully charged and ready to go when you need it. And you'll still be able to demand an immediate recharge when you need it.

In the future, PEVs may play an important part in balancing the energy on the grid by serving as distributed sources of stored energy, a concept called "vehicle to grid." By drawing on a multitude of batteries plugged into the Smart Grid throughout its service territory, a utility can potentially inject extra power into the grid during critical peak times, avoiding brownouts and rolling blackouts. PEVs also have the potential to help keep isolated parts of the grid

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operating during blackouts. They could also help integrate variable power sources into the grid, including wind and solar power. Financial incentives may be available for PEV owners that allow their batteries to be used this way.

There are two basic PEV configurations: Series PEVs, also called Extended Range Electric Vehicles. Only the electric motor turns the wheels; the gasoline engine only generates electricity. Series PHEVs can run solely on electricity until the battery needs recharging. The gasoline engine will then generate the electricity needed to power the electric motor. For shorter trips, these vehicles might use no gasoline at all. Parallel or Blended PEVs. Both the engine and electric motor are mechanically connected to the wheels, and both propel the vehicle under most driving conditions. Electric-only operation usually occurs only at low speeds. PEVs also have varied battery capacities, allowing some to travel farther on electricity than others. PEV fuel economy, like that of electric vehicles and regular hybrids, can be sensitive to driving style, driving conditions, and accessory use.

II. LITERATURE SURVEY

Q. Kang, J. Wang, et al., [1], proposes a novel centralized charging strategy of EVs under the battery swapping scenario by considering optimal charging priority and charging location (station or bus node in a power system) based on spot electric price. In this strategy, a population-based heuristic approach is designed to minimize total charging cost, as well as to reduce power loss and voltage deviation of power networks. We introduce a dynamic crossover and adaptive mutation strategy into a hybrid algorithm of particle swarm optimization and genetic algorithm.

Abdulaal, & Cintuglu, et al., [2], offers a complete solution methodology to the multi-variant EV routing problem (MVEVRP) rather than considering only one or two variants of the problem like in previous research. The variants considered include: a stochastic environment, multiple dispatchers, time-window constraints, simultaneous and non-simultaneous pickup and delivery, G2V and V2G service options. Stochastic demand forecast of the G2V and V2G services at charging stations are modeled using hidden Markov model (HMM). The developed solver is based on a modified custom genetic algorithm (GA) incorporated with embedded Markov decision process (MDP) and trust-region optimization methods.

Badawy et al., [3], propose an optimal power flow technique of a PV-battery powered fast EV charging station is presented to continuously minimize the operation cost. The objective is to help the penetration of PV-battery systems into the grid and to support the growing need of fast EV charging. An optimization problem is formulated along with the required constraints and the operating cost function is chosen as a combination of electricity grid prices and the battery degradation cost. In the first stage of the proposed optimization procedure, an offline particle swarm optimization (PSO) is performed as a prediction layer. In the second stage, dynamic programming (DP) is performed as an online reactive management layer. Forecasted system data is utilized in both stages to find the optimal power management solution.

D. Liang, et al., [4], presents a hierarchical stochastic control scheme for the coordination of PEV charging and wind power in a microgrid. This scheme consists of two layers. Based on the non-Gaussian wind power predictive distributions, an upper layer stochastic predictive controller coordinates the operation of PEV aggregator and wind turbine. The computed power references are sent to the lower layer PEV and wind controllers for execution. The PEV controller optimally allots the aggregated charging power to individual PEVs. The wind controller regulates the power output of wind turbine.

Yazdani-Damavandi, et al., [5], introduces high level of interdependency and the need for integrated models in a multi energy system (MES). Moreover, highlighting environmental aspects facilitates electrification in the transportation sector and integration of plug-in electric vehicles (PEVs). In this paper, aggregation of PEVs' batteries in parking lots (PL) is considered as a bulk electric storage in MES. The energy hub approach is employed for modeling MES considering PL. Due to the profitable behavior of PL in the reserve market, the energy hub model is modified to consider the reserve sources as ancillary services in the output energy vector.

