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Spatial Allocation Model for Vehicle Charging Infrastructure in the Case of Indonesia's New Capital City

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Abstract- Indonesia's new capital city, Ibu Kota Nusantara (IKN), was launched in 2022 to replace Jakarta as a modern, sustainable city where all operating vehicles must be electric (EVs). This study identifies optimal locations for electric vehicle charging stations (EVCS) in support of IKN's 100% electrified transport systems (ETS) target by 2045. Implementing EVs in IKN requires optimum infrastructure readiness, including adequate EVCS distribution; no prior study has simulated this for IKN. This study introduces Spatial Model Simulation (SMS), a novel framework combining an agent-based model (ABM) and Markov Chain Monte Carlo (MCMC). ABM simulates EV mobility behaviour, while MCMC handles EVCS allocation across the Kawasan Inti Pusat Pemerintahan (KIPP) zone. This combination provides a spatially intuitive planning tool for government and policymakers. Results show that at a minimum inter-station range of 250 m, 25 EVCS are optimally distributed within KIPP, achieving an 88% allocation efficiency. Increasing the minimum range to 750 m reduces the total number to 22 stations. Area type also significantly influences optimal location and allocation (LA); misplacement leads to inefficiencies in infrastructure costs and maintenance budgets. Open space is the primary candidate area for EVCS installation, followed by residential and public service zones. Simulated energy demand for 100 vehicles ranges between 1,700 – 2,000 kWh per daily operating cycle. These findings offer practical guidance for decision-makers planning sustainable transport infrastructure in newly developed capital cities.

Keywords Electric vehicles; electrical vehicle charging station; markov chain monte carlo; power grid infrastructure; agent-based model; electrified transport systems.

I. Introduction

Electricity infrastructure is one of many issues that arise when talking about net-zero emissions (NZE). Many policies, practical actions, and plans have been initiated to make NZE be implemented by 2030, which is no exception for Indonesia. The construction of Indonesia's new capital city (Ibu Kota Nusantara/IKN) is one of Indonesia's most significant projects to achieve NZE goals. IKN embodies the vision of a green capital city that relies on renewable energy and electricity from non-fossil sources. However, this vision will remain aspirational without robust planning and effective execution.

A key initial step is adopting low-carbon vehicles and reducing dependence on fossil fuels in electricity generation. In this regard, electric vehicles (EVs) are considered the most viable option for Indonesia's electrification transition program (ETP) [1], [2], [3]. Yet, significant challenges persist beyond policy and regulatory frameworks; infrastructure readiness and gradual economic alignment are essential and must be mutually supportive and inseparable, particularly since most EVs still indirectly rely on fossil-based electricity. In detail, Indonesia's power generation remains dominated by coal, especially in the Greater Kalimantan systems, where coal is favored for its lower cost. Consequently, oil and coal's impact continues to exert substantial influence over Indonesia's energy sector. Hence, reducing dependence on fossil fuels and maintaining vigilance regarding geopolitical conditions are essential in any related infrastructure planning [4]. As part of strengthening the new supportive infrastructure aligned with the ETP, this research adopts a technical perspective on EV infrastructure availability to optimize the allocation of EVCS in a case study of IKN [3]. We scrutinized the road map and borderline of IKN as perimeters of our simulated models. In pair with that, we proposed a novel method to synchronise between Markov Chain Monte Carlo (MCMC) and Agent-Based Models (ABM) in the Spatial Model Simulation (SMS) framework.

In our concern, we do not argue that there is prior research consisting of ABM, MCMC, and TSP, which conduct similar research in terms of allocation of EVCS; their work can be seen in some references with delicate notions to develop the best practical implementation [6], [7], [8], [9]. IKN is in Sepaku Regency, East Kalimantan Province; it will be developed into a green capital city with a sustainable ecosystem directed to stringent NZE targets through the National Determined Contribution (NDC). The Minister of National Development Planning (Bappenas) has received the mandate as coordinator of IKN development as stipulated in Regulation Number 3 of 2022 [10], [11]. Nonetheless, the project is handed to the technical ministry, which supervises and obligates project admission to private companies or vendors.

The prior study related to the IKN as an independent case study, which points out enormous potential renewable energy resources across that area, can be accessed in some literature [12], [13]. In association with that, developing EVCS is obligatory to accelerate the shift and the potential multiplier effects, which will benefit the environment and be environmentally friendly for the future green city in IKN. Generally speaking, the energy demand relies on how many expected inhabitants are at IKN. In a prior study finding, IKN was projected to have 1.5 million residents [12]. Nonetheless, the following challenges arise since EVs are the only type of transport vehicle to be operated in KIPP as the first establishment, and will gradually be followed into another two areas, fulfilling the 100% ETS targets. Consequently, how to provide a stable and adequate electrical energy supply for IKN and find an optimal and cost-effective design, especially for archipelago countries. [13], [14], [15], [16], [17]. As published in previous studies, the proposed work focused on filling the gap by finding the optimal EVCS's LA through spatial model simulation, especially the preliminary ETS city planning design for new development regions, i.e., in our case, the current study is focused on the new capital city of Indonesia, or can be replicated for a similar situation domestically or globally.

2. Literature Review

The new capital IKN was promulgated through Act No. 3 of 2022, and its implementation is through Government Regulation Number 17 of 2022, which explains funding and development regulations. Presidential Regulation Numbers 62 and 63 of 2022 are an effort to align all administrative and technical resources to accelerate the planning and supporting infrastructure development in IKN and realize the mandate of statutory regulations. As stated by de Vries [12], stakeholders must strive for sustainable energy in IKN because the city will be developed, which will require massive development of transportation, markets, housing, and workplaces to support liveable, green cities [12], [13], [14]. On the opposite, if this city carries the concept of a green city, then the best example may originate from the suburban and remote areas where vegetation is taken in place and has more immense proportions compared to the manmade infrastructures; some of the studies mention that EV may not be suitable for the suburban or remote area [18], [19], [20]. Regarding this matter, did the stakeholders consider these premises before designing and starting construction? Another thought from Rodrigues's publication [18], "The expected increase of the charging power required by EV batteries will change the planning processes of power distribution utilities as urban planning agencies," leads to the concept that precautions are required when electricity demand goes high due to EV utilisation getting broadened. Previous studies mention the location and allocation terminology of EVCS modelling, which emphasises two basic meanings, as mentioned by Motoaki [22].

- Node presentation approach (this depends on the road network nodes and the distance between the origin and destination endpoints)
- Flow capture approach (this approach relies on vehicle flow data on each connected road network, requires more computing resources, and indicates monitoring in time series, and stochastic traffic flow modelling is preferred use)

This study uses a node-serving approach where virtual settlements of populated cities can be simulated to reduce the complexity of electric vehicle traffic. The IKN regional classification comprises three zones: 1. KIPP (Government Authority Centre), 2. East Zone (intended for business, workplaces, hotels, etc.), 3. West Zone (intended for universities, settlements, trade centers, workplaces, etc.)

3. Methodology

3.1. Spatial Distribution Framework

The challenge of pinpointing optimal locations for EVCS is identifying the dependent infrastructure that depends on available parking spaces, dedicated power lines, road access, safe locations, and more. In addition, difficulties will increase if the infrastructure has not been constructed yet. Therefore, the best we can do is use SMS since the concept of spatial distribution inside the SMS method is a form of interaction between several variables inside defined ranges or scales without concern for whether the infrastructure exists or not

[20], [21], [22]. The spatial distribution emerges from the interaction between each point variable regarding direction and position; these are useful for various interpolation methods. The expression approach for random spatial distribution with Monte-Carlo can be written as

$$\mathbb{E}_{(X)} = \int x f(x) dx \quad (1)$$

Where $\mathbb{E}_{(X)}$ is the expected value component in random properties, X is a probability density function, and f is the average value generated by infinite or discrete experiments that result in X. Due to this study generating the model inside a discrete road for the EV movements, the equation can be developed as

$$\lim_{n-\infty} \frac{1}{n} \sum_{i=1}^{\infty} \varphi(X_i) = \mathbb{E}_{\varphi(X)} \quad (2)$$

where $\mathbb{E}_{\varphi(X)}$ is the term of finite expectations. However, due to the constrain over the shape boundaries given in spatial, the dependency of the equation can be expressed as

$$\frac{1}{n} \sum_{i=1}^{n} \varphi(X_i), \text{ where } \mathbb{I}_{polygon}(x, y) \begin{cases} 1 & if\ x^2 + y^2 \leq r \\ 0 & otherwise \end{cases} \quad (3)$$

Where the expectation is limited to such two-dimensional (2D) geometrical forms and $x^2 + y^2 \leq r$It is the terminology of the generated boundary area.

