# An agent-based multi-objective optimization model for allocating public charging stations for electric vehicles

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## Abstract

The development of electric mobility and electric vehicles (EVs) has increased significantly over the last couple of years. It is desirable to develop smart supporting infrastructures, such as public charging stations, in order to stimulate the use of EVs. However, a charging infrastructure is only useful when a certain level of EV usage is reached. In this paper, a location allocation model of public charging stations is developed. The focus is on publicly accessible charging station using cables and plugs for recharging, which considers full EVs and plug-in hybrid EVs. The municipality of Eindhoven, the Netherlands, is used as a case study to apply the model. A scenario for the year 2020 is created to determine the settings for the model. Scenario analysis leads to recommendations on locations and quantities of public charging stations, which provides a show case of urban modeling approach to support the public facilities planning.

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## 1. Introduction

The development of electric mobility and electric vehicles (EVs) has increased significantly over the last couple of years. Global awareness about the impact of human activities on the environment has become much greater over the past decades. Resources, such as fossil fuels, are getting scarcer and pollution, especially in densely populated areas, is threatening the quality of life. Global agreements on reducing emissions have been made, targets have been set and actions have been taken to achieve environmental goals. In order to continue the process towards a cleaner and more sustainable environment, innovation is needed. Urban areas can still improve significantly to become more sustainable. New developments in the field of electric mobility will contribute to reach sustainability goals. The use of EVs in urban areas will decrease carbon emissions, increase the air quality and contribute to the overall quality of life.

The use of EVs largely depends on a supporting charging infrastructure. EVs and a charging infrastructure are interdependent. The development of EV usage requires a supporting infrastructure and installing a charging infrastructure is only useful when a certain level of EV usage is reached. This interdependence results in a great challenge for the development of electric mobility. It is assumed that in order to disrupt this dependency circle a supportive charging infrastructure must be in place prior to the introduction of a new technology (Sovacool and Hirsh, 2009).

It is desirable to develop a supporting infrastructure in order to stimulate the use of EVs. However, the development of a public infrastructure is hampered because currently there is no profitable business case for public charging stations in the Netherlands. Most of the developments for a public charging infrastructure are generally initiated as pilot projects by governments, network operators and research institutes. It is expected that after 2015 a profitable business plan for public charging station can be developed (Wouters, 2013) and that the market for public charging services will grow from a developing market to a mature market (Jansen and Lycklama, 2011).

A growing market for public charging services presents new challenges. This paper focuses on the spatial challenges that a growing market for public charging services entails. The objective of this paper is to create a location allocation model for public charging stations. The municipality of Eindhoven will be used as a case study to apply the model to the real world. A scenario for the year 2020 is created to determine the settings for the model. Scenario analysis leads to recommendations on locations and quantities of public charging stations, which provides a show case of urban modeling approach to support the public facilities planning.

The structure of this paper is as follows. This introduction is followed by a section on the background information on public charging stations. Section 3 presents the location allocation model. Thereafter, section 4 discusses the simulation results. Finally section 5 wraps up the paper with a short conclusion.

## 2. Field of public charging station

Over the last couple of years, the development of electric mobility is growing rapidly. The performances and costs of batteries of EVs are perceived as one of the greatest barriers for the development of electric mobility (Boekema and Rumph, 2010). A distinction is made between full electric vehicles (FEV or BEV) and hybrid electric vehicles (HEV). FEVs are solely driven by batteries while HEVs are driven by both a combustion engine and batteries. Plug-in hybrid electric vehicles (PHEV) are hybrids which can be plugged in for recharging. Since this paper focuses on public charging infrastructures for EVs it only considers FEVs and PHEVs.

The sole purpose of a (re)charging station is obviously to replenish batteries of EVs. There is a wide variety of charging stations and applications of charging stations. Besides recognising all modes and types of charging stations, it is most important to acknowledge the different applications of charging stations and usage patterns. In this paper, the focus is on publicly accessible charging station using cables and plugs for recharging, other techniques are not within the scope of this paper. Publicly accessible charging stations can be divided into public charging stations, extended private charging stations and semi-public charging stations.

