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Study on Influence Factors of Electric Vehicles Charging Station Location Based on ISM and FMICMAC

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Abstract: Along with the rapid growth in the number of electric vehicles, there is urgent need to construct electric vehicles charging stations (EVCSs) to satisfy the charging demand. However, during the process of carrying out quantitative and qualitative analysis on location decisions, it is necessary to make clear the relationships and role between various factors which make impacts on charging station location. Studies are inadequate in analyzing the influence factors with regard to this respect. This study aims to identify the influence factors, as well as the driving and dependence power of these factors and to analyze the interactions among them. This work proposes to use interpretive structural modeling (ISM) and Matriced'Impacts Croisés Multiplication Appliquée á un Classement (fuzzy cross-impact matrix multiplication applied to classification) (FMICMAC) based approach which is a novel effort in this sector. Moreover, rankings of the identified factors have also been obtained. Based on review of literature and brainstorming among experts in the EVCS field and academia, this paper puts forward 12 factors that impact EVCS location in five aspects. After ISM and FMICMAC analysis, it is concluded that area attribute and geographical environment are defined as key factors while construction cost and annual operation and maintenance cost are the objective factors. The developed integrated structured model will be beneficial in understanding the interrelationship and dependency among the identified factors.

Keywords: influence factors; electric vehicles; charging station location; ISM; FMICMAC

1. Introduction

With the rapid development of urbanization and a boom in automobile industry, air pollution and energy problems, especially depleting natural oil rising petrol cost, become intense in the world today [1]. It is widely acknowledged that road vehicles are main sources of the phenomenon, and they have been estimated to contribute to about one-fifth of the EU's total emissions of carbon dioxide (CO_2), the main greenhouse gas (GHG) [2].

In 2006, China's carbon emissions surpassed the United States for the first time and became the biggest emitter, which have brought more pressure from the outside world. China has announced plans to reduce CO_2 emission per unit of GDP by 40–45% by 2020. Various actions are promoted to reduce external energy dependence and fossil fuels consumptions. In 2009, "Automobile Industry Development Master Plan" was released by the central government, which declared that new energy vehicles have been proposed as the means to achieve these targets. A series of policies to facilitate electric vehicle industrialization and commercialization were then introduced, including pilot projects (Ministry of Science and Technology (MOST), 2009), production standards (Ministry of Industry and Information Technology (MIIT), 2009) and purchase subsidies (NDRC and MOF,

2010) [3]. Electric vehicles (EVs), as an alternative transport with clean energy, are more efficient than equivalent conventional internal combustion engines (ICE) vehicles [4] and generate lower GHGs emissions. Moreover, EVs reduce noise and may benefit from increasing renewable energy production in the future.

EV is driven by a motor, whose power is supplied by rechargeable battery or other portable energy storage device. There are four main types of EVs: fuel cell electric vehicles (FCEVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). EVs are expected to become the trend of modern cars owing to their obvious characteristics, including increasing performance, energy saving, environmental protection and reasonable price. According to the planning of relevant departments, the number of electric vehicles in China will reach five million by 2020. At present, due to the constraints of battery technology, electric vehicle mileage is relatively short compared to traditional fuel vehicles. The limited number of charging stations generates "range anxiety" among users of electric vehicles and makes them fearful of not reaching their destination [5]. Thus, a complete construction of charging and switching facilities for EVs can not only provide energy supply, but also promote the eventual adoption of EVs.

Charging stations play a critical role to guarantee EVs running normally; consequently, mounting pressure has called for a series of efforts to find outstanding placement. During carrying out quantitative and qualitative analysis on location decisions, we should make clear the relationship and role between various factors which make impacts on EV charging station location. However, to the best of our knowledge, there is little research committed to analyzing this aspect.

Against this backdrop, this paper systematically investigated the major factors responsible for the EVCS location. On this base, ISM (interpretive structural modeling) and FMICMAC (fuzzy cross-impact matrix multiplication applied to classification) analysis were established, which aimed at analyzing relationship and impact degree between these factors. The rest of the paper is organized as follows: Section 2 is the literature review; Section 3 discusses the influence factors; Section 4 provides methodology; Section 5 provides a case evaluation; Section 6 presents the discussion; and Section 7 discusses the conclusion.

2. Literature Reviews

There is extensive literature focusing on the refueling infrastructure problem [6–11]. With the rise of EVs, many scholars have turned to discuss the recharging behavior of EVs with respect to the planning and construction of charging stations. Electric power is clearly different from gasoline, as it cannot be stored in large amounts and must be kept in real-time balance between power generation and consumption, which makes the problem of optimally programing EVCSs much more complicated. In addition, this issue involves multiple elements and a variety of conditions, thus the complexity is further increased. Gong et al. summarized a few challenges behind the problem, i.e., various forms of power sources, different features in different geographical regions, difficulty of obtaining relevant data, diversity and flexibility of travel behavior, multiple entities involved with different interests and objectives, bemusement of modeling the road network and traffic conditions [12].

Thus far, many scholars are committed to optimally planning or operating EVCSs with the aid of various mathematical models. Pan et al. proposed a novel centralized charging station strategy considering urban power network structure strength. In addition, the investment of charging stations and network loss were considered as part of objective functions with power supply moment balance index in order to improve urban power network structure at the minimal economic cost [1]. Andrenacci et al. analyzed real travel patterns on private vehicle usage which was extracted from a big collection of vehicular travel data, aiming at carrying out a strategy for the optimal allocation of EVCSs in an urban area to meet the user demand [2]. A simulation–optimization model that determines where to locate electric vehicle chargers to maximize their use by privately owned electric vehicles was developed by Xi et al. [13]. They found that the optimal location is sensitive to the specific optimization criterion. As existing optimization methods ignore traffic demands and infrastructure, Viswanathan et al. took existing traffic, road network data and the dynamics of individual vehicle movement into consideration when determining charging infrastructure. They described a computational science approach to evaluate both the spatial and temporal aspects of charging station placement based on available real world traffic data [14]. Lam et al. formulated the electric vehicle charging station placement problem (EVCSPP) and proved it to be NP-hard. In addition they proposed four solution methods to tackle EVCSPP and evaluated their performance on various artificial and practical cases considering construction cost, accessibility, and coverage of the stations [15]. Tan and Lin solved the problem of siting EVCSs in a transportation network with consideration of charging demand uncertainty and service coverage rate of fast-charging stations. The deterministic flow capturing location-allocation problem was extended into a stochastic model which can more realistically capture the actual coverage of the demand [16]. Furthermore, Phonrattanasak and Leeprechanon pointed out that EVCSs should be optimally placed in areas of dense traffic under the premise of minimum total cost of the fast charging station and minimum total loss of distribution network [17].