3.1.1. Agent-based model implementation for EV mobility

This study emphasizes the imperative contribution of ABM as a challenging approach toward non-linear modeling of EV mobility. As a derivative of Artificial Intelligence that is commonly used to solve management strategies and services for EVs [26], most ABM studies were employed in particular for specific scopes like human disease spread [23], [24], transportation [25], or hazard modeling [4], [26]. ABM can figure out the distribution of EV in the spatial area and discrete boundaries [27]. Nonetheless, its implementation may illustrate different assumptions depending on the assigned author, but as a scientific approach to random states, it is one of the most reliable methods. The empirical equation is adjusted from the Von Neumann Neighborhood that can be written as [32]

$$Z_{ij} = \{(i, j+1), (i.j-1), (i+1, j), (i-1, j)\}$$

$$s.t. \begin{cases} (i, j) = \alpha, and\ \alpha \neq 0 \\ (i, j) = 0,\ if\ agent\ not\ assigned \end{cases} \quad (4)$$

Where the boundaries have a length with certain spatial dimensions in a two-dimensional shape *(s.t. stands for "so then" in mathematical terms)*. Next, the derivative of eq. 4 that governs the simple forms the *n* as the number of the assigned agent, while $C_{ABM}^{(n)}(t)$, is the occupation of agents in time (t), and *N* is the average agent density over time, then it can be defined as [32]

$$\mathbb{Z}_{ij} = C_{ABM}^{(n)}(t) = \frac{1}{N} \sum_{n-1}^{N} C_{ABM}^{(n)}(t) \quad (5)$$

The observation sections are limited to reduce the computational burden on resources for modeling the ABM in the IKN road network.

3.1.2. Monte-carlo markov chain (MCMC) intervention for EV mobility

In general, MCMC is frequently conducted to gather information about the natural process that formed due to the non-linear conditions, such as the movement of the object in relationship with the others based on their interest [33], [34], [35]. Madrigal-Cianci [8] stated, "Markov-Chain is computed expectation that arises in stochastic simulations where the stochastic model cannot be simulated exactly, but rather approximated. " While Grewal mentioned that MCMC is a form of transition from one state to another depending on the current or past condition, still, the possible approach to estimate it is in discrete time". The sufficient studies about MCMC that are employed to estimate EVCS with GIS have been performed interestingly by Shepero [36] and Martins [37], which deliver "sensing" terminology to achieve their model estimation. Simple empirical equations can be written as published by Sefrozo [38]

$$P\{X_{n+1} = j | X_0, \ldots, X_n\} = P\{X_{n+1} = j | X_n\} \quad (6)$$

$$P\{X_{n+1} = j | X_n = i\} = p_{ij} \quad (7)$$

It can be determined that *X*= $\{X_n : n \geq 0\}$, expected that $\mathbb{M}$ is Markov-chain in finite 2D dimensions $i, j \in \mathbb{M}$, p_{ij} is a matrix generated from transition probabilities and X_{n+1} is defined as independent; however, the distance and direction still refer to the prior conditions.

3.1.3. Performing optimal location in the ratio

In order to identify the optimal conditions for the EV model simulation, it is crucial to assess how often vehicles traverse the designated coverage area. This research aims to achieve this by solving a straightforward equation that incorporates the elements contributing to the ecosystem. This can be articulated as

$$\eta = \sum_{n=1}^{i} (I_n * \frac{d_n(r_n)}{d_{s(r_n)}}) \partial t * 100\% \quad (8)$$

Where η is the optimal ratio, I_n is electricity infrastructure availability, d_n is the number of vehicles in (*n*-steps) inside EVCS ranges, while d_s is the opposite, r_n is the defined range of EVCS in (*n*-steps) in a discrete observed time ∂t. Since the infrastructure can be determined in 0 for non-existing and 1 for available, this study considered that power outlets were available on demand.

3.2. Background and Presumption Setting

Determining the EVCS location can differ for each city; it depends on the infrastructure, geographical setting, policies, crime index, drivers' behaviors, and socioeconomic backgrounds. Since all the non-technical elements are varied and difficult to map, particularly for "ongoing city". This study wipes out *those parameters associated with vandalism, economic influences, tourism, and* other variables. However, technical issues associated with energy demand in KIPP still need to be determined since the city's development is currently being executed. The applied modelling of EVCS refers to what has been done by many studies [39], [40], [41], [42], [43], and the performing simulations with a premise as such.

1. `Steps1-Road-Network Systems (RNS)

Thorough knowledge of RNS is essential for spatial processing. Consequently, acquiring EV datasets related to speed, travel distance, and electricity consumption per kilometer is optional. This can enhance the model's precision. In general, RNS analysis played a vital role in aiding the development of optimal allocation, in addition to the power infrastructure model, which includes components like power lines, transformers, and power outlets. The Road Network System (RNS) is being analyzed within an area measuring approximately 35 km by 41.5 km, where the planned city of IKN is under construction. This area has been selected to facilitate the extensive movement of vehicles to and from the capital city. The RNS is spatially delineated and published by relevant stakeholders to ensure that its predictions align with the infrastructure constructed by the contractors.

2. Steps2-Electric Vehicle Types

Determining the EV types is crucial because different types of EVs can lead to different energy demands and ranges of mobility [44]. Although EV electrical components can vary in durability over time, depending on how they are maintained, factory setup still becomes a reference for their durations [45], [46]. *Premise*—Former studies have conducted research for EVs in existing cities, which is relatively easy to tackle. However, selecting the vehicle for a hovering-on-going town is a different story. Therefore, we use the low-to-medium range of EVs, which was chosen best because they are more reliable for daily workload transit and commuting vehicles.

3. Infrastructure "City-Planning"

Regarding what is stated by IKN Authorities (OIKN), the map of the city can be found in the handbook of IKN published by the Ministry of National Development Planning/National Development Planning Agency [21] where the residential, commercial and government centres separated in the certain distances. in refers to that, the different phases of electricity also distributed to different consumers in the capital city (offices, stores, and housing), its usage for EVs is different. The required power capacity of 1500 megawatts (MW) with varying voltage is generally supplied through the planned transmission lines of 500 kilovolts (kV), then down to the sub-transmission line of the existing 150 kV. It feeds to the distribution feeder of 20 kV and ends at the end-user point-of-connection (PoC) curb [10]. *Premise*—the interconnection of electricity infrastructure in IKN and greater Kalimantan will reverberate that the electricity supply is sufficient. Nonetheless, the underground powerline and conventional network are not yet publicly available in detail; in that scene, we assume sufficient power delivery would be distributed fairly to the KIPP in this study.

3.3. Implementation and Data Modelling

Spatial maps from IKN are available publicly and can be accessed through dedicated platforms. However, the details of the dataset that contains information about infrastructure have not been shared widely for security reasons. It is inferred that essential data has been kept to avoid misinterpretation, but some specific data are disclosed due to the necessity of research on EVCS. This study utilized spatial analysis to estimate Electric Vehicle Charging Stations (EVCS) through the application of the Agent-Based Model (ABM) concept and Markov Chain Monte Carlo (MCMC) methods. These analyses were visually represented within a Geographical Information System (GIS), subsequently integrated into a Spatial Management System (SMS), and provided a detailed preview of the KIPP area within the capital city of IKN.

The analysis of the dataset revealed distinct cluster types: the dark-blue region is designated for workplace construction, while the light green area is allocated for residential housing. According to the Ministry of Energy and Natural Resources, in collaboration with the National Electricity Company, Electric Vehicle Charging Stations (EVCS) are planned to be installed in the office area located in the northeast of IKN. Based on this information, the present study evaluates the effectiveness of these locations in providing electricity to electric vehicles. In determining the placement of EVCS using Markov Chain Monte Carlo (MCMC) methods, it is essential to establish a specific boundary to ensure that random points are not plotted outside the designated region. Furthermore, the assumption was made that outlet power had been installed across all segments of the area of interest. This allows for the estimation of the potential for EV users to drive to and from the nearest charging stations, based on distances and their battery capacities. [41]. This study also proposes several parameters, such as random generation from MCMC, and Figure 1 shows the planning map of IKN with different dedicated boundaries distinguished by colors.

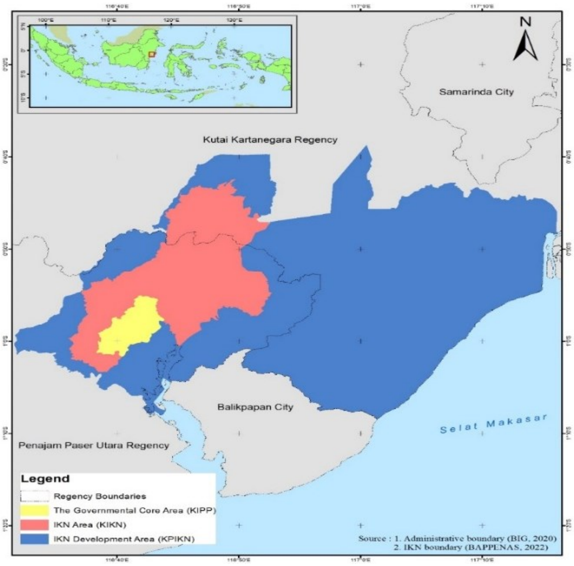

Fig. 1. An overview of the IKN map.

