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Optimal installation of electric vehicle charging stations connected with rooftop photovoltaic (PV) systems: a case study

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Abstract: Electric vehicles (EVs) have been growing to reduce energy consumption and greenhouse gas (GHG) emissions in the transportation sector. The increasing number of EVs requires adequate recharging infrastructure, and at the same time, adopts low- or zero-emission electricity production because the GHG emissions are highly dependent on primary sources of electricity production. Although previous research has studied solar photovoltaic (PV) -integrated EV charging stations, it is challenging to optimize spatial areas between where the charging stations are required and where the renewable energy sources (i.e., solar photovoltaic (PV)) are accessible. Therefore, the primary objective of this research is to support decisions of siting EV charging stations using a spatial data clustering method integrated with Geographic Information System (GIS). This research explores spatial relationships of PV power outputs (i.e., supply) and traffic flow (i.e., demand) and tests a community in the state of Indiana, USA for optimal sitting of EV charging stations. Under the assumption that EV charging stations should be placed where the potential electricity production and traffic flow are high to match supply and demand, this research identified three areas for installing EV charging stations powered by rooftop PV in the study area. The proposed strategies will drive the transition of existing energy infrastructure into decentralized power systems. This research will ultimately contribute to enhancing economic efficiency and environmental sustainability by enabling significant reductions in electricity distribution loss and GHG emissions driven by transportation energy.

Key words: Charging stations, Electric vehicles, Rooftop PV, Vehicle-to-grid (V2G), Site selection, Microgrid

1. INTRODUCTION

Electric vehicles (EVs) adoption has been growing as being expected to reduce energy consumption and greenhouse gas (GHG) emissions compared to conventional internal combustion engine (ICE) cars in the transportation sector [1]. EVs can bring about a 30-50% reduction in CO_2 emissions in comparison with internal combustion engine vehicles (e.g., diesel, gasoline vehicles) [2]. However, the life-cycle GHG emissions of EVs depend on primary sources of electricity [3]. In 2019, electricity production depends on its generation, 32% on oil and 27.1% on coal [4], which largely affects CO_2 emissions. To substitute carbon-intensive energy sources with renewable sources, solar photovoltaic (PV) -assisted EV charging stations have been explored [5]. Solar energy, one of the promising renewable resources, can offer low maintenance costs and high reliability without other pollutions (e.g., noise, radioactive effluent) compared to the fossil fuels causing the global environmental issues.

Meanwhile, EV adoption has been promoted with the progress of required EV techniques (e.g., battery, electric efficiency). According to a study conducted by Deloitte Insight [6], EV sales for annual passenger-car and light-duty vehicles have increased about four times (500,000 to 2,000,000 vehicles) over the last five years (2015 to 2019). Recently, governments have taken action to promote EV adoption with the intention of saving people's fuel costs, cutting pollution, and tackling climate change. For example, the European Union (EU) proposed all cars on the roads should be zero-emission vehicles by 2050 [7]. United States government sets a goal for EVs, achieving 50% vehicle sales share in 2030 [8]. However, EV adoption has often been hindered due to the lack of charging stations causing range anxiety in medium and long-distance travel [9]. Adequate recharging infrastructure is required to support growing EV adoption [7-8]. Although previous research has studied site selection for EV charging stations using a decision-making model (e.g., Fuzzy theory) or deep neural network model with Geographic Information System (GIS) [10-11], applying low- or zero-emissions energy sources (e.g., solar PV) to the charging stations have not been fully discussed. Considering PV as electricity sources for EV charging stations is challenging because electricity produced by PV cannot be sent to the power transmission facility due to the risks of electrical overloads. Unless spatial relationships between the potential solar energy supply and the charging demand are understood, electricity may be wasted without being used for charging stations. Thus, while the areas where have the high potential of solar PV electricity generation are explored, optimal EV charging stations should be searched based on charging demand in the vicinity of the energy production locations

Therefore, this research aims to support optimal decisions of EV charging stations powered by rooftop solar PV using a spatial data clustering method integrated with GIS. This research presents optimal charging locations where both heavy traffic flow that can indicate potential EV users and high generation efficiency from solar PV are satisfied. The sites are planned to be located in the vicinity of PV installed on the rooftops of buildings. The proposed methodology was tested in West Lafayette, Indiana, USA. In particular, to find the areas indicating both heavy traffic flow and high generation efficiency, this research uses a clustering method that can find patterns tightly packed through similar characteristics. Finally, this research can contribute to a new research perspective of community energy system transition by reflecting traffic flow and PV power output into the site selection assessment for energy efficiency.