In particular, some research takes more factors into consideration when dealing with the electric vehicle charging station placement problem. For example, Guo and Zhao built an evaluation index system for EVCS site selection from sustainability perspective, which consists of environmental, economic and social criteria associated with a total of 11 sub-criteria [18]. They made the optimal decision applying TOPSIS method which provided a new research perspective for site selection. Sadeghi-Barzani et al. believed that EVCS development is highly influenced by the government policy in allocating station development costs [19]. For optimal placing and sizing of the EVCS, the station development cost, EV energy loss, electric gird loss as well as the location of electric substations and urban roads should be all taken into consideration. Optimal locating and sizing of charging stations in smart grids is regarded to be essential [20]. Wang et al. accounted that it is necessary to ensure charging service while reducing power losses and voltage deviations of distribution systems with respect to EVCS planning method. Baouche et al. applied trip OD matrix information from household travel survey coupled with a dynamic vehicle model while allocating charging stations in a real network [21]. Simulations showed that the increasing number of semi-fast chargers enables a demand satisfaction and a cost-effective investment in rapid charging station. Chen et al. proposed that in order to determine optimal location EVCS, it is needed to minimize the station access cost of EV users under the constraints of the parking demand, local job, population density and trip attributes [22]. The encouraging results of case study which was conducted by Dashora et al. indicated the viability of the modeling approach and substantiated the importance of considering both employee convenience and appropriate grid connections in the PHEV charging station planning problem [23]. He et al. captured the interactions among availability of public charging opportunities, prices of electricity, and destination and route choices of PHEVs when determining an optimal allocation of charging stations [24].

The main emphasis of studies on EVCS recently can be summarized into two categories: charging mode research and optimal location discussion. In terms of the latter, it is obvious that the related studies have investigated the charging station location problem considering different objectives and various constraints, including cost of charging stations, traffic conditions, and power loss as well as power system security of the power distribution grid and so on. To the best of our knowledge, there is little research focusing on analyzing the influencing factors of EVCS location. In response to this phenomenon, this paper is intended to make up for the research flaws. Based on a review of literature and expert consultation, as well as considering the characteristics of EVs, the paper put forward 12 factors which impact EVCS location from five aspects: charging demand, operating economy, traffic convenience, power grid security, and construction feasibility. In this paper, ISM approach is used to interpret the interdependency among the selected factors. In addition, FMICMAC analysis is applied to illustrate the relative driving and dependence power among the selected factors.

3. Influence Factors of Electric Vehicles Charging Station Location

Influence factors are the conditions, features, or variables that if considered properly and comprehensively can contribute to make a successful choice of EVCS location. Since the appropriate site selection and capacity determination on EVCS can benefit the multiple stakeholders and promote the sustainable development of whole industry [18], it becomes essential to find the elements and factors that influence the location selection. In this section, six experts, of whom four are from the industry dealing with EVCS and two from academia, are identified through the authors' professional and personal networks. All the experts are currently working in EVCS programing. Literature related to station location was circulated to all the experts. Interview based on a semi-structured questionnaire was also conducted with all the experts. After two weeks of sending the relevant literature to experts, a brainstorming session was organized to identify the factors. As an outcome of this session, 20 variables were identified as the influence factors of EVCS location from the aspects of charging demand, operating economy, traffic convenience, power grid security, and construction feasibility. These were further reduced to 12, as some factors were similar in nature and could be explained under a common cause.

3.1. Charging Demand

In the view of the function of electric vehicle charging station, the EVCS location must meet the charging demand. If the charging demand near alternative address is not high, it will cause the charging facilities to be idle and thus unable play their role, resulting in a great waste of resources. In this study, charging demand is considered from the following three aspects:

(1) Area attribute: There are usually a variety of urban functional areas in the vicinity of the alternative site. Different functional areas correspond to different charging need. Area attribute determines the construction scale of EVCS and the type of energy supply system.
(2) Purchase intention: The future potential growth of the charging need is also related to the purchase intention of the residents. Regions with residents that have greater purchase intention will likely have greater future growth in charging demand.
(3) Sales of electric vehicles: Electric vehicles as the future direction of automotive industry have a good market prospect. The sales of electric vehicles in optional area also indirectly reflect the demand for electric vehicle charging.

3.2. Operating Economy

Since electric vehicle charging facilities are infrastructure and have a certain commercial nature, it is necessary to consider the cost and operational benefits. The sub-factors affiliated with economy criteria for EVCS site selection are summarized as below.

(1) Construction cost: Includes land cost, demolition cost, equipment acquisition cost, and project investment cost.
(2) Annual operation and maintenance cost: Includes electric charge, staff wages, financial expenses, tax, battery amortization, etc.

3.3. Traffic Convenience

The impact of traffic convenience on the location of charging station is mainly reflected in three aspects:

(1) Lane situation: Lane situation near the alternative site is required to be taken into consideration, including the number of lanes as well as the property which directly relates to the future development of the charging station.
(2) Traffic flow: The number of electric vehicles now and the future will be great where the traffic flow is large, so the same as charging demand and the benefit of EVCSs.

(3) Pit stop rate: Pit stop rate is the ratio of the number of EVs entering the charging station to charge and the number of EVs passing through the electric vehicle charging station. The pit stop rate is directly related to the number of customers and determines the benefit of the charging station

3.4. Power Grid Security

Electric vehicles rely on electric energy and charging facilities need to be connected to the regional power grid. Fast charging mode requires high current output, which makes the impacts on the power grid more intense. The impacts of electric vehicle charging facilities on the power grid are summarized as the following point based on relevant literature.

(1) Impacts on the transmission and distribution network: Once selecting the address of the electric car charging station, a huge charge load will be added to the area which may affect the safe operation of the grid. When the charging behavior is concentrated in a site or area, it will lead to local area load tension. When the charging behavior is concentrated in the peak load period, the grid current demand will overload the power system and reduce the efficiency of power grid.

(2) Harmonic pollution to the grid: When electric car charging station is connected to the grid, it is equivalent that a charger or other equipment within charging station accesses to the power grid. These charging devices are non-linear load and a large number of non-linear load operations will produce harmonics in the power grid. If a large number of harmonic pollution is not governed timely and effectively, it will affect the power quality. A huge amount of money is required to illustrate harmonic controller, which may also increase the cost of construction and operation of the charging station.

3.5. Construction Feasibility

Charging pile is a kind of service equipment based on the electronic technology. Its operation is greatly influenced by the temperature, humidity and other environmental factors as well as has a certain failure rate. At the same time, the charging station must access the local power grid in order to provide the power, so the performance of the local power grid imposes critical effects on the service quality provide by charging station.

(1) Geographical environment: The geographical environment near the electric car charging station is one of the important factors that should be considered. It directly affects whether the construction of the charging station is feasible. Choosing the right address can facilitate the construction of the charging station, and also can reduce the cost of the future operation.

(2) Social environment: Social environment is one of the important factors that affect the feasibility of electric car charging station construction. The so-called social environment consists of the social and political environment, economic environment, legal environment, science and technology environment and cultural environment. The social environment to be considered for the EVCS location includes the impacts on the residents, the support from the city construction department, the damage to the environment and the regional security situation.