Because KIPP does not allow two-wheeled vehicles, as regulated by OIKN, four-wheeled vehicles and more will be designed to travel inside KIPP. Certainly, the vehicles do not use fossil fuels. So, EVCS allocation becomes critical. The allocation of EVCS should not be too close to each other; 250 meters in distance is deemed sufficient. There is no limitation on the maximum distance of the EVCS, but to be adequate, it must be at a reasonable distance (less than 250 m will be too inefficient in maintenance). Table 1 presents the details of each model, including their parameters. The computational work is conducted using the R programming language and MATLAB, while the results are displayed with ArcGIS. The Agent-Based Model (ABM) was employed to represent the locations of vehicles during their journeys within IKN. To achieve this, five stages were randomly chosen and designated as movement steps, with each agent being assigned its corresponding state of charge (SoC) battery conditions.

Table 1. MCMC for spatial modeling of EVCS within the KIPP area

Attribute	Number of EVCS being generated	Distance (m)	Description
Iteration 1	25	250	This model represents the variable distance between EVCS with a maximum proximity of 250 m.
Iteration 2	25	250	
Iteration 3	25	250	
Iteration 4	25	500	This model represents the variable distance between EVCS with a maximum proximity of 500 m.
Iteration 5	25	500	
Iteration 6	25	500	
Iteration 7	22	750	This model represents the variable distance between EVCS with a maximum distance of 750 m, but due to this, the number of stations was reduced to 22 automatically.

Figure 2 shows the dedicated region in KIPP-IKN as the basis for modeling EVCS.

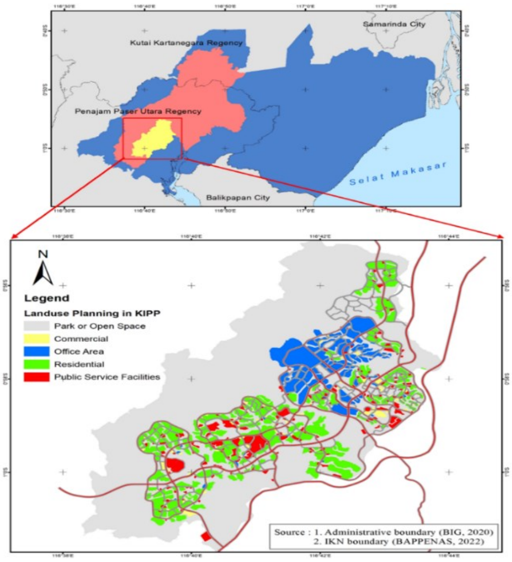

Fig. 2. The dedicated region in KIPP-IKN is the basis for modeling EVCS.

3.4. Workflow and Spatial Interpolation

Spatial interpolation is used to understand the relationship between each model generated by MCMC. This study workflow is shown in Figure 3. The generated models come from the simulation, demonstrating the primary distribution of EVCS, predominantly placed in the "open space area". Moreover, the nine-random model iteration within the KIPP area illustrates to what extent EV issues can be addressed by EVCS availability when batteries drain. The closer to the charging station, the better it is for charging and prolonging the time-use and economic usability.

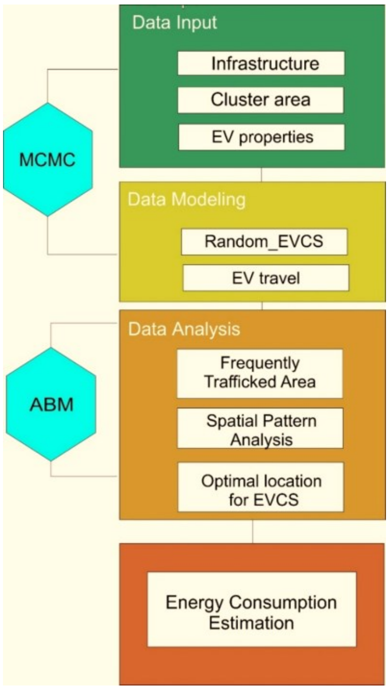

Fig. 3. Schematic workflow diagram of EVCS location-allocation (LA) scenarios.

Furthermore, Table 2 shows the LA cluster of the MCMC-generated model. Proximity ranges between EVCS are adjusted incrementally from 250 m, 500 m, and 750 m to assess the significance of distance on willingness to charge.

Table 2. Generated the location of EVCS by random spatial modeling within the KIPP area

Location and Allocation (LA) Areas					
Model ID	PS	C	R	O	OS
25/250_it1	4	0	5	1	15
25/250_it2	0	1	4	2	18
25/250_it3	1	1	4	0	19
25/500_it1	1	1	7	3	13
25/500_it2	2	1	7	4	12
25/500_it3	3	0	7	2	13
22/750_it1	2	3	7	0	10
22/750_it2	3	0	9	0	10
22/750_it3	3	0	4	4	11

Public Service (PS); Commercials (C); Residential (R); Office (O); Open Space (OS)

The random Electric Vehicle Charging Station (EVCS) location, as previously indicated in Table 2, is identified by the code as either 25 or 22. This number is generated through simulation processes to determine the quantity of EVCS. The proximity distances are set at 250, 500, and 750, with 1 serving as the iteration identifier. The Markov Chain Monte Carlo (MCMC) algorithms yield a dispersed pattern, as evidenced by the high critical value (z-score). This means there is no regular pattern in the distribution of each random point representing an EVCS installation, as seen in Figure 4.

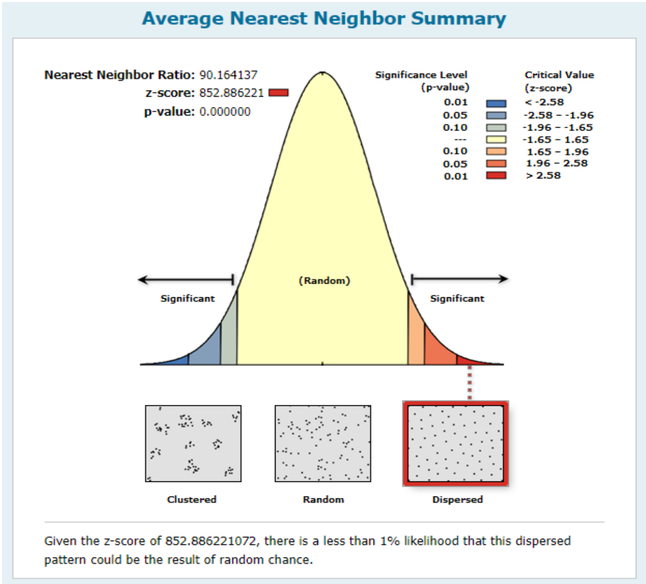

Fig. 4. The average nearest neighbor test result for EVCS's randomly distributed location.

As mentioned, five-stop positions were captured concerning states, indicating the SoC level. The 20% is for a minimum battery level, and 100 % is for the maximum level for each EV allowed to be operated at KIPP and its agglomeration areas, as depicted in Figure 5.

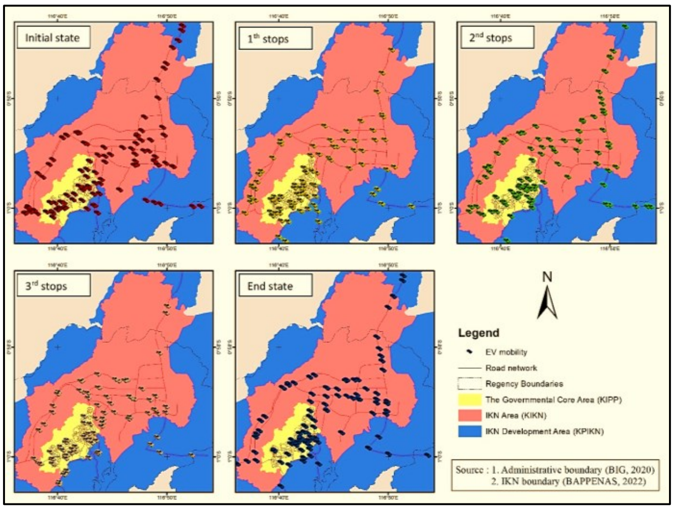

Fig. 5. The five stages of EV mobility captured in the traffic simulation in KIPP and agglomeration areas.