2. DATA AND METHODS

This research explores and presents adequate installations of EV charging stations connected with PV power generation installed in building rooftops based on a case study in West Lafayette, IN, USA. We investigated optimal sites that satisfy the positions of PV power generation (i.e., supply) and traffic flow (i.e., demand) by a geospatial analysis using GIS. The proposed method used the K-nearest neighbors (KNN) algorithm for clustering to identify available and optimal locations for EV charging stations. The KNN is one of conceptualization of spatial relationships [12] that can determine the interactions and influences of spatial features [13].

2.1. Data collection and analysis

This study used two geospatial data: PV power output and traffic count data. All data were digitalized using a uniform coordinate system (i.e., North American Datum (NAD) 1983 Universal Transverse Mercator (UTM) 16N) and the same resolution (i.e., 1×1 m^2). This paper tested the small city of West Lafayette, IN, USA. The study shows a detailed spatial analysis and investigates the optimal sites for installing EV charging stations that are located in the vicinity of PV installed in building rooftops. The city of West Lafayette is geographically located at 40.26° north latitude and 86.54° west longitude.

The traffic count data was collected from continuous numerical maps (e.g., polyline layers) to compute the hot spot for demand for charging the electricity. These traffic count data were collected from the traffic count database system by Indiana Department of Transportation (INDOT) [14]. The database contains the average daily traffic value (i.e., the average day of the year) and the volume of traffic passing the road, in both directions. The traffic count data were transformed from polyline layers to point layers at a fixed interval of 5 m to process the spatial weight analysis.

Solar PV output data is produced by using the method of area solar radiation in ArcGIS and formula of the yearly potential electricity generation of a PV configuration. The solar radiation analysis in ArcGIS derives solar radiation from a raster surface [15]. To prepare a raster surface in the test area, the digital elevation map (DEM), the representation of elevation of the terrain, was computed using a contour map provided from the U.S. Geological Survey (USGS) [16]. The DEM map can be generated through three steps: (1) create the terrain with a triangular irregular networks (TIN) map; (2) convert the terrain TIN map into a raster image; and (3) combine the terrain raster and building raster. First, the contour maps were converted into triangular irregular networks (TIN) maps using data management function in geoprocessing tools. Creating a TIN is the method of interpolating the elevation of terrain by forming the surface triangulation based on the polylines (i.e., contour map). Then, the TIN map was converted into a raster image (i.e., DEM) using the data conversion functions in geoprocessing tools. However, this map did not include the elevation of artificial objects (e.g., buildings); thus we combined the elevation information of the buildings with building footprints. Building footprint data can be obtained from the Open Street Map (OSM), but it does not provide building height information. Building height information was extracted from lidar point cloud (LPC), which contains the original three-dimensional information of spacing and vertical alignment, as laser (LAS) file format from USGS in Figure 1a. The point cloud-based surface elevation values were overlayed and joined into the building footprint layer on GIS. The building footprints with the height, shown in Figure 1b, were rasterized into a raster image as a tagged image file (TIF) format. Finally, the building raster including the height information was obtained using the data conversion function, and terrain and building rasters were combined on a pixel-by-pixel basis using the raster math function.

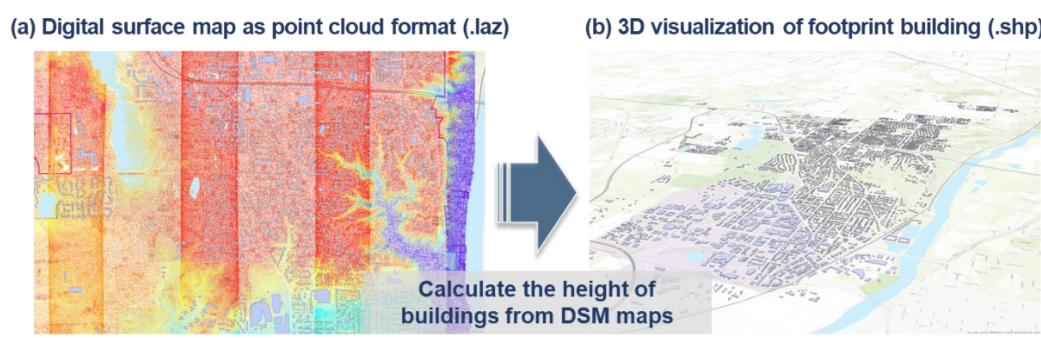

Figure 1. Extraction of the height of building from digital surface model (DSM) map as point cloud format to two-dimensional based building footprint layer as polygon shapefile format