III. SYSTEM IMPLEMENTATION

3.1 EXISTING SYSTEM

During the past decades, the electric power industry has undergone significant changes in response to the rising concerns of global climate change and volatile fossil fuel prices. For more efficient, reliable, and environmentally friendly energy production, it is critical to increase the deployment of distributed generation, especially from renewable

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energy resources (RE), as well as distributed energy storage (ES). This trend has evolved into the concept of a "microgrid" which can be described as a cluster of distributed energy resources, energy storage and local loads, managed by an intelligent energy management system.

Several approaches related to stochastic optimization of operation for renewable-based microgrids have been conducted. In [4], the day-ahead scheduling of a microgrid is developed as a two-stage stochastic problem in which the first stage identifies the optimal dispatch for the distributed units while the second stage considers the variability and uncertainty of photovoltaic (PV) and wind energy generation. The probabilistic UC in [5] is similarly formulated as a two-stage stochastic programming problem in order to incorporate the uncertainty in load and PV forecast. Forecast errors are modeled by normal distribution. A two-stage stochastic programming is also used in [6] and [7]. Most of the existing studies are based on scenario-based stochastic programming [4]–[9]. This approach is based on the replication of deterministic models across scenarios which are generated by Monte Carlo simulations. The computational burden in this approach increases exponentially with the number of investigated scenarios [2]. Scenario reduction using different techniques might ease the problem of computational overhead; however, this approach may overlook low-probability but high-impact scenarios.

3.2 PROPOSED WORK

To propose a novel regional PEV charging station system to serve PEV demand with DC level 3 fast charging, which can fully charge a vehicle in minutes. Electricity resources of this charging station system can be simultaneously supplied by wind, solar power, and the utility grid. To control the proposed regional PEV charging station system efficiently, and the bounds of optimal charge control for maximizing profit of this charging system. Two important stochastic measures are introduced to determine bounds of operational cost including a stochastic gap found by the expected value problem and wait-and-see solution. Furthermore a simulated annealing optimization technique is used to solve the UC.

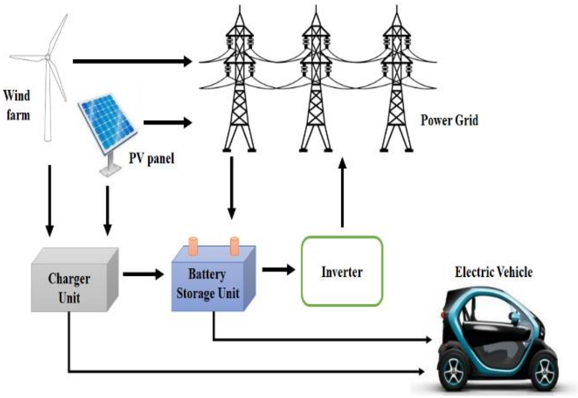

Fig 3.1 proposed block diagram

3.2.1 Regional PEV Charging Station System

Current public charging stations rarely consider the installation of energy storage systems or the integration of renewable energy resources. This is because these charging stations are designed for level 1 or level 2 charging with limited capacity. To support the increasing number of PEV users and to promote sustainable development, the proposed PEV charging station is equipped with a distributed energy storage system charged by wind/solar PV generation and electricity from the power grid, which can simultaneously charge multiple PEVs.

The proposed distributed energy storage system is used as a buffer for the distribution network to alleviate the load strain due to a high number of PEVs charging, which can defer the need for distribution upgrade. In addition, the proposed system can be used to mitigate the mismatch between renewable energy resources and the PEVs' demand by storing excessive wind/solar energy for future demand arriving at the station. Finally and very importantly, these proposed systems enable the charging station to participate in the deregulated market.