To further stimulate EV usage and to increase the deployment of charging stations, standards are essential. The main purpose of standards is to ensure that EV drivers can safely and conveniently enjoy the use of both EV and charging station which increases user acceptance and decreases costs (ACEA, 2012). The (re)charging speed is determined by the capabilities of both charging station and EV. For EVs the on-board charger determines the charging power of the EV. Matching EV usage patterns with types of charging stations will also stimulate the future development of charging infrastructures. The “charging tree” (Ladder van Laden in Dutch) presented by the Dutch Ministry of Economic Affairs and the Taskforce Formule E-Team (Gastel, 2013) is a guideline for the implementation of charging infrastructures on the basis of cost-efficiency, which matches the use of stations by prioritizing the types of charging stations.

In addition, charging stations also have limitations regarding efficiency in terms of utilization. The practical capacity of a station will be significantly less than the theoretical output of the station because in practice the charging station will not be utilized 24 hours a day (Wirges and Linder, 2012). This is directly related to the profitability of the charging station, simply because intensive usage increases revenues which in turn increase profitability.

## 3. The model

In this allocation model, an agent-based model and GIS are integrated to illustrate the spatial distribution while multi-objective optimization is used to determine the decision space of the model.

### *3.1 Allocation problem*

The allocation of a charging station is in line with the facility location problems, in which a facility agent deals with the problem of finding a location that provides services for a spatially distributed demand (Arentze and Timmermans, 2010). Location allocation models, which deal with facility location problems, intend to find a spatial distribution of facilities that maximizes or optimizes objective functions within one or more constraints. A distinction is made between two different location problems: median problems and covering problems. Median problems measure the effectiveness of a facility location by determining the average distance by those who visit it; while covering problems regard a demand as covered when it can be served within a specific time or distance from a facility. Within covering problems, the focus is on setting out to cover all demand and maximal covering problems use given number of facilities to maximize the demand covered.

The location allocation problem considered for the model is neither exactly aligned with the definition of a median problem nor with the definition of a covering problem. For the model the maximum walking distance from destination to EV or charging station is considered to be a crucial factor determining whether a charging station will be used. If a destination is outside the catchment area of a charging station it is assumed that the destination is not covered and that the station will not be utilized. The location allocation problem for the model can be best described as a multi-objective partial covering problem. The problem is multi-objective because it has to deal with two conflicting objectives: using fewer facilities to provide more services. Furthermore, the problem is not a set covering problem but a partial covering problem because it does not cover all demand but only the demand within the decision space of the objectives.

### *3.2 Multi-objective optimization*

In this study, two conflicting objectives are used to define the decision space for the location allocation model: maximize availability and maximize profitability, which are derived from a set of objectives based on reliability, availability, maintainability and costs. The aim is not to find an optimal solution to a single objective, but to find optimum compromise solutions between the objectives (Deb, 2005). A decision space is used which represents a range of options that gives more flexibility. The objectives together with the constraints will determine the decision space of the model, which is further elaborated in the following.

#### *3.2.1 Availability*

The first objective for the model is to maximise availability A(x). Among others, the availability of a public charging station determines the usefulness of a station. The availability of a charging station is determined by demand and supply, in which a high amount of supply and a low amount of demand results in a high level of availability. The objective function for daily availability is:

$$f(x) = A(x) = supply - demand = (o * t * p) - (n * d * e) \qquad (1)$$

where $o$: charging output per plug (kW); $t$: daily effective charging time per plug (hrs); $p$: number of plugs; $n$: number of EVs using the charging station; $d$: daily distance travelled per EV (km); $e$: energy consumption per EV (kWh/km).

The supply is determined by the charging output in kW and the effective charging time that is the assumed maximal capacity of a charging station in practice. The demand for a station is determined by the energy consumption per EV and the number of EVs within the surrounding of a station. The constraint for availability is determined by the relation between demand and supply. If demand exceeds supply, a station will be overloaded, which decreases the availability dramatically. In other words, when demand exceeds supply, a station is more likely to be occupied, which is not desirable for users in need of charging. The limit for the objective space is reached when demand exceeds supply. The constraint $\boldsymbol{g(x)}$ for the availability objective is:

$$g(x) = Demand \leq Supply \quad \text{Or} \quad 1 - \frac{Demand}{Supply} \geq 0 \tag{2}$$