The model corresponding to Table 2 can be shown in Figure 6, which shows the charging station position in different clusters. The KIPP area can be categorised into five types: commercial, residential, public service, office, and open (green) space. In fact, due to confidentiality or strict data access, which resulted in a lack of data on EVs in KIPP, this study could not evaluate the actual energy demand in AOI. However, the best approach is to use traffic modeling using ABM. Table 3 illustrates the random energy consumption associated with ABM modeling performed during the simulation of a hundred vehicles.

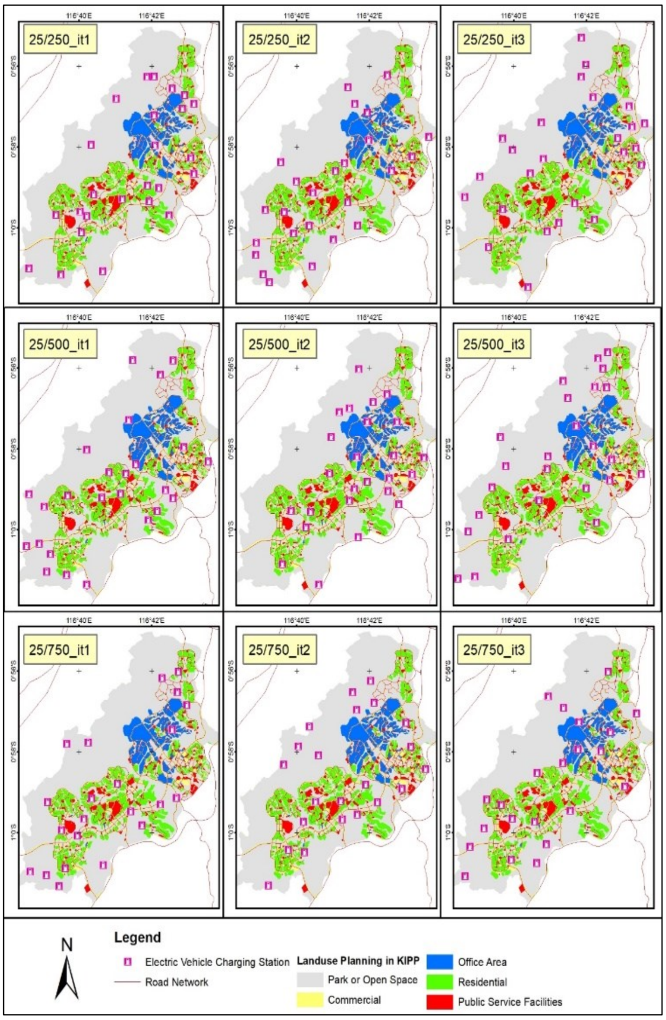

Fig. 6. Model generated for EVCS in the KIPP area using MCMC and plotted in GIS.

The EV properties and brands are selected within their maximum range and their efficiencies. Furthermore, the model references are chosen according to the market share, which includes customization and justification made for research intention and the context of an economic and environmental urban area.

Table 3. EV model reference in this simulation

EVs Model Reference		
Type	Max Range [km]	Efficiency [Wh/km]
Hyundai Kona	390	145-168
Wuling air EV	300	80-92
Nissan Leaf	235	110-128
Tesla Model 3	420	135-142
Kia EV6	410	178-185

In addition, the dataset was obtained from the domestic EV data repository [43], socio-economic potential in another country as a comparison [48], and combined with our previous observations study for the Indonesian EV market share and current potential product acceptance [44]. Subsequently, the random model that produces EV proportionally can be seen in Figure 7. From this, it can be described that out of one hundred EV vehicles that enter and exit the AOI, most are short- and medium-mileage EV types.

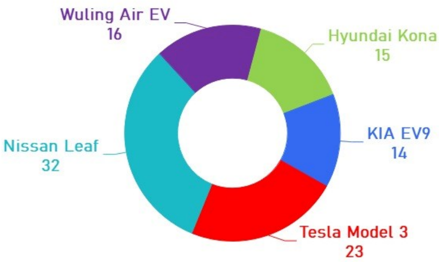

Fig. 7. MCMC generated a portion of the vehicle modelling in this study.

Figure 8 shows the spatial-agent-based model from EV, as illustrated in Figure 7, with a random SoC attached. In addition, that particular battery level will indicate their willingness to stop by the closest charging station.

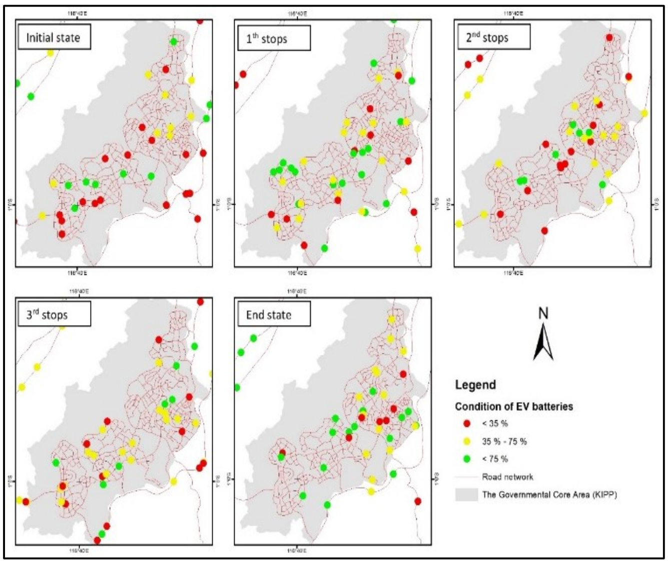

Fig. 8. EV mobility within the KIPP area from ABM modeling with five-step conditions; the red dot indicates the batteries of EVs with less than 35% of their full capacity, the yellow dot is between 35%-75%, and the green dot is >75%.

3.5. Data Modelling and Simulation

3.5.1. Markov chain monte carlo model for EVCS

The initial simulation using MCMC was executed in an open-source statistics platform with R language and R-studio as interpreters, though it can also be done in popular computing languages such as Python, MATLAB, or Julia. For a start, the Markov chain is fundamentally stochastic, capturing randomness and uncertainty. Moreover, its distribution can be helpful in approaching non-linear behaviors, optimizing profits, and simulating vehicle mobility, energy usage, disease, and many more.

Recall that as in eq. 7 to have Monte Carlo transition matrix MCa = P_{ij}

$$P\{X_{n+1} = j | X_n = i\} = P_{ij} \tag{9}$$

Where no time variation in the model [steady state] and p_{ij} is the transition probabilities, where the properties of the stochastic model with random variables are supposed to be $Z_1, Z_2, \dots, Z_n$ and $X_0 = 0$, as the initial stage condition of integer random variables, so it can be understood that

$$X_n = \sum_{i=1}^{n} Z_{(i,i+1,..)}, n \geq 1 \tag{10}$$

Because of $X_{n+1} = X_n + Z_{n+1}$ and Z_{n+1} is an independent variable of $X_0, \dots, X_n$, as described for $i, j \in S$ and n ≥ 0, eq. 7 can be expanded as

$$P\{X_{n+1} = j | X_0, \dots, X_{n-1}, X_n = i\} = P\{X_n + Z_{n+1} = j | X_n = i\} = P\{Z_1 = j - i\} \tag{11}$$

Where X_n = MCh & MCa = $P_{ij} = P\{Z_1 = j - i\}$ (12)
MCh is an abbreviation of Markov Chain, furthermore the recursive equation $X_n = X_{n-1} + Z_n, n \geq 1$, where $X_n; n \geq 0$ is a stochastic process with the probability of a variable that can be written as

$$X_n = f(X_{n-1}, Z_n)|_c; n \geq 1 \tag{13}$$

where c is the probability value in n, Hence, with the addition of transition matrix probabilities, eq.12 can be simplified to

$$P_{ij} = P\{f(i, Z_1)|_c = j\} \tag{14}$$

Hence, it can be substituted into eq. 11, then later can be expressed as

$$P\{X_{n+1} = j | X_0, \dots, X_{n-1}, X_n = i\} = P\{f(i, Z_{n+1}) = j | X_0, \dots, X_{n-1}, X_n = i\} = P\{f(i, Z_{n+1}) = j\} = P_{ij} \tag{15}$$

Algorithm of MCMC for EVCS Allocation
1. Procedure MCMC (*rand_var*= $X_i, X_{i+1}, ..X_n, X_n \in I_i$ where I_i integers)
2. Sample with step size ($\theta^i \sim \theta^{i+k}$); set.seed (*var_S*);
3. for n = 1, …, rand_var (Xn) do
4. Sample of Maxima (R(max)) and Minima(R(min))
5. set ranges of $P\{X_n + Z_{n+1} = j \| X_n = i\} = P\{Z_1 = j - i\} = P_{ij}$
6. through step size θ^{i+k}, where i+k ≥ 1
7. runif $P\{X_n + Z_{n+1} = j \| X_n = i\}\|_{R(min)}^{R(max)}, \theta^{i+k}$
8. end for
9. sets of spatial features (library (sf))
10. func. f(x) = $\int_i^{i+k} g(x)\|_r$ as Boundary
11. st_sample (func. f(x), *rand_var* (Xn))
12. Output $\{Boundary\ [X_n = MC_h]_{n=0}^{N}\}$,

where N is the length of *rand_var*
13. End Procedure

*The terms of MCaMCh are equal to MCMC for simplification in writing

In the nine iterations that are being made through MCMC algorithms, the random position of EVCS falls in the specific cluster area, such as "Public Service", "Commercial", "Residential", "Office", "Open Space", each of them has a different value. However, we do not know in detail whether a public service location should be of better in value than open space or vice versa, since infrastructure readiness may have a discrepancy. However, open spaces will likely need more shelter construction than other areas. For example, two of the best models are given in Figure 9.