The participation of a PEV charging station in the deregulated market highlights the benefit of wind and solar energy as well as distributed energy storage systems with optimal operational strategies. The operation of the charging station should be determined from a regional point of view with the concept of Virtual Power Plant (VPPP) to achieve

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optimization of the above benefits. In addition, one charging station is insufficient to serve all of the PEV users throughout a metro area. Hence, the configuration of a regional PEV charging station system with *n* stations is proposed as shown in Fig.1.

According to Fig.1, all of the electricity from various sources is able to be directly used for charging PEVs, and the surplus can be either stored in the battery or sold back to the power grid. When a PEV arrives at the station, its demands can be served from both the direct charge and the battery storage. As proposed in this design, optimization can be achieved with optimal operation strategies, which highly depend on the available wind/PV energy and the power market price at each charging station location

3.2.1 Battery operation cost model

For a small-scale fossil fuel generator in a microgrid, the operating cost is typically the fuel cost. The cost can be characterized as a function of its output power

$$\begin{aligned} F_{gen}(P_{gen}) &= c_{gen} H_{gen}(P_{gen}) \\ &= c_{gen}\left[a_g P_{gen}^2 + b_g P_{gen} + c_g\right] \ (\$/h) \end{aligned}$$

Where C_{gen} (in \$/gal) is the fuel price, $H_{gen}(P_{gen})$ (in gal/h) is fuel consumption and P_{gen} is output power of generator i.
As opposed to a generator, a battery consumes no fuel to operate. This makes it a challenge to evaluate the operating cost of a battery. However, in terms of the energy conversion process, a battery and a generator are analogous. In a generator, energy is stored in fuel form and generated into electricity via combustion process. Similarly, in a battery, electricity is charged and discharged via an electrochemical process. In general, charging a battery is analogous to refilling fuel for a generator; thus, the input electricity (kWh) can be considered as the "fuel" for the battery. The input electricity cost is denoted as to emphasize this analogy. Therefore, the operating cost of a battery can be determined in the same form as (1) by deriving price and consumption of the battery. In this work, lead-acid, lithium-ion, and vanadium redox batteries are considered.

A. kWh_f price for Battery

For a generator, the price of fossil fuel is composed of c_{gen} two components:

$$c_{gen} = c_{gen}^{fuel} + c_{gen}^{avai}$$

in which C_{gen}^{fuel} represents the cost for fuel and C_{gen}^{avai} represents availability cost. The availability cost includes fuel transportation cost and other service costs such as cost for on-site storage facility. Depending on the location of the generator, C_{gen} can be much larger than C_{gen}^{fuel} due to transportation and other service costs.

Similarly, the kWh_f price for a battery can be determined:

$$c_{bat} = c_{bat}^{kWh_f} + c_{bat}^{avai}$$

Where C_{bat}^{kWhf} the price of energy is used to charge the battery and represents the availability cost of battery capacity. In a microgrid, if renewable energy is used to charge the battery, C_{bat}^{kWhf} can be zero; therefore, C_{bat}^{avai} is the main portion of the price. In this work, C_{bat}^{avai} is be defined as the cost to have 1 kWh of storage capacity available:

$$c_{bat}^{avai} = \frac{\text{Replacement Cost}}{C_{\Sigma}}$$

Where C_{Σ} is the total lifetime cycling capacity of a battery. By convention, an electrochemical battery, such as lead acid or lithium-ion, is often considered to be at the end of its life when it has degraded to 80% of its rated energy capacity [17]. Assuming that a battery will be discharged to its rated depth of discharge every cycle, the average capacity degradation rate is $(0.2/L_r)C_r$ in which C_r is the battery rated capacity and L_r is the rated life time.

As opposed to a lead acid or a lithium-ion battery, a vanadium redox battery (VRB) has negligible capacity degradation from repeated deep discharges and recharges. The cycle life of a VRB mainly depends on the life expectancy of its proton exchange membrane and its pumps. A VRB can last over 10 000 cycles until its membrane degrades or the pumps fail.