#### *3.2.2 Profitability*

The second objective for the model is to maximise profitability. The profitability of a public charging station depends on several variables, such as the profits per kWh and utilisation. The utilisation is one of the most important variables because it almost directly determines the profitability of a charging station. For a charging station to be profitable the actual daily utilisation has to be higher than the required daily utilisation for covering the costs. The objective function for the actual daily utilisation $\boldsymbol{U_a(x)}$ is:

$$f(x) = U_a(x) = \frac{\mathrm{n} * \mathrm{d} * \mathrm{e}}{o * p} \tag{3}$$

where $n$: number of EVs using the charging station; $d$: daily driven distance per EV (km); $e$: energy consumption per EV (kWh/km); $o$: charging output per plug (kW); $p$: number of plugs.

The actual daily utilisation in hours is determined by the energy consumption per EV and the number of EVs within the surrounding of a station divided by the charging output of a station in kW. The actual daily utilisation has to be higher or equal to the minimal required utilisation for a station to be profitable:

$$U_a(x) \geq U_r(x) \tag{4}$$

The daily required utilisation $\boldsymbol{U_r}$(hrs) is determined by calculating the necessary hours of utilisation per day for generating the desired profit. The most important variables used to calculate these hours are initial investment costs, desired rate of return on investment, selling and purchasing prices for electricity, and the charging output of a station.

$$U_r(x) = \frac{y_d}{y_a} = \frac{c_i * (1+r)^a * \dfrac{(1+i)^a * i}{(1+i)^a - 1}}{\big((y_e - c_e) * o * p * 365\big) - \big(c_{op} + c_m + c_n\big)} \tag{5}$$

where $y_d$: annual desired yield (€); $c_i$: initial capital investment costs (€); $r$: annual rate of return; $a$: amortisation period (years); $i$: interest rate of loan; $y_a$: annual actual yield (€); $y_e$: yield for selling electricity (€/kWh); $c_e$: costs for purchasing electricity (€/kWh); $o$: charging output per plug (kW); $p$: number of plugs; $c_{op}$: annual operating costs (€); $c_m$: annual maintenance & management costs (€); $c_n$: annual network costs (€).

#### *3.2.3 Decision space*

The above described objectives are divergent, meaning that if one solution is better in terms of one objective, it comes only from a sacrifice of the other objectives (Deb, 2005). Therefore the aim is not to find an optimal solution to each of the objectives but to find an optimum compromise solution between the objectives. The two objectives combined, determine the decision space for the location allocation model. Using the reference values for the variables (ACEA, 2012) the decision space in this study is that a charging station will be allocated when the number of EVs within the catchment area is between 2 and 8.

### *3.3 Agent-based model, GIS and Scenario analysis*

Agent-based modelling is a simulation technique for modelling complex systems. An agent-based model generally has three elements: a set of agents with attributes and behaviours, a set of relationships and methods of interaction, and the agents' environment (Macal and North, 2010). The modelling system is constructed as a collection of entities called agents. The main benefits of agent-based modelling is that it captures emergent phenomena, provides a natural description of a system and it is flexible (Bonabeau, 2002). The agent based model in this study is constructed with Netlogo program. Netlogo is a programmable modelling environment for simulating natural and social phenomena. It is a relatively simple system but well suited for modelling complex systems.

Geographic information systems (GIS) are used to gather, analyse, modify, manage and present all types of spatial information. GIS is an operational and supporting information system where data can be related to a specific location or area. Combining data with geographic information such as maps, results in numerous forms of output, such as maps, charts, tables and graphs. GIS is commonly used in planning, analysis of traffic, transport, environment, safety, earth sciences and many more applications. As the focus of this study is on the spatial challenges, naturally the agent-based model is integrated with GIS to illustrate the spatial distribution. For this study, the open source software Quantum GIS is used.

The use of scenarios stimulates strategic thinking and helps to overcome thinking limitations by creating multiple futures (Amer, 2012). Scenarios can also be defined as a description of a future situation and the course of events which allows one to move forward from the actual situation to the future situation (Swart, et al., 2004). Scenario development creates a better understanding of plausible future developments by looking at trends on a macro level such as: socio-cultural, technological, ecological, political and economic developments. A scenario for the year 2020 is created to determine the settings for the model.