> Mod1

	Public Service	Commercial	Residential	Office	Open Space
[1,]	0.09037648	0.1922177	0.128976643	0.27356916	0.3148600
[2,]	0.23781785	0.1210023	0.084223487	0.10739478	0.4495616
[3,]	0.34902389	0.0350837	0.123420755	0.11724116	0.3752305
[4,]	0.32416250	0.1790662	0.008996365	0.09992144	0.3878535
[5,]	0.03307515	0.2496851	0.152921951	0.26933801	0.2949798

> Mod9

	Public Service	Commercial	Residential	Office	Open Space
[1,]	0.2633636	0.22839296	0.05071804	0.146907223	0.3106182
[2,]	0.2067878	0.23723789	0.01286492	0.252816829	0.2902926
[3,]	0.0522109	0.28963939	0.13254328	0.087507150	0.4380993
[4,]	0.1081684	0.01592188	0.24601796	0.250359617	0.3795322
[5,]	0.2154239	0.31956314	0.10712984	0.008580713	0.3493024

Fig. 9. MCMC transition matrix from the best iteration made in the 250 m and 750 m range.

As the model goes into further analysis, the visualization of how each transition matrix correlates with the simulation can be illustrated in Figure 10.

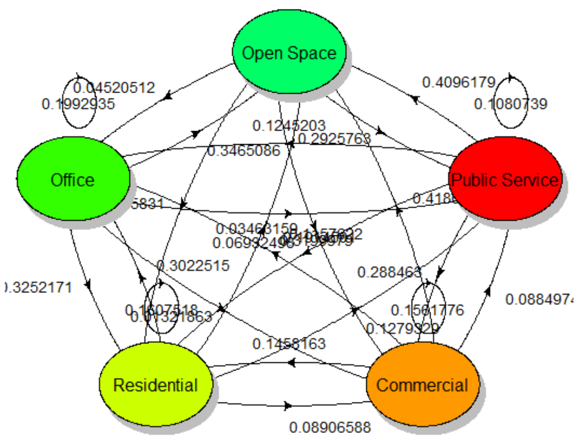

Fig. 10. The MCMC sample from the simulation, used to define EVCS in the KIPP area, shows five categories of designated areas: open space, office, public service, residential, and commercial. The higher the aggregate value directed to the designated area, the more likely it is to be chosen as a location.

In further visualization, an important question emerges regarding the proportion of the optimal location allocation (LA) when categorized by electric vehicle charging station (EVCS) areas within the KIPP boundary. This inquiry is crucial, as it reflects not only the spatial distribution of charging infrastructure but also the balance between different functional zones such as commercial, residential, office/workplace, open space, and public service areas. To address this, we plot steady-state variables derived from the Markov Chain Monte Carlo (MCMC) simulation, which provides a probabilistic representation of vehicle movement and charging demand across the designated clusters. The resulting radar map illustrates the allocation tendencies, highlighting the relative weight of each category and revealing patterns of concentration or dispersion that may influence planning decisions (see Figure 11). This visualization enables a clearer understanding of how optimal LA proportions align with the broader objectives of sustainable urban mobility, while also offering insights into potential adjustments needed to ensure equitable access and efficient utilization of EVCS infrastructure.

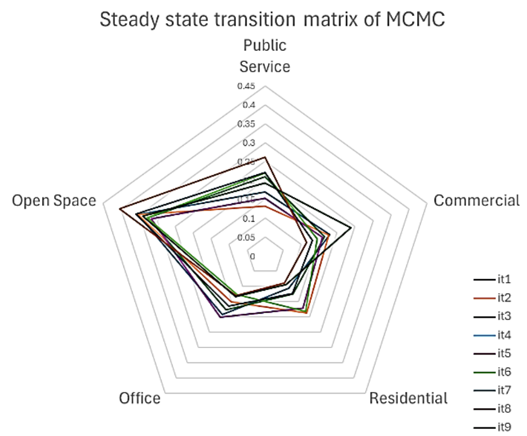

Fig. 11. The radar map illustrates the tendencies of EVCS allocations in KIPP based on the simulation in different area types.

3.5.2. *Simulation of ABM to demonstrate the traffic inside IKN*

We use MATLAB as our simulation platform for ABM, and combined it with the GIS software to have better geo-visualisation; additionally, the diagram of ABM is depicted in Figure 12

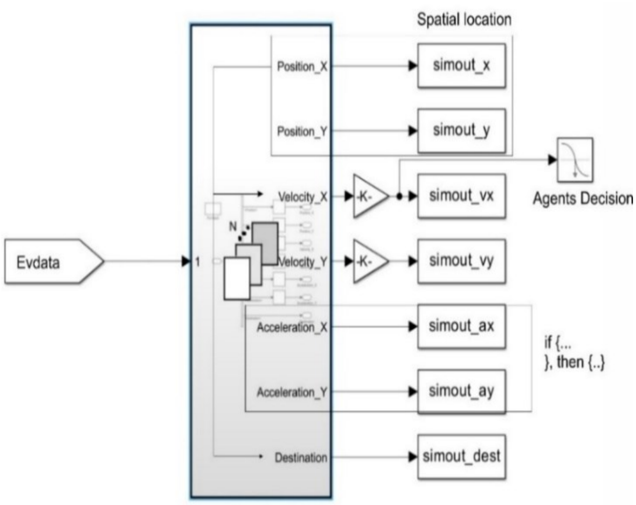

Fig. 12. The ABM simulation design for EV movement inside KIPP with MATLAB platform (Modified from [42]).

In the modelling framework, the size of the model is essential to find the definitive function; while we call this framework the finite dynamical system (FDS), where it is tied to the time-discrete dynamical system, let $a_1, \dots a_n$ as the variables, which are inside the finite set of M. Hence, we realise that the variables are synchronous over time and give an update to the function (f_i). Now, we can express it as $f_i = M^n \to M$, where the terms of "synchronisation" in the finite predefined area were described as the terms of "local update ecosystem", where the *i-th* condition is taking place. This generates the function in a dynamical ecosystem, which can be expressed as

$$\Upsilon = (f_1, \dots, f_n): M^n \to M^n \tag{16}$$

With the dynamic generated by the iteration of ϒ. For instance, if M = {0,1} with the Boolean operators "AND" and "OR" in computational or mathematical models, we can call them as Boolean networks. A simple term for a function n dynamical ecosystem can be written as

$$\Upsilon(a_1, \dots, a_n) = (f_1(a_1, \dots, a_2), \dots, f_n(a_1, \dots, a_n)) \tag{17}$$

Supposed to be $\pi = \{1, \dots, n\}$, the function can be transformed in

$$\Upsilon_\pi = f_{\pi 1} \circ f_{\pi_{n-1}} \circ \dots \circ f_{\pi_n} \tag{18}$$

Because ecosystems are independently updatable and inherent to the behavior of agents when faced with "obstacles" or "fluidity" toward the next state of functioning. It can be expressed as

$\Upsilon_\pi = f_1 \circ f_3 \circ f_2 \circ \dots \circ f_{i \pm r}$ where *i+r* is the recent state relative to the upcoming state. It may be illustrated in terms of a matrix as,

$$\begin{bmatrix} 1 & 4 & n1 \\ 2 & 1 & n2 \\ 7 & 5 & 1 \\ \dots & \dots & \dots \\ n1 & n2 & n3 \end{bmatrix} + \begin{bmatrix} 1 & 8 & s1 \\ 4 & 1 & s2 \\ 8 & 6 & 1 \\ \dots & \dots & \dots \\ s1 & s2 & s3 \end{bmatrix} - \begin{bmatrix} 1 & 3 & d1 \\ 1 & 1 & d2 \\ 4 & 3 & 1 \\ \dots & \dots & \dots \\ d1 & d2 & d3 \end{bmatrix} = \begin{bmatrix} 1 & 9 & n1+s1-d1 \\ 5 & 1 & n2+s2-d2 \\ 11 & 8 & 1 \\ \dots & \dots & \dots \\ n1+s1-d1 & n2+s2-d2 & n3+s3-d3 \end{bmatrix}$$

The condition matrix can be simply defined as {Initial Condition + Accelerates – Brakes = Final Condition}, which can be shown in a simple diagram box as illustrated in Figure 13.