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Therefore, the total lifetime usable capacity of a battery can be estimated as follows:
Lead acid and lithium-ion battery:

$$C_\Sigma = C_r DOD_r \left[L_r - \frac{0.2}{L_r}(1+2+\ldots+L_r) \right] = C_r DOD_r (0.9L_r - 0.1)\ (\mathrm{kWh})$$

Vanadium redox battery:

$$C_\Sigma = C_r DOD_r L_r\ (\mathrm{kWh})$$

Where DoD_r is the depth of discharge. The operating cost model of the battery is built based on the similarity with fuel cost model of a generator, therefore there is little added complexity over standard approaches. The kWh_f price for a battery does not change as frequently as fuel prices. The price includes the replacement cost, the rated capacity, and life cycle which are determined at the time of purchase and do not need to be updated.

B. kWh_f Consumption for Batteries

The consumption of a battery during discharge is defined as the energy usage for supplying a load during a unit time:

$$H_{bat} = P_{bat}^{\Sigma} = P_{bat}^{d} + P_{bat}^{ld} = f\left(P_{bat}^{d}\right)$$

in which P_{bat}^{d} is the battery output power and P_{bat}^{ld} is the power loss during discharge.
The kWhf consumption of a battery during charge is defined as the energy loss for charging the battery during a unit time:

$$L_{bat} = P_{bat}^{lc} = f\left(P_{bat}^{c}\right)$$

in which $P_{bat}^{c}(kW)$ is the battery charge power, $P_{bat}^{lc}(kW)$ is the power loss during charge

3.2.2 Optimization based on Simulated Annealing Algorithm

Simulated annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space. It is often used when the search space is discrete (e.g., all tours that visit a given set of cities). For problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time, simulated annealing may be preferable to alternatives such as gradient descent.

Simulated annealing interprets slow cooling as a slow decrease in the probability of accepting worse solutions as it explores the solution space. Accepting worse solutions is a fundamental property of metaheuristics because it allows for a more extensive search for the optimal solution.

i) Procedure for SA Algorithm

1. Generate a random solution
2. Calculate its cost using defined cost function
3. Generate a random neighboring solution
4. Calculate the new solution's cost
5. Compare them:
   - If $c_{new} < c_{old}$: move to the new solution
   - If $c_{new} > c_{old}$: *maybe* move to the new solution
6. Repeat steps 3-5 above until an acceptable solution is found or you reach some maximum number of iterations.

ii) Pseudo Code for the SA algorithm

The following pseudo code presents the simulated annealing heuristic as described above. It starts from a state s_0 and continues to either a maximum of k_{max} steps or until a state with an energy of e_{min} or less is found. In the process, the call neighbor(*s*) should generate a randomly chosen neighbor of a given state *s*; the call random(0, 1) should pick and return a value in the range [0, 1], uniformly at random. The annealing schedule is defined by the call temperature(*r*), which should yield the temperature to use, given the fraction *r* of the time budget that has been expended so far.

- Let $s = s_0$
- For $k = 0$ through k_{max} (exclusive):

