Available online at www.sciencedirect.com
ScienceDirect
Energy Procedia 142 (2017) 2202–2207
Energy Procedia
www.elsevier.com/locate/procedia

9th International Conference on Applied Energy, ICAE2017, 21-24 August 2017, Cardiff, UK

Mobile Power Infrastructure Planning and Operational Management for Smart City Applications

Nand K. Meena[a], Sonam Parashar[a], Anil Swarnkar[a], Nikhil Gupta[a], K. R. Niazi[a], R.C. Bansal[b,*]

[a]*Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur, India 302017*
[b]*Department of Electrical, Electronics and Computer Engineering, University of Pretoria, South Africa*

Abstract

The paper presents new strategies and algorithms for future mobile power infrastructure planning and operational management in smart cities. The efforts have been made to develop a resilient Electric Vehicle (EV) infrastructure for smart city applications. The goal of this work is to maximize the profit of utility and EV owners participating in real-time smart city energy market subjected to numerous techno-economic constraints of the EVs and power distribution system. For effective real-time applications, the knowledge of artificial intelligence and internet of things (IoT) are used in the proposed model. In order to validate the proposed model for smart city applications, IEEE 33-bus radial distribution network is adopted as a small city power network. The simulation results of proposed model are found to be encouraging when it is compared with the case in which conventional strategies are used.

Peer-review under responsibility of the scientific committee of the 9th International Conference on Applied Energy.

Keywords: Artificial intelligence; distributed resources; electric vehicle; internet of things; smart city.

1. Introduction

The growing urbanizations, global energy crisis, greenhouse gases emission, depleting conventional resources etc. has led to the vision of Smart Cities (SCs) deployment. Currently, cities are the major energy consumers and greenhouse gas emitters which significantly affected the climate and energy security [1]. The key motivation behind SC deployment may be the optimal utilization of available resources which are necessary for survival of the society. However, the definition of SCs is not yet standardized due to the broad vision of smart city deployments [2].

The common scopes of SC deployment may be to increase the living standard of inhabitants by facilitating with basic needs such as electricity, water, gas, transportation, information and communication, traffic and all types of pollution control, basic medical services, etc. Among these, the smart electricity infrastructure planning and

* Corresponding author. Tel.: +27 12 4205446; fax: +27 12 3625000.
E-mail address: rcbansal@ieee.org.

1876-6102 © 2017 The Authors. Published by Elsevier Ltd.
Peer-review under responsibility of the scientific committee of the 9th International Conference on Applied Energy .
10.1016/j.egypro.2017.12.589

management may play a vital role in SC deployment which may include the optimal management of distributed resources such as Distributed Generations (DGs), shunt capacitors, battery energy storage, Electric Vehicles (EVs) and demand response programs. The optimal planning and management of these resources may provide a wide range of benefits for utility and consumer [3], which may include minimized power/energy loss, emission and operating cost, improved voltage profile, stability and reliability etc.

In literature, various optimization models have been investigated for optimal planning and operational management of distributed energy resources to achieve various techno-economic goals for SC applications. In [4], a SC transportation network architecture based on supercapacitor-powered electric buses is developed to improve the grid operation efficiency and to reduce the oil consumption of transportation sector. A particle swarm optimization based EV charging strategy is proposed in [5] to minimize the operating cost of system while meeting the EV owner's requirements. In [6-7], frameworks are developed for realization of SC vision through Internet of Things (IoTs), the frameworks are exploiting the most advanced communication technologies to provide value added administration for SC inhabitants. The statistical behavior of EV charging and effect of DG mix are studied in [8] to reduce the emission in Italian cities. In [9], a hierarchy of decision-making strategy is proposed for energy management applications in SCs. In [10], stochastic dynamic model for optimal charging of electric vehicles is proposed. A multi-objective approach for minimizing load variance and charging cost of electric vehicles is presented in [11]. The discussed and recent literature witnessed the growing interest and importance of energy efficient applications in SC deployment.