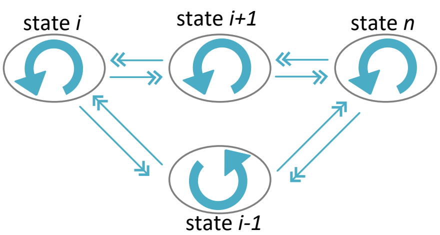

Fig. 13. ABM diagram to illustrate the mechanism of EV movement, where *i* is the initial stage and *n* is the upcoming stage.

The EV's position from ABM could be extracted in terms of longitude and latitude. Those positions can be known as "ongoing" or "final destination"; those terms are always tied to a specific time and space. Later, we plotted using GIS software to see their distribution. On the other side, to give a better perspective on EV scenarios in the IKN, particularly at KIPP, we have illustrations in Figure 14. The steps symbolized by S mean the stages of Ev's condition being taken as samples, whether in power consumption, distance, or position.

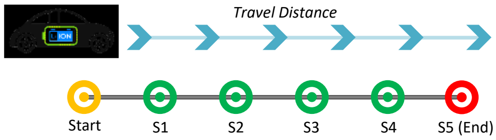

Fig. 14. The traveling scenario of agents to simulate EV mobility in the KIPP area (modified from [18]).

In spatial perspective, with the area as a point of view, the illustration in Figure 14 would not be sufficient to give a better picture of what was going on; therefore, in Figure 15, a spatial illustration is provided

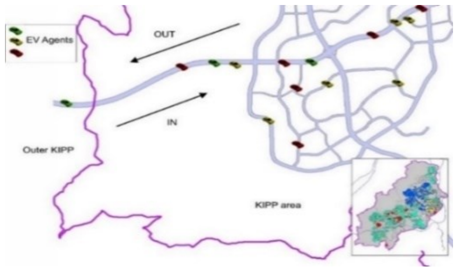

Fig. 15. The illustration of traffic inside KIPP-IKN using ABM simulation to estimate the energy consumption of EVs.

4. Results

The EV simulations were conducted in KIPP and its agglomerate area to provide a broader perspective. Five stops, including start and end points, have been generated using the MCMC method to solve the various vehicle positions. Although it is limited to the KIPP area, EVCS is expected to focus on installation in this region for the initial plan. The detailed dataset from the regional and city planning maps sourced from the IKN authority shows five cluster locations: commercial, residential, office/workplace, open space, and public service area.

Table 4. The optimal ratio generated from the simulation for EVCS placements

Model ID	EVCS Non-optimal LA	Optimal Ratio
25/250_it1	3	88 %
25/250_it2	6	76 %
25/250_it3	7	72 %
25/500_it1	9	64 %
25/500_it2	4	84 %
25/500_it3	11	56 %
22/750_it1	5	80 %
22/750_it2	6	76 %
22/750_it3	3	88 %

Based on Table 4, the high percentage ratio means better LA, where the EVCS will likely be visited more frequently than the lower percentage. In addition, the infrastructure costs can be more efficient because EVs will easily access those stations. The simulation results show that most EVCS are distributed in open spaces, then residential, public services, offices, and commercial. The algorithm distributes the points within that cluster, since KIPP is planned to have more open space (if it follows the minimum closest-range ideal). Figure 10 shows the electricity consumption according to the simulation results, and the programming algorithm assigns random values as a function of range and battery capacity to each mobility agent.

This simulation models the energy consumption of specific electric vehicle (EV) types operating both within and beyond the KIPP-IKN area, with daily energy usage ranging from 1,700 kWh to 2,000 kWh. Although the simulation is limited to 100 EVs, this small-scale approach provides a practical baseline for estimating the power demand necessary to achieve the city's electrification objectives. Building on this baseline, the energy requirements for 100 vehicles entering and exiting KIPP are further examined across five mobility phases, as illustrated in Figure 14. While limited in scale, this phased analysis offers meaningful insights into the engineering design considerations for determining the electricity supply needed once the city becomes inhabited, as presented in the energy consumption model in Figure 16..

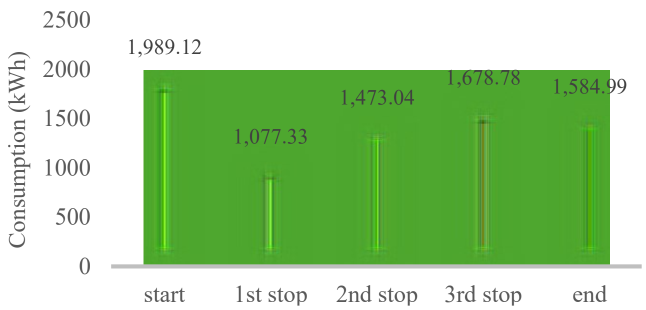

Fig. 16. Electricity consumption [in kWh/per daily activity] for one hundred EV agents in the simulated model (refer to Figure 14).

Fig. 16 shows the daily electricity use of 100 electric vehicles (EVs) in five travel phases in and around the KIPP-IKN area. At the start, energy use is high, at 1,989.12 kWh, because all vehicles begin their trips simultaneously. This quickly drops to 1,077.33 kWh at the first stop, the lowest point, as many EVs reach their first stop and are not moving. Energy use then increases to 1,473.04 kWh at the second stop and 1,678.78 kWh at the third stop as vehicles start moving again. By the end, energy use is 1,584.99 kWh as vehicles finish their trips. Overall, energy use changes throughout the day, ranging from about 1,077 to 1,989 kWh. This shows the need for a flexible charging system that can handle both high and low energy demands in KIPP.

The map associated with the simulation is depicted in Figure 17, illustrating how EVCS should be allocated. Three models of optimal location, based on the simulation in this study, demonstrate that the red dots represent EVs beginning to run low on power and moving in and out of the KIPP area. In this scenario, the driver or agent, in our case, will seek the nearest charging station to avoid stopping and towing. It provides essential information that some EVCSs are far from EVS mobility, and that accessing them is not an option for the agents. three model are 25/250_it1, 22/750_it3, 25/500_it2, which demonstrates percentages of misplacement >80 %

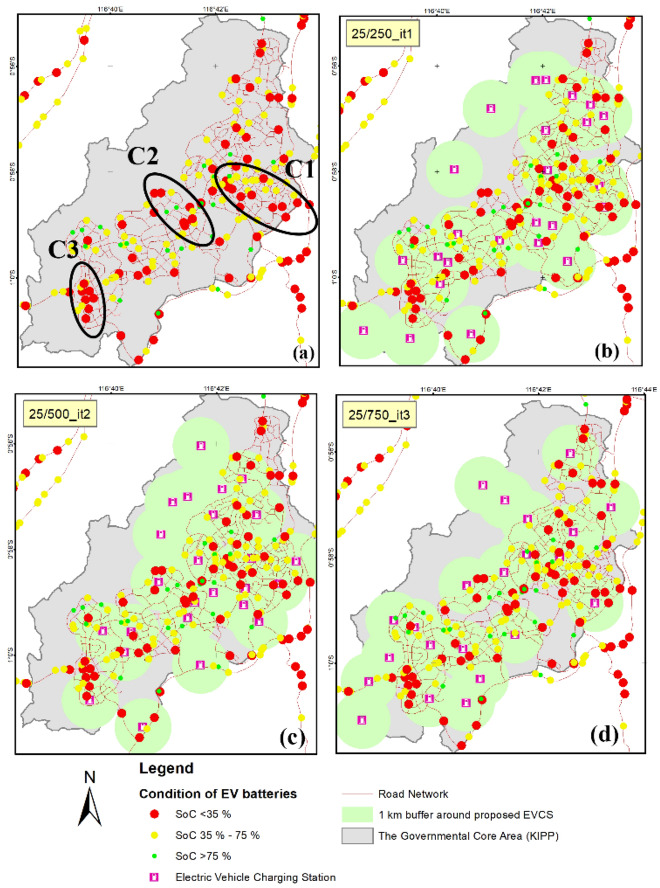

Fig. 17. The three-optimal area (C1, C2, C3) for installing EVCS is based on the traffic (ABM simulation model), which is prone to having denser EV mobility during the simulation (a). 1st preferred model 88% (b), 2nd preferred model 88% (c), 3rd preferred model 84% (d).

5. Conclusion

Using spatial model simulation (SMS) to determine the optimal allocation at KIPP-IKN is a breakthrough. Based on the simulation that was done in this study, we thought that two issues could be solved.

