Review of Electric Vehicle Charging Station Location Planning

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***Abstract* - Government of India is ramping up efforts to increase the use of electric vehicles in the country, by formally announcing higher Electric Vehicle (EV) incentives and on-going discussions on regulating the sale of conventional 2 and 3-wheelers by 2025. National standards for charging infrastructure are expected to be finalized soon, allowing both public and private sector to deploy their charging fleet to cater the EV charging demands. Centralized strategic planning and optimization in charging station location selection is proven to drastically reduce the initial cost required to serve the EV charging demand and reduce range anxiety. This review focuses on the most significant parameters considered in charging station location planning by various researches, its relevance and pitfalls.**

Keywords* - *EV Charging Infrastructure, Smart Charging Solutions & Apps, Smart Grid, V2G and Renewable Integration

I. INTRODUCTION

In recent years global automobile has taken major strides in transition to electric vehicles, to move towards sustainable energy goals and tackle climate change. Rapidly falling battery costs and continuously improving charging technologies are close to making Electric Vehicles on par with conventional vehicles regarding utility. Researchers from Electrical and Transportation industry have been studying optimal ways of distributing the Electric Vehicle Charging Stations(EVCS) in the past decade. The transportation-based researches focused on the cost minimization with accessibility and demand coverage considering vehicle movement pattern, user behavior and other constraints imposed by the user or the road network. But as identified by [1] the power system loading margins are highly influenced by the EVCS loads, as they display combination of constant power with an exponential load behavior with a negative α. The study also proved that the impact of EVCS load on the Distribution Grid(DG) can be greatly minimized by proper selection of location in the distribution bus system. Hence the electrical based research focused on the optimal distribution of EVCS to minimize impact on the DG, while covering the total demand. Other researches also point that highly stochastic nature of mobile EV loads can cause functional uncertainty in the power network. Thereby pointing the need for a well-equipped centrally planned charging infrastructure, that can enable control over the point of load dispatch and enforce power quality requirements on macro level rather than user level[2]. The purpose of this review is to analyze the merits and viability of the previous researches in this topic and identify the significant constraints to be considered for an ideal EVCS allocation model.

In the first section major algorithms employed are discussed briefly based on the complexity of the model and results achieved. The second section is dedicated to the discussion of different mathematical models and the relevant input data utilized for the optimization, focusing on the ease of access, complexity and reliability of data.

II. ALGORITHMS IN PRACTICE

In the initial stages of EVCS location optimization research, the optimization models were based on exact method approaches like Branch and Bound[3], [4] Mixed Integer Linear Programming[5], [6], Voronoi Diagram[7], [8] etc. providing accurate points of solutions. These methods required the input data to be pre-processed to find shortest paths, feasible combinations, OD pairs etc. and consumed large computation time to acquire. It was also concluded by multiple researches that it is almost impractical to even pre-generate the combinations for real systems with large and complex data set and even more demanding to solve the optimization model. Also, Linear models focus on minimizing/maximizing each objective function in the constraint, which may not give a global optimum with non-ideal combination of objective. It is in this context Heuristic algorithms are put into practice..