Solar radiation was evaluated by using the area solar radiation tool in GIS based on the combined elevation map. This tool calculates the solar radiation over a specific location with considering the characteristics of geographic (e.g., latitude, longitude) and meteorologic (e.g., sky view factor) conditions. This paper generated the yearly solar radiation map for 2020 in West Lafayette, IN, USA. Based on the solar radiation map, the daily electricity generation from the rooftop PV E (Wh/day) was estimated using the Equation 1 based on [17]; where P_k denotes the capacity of PV (Wh/year), r_k denotes the system performance ratio (i.e., default value for roof mounted PV systems is 0.75), and $H_{h,i}$ denotes the yearly average value of solar irradiation on the inclined surface (Wh/m^2). Figure 2 shows the daily PV output at the test site.

$$E = \frac{P_k r_k H_{h,i}}{365} \times cell\ size\ (1\ m^2) \tag{1}$$

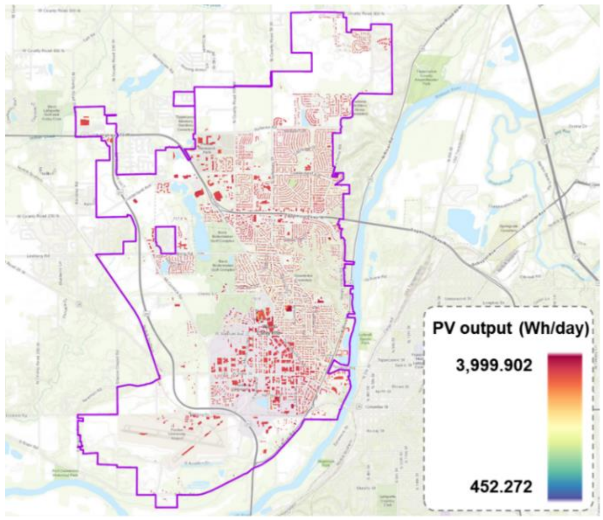

Figure 2. PV output using the area solar radiation tool in GIS

2.2. Modeling spatial weights

High/Low Clustering analysis was performed to evaluate spatial cluster of PV power output and traffic flow in the West Lafayette based on Getis-Ord Gi statistic using K nearest neighbors (KNN) technique in ArcGIS environment [18]. The High/Low clustering statistic is an inferential statistic, which means the process of inferring properties of an underlying distribution or continuous of probability. The results are interpreted within the context of the null hypothesis, stating that there is no spatial clustering of feature values (i.e., complete spatial randomness). The general G statistic of overall spatial association is computed using Equation 2 where x_i and x_j denote the attribute values for features *I* and *j*; w_{ij} is the spatial weight between feature *i* and *j*; and *n* is the number of features in the dataset given that the feature *i* and *j* cannot be the same feature. The p-value is used to reject or retain the null hypothesis and is computed from the z-score. The z-score is the standard deviation of spatial patterns based on Equation 3. For example, a high or low z-score (> +2.58 or <−2.58) and a small p-value (<0.01) indicate that the null hypothesis can be rejected at a confidence level of 99%, which means the dataset can be spatially clustered based on spatial features. When the z-score value is positive, the observed general G is higher than expected general G, indicating that high values in the attribute (e.g., high values of PV generation/traffic flow) are clustered in the study area. The expected general G can be measured using Equation 4.

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j} \tag{2}$$

$$Z_G = \frac{G - E[G]}{\sqrt{V[G]}} \tag{3}$$

$$E(G) = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}{n(n-1)} \tag{4}$$

3. RESULTS AND FINDINGS

3.1. Spatial weight evaluation

In Table 1, the spatial relationships among the features (e.g., PV power output, traffic count) were identified using p-value which measures statistical significance to reject or retain the null hypothesis with a 99% confidence interval (p-value = 0.01) and z-score which is based on the randomization null hypothesis computation (the higher (or lower) the z-score, the stronger the intensity of the clustering). As a result, the p-values were found to be less than 0.01 in both cluster analysis of PV power output and traffic count. The null hypothesis can be rejected, and it implies that spatial patterns are not the result of random processes. The spatial distribution of high or low values in the spatially clustered. In that the observed General G index is greater than the expected General G with the positive z-score, high values for the attribute are clustered in the study area.