1. Optimal LA design scenario of EVCS in KIPP
2. Small-scale energy demand from 100 vehicles with different factory designs inside IKN

The first point is necessary because installing the charging station in the middle of nowhere or far from road access is wasting resources. Additionally, a settlement area was likely to contribute toward infrastructure capital expenditure (CAPEX) costs, as open space will need extra shelter rather than in the commercial or public space parking lot. Office location, for example, will be more reliable regarding safety and usage than in a commercial area. The terms are also applied to residential home chargers (HCs), whether they will be useful enough, since each house could have its own HC. From our simulation, if the construction in IKN follows the minimum distance between EVCS, 250 m is logically close enough, and less than that will be wasting money and resources. We achieved 88% from the simulation as an optimal allocation, meaning misplacement is always generated due to the range threshold. In summary, we see varying results by tabulating the simulation results in Table 5, which elaborates on the pros and cons. As a result, it provides stakeholders with greater insight (for decision-making), which is expected to speed up the transition process for infrastructure development, while also reducing the chance of failure and potential inefficiencies in investment infrastructure development. The latter term is strategic in the case of limited financial budget allocation.

Table 5. Results tabulation based on the simulation models

No	Simulation	Optimal Model	Description
1	250 m threshold range between stations	88 % (first iteration)	In this state, the misplacement of EVCS is 3 from 25 simulated stations. In addition, it still complies with the threshold ranges, so overlapping services and over-constructions are not an issue.
2	500 m threshold range between stations	84 % (second iteration)	In this state, the misplacement of EVCS is 4 from 25 simulated stations. Though it is better than the previous model, it still maintains the threshold of 25 stations inside KIPP.
3	750 m threshold range between stations	88 % (third iteration)	In this state, the misplacement of EVCS is 3 from 22; due to the increment of minimum threshold ranges, this model is less optimal compared to the previous one, even though the ratio is similar to the first model.

From Table 5 and the conducted simulation, we understand that designing the optimal EVCS is complex; many variables play a role, even with simplifications, and trial-and-error is unavoidable. However, iteration is still relevant in science and engineering as a learning part of the MCMC and ABM methods.

6. Future Work

Based on the results of this research, the following studies can be carried out, including: a). developing spatial optimization algorithms to improve the accuracy and efficiency of EVCS allocation; b) exploring dynamic spatial modeling methodologies to analyze temporal variations in EVCS utilization and energy consumption; c) simulating energy needs in the new capital city of IKN for vehicles and train, port, and airport operations; d) developing a scalable and adaptable framework to various contexts, considering multiple factors and input from different stakeholders.

7. Nomenclature

EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
MCMC	Monte Carlo Markov Chain
ABM	Agent-Based Model
SMS	Spatial Model Simulation
IKN	Ibu kota Negara (New Capital City)
RNS	Road Network System
KIPP	Kawasan Inti Pusat Pemerintahan (Government Centre Area)
GIS	Geographical Information System
AOI	Area of Interest
NZE	Net Zero Emission

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Author Contributions

G.P.D.: Conceptualization, Methodology, Software, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, Visualization, Analysis. N.S.: Investigation, Resources, Data Curation, Methodology, Writing – Review & Editing. L.G.: Investigation, Resources, Writing – Review & Editing. A.W.S.: Conceptualization, Resources, Writing – Review & Editing, Supervision. A.W.: Resources, Software, Project administration, external communication. D.Y.: Resources, analysis. A.K.: Project Administration, external communication, resources. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

[1] I. Veza, M. Z. Asy'ari, M. Idris, V. Epin, I. M. Rizwanul Fattah, and M. Spraggon, "Electric vehicle (EV) and driving towards sustainability: comparison between EV, HEV, PHEV, and ICE vehicles to achieve net zero emissions by 2050 from EV," Alexandria Engineering Journal, vol. 82, pp. 459-467, Nov. 2023, doi: 10.1016/j.aej.2023.10.020.

[2] H. N. Durmus Senyapar, U. Cetinkaya, S. Ayik, Z. A. Altinok, and R. Bayindir, "Importance of charging infrastructure for the public adoption of electric vehicles - recommendations for Turkey," in Proc. 11th International Conference on Smart Grid (icSmartGrid), June 2023, pp. 1-5, doi: 10.1109/icSmartGrid58556.2023.10170969.

[3] A. S. Türkoğlu, H. C. Güldorum, and O. Erdinç, "Multi-objective EV charging and comfort management considering V2G functionality and distribution system constraints," in Proc. 11th International Conference on Smart Grid (icSmartGrid), June 2023, pp. 1-6, doi: 10.1109/icSmartGrid58556.2023.10170953.

[4] D. S. Renné, "Progress, opportunities and challenges of achieving net-zero emissions and 100% renewables," Solar Compass, vol. 1, p. 100007, May 2022, doi: 10.1016/j.solcom.2022.100007.

[5] Junaidi, S. A. Adisasmita, M. S. Pallu, and M. I. Ramli, "Investigating local resources and wisdom in partner regions surrounding the nation's capital for road network development," Civil Engineering Journal, vol. 8, no. 5, pp. 926-937, May 2022, doi: 10.28991/CEJ-2022-08-05-06.

[6] F. W. Akashah, R. Ouache, J. Zhang, and M. Delichatsios, "A model for quantitative fire risk assessment integrating agent-based model with automatic event tree analysis," in Handbook of Probabilistic Models, Elsevier, pp. 107-129, 2020, doi: 10.1016/B978-0-12-816514-0.00004-7.

[7] J. K. Grewal, M. Krzywinski, and N. Altman, "Markov models-Markov chains," Nature Methods, vol. 16, no. 8, pp. 663-664, Aug. 2019, doi: 10.1038/s41592-019-0476-x.

[8] J. P. Madrigal-Cianci, F. Nobile, and R. Tempone, "Analysis of a class of multilevel Markov chain Monte Carlo algorithms based on independent Metropolis-Hastings," Journal on Uncertainty Quantification, vol. 11, no. 1, pp. 91-138, Mar. 2023, doi: 10.1137/21M1420927.

[9] K. P. Venkata and K. Swarnasri, "Multi-objective optimal allocation of electric vehicle charging stations in radial distribution system using teaching learning based optimization," International Journal of Renewable Energy Research, vol. 10, no. 1, pp. 366-377, 2020.

[10] D. A. Permatasari and S., "New national capital city (IKN) in legal polemic," KnE Social Sciences, Jan. 2024, doi: 10.18502/kss.v8i21.14801.

[11] National Government Legislators, The Act Number 3 of 2022 concerning the national capital city, 2022. [Online]. Available: https://peraturan.bpk.go.id/Details/198400/uu-no-3-tahun-2022

[12] W. T. de Vries and M. Schrey, "Geospatial approaches to model renewable energy requirements of the new capital city of Indonesia," Frontiers in Sustainable Cities, vol. 4, May 2022, doi: 10.3389/frsc.2022.848309.

[13] D. A. Ristanto, A. Jatayu, and R. Z. F. Sihotang, "Towards a sustainable new state capital (IKN): sustainable zoning plan formulation based on quantitative zoning approach," IOP Conference Series: Earth and Environmental Science, vol. 1108, no. 1, p. 012051, Nov. 2022, doi: 10.1088/1755-1315/1108/1/012051.

[14] E. Praditya, F. A. Suprapto, Y. Ali, S. Surjaatmadja, and R. Duarte, "Nusantara capital city (IKN): threats and defense strategies for Indonesia's new capital," The Journal of Indonesia Sustainable Development Planning, vol. 4, no. 1, pp. 21-34, Apr. 2023, doi: 10.46456/jisdep.v4i1.420.

[15] M. A. Berawi, "City of tomorrow: the new capital city of Indonesia," International Journal of Technology, vol. 13, no. 4, p. 690, Oct. 2022, doi: 10.14716/ijtech.v13i4.6011.

[16] R. Rifaid, M. T. Rachman, T. Baharuddin, and S. Gohwong, "Public trust: Indonesian policy in developing a new capital city (IKN)," Journal of Governance and Public Policy, vol. 10, no. 3, pp. 263-273, Oct. 2023, doi: 10.18196/jgpp.v10i3.17681.

[17] A. W. Syamroni, G. P. Dinanta, A. Kurniasari, and T. A. A. Jamaluddin, "Behavioral-alike model-driven residential charger power projection in serving private electric mobility in the new capital city of Indonesia," IOP Conference Series: Earth and Environmental Science, vol. 1267, no. 1, p. 012044, Dec. 2023, doi: 10.1088/1755-1315/1267/1/012044.

[18] M. S. Mastoi, S. Zhuang, H. M. Munir, M. Haris, M. Hassan, M. Usman, S. S. H. Bukhari, and J. S. Ro, "An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends," Energy Reports, vol. 8, pp. 11504-11529, Nov. 2022, doi: 10.1016/j.egyr.2022.09.011.

