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Combined Solar Charging Stations and Energy Storage Units Allocation for Plug-In Electric Vehicles by Considering Uncertainties

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Abstract— **Plug-in electric vehicles (PEVs) are becoming a key feature of smart grids. PEVs will be embedded in the network as a mobile load-storage with probabilistic behavior. In order to manage PEVs as flexible loads, charging stations (CSs) have essential roles. In this paper, a new method for optimal sitting and sizing of solar CSs using energy storage (ES) options is presented. Also, behavior of PEVs in the presence of other loads, electricity price and solar power generation uncertainties are considered. The proposed optimization model maximizes the distribution company (DisCo) benefit by appropriate use of CSs, maximizes the benefit of CSs owners and minimizes the power loss, load demand and voltage sags during peak times considering different technical constraints. The optimization variables are the location and capacity of CSs (consists of solar units and energy storage systems). In this paper, charge-discharge actions of PEVs are regulated based on time-of-use demand response programs. In order to solve the optimization problem considering uncertainty of load growth, number of EVs, electricity price, initial state of charge in PEV batteries and solar power generation, genetic algorithm method using Monte-Carlo simulation is used. The simulation results show that the proposed method has several advantages for DisCo and owners of CSs.**

Keywords— Plug-in electric vehicles, charging station allocation, multi-objective optimization, energy storage, demand response program, smart grid.

I. INTRODUCTION

Nowadays, different technical, economic and political reasons cause plug-in electric vehicles (PEVs) become more attractive than internal combustion engine vehicles. This trend is accelerated by environmental pollution concerns [1]-[2] as well as the needs for sustainable and cost-efficient smart energy systems [3]-[4]. PEVs are not only more emission-aware, but also more cost-effective compared to the traditional vehicles. Energy demand incensement due to PEVs is a real challenge for distribution companies (DisCos) from both technical and economic aspects. Fortunately, PEVs are usually flexible loads that can be utilized as energy storages (ESs) to inject power to the grid through a vehicle to grid (V2G) process. There are several studies about V2G process and its effects on distribution networks [7]-[13]. Energy of PEVs can be used in reduction of power losses and voltage sags [7]-[9], peak shaving [10], voltage and frequency control of microgrids [11]-[12], reserve power [13], etc. Investigating on the behavior of vehicle owners have shown that over 90% of cars don't run each day periodically. So, vehicles can connect to the power grid at peak hours as power sources [14]. In condition that there are a lot of PEVs connected to grid, PEVs can be considered as flexible loads with energy storage capabilities. In other words, allocation of charging stations for PEVs can be used as an effective tool in order to solve network problems such as peak load, load growth, etc. Also, various demand response programs (DRPs) could be applied in the mentioned networks [15].

There are considerable distributed energy resources (DERs) in modern grids that they can cooperate with PEVs as flexible load-storage units. There are a huge number of researches that have studied integration of DERs into grids with flexible loads, PEVs and ESs by considering various DRPs [16]. For example, in [17], a new model is proposed to evaluate the contribution of V2G as a tool for DRPs. In [18], a technique for CS allocation which provides V2G power as distributed generation is presented. In [19], management of the PEVs in a CS is studied. In this reference, the method is applied to maximize the state of charge (SOC) of each PEV's storage. In [20], a method is used to schedule EVs charging in a parking considering constraints for PEV battery and utility limits.

In smart grids with considering CSs and DERs, the operation cost of grid will be reduced. The studies have shown that there is a perfect match between the PEVs and non-dispatch able energy resources in the smart grid infrastructure. In this paper, optimal allocation of solar CS is introduced as a multi-objective problem considering both technical and economic issues. The proposed method maximizes profits for DisCo and charging station owner (CSO). Probabilistic behavior of solar units and PEVs load are also considered.