Table 1. Results of cluster analysis by PV power output and traffic flow.

Analysis type	Observed General G	Expected General G	Z score	P value	Pattern
PV power output	0.000325	0.000161	15.873	<0.01	Clustered
Traffic flow	0.000120	0.000076	131.731	<0.01	Clustered

3.2. Site selection of EV charging stations

The potential sites of EV charging stations with lower or higher values are extracted in the local cluster analysis using the High/Low clustering (Getis-Ord General G, and Cluster and Outlier Analysis (Anselin Local Moran`s I). Figure 3 illustrates significant clusters of installed PV generation on rooftops of buildings as a supply aspect (Figure 3a) and of traffic flow as a demand aspect (Figure 3b). In particular, the clustering analysis is represented by classifying five classes from significant clusters (HH, high high) as pink color to low clusters (LL, low low) as sky blue color, and even not significant values as gray color in Figure 3. To be specific, the HH class has a high value of z-score (>2.58) and high significance of p-value (<0.01), and there is a less than 1% likelihood that this high-clustered pattern can be the result of randomness.

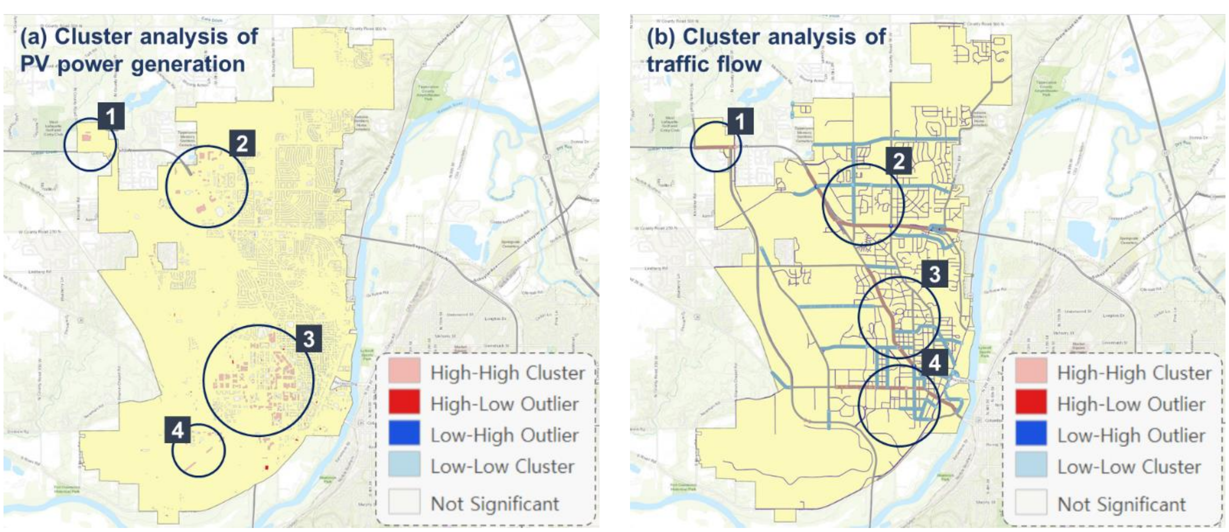

Figure 3. Clustered areas (high to low value): (a) PV power generation and (b) traffic flow

In the clustering analysis of PV power output in Figure 3a, four clusters were found in which high energy is generated by rooftop PV. In particular, clustered areas appeared in commercial areas (1 & 2), a university campus (3), and airports (4). Installation of rooftop PV is more economical in the commercial areas or campus buildings where buildings have relatively large rooftop areas than in residential areas where many small detached houses are gathered. In addition, the clustering analysis of traffic flow in Figure 3b shows that four clusters can be built where there are high traffic volumes. High traffic volume roadways were in the university campus, commercial areas, or in the areas bridging West Lafayette with neighboring a town (Montmorenci, IN, in the west of the study area) and a city (Lafayette, IN, in the east of the case area). The areas with high solar energy potentials and high traffic volumes were somewhat overlapped.