4. Method and Methodology

4.1. ISM Methodology

ISM is an analytical method that helps explore the complex relationships between several elements involved in complicated scenarios. The fundamental thought of ISM is to decompose a complex system into several segments based on experts' practical experience and knowledge in the interest of constituting a multi-level hierarchical structure model ultimately. ISM can transform the fuzzy ideas into intuitive models with good structural relations, which is especially suitable for analyzing the complex relationships among specific variables. Its application is very broad [25–30], from energy and other international issues to the regional economic development, enterprises and even the scope of personal problems. Mathiyazhagan et al. applied ISM to understand the mutual influences amongst the factors for the implementation of Green Supply Chain Management (GSCM) in Indian auto component manufacturing industries [29]. Yadav and Barve used ISM approach to interpret the interdependency among the selected critical success factors of humanitarian supply chain [30].

ISM operates without knowing any prior history of the system and imposes rank to the elements. Since the contextual relation among the variables is determined by the experts' knowledge, the final results would be influenced by subjective judgment inevitably. However, compared to other techniques, such as Delphi and structural equation modeling (SEM), ISM needs fewer experts and has fewer limitations. There are two basic concepts in ISM, i.e., transitivity and reachability. Suppose that there are three elements named "*i*", "*j*", and "*k*", transitivity implies that if *i* is related to *j* and *j* is related to *k*, then *i* and *k* will be inter-related to each other. Reachability matrix is conducive to partition the various levels in ISM. The various steps involved in the ISM methodology are described as follows and also shown in Figure 1.

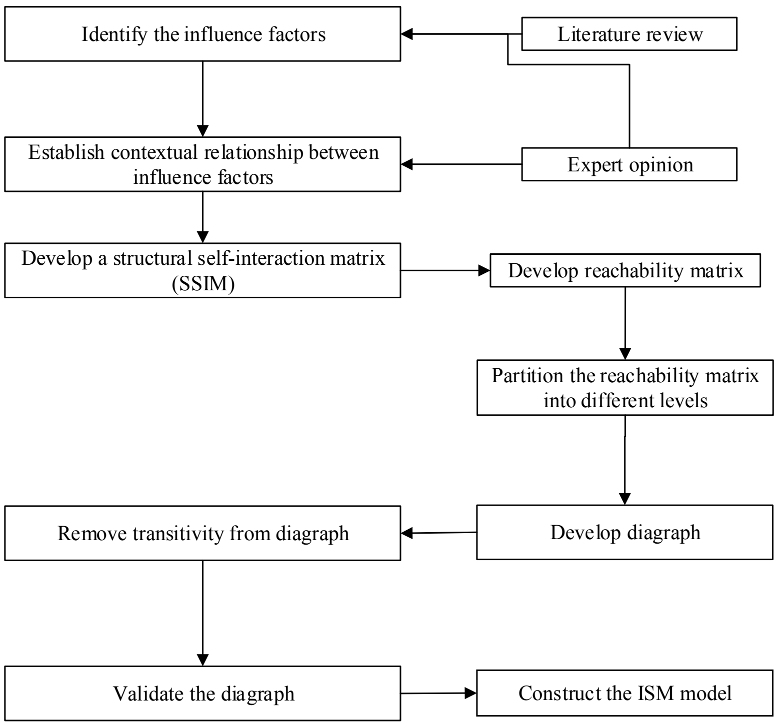

Figure 1. Flow diagram of ISM (interpretive structural modeling) construction.

Step 1: Identify the relevant variables through survey or other group problem solving technique.

Step 2: Establish contextual relationship among the variables in order to identify which pairs of variables should be examined.

Step 3: Develop a structural self-interaction matrix (SSIM) of variables, which indicates pairwise relationships among variables of the system.

Step 4: Develop a reachability matrix from the SSIM and checking the matrix for transitivity. The transitivity of the contextual relation states that if a variable A is related to B and B is related to C, then A is necessarily related to C.

Step 5: Partition the reachability matrix obtained in Step 4 into different levels.

Step 6: Draw a directed graph and remove the transitive links based on the relationships given above in the reachability matrix.

Step 7: Validate the diagraph through a panel of experts and construct the ISM model.

4.2. FMICMAC Methodology

Some factors that have a strong direct relationship prevent us from finding hidden indicators with possible relationships, and sometimes these hidden factors may make large impacts on the system under study. The indirect relationship between these factors can influence the system through transitivity, chain of reaction cycles, or feedback from itself. In order to draw the hierarchical relationships among them, and also determine which indicators are independent in their impacts and which ones may produce secondary and higher order impacts, Matriced'Impacts Croisés Multiplication Appliquée á un Classement (cross-impact matrix multiplication applied to classification) (MICMAC) was proposed by Duperrin and Godet in 1975 [31]. The basic idea of MICMAC is multiplication properties of matrices, which states that if criteria i has direct influence on criteria j and j has direct influence on criteria k, then any change affecting i can have repercussions on k.

In traditional MICMAC analysis, the relationship between two factors is expressed in binary digits and is represented by 0 or 1, when 0 stands for that there is no relation between two factors and 1 stands for that there is a relationship. For example, the relationship between F1 and F2, F3 and F4 will be equal important and is represented by 1. The problem is that the relationship between these causes is not always equal. The degree of correlation cannot be captured in traditional MICMAC analysis. In order to fill this gap, fuzzy scales have been utilized to explain the dominance of interactions. The strength of relationship varies among no, weak, very weak, medium, strong, very strong and full. Compared with the traditional ISM, FMICMAC can obtain a better and meaningful classification of selected factors and is very beneficial for arriving at the precise relationships based on the expert opinions. The rankings of the factors are significantly different and are closer to reality when applying fuzzy scales. In this research, the objective of FMICMAC analysis is to identify and analyze the influence factors of EVCS location based on their driving and dependence power. Factors can be divided into four clusters, i.e., autonomous variables, dependent variables, linkage variables, and driving variables based on dependence and driving power. Higher dependence power of a factor signifies that in order to eliminate the influence which is made by this factor it is required to remove many factors and higher driving power signifies that many factors' influence can be eliminated by removing this factor. The specific process of FMICMAC analysis is explained in Section 5.

5. Case Evaluation

The purpose of the case evaluation is to demonstrate the proposed model's capability and usefulness in analyzing the influence factors of EVCS location. The experiments are based on implementing the model described in Section 4 in a Beijing context. Suppose that the research area covers about 8000 km^2 and includes 1.8 million inhabitants and 62 thousand electric vehicles in 2016.

Before constructing the EVCS, it is necessary to identify the factors which would influence the selection of EVCS location. This research was conducted to assess the major influence factors of EVCS location in the studied area. The results of the proposed model could enable and enhance managerial decision making through identifying, classifying and enhancing major factors for deciding where is suitable to build a charging station. During the analysis, data were collected from experts for structural self-interaction matrix to get the mutual relationships among these 12 variables and also for fuzzy reachability matrix which would be explained in the subsequent sections. Any discrepancies in the data were sorted out by consensus among the experts. The results of the analysis were circulated to the experts and have their consent. These causes are described below without any particular order.