Year	Title	Algorithm and Model used	Conclusion/Remarks
2005	The flow-refueling location problem for alternative-fuel vehicles[10]	MILP to solve OD shortest distance based FCLM	One of the first research papers to apply modified FCLM models for EVCS location planning. Sets ground rules for models. Does not consider multiple charging instances in one trip.
2007	An optimal location choice model for recreation-oriented scooter recharge stations[3]	LINDO's Branch and Bound	Results assume Range is greater than the maximum distance between 2 destinations
2008	The fuel-travel-back approach to hydrogen station siting[5]	Mixed Integer Linear Programming on Vehicle-Miles-Travelled	Proved 18% of the number of gas stations can serve the entire demand
2008	Locating battery exchange stations to serve tourism transport: A note[4]	Arc Cover Model	Analysed the impacts of including battery swap stations in charging infrastructure
2009	Locating road-vehicle refueling stations[6]	Mixed Integer Linear Programming on OD shortest distance matrix	Demonstrated the effects of varying Range and demand coverage in number of stations required at minimum cost.
2010	Heuristic algorithms for siting alternative-fuel stations using the Flow-Refueling Location Model[9]	Comparison between MILP and heuristic algorithms Greedy-Adding, Greedy-Adding with Substitution and Genetic Algorithm to solve Flow-Refueling Location Model (FRLM)	Demonstrates the superiority of heuristic based algorithms in solving large and complex problems
2011	An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles[11]	General Algebraic Modeling System(GAMS) coupled with ILOG CPLEX 10.0 Solver - Integer based Programming method in GIS	Discusses in detail the traffic intercepted with varying number of EVCS. Demonstrates cost benefits of retrofitting a marginal number of gas stations with charging stations to cover the total demand.
2012	Planning of electric vehicle charging infrastructure[2]	Particle Swarm Optimization(PSO)	Solved for optimal EVCS location, based on voltage regulation and power loss constraints in the grid, minimizing the distance from EV user to the EVCS
2013	Optimal placement of charging infrastructures for large-scale integration of pure electric vehicles into grid[12]	Taboo Mechanism based Binary Particle Swarm Optimization(BPSO)	Candidate nodes assumed at the intersections in Road network. TMBPSO proved to prevent premature convergence of BPSO.
2016	Planning of Electric Vehicle Charging Station Based on Real Time Traffic Flow[7]	Weighted Voronoi Diagram on Geographical Map	Considered traffic flow density to allocate new stations each with similar charging station capacity
2016	Charging station location problem of plug-in electric vehicles[13]	Genetic Algorithm to solve expanded candidate model by considering midpoint of links between nodes.	Emphasizes on optmizing land use and cost of installation
2017	Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm[14]	Genetic Algorithm based Improved Particle Swarm Optimization(GAIPSO)	Optimizes the distribution of N charging stations in the DG subfeeders, to minimize power loss and instability, assuming similar power consumption on all EVCSs. Demonstrates drastically improved convergence rates, compared to GA or PSO alone.
2018	An optimal charging station location model with the consideration of electric vehicle's driving range[15]	Frank-Wolfe Algorithm on the Linearized model of Bi-Level optimization model	Discusses Linearization techniques in detail to implement multi-objective optimization problems using single-level algorithms. Shows trend of number of long route journeys possible with variation in range.
2019	Joint planning of distributed generation and electric vehicle charging stations considering real-time charging navigation[8]	Mixed Integer Second Order Cone Programming(MISOCP) on coupled Geographical-Electrical System	Discusses EV to Grid integration along with location planning.
2019	A bi-objective model for location planning of electric vehicle charging stations with GPS trajectory data[16]	NSGA-II to optimize cost and accessibility of EVCS	Optimization model including decisions on locations, service types, locating modes and capacity options.

Table.1 – Researches that addressed road network and user accessibility-based location optimization

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Year	Title	Remarks/Conclusion
2012	Modeling and planning of EV fast charging station in power grid	Modelled EV Fast charger. Identified Power system loading margin is greatly influenced by EV load. Confirms proper selection of EVCS location can bring reduced system losses, higher loading margins and lower reinforcement costs.
2014	Optimal fast charging station placing and sizing	Station sizing and line loss analysis with real data.
2018	Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems	Analysis of impact of fast chargers in grid with renewable sources to find optimal times to buy and sell charge from the EVs for load balancing and peak shaving.
2019	GIS-Based Multi-Objective Particle Swarm Optimization of charging stations for electric vehicles	Multi-Objective Particle Swarm Optimization (MOPSO) on GIS with empirical spatial data of Electric DG and road networks
2012	Electric vehicle charging infrastructure assignment and power grid impacts assessment in Beijing	Discusses integration of fast charging stations, battery swapping stations and Vehicle to Grid power transfer. Suggests 2km service radius for EVCS deployment and charging time management strategies to handle peak shaving.
2019	Optimization model for charging infrastructure planning with electric power system reliability check	Discusses the grid overloading concerns with a DC power flow model. Location optimization discussed by overlapping road network grid with an IEEE 16 bus standard.

Table.2 – Researches that addressed impacts on Electric Distribution Grid by charging stations and location optimization

The heuristic algorithms does not require pre-generation of combinations and are proven to solve the large and complex optimization models within a reasonable timeframe compared to exact methods[9]. A few majorly used algorithms are summarized in Table.1 and Table.2 and briefly discussed below. Greedy Adding and Greedy Adding with substitution were first proposed by in 1995 by Daskin [17]. The greedy adding algorithm first adds the facility that optimizes the objective to the set and keeps adding the best fitting object that makes the selected set better optimized for the objective, till the required number of objects are selected. This method does not look ahead for an optimal set, rather selects the one object that optimizes the selected set at each iteration, hence a bad object in the set may remain in the final selection though it does not positively contribute. Greedy adding with substitution overcomes this flaw by checking for a better substitute for each element from the selected set, after each iteration of selecting a new object into the set[9][10]. Though Greedy adding with substitution took much more time than without substitution, the results were promisingly close to the ideal optima and was found to achieve it with as little as 3 substitutions.

Genetic Algorithms, as the name suggests mimics the evolutionary aspect of candidate population to improvise the current set selection. Using genetic algorithm to a problem requires careful design decisions to adapt the algorithm to the problem. The gene-encoding scheme, its cross-over mechanism and fitness functions directly influences the ability of the algorithm to find best results. Also, a large pool of diverse data pool is required to ensure the algorithm doesn't get trapped in the local minima. This is generally done by random selections of genes for crossover, resulting in a slower convergence rate, while ensuring exploration. While the population size improves the solution of genetic algorithm, it also increases the computation time drastically, though the improvement in the solution may be marginal [9][18]–[20].