In this paper, mobile power infrastructure model is developed for SC applications to achieve various techno-economic benefits. The work introduces few new strategies and algorithms for effective planning and real-time management of EV and distribution system infrastructure. An optimization framework is developed to maximize the techno-economic benefits of EV owners and utilities comprises of 24-hours activities of distribution system and EVs using artificial intelligence and IoTs. In order to validate the proposed model, IEEE 33-bus distribution network is considered as a smart city distribution network. The simulation results of proposed strategy are compared with that of the case in which such strategies are absent. The comparison results show the superiority of the proposed model.

2. Proposed Mobile Power Infrastructure Model for Smart City Applications

The future rapid growth of EVs may raise many challenges and issues for future distribution system operators as it will introduce more uncertainties in the system. In order to alleviate some of the issues, optimization models and strategies may play a vital role in the future mobile power infrastructure planning and management. The proposed mobile power infrastructure planning and management model based on artificial intelligence and IoTs is shown in Fig. 1.

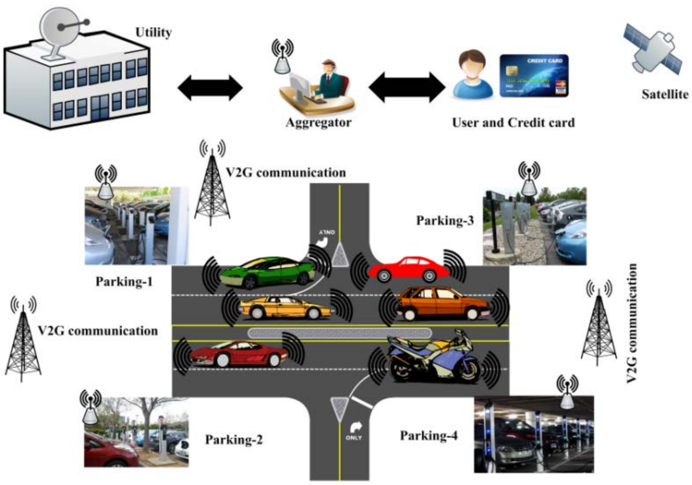

Fig. 1 Basic structure of proposed mobile power infrastructure planning and operational management in smart cities

It may be observed that majority of professionals are found to be in commercial and industrial areas in daytime. In proposed work, each vehicle is assumed to be associated with unique smart ID and IoT chip with the information and communication modules which can be linked through the public or private networks in SCs. The smart ID will also be linked through the credit card of respective EV owner for immediate daily transactions. The EV chargers available in car parking are assumed to have power line/wireless communication link to communicate with aggregator/utility servers. According to the proposed model, each EV will contain the information of distance travelled, State of Charge (SOC), the mean energy pricing till last charge, associated IoT infrastructure etc. It is also assumed that whenever be the car is in the parking, it will be connected to a charger but charging will depend on the aggregator's decision algorithms.

3. Objective Function

In this paper, the problem is formulated as a multiple objectives comprising of utility and consumer objectives simultaneously. The utility objective includes the cost of instantaneous power loss minimization i.e. $f_u(t)$, whereas the objective of EV owner is to minimize the instantaneous cost of total energy stored in Batter Energy Storage System (BESS) of EV i.e. $f_c(t)$ subjected to various system and storage operating constraints Therefore, the aim of an aggregator is to maximize the real-time profit of distribution utility and EV owners. The objective function of aggregator combining the objectives of power distribution utility and EV owner can be expressed as

$$\min F(t) = k_1 f_u(t) + k_2 f_c(t) \tag{1}$$

where, $f_u(t) = K_e(t)\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_{ij}[P_i(t)P_j(t) + Q_i(t)Q_i(t)) + \beta_{ij}(Q_i(t)P_j(t) - P_i(t)Q_j(t)]$;