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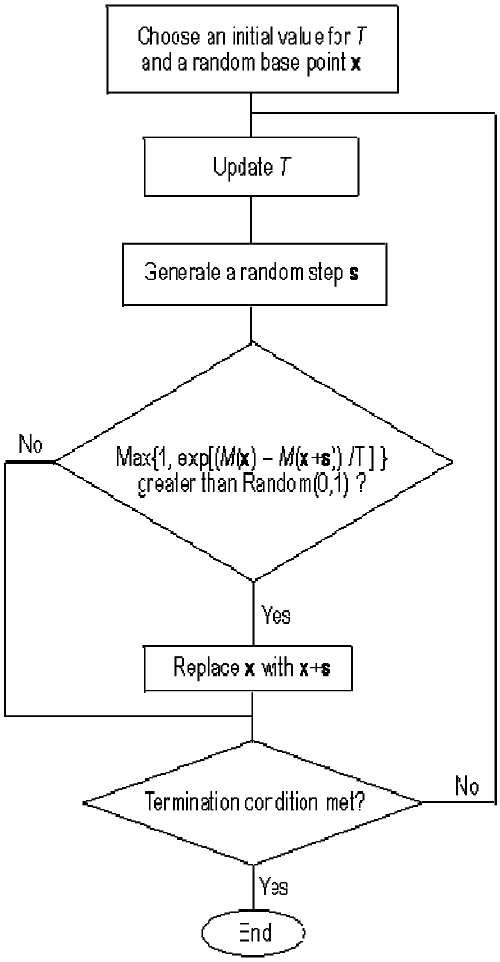
- $T \leftarrow$ temperature(k / k_{max})
- Pick a random neighbour, $s_{new} \leftarrow$ neighbour(s)
- If $P(E(s), E(s_{new}), T) \geq$ random(0, 1), move to the new state:
  - $s \leftarrow s_{new}$
- Output: the final state s

The following figure represents the flow chart of the simulated annealing algorithm



IV. RESULTS AND DISCUSSION

A 6 bus multi- machine system is taken here for the analysis purpose as shown in the figure. It consists of 6 buses, 3 feeders, 1 diesel generator, 2 wind generators, 1 PV generator and 3 battery storage systems 1 transformer and 15 loads are connected on a 13.8kV main grid. The length of each cable is 50 km and positive, zero sequence component of impedance is (0.015240+j 0.027432) ohms per conductor per phase. The rating of generators and battery are given below in the following tables. The renewable energy source and batteries are having the rating as like in the table 4.1

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Table 4.1 Generation and load specifications

S.No.	Details	Power
1	Diesel Generator	50Kw
2	Solar plant	50kW
3	Wind plant 1	20kW
4	Wind plant 2	20kW
5	VRB battery	10kW
6	AGM battery	12kW
7	Maximum load	50kW

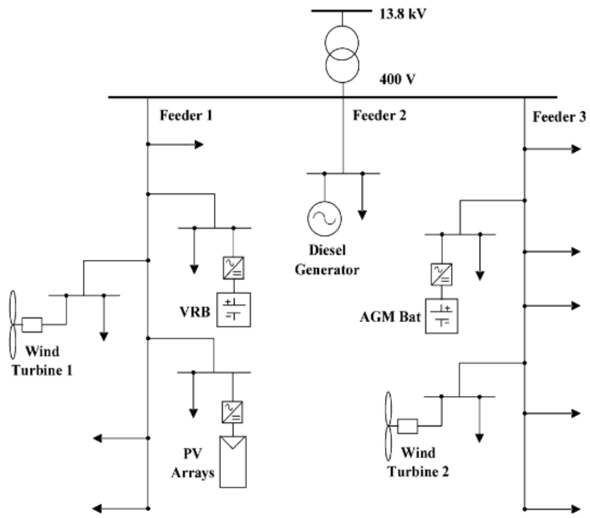

Figure 1 Single line diagram of 6 Bus system

Table 4.2 Diesel Generator data

a_{dg}	b_{dg}	c_{dg}	Start-up	c_{gen}
$3.10^{-4}\frac{gal/h}{kW^2}$	$0.052\frac{gal/h}{kW}$	$0.8gal/h$	$1	$4/gal
$T_{dg}^{up,min}$	$T_{dg}^{dw,min}$	P_{dg}^{min}	P_{dg}^{max}	Ini. state
$2hr$	$2hr$	$5kW$	$50kW$	$1hr$

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Table 4.3 Battery data

	L_r	DOD_r	C_r	V_r
VRB	10000 cycles	30%	$40kWh$	$60V$
AGM	1000 cycles	50%	$30kWh$	$60V$