5.1. ISM Analysis

Step 1: Identify the influence factors.

The various influence factors of EVCS site location were identified based on literature review and experts' opinion. This research considered 12 influence factors from the discussion. The final lists of selected factors are given in Table 1 and explained in Section 3.

Table 1. Influence factors of EVCS (electric vehicles charging station) location.

Perspective	Influence Factors
Charging demand	Area attribute Purchase intention Sales of electric vehicles
Operating economy	Construction cost Annual operation and maintenance cost
Traffic convenience	Lane situation Traffic flow Pit stop rate
Power grid security	Impacts on the transmission and distribution network Harmonic pollution to the grid
Construction feasibility	Geographical environment Social environment

Step 2: Establish structural self-interaction matrix (SSIM).

Literature survey and experts' opinion has been utilized to recognize the contextual relationship among the selected factors. The expert panel made pair-wise comparisons to identify the contextual relationship. Following four symbols are applied for denoting the direction of the relationship between factors.

V, when variable *i* helps achieve variable *j*;
A, when variable *j* helps achieve variable *i*;
X, when variable *i* and *j* help achieve one another; and
O, when variable *i* and *j* show no relation to one another.

Based upon their objective judgment, a contextual relationship of "lead to" type is prepared as SSIM and also depicted in Table 2. Factor 1 is leading to factor 13 so symbol "V" has been used in the cell (1, 13); factor 12 is leading to factor 1 so symbol "A" has been used in cell (1, 12); factor 3 and 13 are leading to each other so symbol "X" has been used in cell (3, 13); factor 1 and 5 are not related with each other so symbol "O" has been used in cell (1, 5); etc.

Table 2. Structural self-interaction matrix (SSIM) for influence factors of EVCS location

No.	Influence Factors	12	11	10	9	8	7	6	5	4	3	2	1
1	Area attribute (F1)	O	X	V	V	V	V	V	V	V	V	V	
2	Purchase intention (F2)	O	A	V	V	V	V	O	O	O	V		
3	Sales of electric vehicles (F3)	V	O	V	V	V	V	A	V	V			
4	Construction cost (F4)	A	A	A	O	A	A	A	X				
5	Annual operation and maintenance cost (F5)	A	A	A	O	A	A	A					
6	Lane situation (F6)	O	A	V	V	V	V						
7	Traffic flow (F7)	O	A	V	V	X							
8	Pit stop rate (F8)	V	A	V	V								
9	Impacts on the transmission and distribution network (F9)	X	O	X									
10	Harmonic pollution to the grid (F10)	X	O										
11	Geographical environment (F11)	O											
12	Social environment (F12)												

Step 3: Construct reachability matrix.

The SSIM is transformed into initial reachability matrix by replacing symbols V, A, X, and O with 1 and 0 according to certain rules. The rules for synthesis of initial reachability matrix are the following:

(1) If the (i, j) entry in the SSIM is V, then the (i, j) entry in the reachability matrix becomes 1 and the (j, i) entry becomes 0.
(2) If the (i, j) entry in the SSIM is A, then the (i, j) entry in the reachability matrix becomes 0 and the (j, i) entry becomes 1.
(3) If the (i, j) entry in the SSIM is X, then the (i, j) entry and the (j, i) entry in the reachability both become 1.
(4) If the (i, j) entry in the SSIM is O, then the (i, j) entry and the (j, i) entry in the reachability both become 0.

Adhering to these rules, initial reachability matrix for the criteria is shown in Table 3. The final reachability matrix, shown in Table 4, for the criteria is obtained by incorporating the transitivity as enumerated in Step 4 of the ISM methodology mentioned in Section 4.1. Then, the driving and dependence power of each criteria which is derived from the final reachability matrix will be used in the FMICMAC analysis, where the criteria will be classified into four different groups, i.e., autonomous, dependent, linkage, and independent criteria.

Table 3. Initial reachability matrix of influence factors of EVCS location.

No.	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	1	1	1	1	1	1	1	1	0
2	0	1	1	0	0	0	1	1	1	1	0	0
3	0	0	1	1	1	0	1	1	1	1	0	1
4	0	0	0	1	1	0	0	0	0	0	0	0
5	0	0	0	1	1	0	0	0	0	0	0	0
6	0	0	1	1	1	1	1	1	1	1	0	0
7	0	0	0	1	1	0	1	1	1	1	0	0
8	0	0	0	1	1	0	1	1	1	1	0	1
9	0	0	0	0	0	0	0	0	1	1	0	1
10	0	0	0	1	1	0	0	0	1	1	0	1
11	1	1	0	1	1	1	1	1	0	0	1	0
12	0	0	0	1	1	0	0	0	1	1	0	1

Table 4. Final reachability matrix of influence factors of EVCS location.

No.	1	2	3	4	5	6	7	8	9	10	11	12	Driving Power
1	1	1	1	1	1	1	1	1	1	1	1	1*	11
2	0	1	1	1*	1*	0	1	1	1	1	0	1*	6
3	0	0	1	1	1	0	1	1	1	1	0	1	8
4	0	0	0	1	1	0	0	0	0	0	0	0	2
5	0	0	0	1	1	0	0	0	0	0	0	0	2
6	0	0	1	1	1	1	1	1	1	1	0	1*	8
7	0	0	0	1	1	0	1	1	1	1	0	1*	6
8	0	0	0	1	1	0	1	1	1	1	0	1	7
9	0	0	0	1*	1*	0	0	0	1	1	0	1	3
10	0	0	0	1	1	0	0	0	1	1	0	1	5
11	1	1	1*	1	1	1	1	1	1*	1*	1	1*	8
12	0	0	0	1	1	0	0	0	1	1	0	1	5
Dependence Power	2	3	4	10	10	3	7	7	9	9	2	5	70

Note: 1* indicates transitivity.

Step 4: Partition level.

From the final reachability matrix, each variable is grouped into reachability and antecedent set. The reachability set for a particular variable comprises the variable itself and other variables that it help accomplish. The antecedent set consists of the variable itself and the other variables that help in accomplishing it. Subsequently, the intersection set is derived for all variables. The variable which has the same reachability and the intersection sets holds the top level in the hierarchy. After the identification of the top-level elements, they are removed and the same process is repeated for several iterations. For instance, in the first iteration as shown in Table 5, factor 4 and 5 have the same reachability set and intersection set. Then, the two factors are removed in the next iteration and the process is repeated until levels of each factor are obtained. The final level partitions are described in Table 6. These multi-levels assist in establishing the digraph and the final model of ISM.

Table 5. First step of iteration for partition the levels of influence factors.