$f_c(t) = W_{EV}^{Stored}(t)K_e^{Avg} \pm P^{EV}(t)K_e(t)$; $\alpha_{ij}(t) = \dfrac{r_{ij}}{V_i(t)V_j(t)}\cos\left(\delta_i(t) - \delta_j(t)\right)$; and $\beta_{ij}(t) = \dfrac{r_{ij}}{V_i(t)V_j(t)}sin\left(\delta_i(t) - \delta_j(t)\right)$

subject to

$$P_i(t) = V_i(t)\sum_{j=1}^{N}V_j(t)Y_{ij}\cos\left(\theta_{ij} + \delta_j(t) - \delta_i(t)\right) \quad \forall i,t \tag{2}$$

$$Q_i(t) = -V_i(t)\sum_{j=1}^{N}V_j(t)Y_{ij}\sin\left(\theta_{ij} + \delta_j(t) - \delta_i(t)\right) \quad \forall i,t \tag{3}$$

$$V_{\min} \le V_i(t) \le V_{\max} \quad \forall i,t \tag{4}$$

$$I_u(t) \le I_u^{Max} \quad \forall t,u \tag{5}$$

$$P_{k,\min}^{EV} \le P_k^{EV}(t) \le P_{k,\max}^{EV} \quad \forall k,t \tag{6}$$

The objective function of (1) is subjected to various constraints given in (2)-(6) such as active & reactive power balance, node voltage limits, thermal capacity of feeder and EVs charging/discharging limits respectively. Where, k_1 and k_2 are the weighing coefficients; $P_i(t)$, $Q_i(t)$, $V_i(t)$, $\delta_i(t)$ are representing the instantaneous real & reactive power injection, voltage magnitude and angle respectively at bus i. Similarly, r_{ij}, x_{ij}, θ_{ij}, $I_{ij}(t)$, I_{ij}^{Max} are resistance, reactance, impedance angle, flow of current, maximum thermal limit of line respectively connected between bus i and bus j. $W_{EV}^{Stored}(t)$, $K_e^{Avg}(t)$, $P^{EV}(t)$ and $K_e(t)$ are the instantaneous energy stored in EV, average energy price of stored energy, charging or discharging power of EV and grid energy price respectively. N, N_b, V_{Min}, V_{Max}, $P_{k,\min}^{EV}$ and $P_{k,\max}^{EV}$ are the total number of buses, number of branches, minimum and maximum allowable voltage limits of the system nodes respectively, minimum and maximum allowable charging/discharging limits of the EV respectively.

4. Artificial Intelligence based Mobile Power Infrastructure Planning and Operational Management

The proposed mobile power infrastructure planning and operational management problems for smart city applications are solved in two stages. In stage-I, electrically optimal allocation of EV charging enabled parking lots are determined. The optimal operational management of EVs charging are performed in stage-II. Due to the complex mixed integer and non-convex nature of the problem, an improved Genetic Algorithm (GA) has been adopted from [12]. The GA is a powerful meta-heuristic technique which is capable to solve various complex power system optimization problems. The chromosome structure of GA used in the study comprises of the system nodes and maximum charging capacities of respective parking lots as decision variables is shown in Fig. 2.

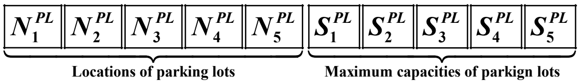

Fig. 2 Chromosome structure of GA for optimal allocation of EV parking lots

In stage-I, the optimal allocation of Charging Stations (CSs) are obtained such a way that the daily energy loss is minimized for the installed capacity. In this work, it has been assumed that the EVs will charge if the instantaneous energy price is detected to be less than the average daily energy price otherwise EVs will discharge. Therefore, the EVs will export power to the grid in peak hours and vice-versa.

In stage-II, optimal operational management of EVs is performed in which instantaneous optimal charging/discharging of each EV is determine to minimize the instantaneous profit of EV owner and utility both. The flowchart of adopted GA and the algorithm introduced for stage-II are shown in Fig. 3(a) and (b) respectively; where, t and 0.01η are the time and instantaneous converter power loss factor associated with BESS of each EV respectively. In stage-II, the optimal dispatches of EVs are also determined using the GA. The chromosome structure used in this GA will be the second half section of the chromosome shown in Fig. 2.