	SOC_{min}	SOC_{max}	Ini. SOC	kWh_f price
VRB	0.3	0.8	0.5	$0.1\$/kWh_f$
AGM	0.5	1	0.5	$0.59\$/kWh_f$

Table 4.5 Wind and Solar power generation data

Hour	Wind Power1 (kW)	Wind Power2 (kW)	Solar Power (kW)
1.00	2.31	16.95	0.00
2.00	3.36	15.70	0.00
3.00	3.80	15.10	0.00
4.00	5.00	14.00	0.00
5.00	5.57	9.00	1.81
6.00	7.33	7.35	8.81
7.00	8.91	6.05	20.07
8.00	10.07	5.70	31.09
9.00	10.86	4.50	40.05
10.00	10.93	4.00	46.08
11.00	13.36	3.65	49.03
12.00	16.90	3.45	48.77
13.00	17.47	3.70	46.05
14.00	19.83	3.25	41.06
15.00	21.43	2.70	33.33
16.00	21.76	3.40	23.82
17.00	18.76	3.45	0.00
18.00	18.67	2.30	0.00
19.00	17.21	2.70	0.00
20.00	17.24	2.85	0.00
21.00	18.21	3.05	0.00
22.00	19.40	3.45	0.00
23.00	16.91	4.10	0.00
24.00	17.73	4.25	0.00

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Table 4.6 Load demand data

Hour	Demand (kW)	Hour	Demand (kW)	Hour	Demand (kW)	Hour	Demand (kW)
1:00	32.93	7:00	33.06	13:00	49.20	19:00	47.76
2:00	30.40	8:00	39.71	14:00	48.27	20:00	44.71
3:00	29.13	9:00	44.94	15:00	47.93	21:00	42.69
4:00	28.43	10:00	47.37	16:00	47.69	22:00	42.19
5:00	28.60	11:00	47.91	17:00	48.99	23:00	41.07
6:00	28.74	12:00	48.39	18:00	49.94	24:00	36.53

The power generated form the renewable generation like wind and solar power outputs (in kW) is plotted in the bellowed figure.

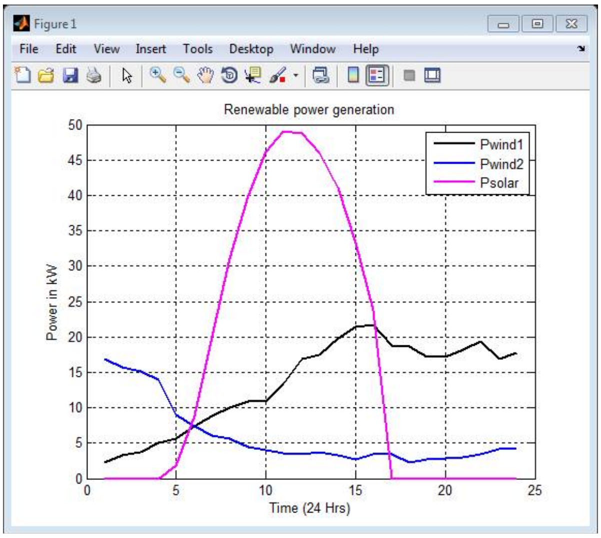

Figure 4.2 Renewable power generation

The load demand and the P_net values are tabulated in the following table and the curve response is shown in figure.

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Table 4.7 Pload and Pnet value

Hour	Load demand (kW)	Pnet (kW)	Hour	Load demand (kW)	Pnet (kW)
1.00	32.93	13.66	13.00	49.20	-18.02
2.00	30.40	11.34	14.00	48.27	-15.86
3.00	29.13	10.23	15.00	47.93	-9.53
4.00	28.43	9.43	16.00	47.69	-1.30
5.00	28.60	12.22	17.00	48.99	26.78
6.00	28.74	5.25	18.00	49.94	28.97
7.00	33.06	-1.98	19.00	47.76	27.84
8.00	39.71	-7.15	20.00	44.71	24.62
9.00	44.94	-10.46	21.00	42.69	21.42
10.00	47.37	-13.64	22.00	42.19	19.34
11.00	47.91	-18.13	23.00	41.07	20.06
12.00	48.39	-20.74	24.00	36.53	14.55