No.	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	1, 11	1, 11	
2	2, 3, 4, 5, 7, 8, 9, 10, 12	1, 2, 11	2	
3	3, 4, 5, 7, 8, 9, 10, 12	1, 2, 3, 6, 11	3	
4	4	1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12	4	I
5	5	1, 2, 3, 5, 6, 7, 8, 8, 10, 11, 12	5	I
6	3, 4, 5, 6, 7, 8, 9, 10, 12	1, 6, 11	6	
7	4, 5, 7, 8, 9, 10, 12	1, 2, 3, 6, 7, 8, 11	7, 8	
8	4, 5, 8, 9, 10, 12	1, 2, 3, 6, 7, 8, 11	8	
9	4, 5, 9, 10, 12	1, 2, 3, 6, 7, 8, 9, 10, 11, 12	9, 10, 12	
10	4, 5, 9, 10, 12	1, 2, 3, 6, 7, 8, 9, 10, 11, 12	9, 10, 12	
11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 11	1, 11	
12	4, 5, 9, 10, 12	1, 2, 3, 6, 7, 8, 9, 10, 11, 12	9, 10, 12	

Table 6. Various levels of influence factors of EVCS location.

Level	Influence Factors
I	F4, F5
II	F9, F10, F12
III	F7, F8
IV	F3
V	F2, F6
VI	F1, F11

Step 5: Develop the digraph.

Finally, the structural model is generated from the final reachability matrix. An arrow is applied pointing from criteria *i* to *j* to demonstrate the relationship between them. Removing the transitivity described in the ISM methodology, the digraph could be converted into the ISM model as depicted in Figure 2. The figure shows that area attribute (F1) and geographical environment (F11) are with great significance for the selection of EVCS location as they occupy the basic level of the ISM hierarchy. Construction cost (F4) and annual operation and maintenance cost (F5) are the influence factors on which the effectiveness of the selection of EVCS location depends as they have appeared at the top level of the ISM hierarchy. The digraph and the final model of ISM for the influence factors are shown in Figure 2.

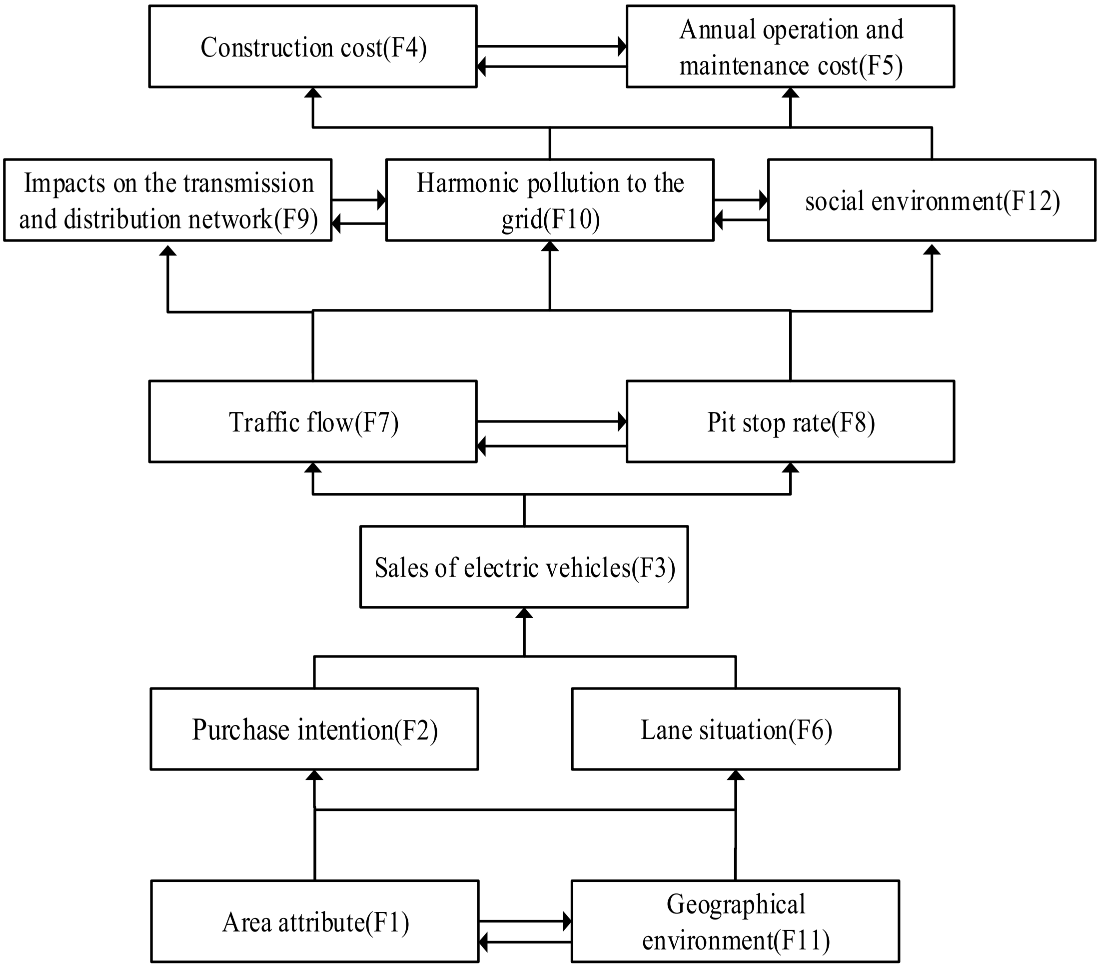

Figure 2. Diagraph representing prominent relations of the ISM model.

Step 6: Validate the digraph and construct the ISM model.

In order to validate the constructed digraph, this paper intends to use an expert panel of five EVCS location analysts. It is supposed that the prominent relations in the digraph are rated on a scale from one to five which represents the importance of relations. Specifically, one signifies a not so important influential relation and five signifies a most important one. If the average scores reach three or above, those relations are retained in the digraphs and other relations are removed to achieve the final digraph. The validated model can be interpreted logically for detailed understanding each link in the digraph to form the ISM model. The validation of the relations represented in links as in digraphs is indicated in Table 7. The validated model and the digraph representing the relations are shown in Figure 3.

Table 7. Validation of the ISM model.

Relation Link	Interpretation	Average Score	Accept/Reject
F1–F2	Area attribute effects purchase intention	3.8	Accept
F1–F6	Area attribute effects lane situation	3.6	Accept
F1–F11	Area attribute effects geographical environment	2.8	Reject
F2–F3	Purchase intention effects sales of electric vehicles	4.4	Accept
F3–F7	Purchase intention effects traffic flow	4.2	Accept
F3–F8	Purchase intention effects pit stop rate	3.8	Accept
F4–F5	Construction cost effects annual operation and maintenance cost	3.2	Accept
F5–F4	Annual operation and maintenance cost effect construction cost	2.8	Reject
F6–F3	Lane situation effects sales of electric vehicles	3.2	Accept
F7–F8	Traffic flow effects pit stop rate	4.4	Accept
F7–F9	Traffic flow effects impacts on the transmission and distribution network	3.2	Accept
F7–F10	Traffic flow effects harmonic pollution to the grid	3.2	Accept
F7–F12	Traffic flow effects social environment	3.2	Accept
F8–F7	Pit stop rate effects traffic flow	4.2	Accept
F8–F9	Pit stop rate effects impacts on the transmission and distribution network	3.2	Accept
F8–F10	Pit stop rate effects harmonic pollution to the grid	3.4	Accept
F8–F12	Pit stop rate effects social environment	3.2	Accept
F9–F10	Impacts on the transmission and distribution network effects harmonic pollution to the grid	3.4	Accept
F10–F4	Harmonic pollution to the grid effects construction cost	3.2	Accept
F10–F5	Harmonic pollution to the grid effects annual operation and maintenance cost	3.4	Accept
F10–F9	Harmonic pollution to the grid effects impacts on the transmission and distribution network	3	Accept
F10–F12	Harmonic pollution to the grid effects social environment	3	Accept
F11–F1	Geographical environment effects area attribute	4.2	Accept
F11–F6	Geographical environment effects lane situation	3.4	Accept
F12–F4	Social environment effects construction cost	2.8	Reject
F12–F5	Social environment effects annual operation and maintenance cost	3.6	Accept
F12–F10	Social environment effects harmonic pollution to the grid	2.8	Reject