### *3.4 Simulation setting up*

The initialization of the model is set up a distribution of EVs within the study area for scenario 2020. Based on a prediction of national growth of car ownership and the proportion of EVs by 2020, the number of EVs is generated for the study area and distributed according to where owners of EVs live, work or visit at the neighbourhood level on a map cross a day.

#### *3.4.1 The time-spatial development of EVs*

The environment for the model is determined by a distribution of EVs within the study area. The study area for the model is the municipality of Eindhoven. In terms of population Eindhoven is the fifth biggest city of the Netherlands but with a population of 218.433 inhabitants (Gemeente Eindhoven, 2013) Eindhoven is a relatively small city. The municipality of Eindhoven is located in the south of the Netherlands and it has a total area of 88.87 km2 including water. Eindhoven is divided in to 7 districts and 116 neighbourhoods. A map of the municipality of Eindhoven is shown in figure 1.

The distribution of EVs within the study area is based on a forecast of EVs in Eindhoven in the year 2020. Based on the national objectives for EVs in 2020, the national growth of car ownership and the proportion of represented cars in Eindhoven, the number of EVs in Eindhoven are calculated to be 2000 by 2020. As mentioned before among EVs only FEV and PHEV are considered in this study.

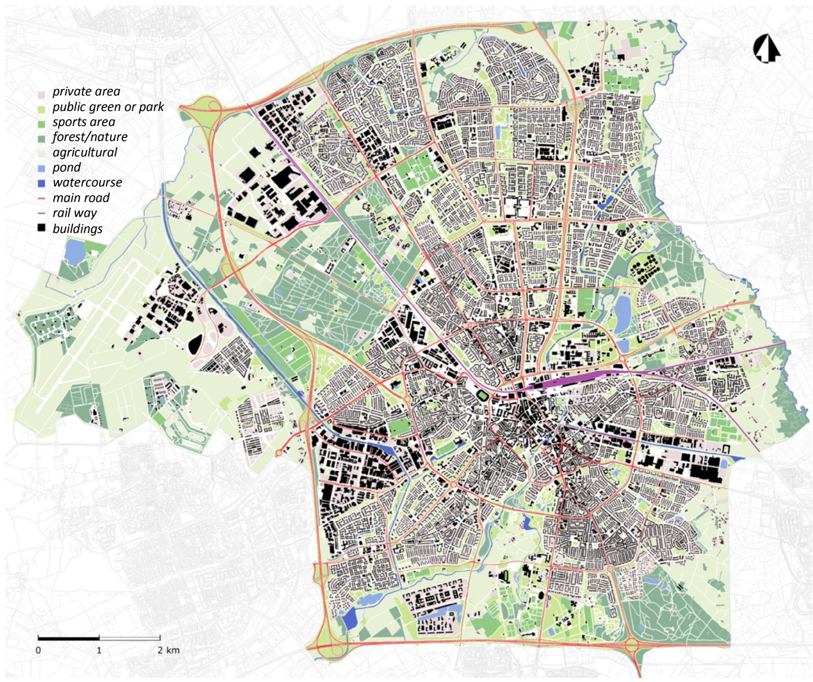


**Figure 1 Map of municipality Eindhoven, the Netherlands**

### *3.4.2 The demand distribution for charging stations*

According to the function of living, working and visiting, three distributions are created for all 2000 EVs at neighbourhood level. For the three distributions the EVs per neighbourhood are in proportion with the number of cars owned, the number of workplaces and the total floor area for retail.

The number of EVs per neighbourhood, regardless for which function, will change over time because EVs are used for transportation and the movements over the course of a day cannot be ignored. For the locations of EVs during a day, a distinction is made between static (e.g., parking at home, at work, at facilities that can be recharged) and dynamic (i.e., travelling that can not be recharged). Following the general daily activity patterns (Cloïn, et al., 2011), the three distributions per function and the movement of EVs over the course of a day are combined to create snapshots of distribution for every hour of the day. With these 24 snapshots the movements of EVs during a day are illustrated. Figure 2 provides an overview of locations of people during the day, which indicates, for example, at 10:00 AM of all EVs 53% is at home, 40% is at work, 4% is at facilities and another 3% is travelling meaning that in total there are 1940 static or parked EVs.