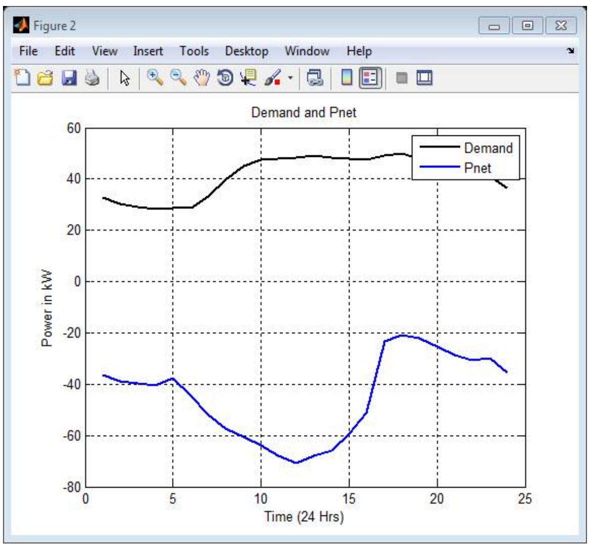

Figure 4.3 Demand and Pnet profile

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The proposed work addressing a stochastic optimization of micro grid based on battery cost model. This work proposes an idea of optimizing the micro grid power delivery based on battery operating condition.

Because batteries are clean to environment and can introduce minimum fuel cost when compared to the existing Diesel generators. The cost model is I need of the battery specification especially VRB batteries are highly recommended for the microgrid operation because of its lower DoD compared to other battery. In order to include the battery cost model, the following table 4.8 has been referred in this work. The detailed co-efficient of the battery during charging and discharging is shown in the following table.

Table 4.8 VRB battery model coefficients

(i,k)	a_k^i	b_k^i	c_k^i	d_k^i
(o,v)	$0.2414V_r$	$0.9925V_r$	–	–
(d,i)	$\frac{1.0719}{V_r \times 10^{-3}}$	$0.0183I_r$	$0.0210I_r$	–
(c,i)	$\frac{-0.3093}{V_r \times 10^{-3}}$	$\frac{1.0397}{V_r \times 10^{-3}}$	$0.0604I_r$	$-0.122I_r$

The simulated annealing algorithm is implemented in this work for the optimization of unit commitment as well as economic dispatch. The following table is showing the parameters utilized for the simulated annealing algorithm in this work.

Table 4.9 SA parameters

No of variable	3
No of iterations	20
No of sub iterations	5
Initial Temperature	10
Temperature reduction rate	0.99
Needed solution	Global minimum
DG min	5
DG max	50
VRB min	3
VRB max	10
AGM min	6
AGM max	12
VRB: Initial SOC	0.5
AGM: Initial SOC	0.5

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The simulated annealing algorithm optimizing the power required for compensating the load demand as well as reducing the cost for the while system. Where the battery storage systems are not allowed to charge form the Diesel generator outputs and also not allowed to discharge beyond its own DOD as depicted in Chapter 3.

The Economic dispatch from the proposed stochastic model is shown in the following table 4.11. The power delivery is based on the load requirement as well as battery SOCs, renewable energy generations.