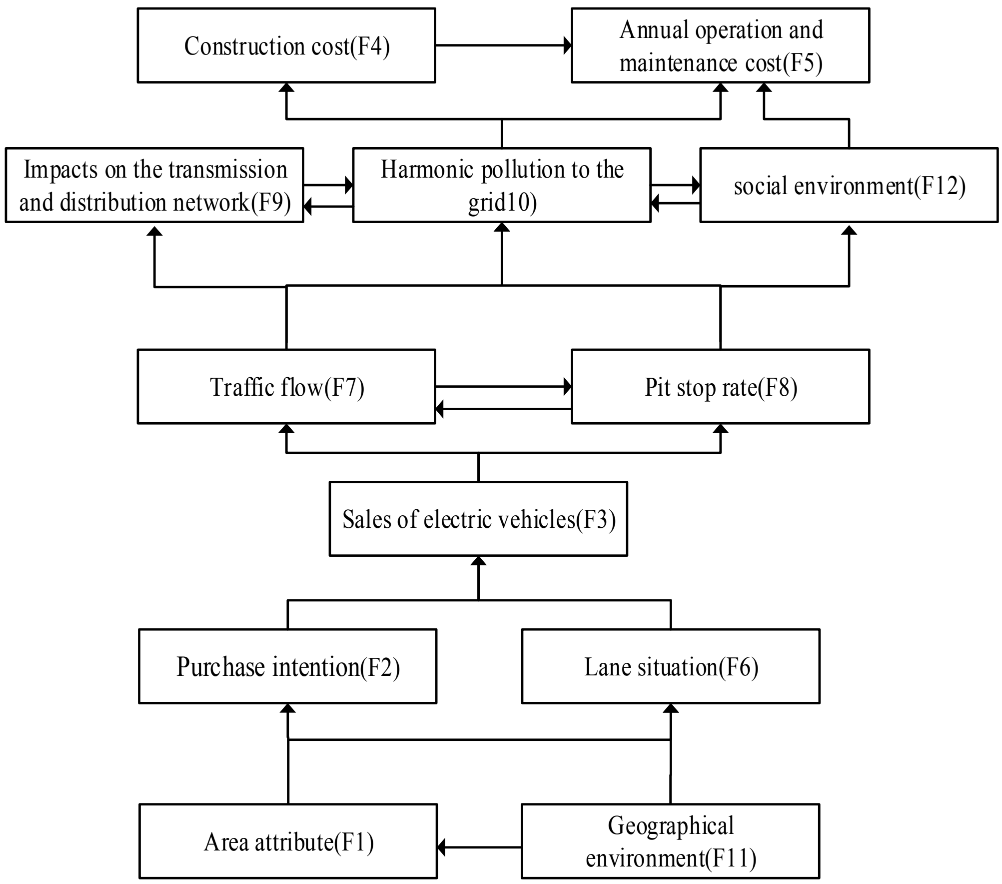

Figure 3. Validated diagraph representing prominent relations of the ISM model.

5.2. FMICMAC Analysis

To classify the barriers, MICMAC analysis has been utilized. MICMAC is basically cross-impact matrix multiplication applied for the purpose of classification. MICMAC analysis is done on the basis of obtained driving and dependence powers. With MICMAC analysis, factors can be categorized into four parts: linkage, autonomous, independent and dependent barriers. Figure 4 depicts MICMAC analysis for influence factors of EVCS location.

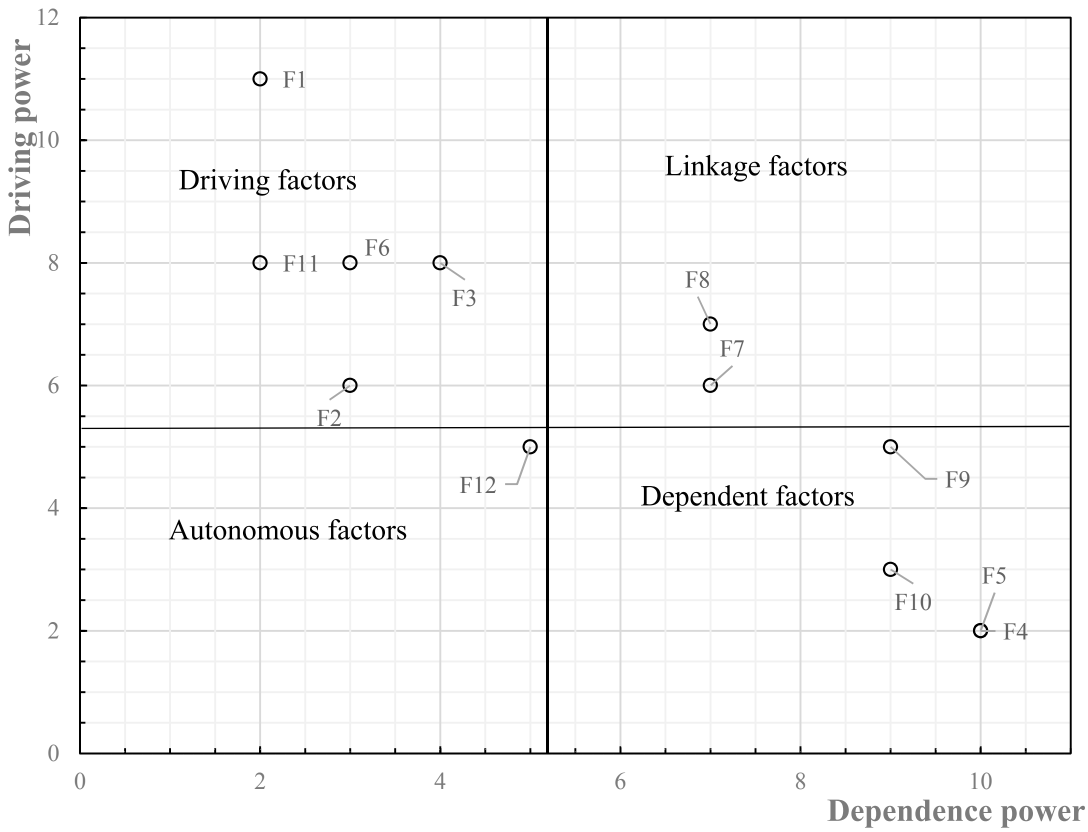

Figure 4. Driving and dependence power using MICMAC (fuzzy cross-impact matrix multiplication applied to classification) analysis.