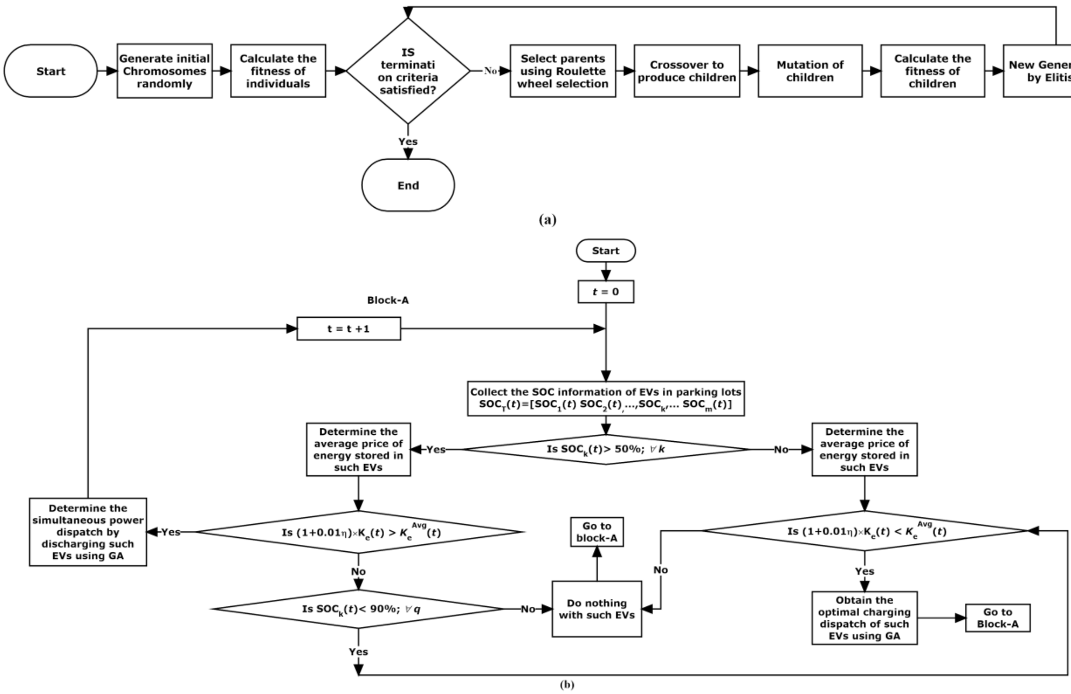

Fig. 3 Flow chart of (a) adopted GA and (b) proposed operational management model

5. Simulation Results

In order to demonstrate the applicability and effectiveness of proposed model for optimal planning and operational management of mobile power infrastructure in smart cities, IEEE 33-bus radial distribution network is adopted as a smart city power network. The basic information of the system can be obtained from [13]. Fig. 4 shows the hourly base system demand multiplier and energy price used in this study. In order to generate the actual hourly demand, nominal demand of the system is multiplied by the multiplier factor presented in the Fig 4(a). The simulation results and discussion of the case study are presented in following sections.