II. PROBLEM DEFINATION

In this paper, the proposed model maximizes two objective functions, namely total benefits of DisCo and CSO. It is assumed that private sector invests on the solar charging stations using ESs and DisCo will only guide CSs to operate properly. DisCo is responsible for aggregating EVs, the CSs investment, and optimal operation of the distribution system. The annual load profile is modeled by multiplication of three parameters. A normal probability density function (PDF)

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model is used for demand level factor, $DLF_{i,t,h}$. The uncertainty of $DLF_{i,t,h}$ is modeled as follows:

$$DLF^{e}_{i,t,h} = \mu^{D}_{i,t,h} + \lambda^{D,e}_{i,t,h} \times \sigma^{D}_{i,t,h} \quad (1)$$

where $\lambda^{D,e}_{i,t,h}$ is a random variable generated for demand at bus i, operation in year t and demand level h, using a normal PDF with a zero mean and unity standard deviation. The values of load level factor and its standard deviation are $\mu^{D}_{i,t,h}$ and $\sigma^{D}_{i,t,h}$, respectively. It is assumed that a load growth rate, α, in bus i in each year will be applied.

DRPs are used to shift the load from peak times to other periods in order to decrease energy purchase costs. In this paper, it is assumed that the consumers only participate in time of use (TOU) programs with considering a limited capability of shifting demand. The load after applying the DRP is defined as follows:

$$P^{DR}_{i,t,h} = (1 - DR_h) \times P^{D}_{i,t,h} + ldr_h \quad (2)$$

$$P^{D}_{i,t,h} - P^{DR}_{i,t,h} = DR_h \times P^{D}_{i,t,h} \quad (3)$$

where $P^{D}_{i,t,h}$ is the base load at time period h, and $P^{DR}_{i,t,h}$ is load after applying DRP in the same period. DR_h factor shows the consumer participation in DRP. Equations (4)-(7) express the ESs constraints. The constraints (4) and (6) capture the limits on the charging and discharging power.

$$0 \le P^{c}_{k,h,s} \le b^{c}_{k,h} P^{c,\max}_{k,h}, 0 \le P^{disc}_{k,h,s} \le b^{disc}_{k,h} P^{disc,\max}_{k,h} \quad (4)$$

$$E^{\min}_{k} \le E_{k,h,s} \le E^{\max}_{k} \quad (5)$$

$$b^{c}_{k,h,s} + b^{disc}_{k,h,s} = 1; b^{c}_{k,h,s}, b^{disc}_{k,h,s} \in \{1, 0\} \quad (6)$$

$$E_{k,h+1,s} = E_{k,h,s} + (\eta^{C}_{k} \times P^{c}_{k,h,s} - \frac{P^{disc}_{k,h,s}}{\eta^{disc}_{k}}) \quad (7)$$

PEV access to the CS is a probabilistic parameter and depends on the PEVs owners' behavior. Availability of PEVs in the charging stations i, in the demand level h and in each Monte-Carlo experiment e, is calculated as follows:

$$M^{e}{}_{i,h} = \mu^{P}_{i,h} + 0.1 \times \mu^{P}_{i,h} \times \lambda^{Pe}_{i,h} \quad (8)$$

where $\lambda^{Pe}_{i,h}$ is a random variable generated by using a normal PDF with and a mean of 13.6 and standard deviation of 4.5 for PEVs in the charging station i and in the demand level h. Initial SOC of batteries in PEVs are determined by different uncertain and non-identical parameters. The remaining energy in the vehicles' battery can be calculated randomly. Initial SOCs of PEVs' batteries are calculated through a scenario-based approach which is divided into three areas with normal PDF, and each area is identified as a scenario. Initial SOCs of PEVs' batteries are calculated by the scenario-based approach as Fig. 1. CS output depends on solar parking output and initial *SOC* of PEV batteries, number of available vehicles, and output power of each vehicle. Presence percentage of hourly PHEV in the CS is presented in Fig. 2 .

Also, the required time for full charging/discharging of a PEV depends on initial SOC, minimum and maximum acceptable battery's SOC and the charge/discharge rate of PEV. The required time for full charging or discharging of a PEV depends on initial SOC can be calculated as follows:

$$t_{charge}(j) = \frac{(SOC_{\max} - SOC_j) \times ES_j}{P_v} \quad (9)$$

$$t_{discharge}(j) = \frac{(SOC_j - SOC_{\min}) \times ES_j}{P_v} \quad (10)$$

where SOC_{min} and SOC_{max} are the minimum and maximum acceptable battery's state of charge respectively, ES_j is the battery capacity of PEV$_j$, and P_v is the charge-discharge rate of PEV.