[19] K. P. Venkata, K. Swarnasri, and P. Vijetha, "Multi-objective optimal planning of renewable energy sources and electric vehicle charging stations in unbalanced radial distribution systems using Harris Hawk Optimization Algorithm," International Journal of Renewable Energy Research, vol. 12, no. 1, pp. 58-69, 2022.

[20] A. Simarro-García, R. Villena-Ruiz, A. Honrubia-Escribano, and E. Gómez-Lázaro, "Impact of electric vehicle integration on an industrial distribution network: case study based on recent standards," in Proc. 11th International Conference on Smart Grid (icSmartGrid), June 2023, pp. 1-5, doi: 10.1109/icSmartGrid58556.2023.10170797.

[21] J. L. Rodrigues, H. M. Bolognesi, J. D. Melo, F. Heymann, and F. J. Soares, "Spatiotemporal model for estimating electric vehicles adopters," Energy, vol. 183, pp. 788-802, Sept. 2019, doi: 10.1016/j.energy.2019.06.117.

[22] Y. Motoaki, "Location-allocation of electric vehicle fast chargers-research and practice," World Electric Vehicle Journal, vol. 10, no. 1, p. 12, Mar. 2019, doi: 10.3390/wevj10010012.

[23] A. M. Johansen, "Monte Carlo methods," in International Encyclopedia of Education, Elsevier, pp. 296-303, 2010, doi: 10.1016/B978-0-08-044894-7.01543-8.

[24] A. Getis, "Spatial pattern analysis," in Encyclopedia of Social Measurement, Elsevier, pp. 627-632, 2005, doi: 10.1016/B0-12-369398-5/00336-4.

[25] Z. Xu, L. Zhang, and R. Ma, "An algorithm to generate random points in polygon based on triangulation," IOP Conference Series: Earth and Environmental Science, 2020, doi: 10.1088/1755-1315/428/1/012064.

[26] S. Ruiz, J. Hernandez, and D. Borge-Diez, "V2G ancillary services management strategy for EVs with solar powered charging stations based on artificial intelligence algorithms," International Journal of Smart Grid, vol. 7, no. 4, 2023, doi: 10.20508/ijsmartgrid.v7i4.314.g304.

[27] E. Bonabeau, "Agent-based modeling: methods and techniques for simulating human systems," Proceedings of the National Academy of Sciences, vol. 99, suppl. 3, pp. 7280-7287, May 2002, doi: 10.1073/pnas.082080899.

[28] J. Panovska-Griffiths, C. C. Kerr, W. Waites, and R. M. Stuart, "Mathematical modeling as a tool for policy decision making: applications to the COVID-19 pandemic," pp. 291-326, 2021, doi: 10.1016/bs.host.2020.12.001.

[29] A. M. Wilson, P. Romero-Lankao, D. Zimny-Schmitt, J. Sperling, and S. Young, "Linking transportation agent-based model (ABM) outputs with micro-urban social types (MUSTs) via typology transfer for improved community relevance," Transportation Research Interdisciplinary Perspectives, vol. 17, p. 100748, Jan. 2023, doi: 10.1016/j.trip.2022.100748.

[30] N. Hooshangi and A. Alesheikh, "Developing an agent-based simulation system for post-earthquake operations in uncertainty conditions: a proposed method for collaboration among agents," ISPRS International Journal of Geo-Information, vol. 7, no. 1, p. 27, Jan. 2018, doi: 10.3390/ijgi7010027.

[31] X. Huang, Y. Lin, M. K. Lim, F. Zhou, and F. Liu, "Electric vehicle charging station diffusion: an agent-based evolutionary game model in complex networks," Energy, vol. 257, Oct. 2022, doi: 10.1016/j.energy.2022.124700.

[32] J. T. Nardini, R. E. Baker, M. J. Simpson, and K. B. Flores, "Learning differential equation models from stochastic agent-based model simulations," Journal of the Royal Society Interface, vol. 18, no. 176, Mar. 2021, doi: 10.1098/rsif.2020.0987.

[33] M. G. Conners, T. Michelot, E.I. Heywood, R.A. Orben, "Hidden Markov models identify major movement modes in accelerometer and magnetometer data from four albatross species," Movement Ecology, vol. 9, no. 1, p. 7, Feb. 2021, doi: 10.1186/s40462-021-00243-z.

[34] J. T. Paterson, A. N. Johnston, A. C. Ortega, C. Wallace, and M. Kauffman, "Hidden Markov movement models reveal diverse seasonal movement patterns in two North American ungulates," Ecology and Evolution, vol. 13, no. 7, July 2023, doi: 10.1002/ece3.10282.

[35] T. A. Patterson, M. Basson, M. V. Bravington, and J. S. Gunn, "Classifying movement behaviour in relation to environmental conditions using hidden Markov models," Journal of Animal Ecology, vol. 78, no. 6, pp. 1113-1123, Nov. 2009, doi: 10.1111/j.1365-2656.2009.01583.x.

[36] M. Shepero and J. Munkhammar, "Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data," Applied Energy, vol. 231, pp. 1089-1099, Dec. 2018, doi: 10.1016/j.apenergy.2018.09.175.

[37] A. Martins, I. Fonseca, J. T. Farinha, J. Reis, and A. J. M. Cardoso, "Maintenance prediction through sensing using hidden Markov models-A case study," Applied Sciences, vol. 11, no. 16, p. 7685, Aug. 2021, doi: 10.3390/app11167685.

[38] R. Serfozo, Basics of Applied Stochastic Processes. Berlin, Heidelberg: Springer, 2009, doi: 10.1007/978-3-540-89332-5.

[39] X. Li and A. Jenn, "An integrated optimization platform for spatial-temporal modeling of electric vehicle charging infrastructure," Transportation Research Part D: Transport and Environment, vol. 104, 2022, doi: 10.1016/j.trd.2022.103177.

[40] D. Ji, Y. Zhao, X. Dong, M. Zhao, L. Yang, M. Lv, and G. Chen, "A spatial-temporal model for locating electric vehicle charging stations," in Communications in Computer and Information Science, Springer, pp. 89-102, 2018, doi: 10.1007/978-981-13-1026-3_7.

[41] M. P. Anand, B. Bagen, and A. Rajapakse, "Probabilistic reliability evaluation of distribution systems considering the spatial and temporal distribution of electric vehicles," International Journal of Electrical Power and Energy Systems, vol. 117, 2020, doi: 10.1016/j.ijepes.2019.105609.

[42] J. A. Sanguesa, V. Torres-Sanz, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "A review on electric vehicles: technologies and challenges," Smart Cities, vol. 4, no. 1, pp. 372-404, Mar. 2021, doi: 10.3390/smartcities4010022.

[43] A. Saldarini, D. Martini, M. Longo, F. Foiadelli, and W. Yaici, "Assessing electric vehicle charging patterns: a comprehensive analysis of charging stations usage," in Proc. 12th International Conference on Renewable Energy Research and Applications (ICRERA), Aug. 2023, pp. 128-133, doi: 10.1109/ICRERA59003.2023.10269386.

[44] M. Gellrich, A. Block, and N. Leikert-Böhm, "Spatial and temporal patterns of electric vehicle charging station utilization: a nationwide case study of Switzerland," Environmental Research: Infrastructure and Sustainability, vol. 2, no. 2, p. 021003, June 2022, doi: 10.1088/2634-4505/ac6a09.

[45] M. Akil, E. Dokur, and R. Bayindir, "Analysis of electric vehicle charging demand forecasting model based on Monte Carlo simulation and EMD-BO-LSTM," in Proc. 10th International Conference on Smart Grid (icSmartGrid), June 2022, pp. 356-362, doi: 10.1109/icSmartGrid55722.2022.9848555.

[46] A. Di Martino, M. Longo, G. S. Prasad, F. Foiadelli, W. Yaici, and D. Zaninelli, "Implementation and validation modelling of energy demand of electric buses for local public transport," in Proc. 10th International Conference on Smart Grid (icSmartGrid), June 2022, pp. 266-270, doi: 10.1109/icSmartGrid55722.2022.9848756.

[47] S. Elmi and K. L. Tan, "Energy consumption prediction under real-world driving conditions for smart cities," in Proc. The Web Conference 2021, Apr. 2021, pp. 1880-1890, doi: 10.1145/3442381.3449983.

[48] M. Benayad, A. Rochd, N. Houran, A. Benazzouz, M. Maanan, and H. Elarabi, "Assessing the socio-economic potential of electric vehicle charging infrastructure: a machine learning based approach for Marrakech-Safi region, Morocco," in Proc. 12th International Conference on Renewable Energy Research and Applications (ICRERA), Aug. 2023, pp. 166-174, doi: 10.1109/ICRERA59003.2023.10269379.

[49] WGL, "Agent based modelling," MATLAB Central File Exchange, 2018. [Online]. Available: https://www.mathworks.com/matlabcentral/fileexchange/68720-agent-based-modeling