NSGA-II (Non-Dominated Sorting Genetic Algorithm) [21] is a powerful meta-heuristic multi-objective genetic algorithm, used widely to solve multi-objective optimization problems in various applications like facility allocation[22], supply network design[23] and congested facility location[24]. NSGA-II classifies the population into multiple fronts of non-dominated chromosomes. The chromosomes from every set is ranked based on its diversity. This enables NSGA-II to preserve diversity and convergence by non-dominated classification and crowding distance measurement[25]. In a unique approach, Xue Bai et.al[16] suggested a hybrid NSGA-II to include continuous variables as decision variables by incorporating Linear programming and neighborhood search.

Another popular and efficient algorithm is Particle Swarm Optimization (PSO), it uses real number randomness and global communication among particles to optimize its performance. The swarm of potential solutions (particles) explore the search space to look for optimal solutions, continuously communicating and updating the personal best and global best. At the beginning of each iteration, each particle travels in a direction vector obtained from its personal best and global best, eventually converging into the global optima[2]. Several enhancements to the original PSO was made aiming at better computation time and more accurate solutions were made recently, Improved Particle Swarm optimization (IPSO) [14], Binary Particle Swarm Optimization(BPSO) with Taboo Mechanism[26] to name a few, are proven to display better convergence rates while not sacrificing exploration for global optima. PSO based algorithms are proven to perform better with multi-objective optimization problems.

III. MATHEMATICAL MODELS

Mathematical modelling of the system under study is foremost and significant part in optimization problems. Real world systems with multiple decision variables and optimization objectives often will be represented by complex multi-level mathematical models. For ease of implementation these models are reformulated as single-level model by Linearization techniques and solved using Heuristic or Exact methods[15]. As most researches focus on optimizing the cost of installation, ease of access and quality of service, the input data required are Origin-Destination(OD) pair distances, Spatial distribution of Vehicle Miles Travelled(VMT), the road network map data using GIS[11][27] etc. For researches that consider the influence on Electric Distribution grid, one of the IEEE standard bus systems are considered. Researches have used GIS based tools to overlap road network with electric distribution system network (Figure.1) to find optimal placing of EVCS by minimizing wire laying costs[25] and

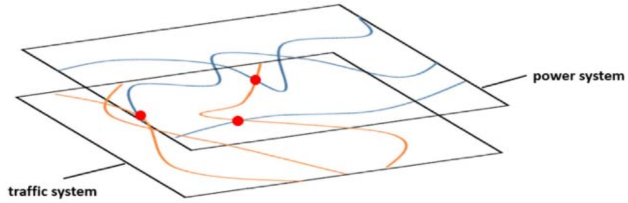

Fig. 1. A schematic diagram of overlapping traffic system and power system.

assessing the impact on grid stability [27]. Researchers has also attempted in developing mathematical models to provide a Ranking based solution to the service providers, so that implementation and maintenance can be organized more profitably[28].

IV. CONCLUSION

The discussion of several researches in EVCS location optimization shows that simpler exact methods of optimization are not viable for real world systems with multiple objectives to optimize and large complex data sets. Heuristic approaches on the other hand does not give the ideal accurate solution but provides reasonably accurate solutions in a fraction of time. Figure.2 shows the

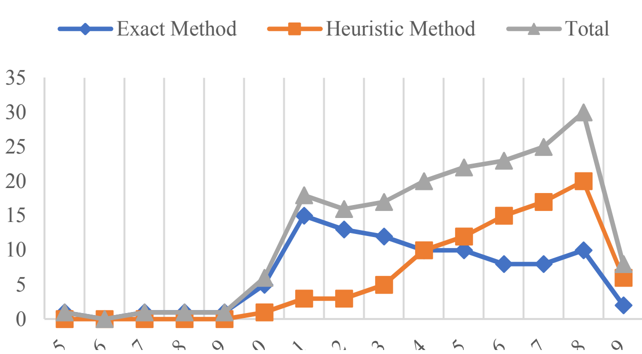

Figure.2 Trend of researches published in EVCS location planning

increasing trend of Heuristic algorithm-based researches being published every year. The data was obtained adding the relevant research publications from both IEEE and ScienceDirect with search query "Vehicle charging AND (station OR infrastructure) AND (planning OR Optimization)". It should be noted that data for 2019 is incomplete, but the trend is still the same.

It can also be noticed from Table.1 and Table.2 that location planning studies considering the impacts on electric distribution system is rarely considered, while several researches warn about the consequences of disregarding the distribution grid impacts. Methods integrating spatial distribution of both electric DG and traffic flow to find optimal locations with minimal impact on DG and ease of access to users are required to find more viable and sustainable solutions.

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