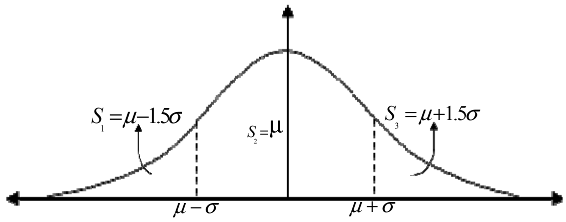

Fig. 1. Probability distribution function (PDF) for DLF, PLF and SOC of PEV's batteries

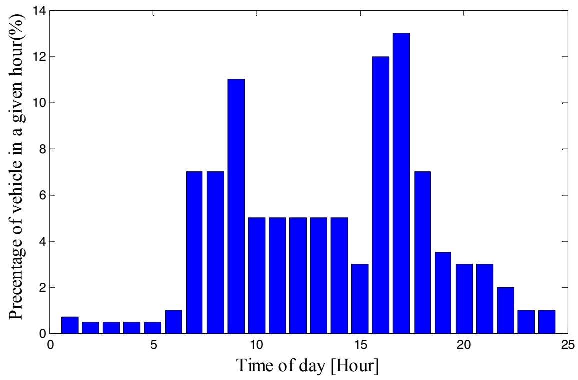

Fig. 2. Presence percentage of hourly PHEV in the CS

The output power of the CS can be shown as fellow:

$$P_{cs} = n \times P_v + P_{Solar} \quad (11)$$

The output power of the CS is a function of solar units output and SOC of PEVs batteries. The generation of solar unit highly depends on the sun radiation in the site. In this paper, the stochastic behavior of sun radiation in each forecasted period is modeled by the normal PDF.

The price of electricity purchased from the upstream grid is determined by market mechanism. The price value is considered variable for each demand level. A normal PDF is considered to follow spot price using Monte-Carlo experiment. DRPs are used to shift the load from peak times to other periods to decrease energy purchase costs. It is assumed that the consumer only participates in TOU program with considering a limited capability of shifting demand. Also, DRP and charging-discharging constraints are modeled.

In this paper, the first objective function (OF$_1$) consists:

- *Investment cost of CS considering solar and ESs costs*

The installation cost and site of CS are considered in investment cost. This cost is evaluated by the following equation:

$$C^{inv}_{Total} = \sum_{i=1}^{N_{CS}} (C^{equ}_{i} + C^{cons}_{i}) \times CP_i = \sum_{i=1}^{N_{CS}} C_{ac} \times CP_i \quad (12)$$

- *Net benefit of day-time charging PEV*

The total net benefit from providing day-time charging services for PHV drivers are obtained as follows:

$$C_{Total}^{charge} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{CS}}(\frac{\rho_{t,h,pur}^{grid}}{\mu_{conv}} + c_d)\times P_{i,t,h}^{CS}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (13)$$

$$R_{Total}^{charge} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{CS}}\rho_{t,h}\times P_{i,t,h}^{CS}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (14)$$

$$B_{Total}^{charge} = R_{Total}^{charge} - C_{Total}^{charge} \quad (15)$$

where $\rho_{t,h,pur}^{grid}$ is the energy price purchased from market at demand level h in \$/kWh.

- *Net benefit of discharging PEV*

The stored energy in PEV can be injected to the grid during peak hours with lower price rather than the price of the peak-load level. Discharge scheduling of PEV batteries is calculated as follows:

$$C_{Total}^{discharge} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{CS}}(\frac{\rho_{t,h,pur}^{EV}}{\mu_{conv}} + c_d)\times P_{i,t,h}^{CS}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (16)$$

$$R_{Total}^{discharge} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{CS}}\rho_{t,h}\times P_{i,t,h}^{CS}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (17)$$

$$B_{Total}^{discharge} = R_{Total}^{discharge} - C_{Total}^{discharge} \quad (18)$$

where c_d is the cost of equipment degradation due to the extra use of V2G, and μ_{conv} is the inverter efficiency.