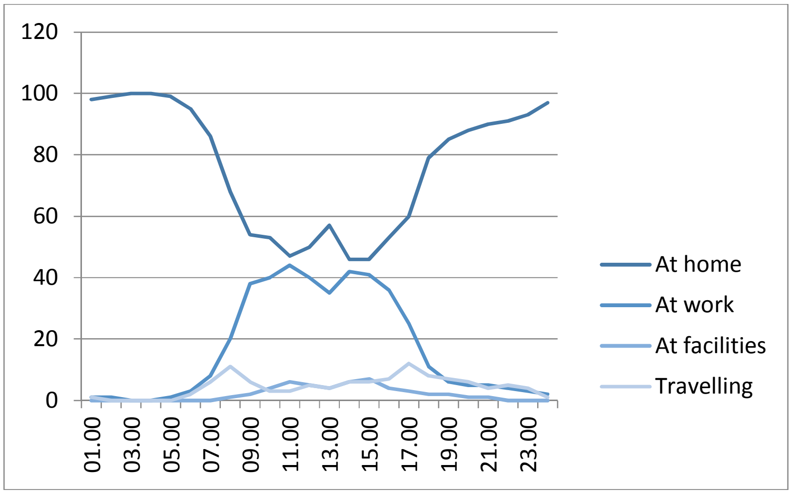


**Figure 2 location of people during the day (Cloïn, et al., 2011)**

A final distribution is needed because in the real world charging stations are static and the model needs one distribution on which the locations of charging station can be determined. A straightforward approach is used to create such a distribution in the current study. For all neighbourhoods, especially which are primarily working or shopping areas, presenting a substantial higher or lower amount of EVs between day-time and night-time, the average numbers of EVs during these periods is used. In other words, for all neighbourhoods that show a substantially higher or lower number of EVs over a period of time, the averages of this period is used for a final distribution. For all the other neighbourhoods which show no substantial difference the average of EVs over all 24 hours is used for a final distribution. As such, the final distribution also takes into account that EVs might be recharged at different locations during a day.

### *3.5 Simulation process*

The model has two buttons to run a simulation: the "setup" button and the "go" button. When the "setup" button is used the model responds by first deleting all previous settings and simulations. Next, the model is (re)set to an initial state and generates an initial distribution of EVs in the study area based on the calculated the amount on the neighbourhood level.

The scenario created to determine the values of the variables in the model is a base case scenario, since the main purpose is to demonstrate how the proposed model works. The scenario will present an outlook for the year 2020 and the general assumption for this scenario is moderate growth of electric mobility in the Netherlands. It is assumed that the average capacity of EV is no longer limited to 3.7 kW charging but will be 11 kW. On the charging infrastructures side, it is assumed that the types and techniques used for charging stations in 2020 are comparable with the charging stations used now (ACEA, 2012). Communications between EV drivers and charging stations have also not improved significantly meaning that the efficiency of charging stations will remain relatively low. The detailed the variable settings are shown in figure 3 together with the interface of the model. To find a solution for the location problem the model is used to explore the base case scenario.

When the “go” button is pressed a simulation starts and charging stations will appear. When a simulation is run, it uses a heuristic method with two radiuses of catchment area to allocate charging stations. These two radiuses reflected the walking distance from the distributed EVs to the potential charging station. The algorithm first uses the minimum catchment area of a station to calculate the scores of the objectives and swaps all cells to determine if a location is in the decision space that defined by the two objectives and its constraints (Eqs. 1-5). When no more locations can be found the maximum catchment area is used and again all cells are swapped to determine if a location is within the decision space. A location is allocated with a charging station when it is in the decision space and can provide the required service to the EVs in the catchment area. The simulation stops when no more locations can be allocated.

### *3.6 Interface*

The interface of the model displays the map with generated EVs distribution and monitor windows that show the variable settings and the performance of the model (e.g., the number of serviced EVs and the number of allocated charging stations, etc). Figure 3 shows the interface of the model with all the buttons, sliders and monitor windows. The sliders in the interface represent the variables mentioned before and the value settings for the base case scenario. Users can also use the slider to adjust the decision space of the model by setting the variables to the preferred or expected values, and compare the simulation results. As simulation proceeds, the charging stations are allocated and appear on the map, EVs change colour from red to green when serviced.