MICMAC analysis can be improved by incorporating the fuzzy set concept to overcome the limitations of the existing analysis by using "0" and "1". The process of FMICMAC analysis is described as below.

Step 1: Synthesize the direct relationship matrix (DRM).

In FMICMAC analysis, the diagonal elements in the initial reachability matrix are converted to zero to form the direct relationship matrix (DRM) which is basically the calculation of direct relationship among the influence factors as shown in Table 8.

Step 2: Develop the fuzzy direct relationship matrix (FDRM).

To establish the fuzzy direct reachability matrix (FDRM), additional inputs are acquired from experts to explain the strength of dominance among the influence factors adhere to fuzzy scales, as shown in Table 9. The FDRM is depicted in Table 10.

Table 8. Binary direct relationship matrix.

No.	1	2	3	4	5	6	7	8	9	10	11	12
1	0	1	1	1	1	1	1	1	1	1	1	0
2	0	0	1	0	0	0	1	1	1	1	0	0
3	0	0	0	1	1	0	1	1	1	1	0	1
4	0	0	0	0	1	0	0	0	0	0	0	0
5	0	0	0	1	0	0	0	0	0	0	0	0
6	0	0	1	1	1	0	1	1	1	1	0	0
7	0	0	0	1	1	0	0	1	1	1	0	0
8	0	0	0	1	1	0	1	0	1	1	0	1
9	0	0	0	0	0	0	0	0	0	1	0	1
10	0	0	0	1	1	0	0	0	1	0	0	1
11	1	1	0	1	1	1	1	1	0	0	0	0
12	0	0	0	1	1	0	0	0	1	1	0	0

Table 9. Fuzzy scale for dominance of interaction.

Strength of Relationship Between Causes							
Dominance	No	Very weak	Weak	Medium	Strong	Very strong	Full
Numerical Value	0	0.1	0.3	0.5	0.7	0.9	1

Table 10. Fuzzy direct relationship matrix.

No.	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0.7	0.9	0.3	0.3	0.7	0.7	0.7	0.5	0.5	0.3	0
2	0	0	1	0	0	0	0.5	0.5	0.3	0.3	0	0
3	0	0	0	0.9	0.9	0	0.7	0.9	0.7	0.7	0	0.9
4	0	0	0	0	0.5	0	0	0	0	0	0	0
5	0	0	0	0.3	0	0	0	0	0	0	0	0
6	0	0	0.5	0.7	0.3	0	0.9	1	0.3	0.1	0	0
7	0	0	0	0.7	0.5	0	0	1	0.5	0.3	0	0
8	0	0	0	0.3	0.5	0	0.9	0	0.5	0.7	0	0.5
9	0	0	0	0	0	0	0	0	0	0.5	0	0.7
10	0	0	0	0.3	0.5	0	0	0	0.3	0	0	0.7
11	0.7	0.5	0	1	1	0.9	0.9	0.7	0	0	0	0
12	0	0	0	0.5	0.3	0	0	0	0.7	0.7	0	0

Step 3: Obtain the fuzzy stabilized matrix.

The concept of fuzzy multiplication is applied on FDRM to get fuzzy stabilized matrix. This concept states that matrix is multiplied until the values of driving and dependence powers are stabilized [32]. According to Fuzzy set theory, when two fuzzy matrices are multiplied the resultant matrix is also a fuzzy matrix. Fuzzy multiplication follows the rule as below:

$$\text{Let } A = (a_{ik})_{m\times s}, B = (b_{kj})_{s\times n}, \text{ then } C = A \circ B = (c_{ij})_{m\times n} = (\vee\left\{(a_{ik} \wedge b_{kj})|1 \leq k \leq s\right\} \quad (1)$$

Driving and dependence power are obtained through adding row and column entries separately in respective way. The stabilized matrix in FMICMAC for influence factors in selection of EVCS location is achieved as shown in Table 11.

Table 11. Fuzzy stabilized matrix.

No.	1	2	3	4	5	6	7	8	9	10	11	12	Driving Power	Rank
1	0	0	0	0.7	0.5	0	1	1	0.7	0.7	0.3	0.7	6.1	2
2	0	0	0	0.7	0.5	0	0.9	0.7	0.7	0.7	0	0.7	4.9	4
3	0	0	0	0.7	0.5	0	0.7	0.9	0.7	0.7	0	0.7	4.9	4
4	0	0	0	0	0.3	0	0	0	0	0	0	0	0.3	11
5	0	0	0	0.3	0	0	0	0	0	0	0	0	0.3	11
6	0	0	0	0.7	0.5	0	0.9	0.9	0.7	0.7	0	0.7	5.1	3
7	0	0	0	0.7	0.5	0	0	0.9	0.5	0.5	0	0.7	3.8	6
8	0	0	0	0.5	0.5	0	0.9	0	0.7	0.7	0	0.5	3.8	6
9	0	0	0	0.5	0.5	0	0	0	0.5	0.5	0	0.7	2.7	9
10	0	0	0	0.5	0.5	0	0	0	0.5	0.5	0	0.7	2.7	9
11	0.3	0.3	0.3	0.7	0.5	0.3	0.9	0.9	0.7	0.7	0	0.7	6.3	1
12	0	0	0	0.5	0.5	0	0	0	0.7	0.7	0	0.5	2.9	8
Dependence Power	0.3	0.6	0.6	6.5	5.3	0.6	5.2	5	6.4	6.4	0.3	6.6		
Rank	11	8	8	2	5	8	6	7	3	3	11	1		

Step 4: Classify factors using FMICMAC analysis.

According to their driving and dependence power, the driver power and dependence diagram is constructed as shown in Figure 5.

- The first cluster consists of autonomous factors with less driving and dependence power. Autonomous factors lie nearby origin and remain disconnected to the whole system which have no influence on the system and also do not get affect by the system.
- The second cluster consists of dependent factors with less driving power and high dependence power.
- The third cluster consists of linkage factors with high driving and dependence power. Linkage factors are unstable in nature as any step taken on them can affect other factors as well as feedback on themselves.
- The fourth cluster consists of driving factors with high driving power and less dependence power. These are therefore termed as key factors.