- *Net benefit of providing power from upstream-grid*

The net benefit obtained from providing power to the grid loads can be obtained as follows. During peak-time demand is provided by CSs through V2G.

$$C_{total}^{load} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}(P_{t,h,pu}^{grid}\times\rho_{t,h}^{grid}\times\tau_{t,h}^{grid})\times(\frac{1+InfR}{1+IntR})^t \quad (19)$$

$$R_{total}^{load} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}(P_{t,h}^{Load}\times\rho_{t,h}\times\tau_{t,h}^{load})\times(\frac{1+InfR}{1+IntR})^t \quad (20)$$

$$B_{Total}^{load} = R_{Total}^{load} - C_{Total}^{load} \quad (21)$$

- *Benefit of active power losses reduction*

Energy injection through PEV during peak time will reduce the power loss. Benefits obtained from power loss reduction can be calculated by the following equation:

$$B_{Total}^{loss} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}[(Ploss_{t,h}^{without\ CS} - Ploss_{t,h}^{with\ CS})\times\rho_{t,h}\times\tau_{t,h}]\times(\frac{1+InfR}{1+IntR})^t \quad (22)$$

where $Ploss_{t,h}^{withoutCS}$ and $Ploss_{t,h}^{withCS}$ are active power losses without and with CS.

Also, the second objective function (OF_2) consists:

- *Operating benefit of solar units*

Operation benefit of solar units is depended on energy generation and price of energy. Operation cost of the solar units is assumed equivalent to the repair and maintenance service.

$$C_{solar} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{s=1}^{N_{CS}}(P_{i,t,h}^{Solar}\times OC_{Solar}\times\tau_{t,h} + Cost_{main})\times(\frac{1+InfR}{1+IntR})^t \quad (23)$$

$$R_{solar} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_b}\sum_{s=1}^{N_{CS}}(P_{i,t,h}^{Solar}\times\rho_{t,h}\times\tau_{t,h})\times(\frac{1+InfR}{1+IntR})^t \quad (24)$$

$$B_{solar} = R_{solar} - C_{solar} \quad (25)$$

Where OC_{solar} is the operation cost of any solar units in \$/MWh and $\rho_{t,h}$ is the price of sold electricity to customers by DSM in year t and in demand level h. τ_h is the time duration of selling energy to customers at demand level h in hour.

- *Investment cost of CS units*

The installation cost of solar unit and price of site, construction, etc. are included in solar unit's investment cost.

$$C_{total}^{inv} = \sum_{t=1}^{T}\sum_{i=1}^{N_b}\sum_{s=1}^{N_s} S_{i\,\max}^{solar}\times IC_s\times(\frac{1+InfR}{1+IntR})^t \quad (26)$$

where ICs is the investment price of each MW of solar unit.

- *cost of day-time charging ES*

The total net benefit from providing day-time charging services is obtained as follows:

$$C_{Total}^{chargeES} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{ES}}(\frac{\rho_{t,h,pur}^{grid}}{\mu_{conv}} + c_d)\times P_{i,t,h}^{ES}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (27)$$

where $\rho_{t,h,pur}^{grid}$ is the purchasing price of energy from wholesale market at demand level h in \$/kWh.

- *Net benefit of discharging ES*

The net benefit obtained from selling power to the network loads generally can be expressed as follows:

$$B_{Total}^{dischargeES} = \sum_{t=1}^{T}\sum_{h=1}^{N_h}\sum_{i=1}^{N_{ES}}\rho_{t,h}\times P_{i,t,h}^{ES}\times\tau_{t,h}\times(\frac{1+InfR}{1+IntR})^t \quad (28)$$

In this paper, benefit function for DisCo is defined as follows:

$$OF_1 = B_{total}^{discharge\,EV} + B_{total}^{charge\,EV} + B_{total}^{grid} + B_{total}^{loss} - C_{total}^{inv} \quad (29)$$

where the above-mentioned terms denote the net benefit of day-time PEV charging/discharging programs, net benefit of providing power from upstream-grid, benefit of active power losses reduction and investment cost of CS considering solar and ESs costs, respectively. Also, the benefit function for CSO is defined as follows:

$$OF_2 = B_{total}^{discharge\,ES} - C_{total}^{charge\,ES} + B_{total}^{Solar} - C_{total}^{inv} \quad (30)$$

where the terms describe the net benefit of ES discharging programs, cost of day-time ES charging, operating benefit of solar units and investment cost of CS units, respectively.