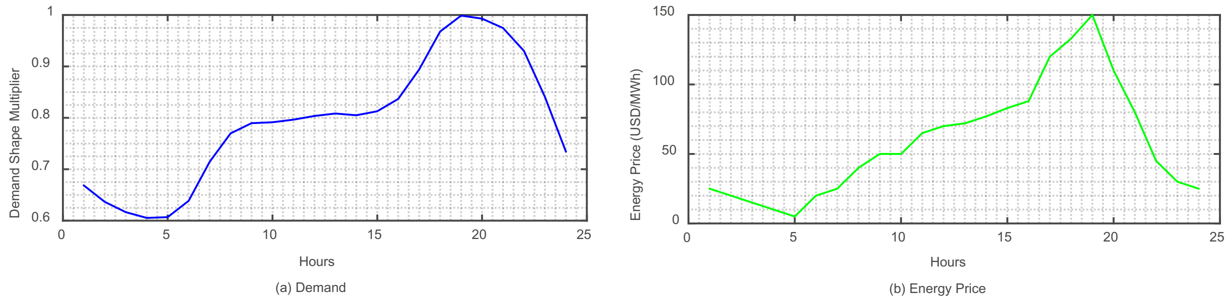

Fig. 4 The hourly demand shape multiplier and energy price adopted in the study

5.1. Stage-I Optimal allocation of parking lots associated with CSs

In stage-I, optimal location and maximum allowable charging capacities of five parking lots are identified. The minimum and maximum charging capacity limits of each CS is assumed to be 100 kW and 1000 kW respectively. For electrically optimal allocation of CSs, the EV is considered to be discharging the energy during peak demand and charging during light load hours. Therefore, in planning stage, the EV will assumed to be charged if grid energy price is found to be less than the mean energy price of 24 hours and vice-versa. This is the commonly used strategy for EV charging/discharging management i.e. called as no strategy case in the work. The motivation behind the optimal accommodation of CSs is to minimize the cost of energy loss under the penetration of EVs in distribution system. The GA is applied to obtain the optimal sites and sizes of CSs. The simulation results are presented in Table 1, which shows that proposed strategy provides reduced cost of energy loss as compared to the base case while generating the profit to EV owners.

Table 1. Optimal location and maximum charging capacities of EV charging stations

Cases	Optimal node (Sizes in kW)	Cost of energy loss (USD)
Base case	-	212.206
After allocation of EV CSs	6 (413), 14(214), 24(234), 25(196), 31(266)	170.842

5.2. Stage-II Optimal management of EV charging/discharging

In stage-I, the optimal allocation of CSs are determined such that the cost of daily energy loss is minimized. The optimal operational management of EVs in a smart city is performed in stage-II. Without loss of generality and simplicity of the model, 550 EVs of Nissan leaf are considered as given in [8]. Each EV has a storage capacity of 24 kWh and can travel up to 160 km if fully charged. Moreover, equal numbers of vehicles are parked in above obtained five parking lots. It is assumed that maximum EVs will remain in any of the parking lots for small geographical towns such as in offices, shopping complexes, restaurants, institutions, residential complexes etc. Therefore, the model shown in Fig. 3 is applied for 24 hours by randomly generating the initial State-of-Charge (SOC) of EVs between 40 to 100 % with $K_e^{Avg}(t)$ =0.050 \$/kWh.

The simulation results of proposed optimal EVs power management are summarized in Table 2. The table shows that proposed approach further reduces the system energy loss. It may be observed that the EV owner benefits are more for conventional approach in which EVs are charged during light load hours and discharged in peak load hours. However, conventional approach increases the variation in the demand as shown in Fig. 5(a). Whereas, proposed approach smoothly shifts the peak demand. Moreover, the minimum node voltage appeared in 24 hours using conventional and proposed approaches are found to be 0.8948 and 0.9345 p.u. respectively. Fig. 5(b) shows the charging/discharging powers of five CS which shows that all the CSs are competitively participating in real-time operational management of EVs available in SC.

In proposed approach, daily maximum amount added or deducted to an individual's credit card are found to be 2.4883 and 0.1398 USD respectively which shows that proposed strategy is generating benefits for EV owners. In this case study, 308 vehicles are participated in energy management out of 550 vehicles while the SOC of 242 vehicles remain unaltered due to constraints or not found to be optimal for the scheme. Moreover, the average price of energy stored in the EVs is reduced to 43USD/kWh from 50 USD/kWh.

Table 2. Simulation results for optimal operation management of mobility in smart city

Cases	Profit of parking lots location (profit in USD)	Cost of energy loss (USD)	Total profit to EV owners (USD)
Conventional strategy	-	170.842	1042.524
Proposed strategy	25(173.992), 6(177.016), 14(175.524), 31(184.332), 24(158.226)	158.842	0869.090