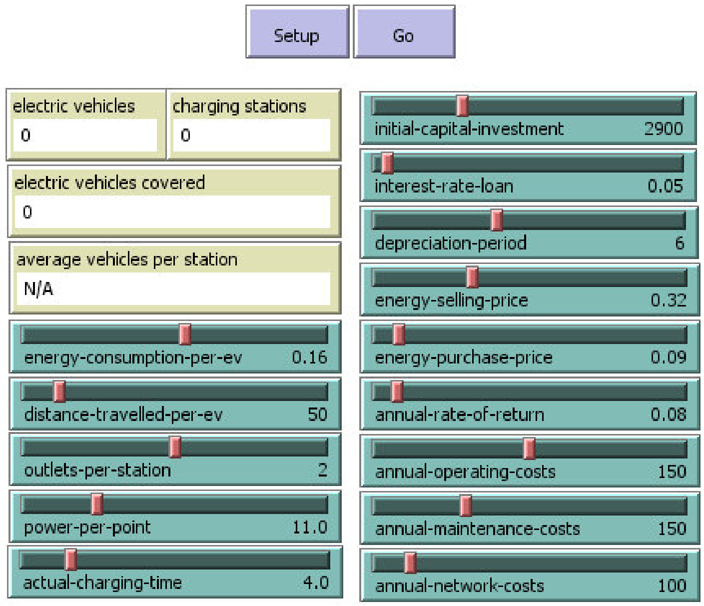


**Figure 3 Interface of the model with the base case variable settings**

### *3.7 Simulation results*

Ten random distributions of EVs are created at neighbourhood level as initial situations. Each initial situation runs for 12 simulations, which results in total 120 simulations. All of these simulations present reasonable distributions of charging stations, which provide a set of solutions for the location problem. It must be realised that the solutions provided by the model are not ultimate solutions to the problem. The model itself does not use exhaustive calculations to find the ultimate solution. Instead near optimal solutions are provided by the model.

To analyze the set of solutions of the base case scenario, different criteria are used. The used criteria are maximal facilitation (i.e., maximal amount of serviced EVs), maximal profitability (i.e., maximal amount of serviced EVs per charging station), maximal availability (i.e., minimal amount of serviced EVs per charging station), and minimal amount of charging stations. According to each criterion a different solution can be selected from the total set of solutions which is shown in table 1 with its performance.

**Table 1 Solutions according to criteria**

| | Maximal facilitation | Maximal profitability | Maximal availability | Minimal charging stations |
|---|---|---|---|---|
| *Charging stations* | 724 | 687 | 741 | 687 |
| *EV's serviced* | 1995 | 1963 | 1974 | 1963 |
| *EV's/Station* | 2.756 | 2.857 | 2.664 | 2.857 |

The table reveals that the criteria maximal profitability and minimal charging stations result in the same solution of 687 charging stations severing 1963 EVs, which leads to about 2.857 EVs serviced per station per day. The map of this solution is shown in figure 4, in which slightly big black dots represent allocated charging stations, green dots represent EVs serviced and red dots are those not serviced. This can be explained because profitability is determined by utilisation, which implies highest profit comes with a minimal amount of charging stations covering a maximal amount of EVs.