III. Multi-Objective Optimazation Problem

The first objective function, OF_1, indicates the total benefit of DisCo and the second objective function, OF_2, indicates CSO owing to the ESs units and solar CSs in the distribution system. This paper introduces a multi-objective optimization framework for optimal PEV and CS planning with regard to several constraints. To handle uncertainties in the planning phase, Monte-Carlo simulation (MCS) is used. Also, to handle the allocation and optimization problem, Genetic Algorithm (GA) is combined with MCS. The proposed solution algorithm consists of two steps. In the first step, the Pareto-optimal front is specified and in the second step the best solution is selected based on a crowding distance index (CDI) considering the planner's preferences:

$$d_i^1 = \frac{\left|OF_1^{i+1} - OF_1^{i-1}\right|}{OF_1^{\max} - OF_1^{\min}} ; d_i^2 = \frac{\left|OF_2^{i+1} - OF_2^{i-1}\right|}{OF_2^{\max} - OF_2^{\min}} \tag{31}$$
$$d_i = d_i^1 + d_i^2$$

In order to model optimization problem, the uncertainties of four parameters are taken into account, namely load demand, electricity price, solar power generation of CS and the input/output power of charging station owing to the daily behavior of drivers. MCS, scenario based approach and normal distribution are used to handle uncertainties. The mechanism of this method is described as the following steps:

Step 1: consider e=1, Avg = {}.
Step 2: For each input variable s_i, produce a value, that is s_i^e , using its PDF.
Step 3: Evaluation of z_e using $z_e = L(s_1^e, ..., s_n^e)$.
Step 4: Evaluation of $\tilde{z}_e = (1/e)\sum_{m=1}^{e} z_m$.
Step 5: Store $\tilde{z}_e$ in Avg.
Step 6: Check if $\tilde{z}_e$ converged then go to step 7; else e=e+1 then go to step 2.
Step 7: End

In the above steps, a function namely z is considered, that is, $z_e = L(s_1^e, ..., s_n^e)$. The variables s_1 to s_n are random variables with their specified PDF. The problem is finding the PDFs of all input variables which is s_1 to s_n. The concept of MCS is obtaining the PDF of z_e using the PDFs of input variables s_i.

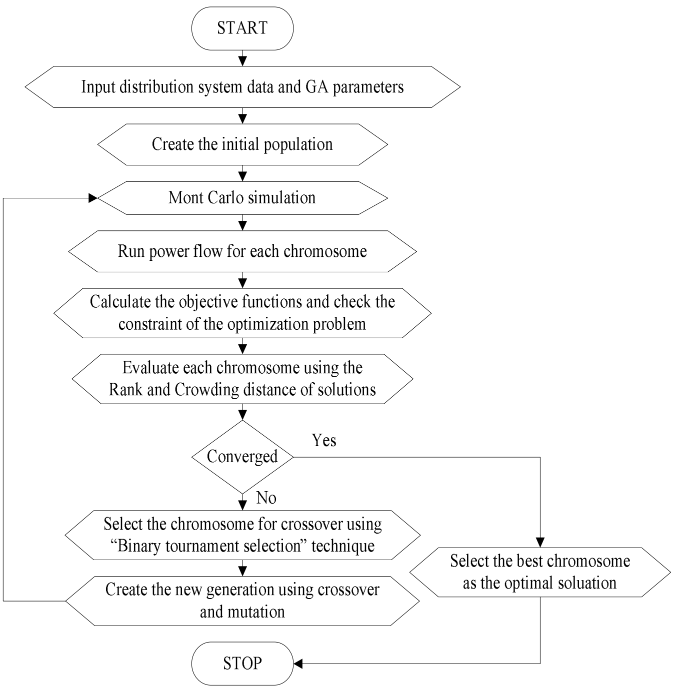

Fig. 3. Flowchart of proposed optimization method

At the end, the PDF of the output function, z is estimated as a normal PDF with a mean and standard deviation calculated as follows:

$$\mu_z = \mu_{\tilde{z}_e}$$
$$\sigma_z = \sqrt{\frac{\sum_{m=1}^{e}(z_m - \mu_z)^2}{e}} \tag{32}$$

Flowchart of proposed method is shown in Fig. 3.

IV. Simulation Results

The proposed methodology is applied to IEEE 33-bus standard test system. The proposed method is applied to 30-bus standard test system which is shown in Fig. 4. The system technical data and loads are given in [21].

In order to illustrate effects of proposed method on operating cost, three different scenarios for CS allocation are considered.

- Scenario 1: CS allocation considering DRP and Solar units.
- Scenario 2: CS allocation considering DRP and ESs.
- Scenario 3: CS allocation considering DRP, Solar units and ESs.