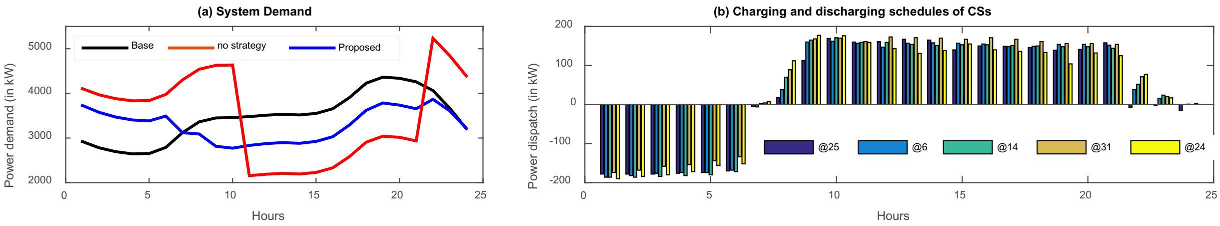

Fig. 5. Hourly system power demand and power dispatch of parking lot CSs

6. Conclusions

The paper presents an effective model of future mobile power infrastructure planning and operational management for smart city applications. The proposed aggregator based model effectively minimizes the system energy losses while simultaneously maximizing the profit of EV owners. Further, the daily profit of each EV owner is credited to respective credit cards. Moreover, it also reduces the variation in the hourly demand of the system. The proposed model may be further extended for larger system having different type of EVs along with renewable power generations.

References

[1] Editorial. Cleaner energy for transition of cleaner city. Applied Energy 2017; 196:97-99.
[2] Wenge R, Zhang X, Dave C, Chao L, Hao S. Smart city architecture: A technology guide for implementation and design challenges. China Communications 2014; 11(3):56-69.
[3] Meena NK, Swarnkar A, Gupta N, Niazi KR. A Taguchi-based approach for optimal placement of distributed generations for power loss minimization in distribution system. Proc. Power & Energy Society General Meeting 2015:1-5.
[4] Agrawal A, Kumar M, Prajapati DK, Singh M, Kumar P. Smart public transit system using an energy storage system and its coordination with a distribution grid. IEEE Transactions on Intelligent Transportation Systems 2014; 15(4):1622-1632.
[5] Yang J, He L, Fu S. An improved PSO-based charging strategy of electric vehicles in electrical distribution grid. Applied Energy, 2014; 128:82-92.
[6] Zanella A, Bui N, Castellani A, Vangelista L, Zorzi M. Internet of things for smart cities. IEEE Internet of Things Journal 2014; 1(1):22-32.
[7] Jin J, Gubbi J, Marusic S, Palaniswami M. An information framework for creating a smart city through internet of things. IEEE Internet of Things Journal 2014; 1(2):112-121.
[8] Donateo T, Licci F, D'elia A, Colangelo G, Laforgia D, Ciancarelli F. Evaluation of emissions of CO_2 and air pollutants from electric vehicles in Italian cities. Applied Energy 2015; 157:675-687.
[9] Carli R, Dotoli M, Pellegrino RA. Hierarchical Decision-Making Strategy for the Energy Management of Smart Cities. IEEE Transactions on Automation Science and Engineering 2017; 14(2):505-523.
[10] Iversen EB, Morales JM, Madsen H. Optimal charging of an electric vehicle using a Markov decision process. Applied Energy 2014; 123:1-12.
[11] Villalobos JG, Zamora I, Knezovic K, Marinelli M. Multi-objective optimization control of plug-in electric vehicles in low voltage distribution networks. Applied Energy 2016; 180:155-168.
[12] Swarnkar A, Gupta N, Niazi KR. Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization. Swarm and Evolutionary Computation 2011; 1(3):129-137.
[13] Baran ME, Wu F. Network Reconfiguration in Distribution System for Loss Reduction and Load Balancing. IEEE Transactions on Power Delivery 1989; 4(2):1401-1407.

Biography

Prof. Ramesh Bansal has over 25 years of experience and currently he is a Professor and group head (Power) in the Department of EEC Engineering at University of Pretoria. He has published over 250 papers. Prof. Bansal is an Editor of IET-RPG & Electric Power Components and Systems. He is a Fellow and CEngg IET-UK, Fellow Engineers Australia and Institution of Engineers (India) and Senior Member-IEEE.