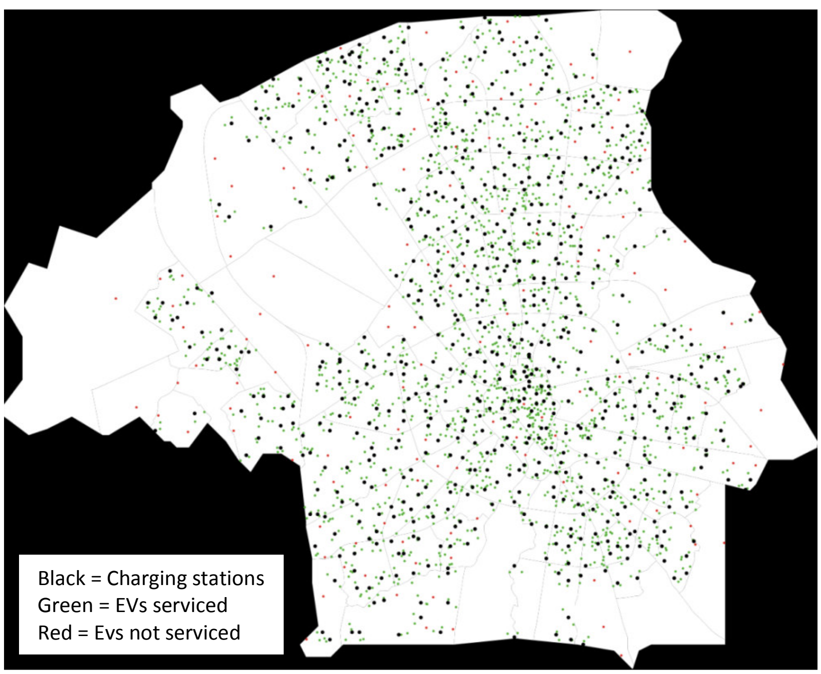


**Figure 4 Map with charging stations for maximum profitability & minimal charging stations**

In total three solutions can be identified. In terms of the number of EVs serviced, all solutions are relatively close to each other. However, when considering the amount of charging stations, the differences are substantial, especially when associate it with cost. In the base case scenario it is assumed that the initial investment cost for realising a single public charging station is € 2900,-, which means that the investment difference between maximal availability with 741 charging stations and maximal profitability with 687 stations is about € 156600,-.

## 4. Discussion

For further research it is recommended to refine the model along the following lines. First, the location allocation problem in this study is defined as a partial covering problem but instead it could also be defined as a maximal covering problem. In case of a maximal covering problem the number of public charging stations is known upfront and the model will allocate locations to achieve maximal coverage. It is more suitable to construct the model in this way when the amount of public charging stations to be developed is limited or the financial consideration is dominated to make a profit. However, such a strategy will not be a good one to promote EVs.

Secondly, the current model does not use distances between EVs and a station directly. The only way distances are used is by setting the catchment radius of a charging station. The distances between EVs and station could also be incorporated in the model. With the use of average distances the model would solve a median problem or even a combined problem between a median and a covering problem.

Thirdly, the location problem is approached as a static problem in the current study. This is obviously true because both parked EVs and charging stations are static. However, EVs can also be considered as dynamic elements in a model. This will transform a static problem into a dynamic problem, which has dramatic consequences for the construction of the model. This approach will include flows of EVs and queuing components. Especially for fast charging stations, this approach might be very interesting because in most cases they are situated along major roads or exit of high ways. It could also help to integrate activity-travel models to decide the location of EVs more precisely based on typical activity patterns.

Moreover, the created environment in GIS can contain more details, such as street map, and in Netlogo candidate locations can be precisely indicated. Policies related to the detailed local environment can be integrated in the model because in most cases policies of municipalities provide information about exact location requirements for charging stations at street level.

Furthermore it is extremely important to monitor the developments of electric mobility very closely. The future of EVs is unknown and even within the relatively short period of this study radical changes within the field of electric mobility have occurred. The field of electric mobility offers great challenges but also opportunities. With the fast change of ICT technology, the new application can improve the communications between EV drivers and charging stations significantly and consequently improve the utilization efficiency of charging stations. It is recommended to respond to these changes adequately and effectively.

## 5. Conclusion

The model can provide a set of solutions for the location allocation problem by simulation and visualization on maps. As the model is not designed using an exhaustive calculation for an ultimate solution, near optimal solutions are generated and further analysed using various criteria (e.g., maximal facilitation, maximal availability, maximal profitability, etc).

It can provide decision support for different stakeholders. The municipality can use the model to gather information about locations and quantities of charging stations. They can also adjust the variables in the model to explore their strategic policies (e.g., make it a profitable business case for private company to participate and check the consequences).

The case study area of Eindhoven is a relative small city. However, the basic principles presented in the model can also be used for big cities with large amount of EVs. Users need to adjust the decision space of the model by setting the variables to the proper values.

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