Hour	P_{DG} (kW)	P_{VRB} (kW)	P_{AGM} (kW)
1:00	24.53863327	8.498316914	7.829290378
2:00	37.75158163	0	0
3:00	19.12984461	0	0
4:00	41.71981127	0	0
5:00	34.69597582	0	0
6:00	18.3610523	0	0
7:00	0	-8.500420594	-11.28708744
8:00	0	7.900172585	9.655080735
9:00	0	-8.641011008	-8.577586003
10:00	0	4.787126689	7.880885175
11:00	0	-5.461360412	-10.95842804
12:00	0	3.34086342	10.49218668
13:00	0	8.813745681	-9.969201723
14:00	0	-4.271608701	6.428821528
15:00	0	-8.379646054	-7.345278887
16:00	0	8.090671491	8.08952564
17:00	7.414016911	0	0
18:00	28.79407917	0	0

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19:00	23.10610808	0	0
20:00	32.04408092	0	0
21:00	40.52697577	0	0
22:00	10.28414414	0	0
23:00	29.23075313	0	0
0:00	39.85192289	0	0

The above table consist of optimized power ratings of Diesel generators, VRB battery and AGM battery. The positive power represents the power delivery to the grid, and negative power represents (especially batteries) charging instances. The battery as well as Diesel generators may kept idle whenever the load demands very low. The stochastic optimization of micro gird is shown as a curve in the following figure

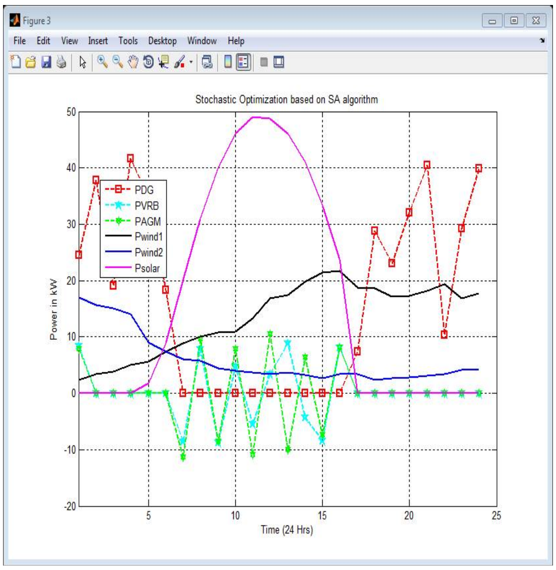

Figure 4.4 power responses after stochastic optimization of microgrid

The above plot represents the following notes about the superiority in the proposed work.

- By incorporating the operation cost functions of the batteries, the ED tends to dispatch power to the batteries which have a longer cycle life, lower replacement cost, and higher efficiency.
- In this case, the VRB has lower $kWhf$, however the AGM battery has higher efficiency, therefore their dispatched powers, as shown in the results, are close.
- Compared to the diesel generator, the batteries have lower operating cost due to lower “fuel” price and higher efficiency. However, the batteries are limited by their maximum depth of discharge.
- For that reason, the batteries can only discharge for few hours at night, as observed in the results.
- Furthermore, note that although not explicitly expressed, the two energy storage units were committed in accordance with their individual operating profiles as detailed in chapter - III to maximize their life spans.
- Furthermore, both batteries were more cost effective than the diesel generator. Thus, it makes better economic sense to increase the size of the energy storage system with respect to the diesel generator.

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V. CONCLUSION

The main aim of the work is to promote the battery operation in power grids and to improve the electricity distribution as well as to reduce the fuel cost. This proposed work is most suitable for the stand alone system. Still now, the diesel generators are the only a bulky source to face the peak loads in standalone systems because the renewable energy resources are stochastic in nature. This can be solved by operating the system by adding vehicle battery storage system and it is possible to schedule the diesel generators and also can reduce the fuel cost. This project to design optimal control for a novel regional PEV charging station system, which serves its demand by wind/solar generation and electricity from the utility grid. This project genesis a simulated annealing optimization based economic schedule of microgrid based on battery storage system. This optimal control system is focused on minimizing its operational cost. The MATLAB simulation results are showing the effectiveness of the proposed work on 7 bus stand-alone systems.

FUTURE WORK

The future work is planned to execute with the robust optimization which can overcome the performance of simulated annealing algorithm and so it is possible to bring good optimum results in further work.

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