To show the DRPs effect on the proposed model, load curve considering PEVs effect and DRP is shown in Fig. 5. As shown in this figure, DRP reduce peak value and shifts loads from peak time to off peak times.

The data used in simulation and results of simulation is presented in Table I. Results of allocation considering optimal buses and capacities and also, benefit-cost amounts for DisCo is presented in Table II.

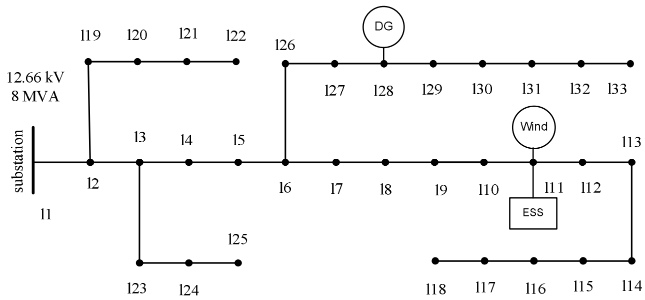

Fig. 4. Single line diagram of the 33-bus system [21]

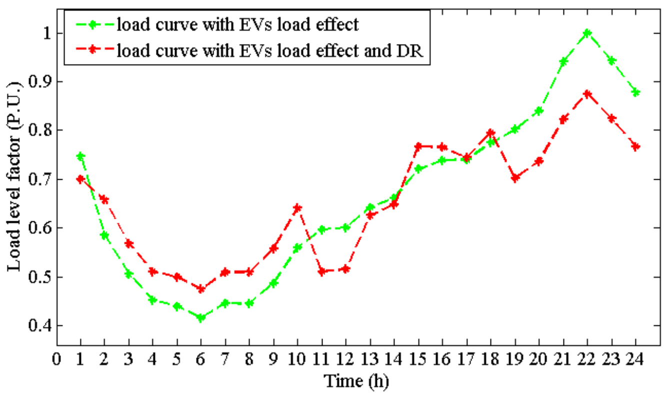

Fig. 5. PEV and DR effects on load curve

TABEL I. DATA AND PARAMETERS VALUE IN SIMULATION

$\rho^{grid}_{t,h,pur}$	65	\$/MWh	Electricity wholesale purchasing base price
$\rho^{EV}_{t,h,pur}$	60	\$/MWh	Electricity purchasing price from vehicle owners
C_{ac}	3000	\$	Investment cost per vehicle
C_d	0.001	\$/kWh	Degradation cost of V2G
$InfR$	4	%	Inflation rate
$IntR$	5	%	Interest rate

TABEL II. COST –BENEFIT ANALYSIS IN SCENARIO 2 AND 3 (IN 10^4 \$)

Load condition	**Without ESs**		**With ESs**	
Bus number Optimum capacity of solar units (kw)	13 300	31 500	15 350	31 500
Bus number Optimum capacity of ESs (kwh)	- 	- 	11 1200	31 900
Benefit of providing power during peak time (\$)	16.349		23.546	
Benefit of charging service (\$)	-		4.285	
Benefit of loss reduction (\$)	7.151		7.939	
Benefit of solar units output (\$)	1.94		2.14	
Total benefits for DisCo (\$)	23.694		37.91	

In order to compare difference between traditional system operation, systems with ESs and without ESs, simulation results are presented in Table II. According to this table, the benefit of providing power during peak-time is much more from charging or power loss reduction benefits due to DRP implementation in system. With considering DRP, the losses are also reduced. According to Table II, Planning has been done for two CSs and two solar units. In systems using ESS, solar units output will be more controllable and then economic profit will be increased as presented. In other words, ESS increase flexibility of generation and consumption profiles and help DisCo to mitigate demand with minimum cost. So, benefits due load shifting and active power loss reduction during peak times will be increased in systems with ESS. Considering ESS allocation in grid, changes the results of solar unit's allocation and operational planning of grid. In this paper, results showed that using ESS increase optimum capacity of solar units and their location.