The two clustering analyses are overlayed on a map in Figure 4 to select potential sites for installation of EV charging stations. Three areas where both PV power generation and traffic flow are very high were selected as suitable sites. In particular, in the first and second candidate sites, there are currently no/lack EV charging stations installed; thus it is necessary to install new charging stations. On the other hand, at the third candidate site, six EV charging stations are currently serving (green markers in Figure 4). On this site, we can consider connecting solar PV panels with existing charging stations as low- or zero-emissions energy sources. In addition, the fourth candidate area in Figure 3-a, where solar power generation is high but traffic flow is low, can be used to transmit electricity to nearby areas through a microgrid approach. By doing so, high-traffic demand areas can accommodate additional energy to operate charging stations efficiently.

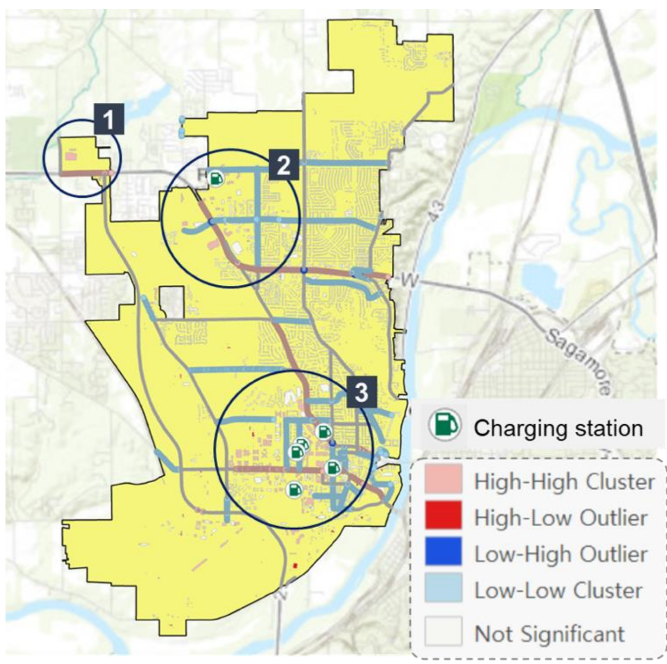

Figure 4. Suitable sites for EV charging stations powered by rooftop solar PV

4. DISCUSSION AND CONCLUSIONS

Combining EV charging stations with rooftop PV can derive the plan for a forthcoming transition of energy management systems while conserving the global environment. This paper presents a geospatial analysis-based optimal site selection for installing EV charging stations considering PV power generation and traffic flow as supply and demand aspects. The potential installation sites were suggested in the case study, West Lafayette using a clustering method based on spatial weight analysis with GIS. The result discovered that in this experiment, traffic flow with PV output can be used to investigate the optimal sites for installing EV charging stations represented as highly clustered areas in Figure 3~4. EV charging stations are then planned to be installed in areas with high production potential and where there is a lot of traffic, such as university, commuting areas, and highways. The optimal sites for EV charging stations which can be connected to rooftop PV were identified. The results suggested the strategies to build the EV charging stations: (1) connecting the installed EV charging stations and rooftop solar PV in the areas where existing EV charging stations are already installed and low- and zero- emissions resources are available but not used, and (2) installing the EV charging stations newly in the areas where EV charging stations are lack or absence and supply and demand is high.

Previous site selection approaches for EV charging stations have mainly focused on evaluating correlation between several criteria (e.g., environment, economy, society) and alternatives (e.g., electric power system, transportation system) using decision-making model such as the Bayesian network model and fuzzy model [19-20]. On the other hand, this study showed that understanding spatial relationships between traffic flow and PV output can be used to identify the potential areas for installing the EV charging stations through clustering analysis. Through the proposed clustering analysis approach, a viable plan for supplying sufficient electricity to potential EV users can be found. In addition, this study can contribute to reducing carbon dioxide emissions by using electricity generated not from fossil fuels-based thermoelectric power plants but from solar PV.

However, the current approach cannot fully include the complex characteristics of traffic flow, such as urban density and traffic volume for time intervals due to a relatively simple traffic pattern in the study area. Thus, the proposed approach should be improved by extending the model to other areas that can present complex built environments, such as urban areas (e.g., Chicago) to generalize its usability.

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