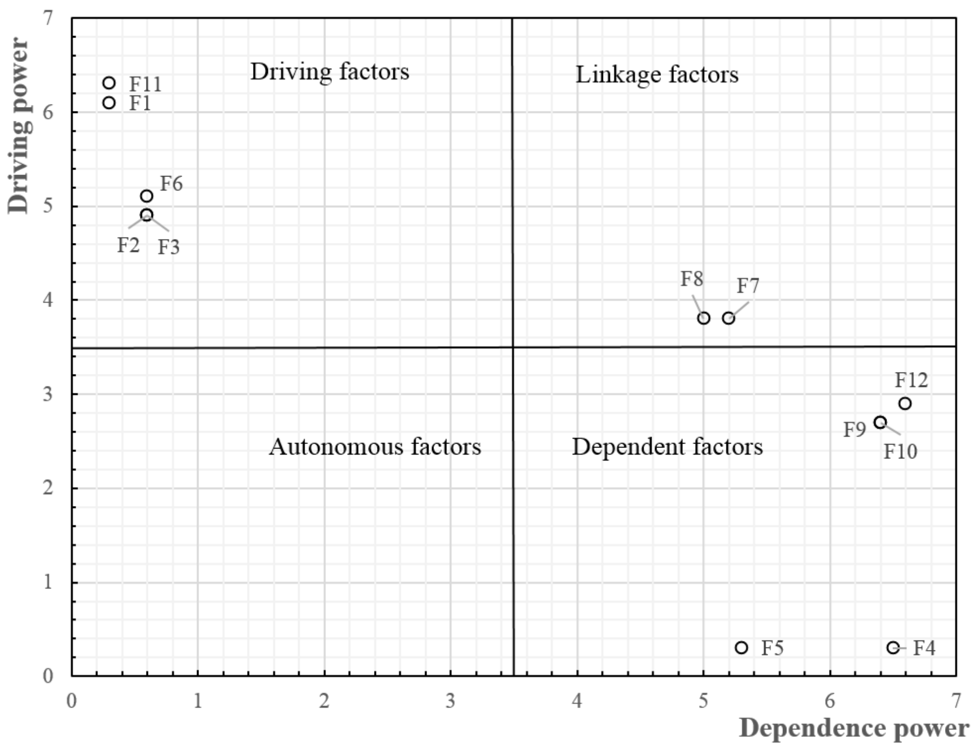

Figure 5. Driving and dependence power using FMICMAC analysis.

6. Discussion

Selection of EVCS location is an issue that has attracted the attention of researchers since last decades due to an increase in number of EVs. Charging station plays a critical role to guarantee EVs running normally; thus, mounting pressure has called for a series of efforts in charging station programming in order to find an outstanding placement. Before making the decision, it is necessary to consider comprehensive factors which have influence on the EVCS location and the operation in future. In this study, the authors have attempted to address the critical issues related to EVCS site location and analyze the relationships among these factors.

The number of factors should not be much in order to minimize the misunderstanding, and difficulty in practices. Keeping effective and efficient management in mind, this research has been conducted and 12 influence factors are selected. This work also investigates the interdependence among the identified factors and establishes a hierarchical structure model via ISM methodology.

Based on this, FMICMAC is further applied to identify and analyze the influence factors of selection of EVCS location according to their driving and dependence power. It can be observed from Figure 4 that there is no factor positioned in cluster I, which indicates that no factor is disconnected to the system. Construction cost (F4), annual operation and maintenance cost (F5), impacts on the transmission and distribution network (F9), harmonic pollution to the grid (F10), and social environment (F12) are dependent factors and positioned in cluster II. These factors have weak driving power and a strong dependence and are the outcome kind of critical influence factors. Traffic flow (F7) and pit stop rate (F8) fall in this cluster III. It is evident from the results that any action of them will have an effect on others and feedback on themselves. Further analysis from Figure 5 conveys that area attribute (F1), purchase intention (F2), sales of electric vehicles (F3), lane situation (F6), and geographical environment (F11) are positioned in cluster IV. As these factors having strong driving power, they form the base level of ISM hierarchy. Strong driving power and weak dependence associated with these influence factors requires treating them as decisive critical factors. Decision makers and practitioners should give priorities while considering these factors to select an EVCS site location. Compared to MICMAC analysis using "0" and "1", the proposed method assumes intermediate values between "0" and "1", which may help to improve the sensitivity and to understand the intensity of relationship between influence factors.

7. Conclusions

Because EVs are more efficient than equivalent conventional internal combustion engines (ICE) vehicles [4] and generate lower GHGs emissions, there are increasing EVs sales; this tendency necessitates constructing more EVCS to satisfy charging demand. Most existing studies have paid much more attention on the role of strategic planning and investigated the charging station location problem considering different objectives and various constraints. There is little research focusing on analyzing the influence factors of EVCS location. Thus, it is required to find out such influencing factors affect the selection process. Based on a review of literature and expert consultation, as well as considering the characteristics of EVs, the paper put forward 12 factors which impact EVCS location from five aspects, including charging demand, operating economy, traffic convenience, power grid security, and construction feasibility. In this paper, ISM approach is used to interpret the interdependency among the selected factors. In addition, FMICMAC analysis is applied to illustrate the relative driving and dependence power among them.

The proposed ISM structural model has been applied successfully to make the system visible and well-presented interrelationship among selected factors. From the ISM formation diagram (see Figure 2), it is concluded that 12 critical influence factors of EVCS location are formed into six levels based on their driving and dependence power. It is evident that area attribute and geographical environment are the most significant influence factors as they occupy the bottom position in the hierarchy. Area attribute and geographical environment dispatch more impact on the whole relief system. Area attribute determines the construction scale of EVCS and the type of energy supply system while geographical environment directly affect feasibility. They both drive other critical factors and are considered as key influence factors. The critical factor construction cost and annual operation and maintenance cost occupy the highest hierarchical level when impacts on the transmission and distribution network, harmonic pollution to the grid, and social environment are placed below it in the same hierarchy. These top level factors represent the desired objectives of EVCS location through the selecting process. To obtain these objectives, the critical success factors positioned at the bottom level in the hierarchy should be taken as the starting point and the breakthrough point to coordinate other intermediate factors. Moreover, the constructed digraph is validated using an expert panel of five EVCS location analysts. A comparison of the results of both helps to identify those influences factors which should be taken into consideration when deciding to construct a charging station.

FMICMAC analysis is used to rank and classify the 12 selected influence factors based on driving and dependence power. Since there are no autonomous factors that have low driving power and dependence, all factors significantly influence the choice of EVCS location. Construction cost, annual operation and maintenance cost, impacts on the transmission and distribution network, harmonic pollution to the grid, and social environment have high dependence and low driving power. Area attribute, purchase intention, sales of electric vehicles, lane situation, and geographical environment are significant influence factors of EVCS location because they have high driving power and less dependence. It is evident that applying the fuzzy scale, the ranking of the factors differs significantly and is closer to reality because the strength of dominance among the causes is fully quantified.

In the present investigation, 12 critical influence factors of EVCS location are identified to establish ISM while some other factors may be ignored. Since the lager number of factors is, the more complex the ISM methodology will be, this research only considered some rather important ones. Nonetheless, ISM provides an insight of the interrelationship between the identified factors, but their individual impacts cannot be quantified. For future study, graph theory and matrix approach can be used to quantify the effect. Besides, the proposed model is based upon the personal judgment of expert as well as validation, hence, structural equation modeling (SEM) defined as linear structural relationship approach may be used in future for statistical validation of this model.

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