Fig. 6 and Fig. 7 show the annual active power loss and demanded power from upstream grid, respectively. Power loss value at peak hours is significantly reduced in the planning period. On other hand, the selected CSs which specified by the proposed model will impose the lower total active power loss during the operation time compared to without ESS option. The mentioned results are shown in Fig. 6. Demand response implementation has decreased losses effectively. In this paper using solar units is more effective than using ESS. The reason of this result is depended on values of selected optimal ESS, solar unit's capacity and behavior of loads during operational planning horizon. Daily demand for active power and voltage profiles are shown for DLF=1 in Fig. 7 and Fig. 8, respectively. As, shown in Fig. 8, the best results for smoothing load profile is obtained in case that both ESS and solar units are considered. As, storages are more flexible and controllable in compare with solar units, using ESS in this paper is more effective due to peak load time period (7 P.M - 12 P.M).

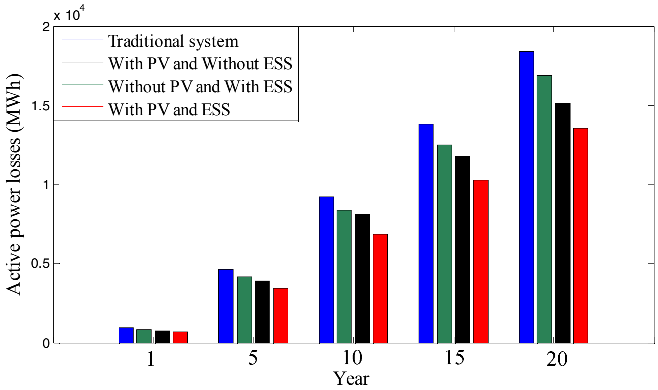

Fig. 6. Annual active power loss during operating period

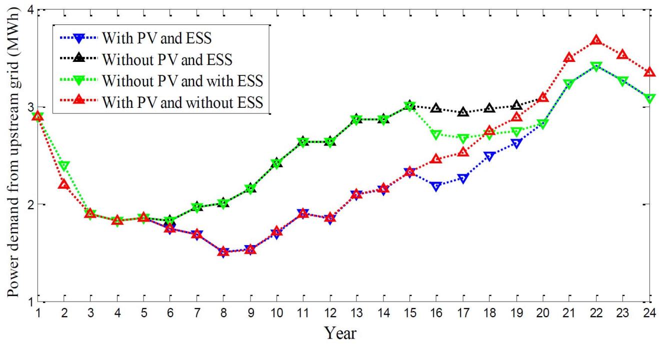

Fig. 7. Annual active power demand from upstream grid

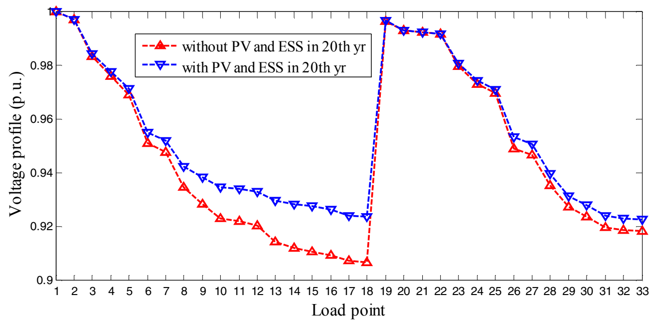

Fig. 8. Voltage profile after and before of applying proposed method

In the simulated network, the buses which they are far from substation will face the voltage drop problem. As it can be observed from Fig. 8, the proper placement of the CS and solar units can improve voltage profile. In this paper, a load growth for 20 years is considered. Results showed that load growth will lead to unacceptable voltage sag after few years. But, optimal allocation of ESS with solar units can mitigate load growth effects during couple of decades.

V. CONCLUSION

This paper introduced a multi-objective method to optimal integration of PEV's CSs with solar units and ESs, simultaneously. An optimization method using GA and MCS was used to solve the optimization problem. The proposed two-step algorithm provided the non-dominated solutions by maximizing the benefits of DisCo and CSO in the first step. In the second step, a satisfying method selected the best solution from the available set. The presented method helped the

DisCo to be an aggregator to collect the dispersed PEVs in the network and manage their capacities. This optimization problem was also performed to find the optimum sitting and sizing of the solar-based CS and ESS to minimize the power losses and also to improve the voltage profile. The proposed methodology considered the uncertainties of input parameters and could help DisCo operators to make more robust decisions. In order to improve the applicability and effectiveness of the proposed approach several case studies and computer simulations under different working conditions demonstrated. Results illustrated that proposed method can improve economic operation and meet technical needs of the grid.

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