Supporting the implementation by NRAs of renewable energy technologies in the road infrastructure

ENROAD

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A methodology for evaluation of system topologies and locations for future energy hubs with renewable generation

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API	Application Programming Interface
BFS	Breadth-First Search
CO	Charging Operator
CS	Charging Station
DG	Distributed Generation
DSO	Distribution System Operators
EH	Energy Hub
EHCS	Energy Hub Charging Station
EV	Electric Vehicle
MILP	Mixed-Integer Linear Programming
MOLP	Multi-Objective Linear Programming
MOO	Multi-Objective Optimization
OIM	Open Infrastructure Map
OSM	OpenStreetMap
NRA	National Road Administration
RES	Renewable Energy Source
ROI	Return on Investment
V2G	Vehicle-to-Grid

1 INTRODUCTION

Fostering the generation and use of clean and renewable energy is nowadays one of the main actions of the European Union to counteract global warming. This trend is impacting different energy sectors. The electrification of transport is seen as one of the most important drivers for reducing greenhouse gas emissions from human activities. For this reason, the transportation system is among the most affected energy sector in the context of this energy transition.

The number of electric vehicles (EVs) is rapidly increasing all over the world. According to Canalys, in 2020 the global sales of EVs increased by 39%, compared with a sales decline of total passenger cars by 14%. By 2030, the report forecasts 48% of vehicle sales share to be represented by EVs (Canalys, 2020).

The increase in EV penetration rate represents undoubtedly a resource in terms of pollution level reduction, due to the usage of electricity as an energy vector as a substitution for fossil fuels. Another opportunity coming from the electrification of the transportation system is represented by the possibility to use EVs as energy storage units, and implement Vehicle-to-Grid (V2G) systems (Lu & Hossain, 2015, p.; Noel et al., 2019). Finally, EV Charging Stations (CS) can integrate both the EV energy feeding function with Generation and Storage Devices, and become fully autonomous Energy Hubs (Hafez & Bhattacharya, 2017), where an Energy Hub (EH) can be defined as an interface between generating units, the energy consumers and transportation infrastructure (Moeini-Aghtaie et al., 2017).

In this report, with Energy Hubs we refer to joint units of generation and consumption of electrical energy. In the following, the electric consumption we will mostly refer to is the electrical load associated to a CSs connected to the EH, and the generation being fed from renewable energy sources. Nevertheless, the definition of EH is to be intended as generically represented by a generation power plant and any electrical appliances alimented by the local generation unit.

The potential integration of EHs in the context of Smart Grids expands further the opportunities mentioned above (Kong et al., 2018; Tagliapietra et al., 2019). Nevertheless, along with these advantages, several criticalities are foreseen from the electrification of the transport system. Distribution grids were not originally designed to host such a high power density, and a lack of hosting capacity in handling EVs and Distributed Generation (DG) with today's aggressive vehicle electrification goals is observed (Xie et al., 2021). This brings to potential power quality issues, such as high power losses, undervoltages and instabilities. Moreover, another issue is potentially represented by power flow reverse from Low and Medium Voltage distribution networks up to High Voltage transmission networks when generation exceeds the power demand, which collides with the current distribution grid protection design (Xie et al., 2021). In this context, EHs can represent a powerful tool from several aspects:

- In EH, the alignment of power generation units with high-density loads such as EV charging stations reduces the power demand from the distribution grids, reducing losses, voltage drops and environmental impact of the transport system;
- EHs can be considered not only as energy providers to the EVs, but also as distributed providers of flexibility to the distribution grid. This opens several opportunities in the future energy market scenario under development.

A convergence between electrical generation and load is important to have a smooth integration of EHs in distribution grids and avoid the above-mentioned potential power quality issues. Nowadays, even small DG units are capable of several hundred kW of power production in small installation areas. EV charging stations represent the perfect balancing load for such generation power plants.

The current trend towards an increasing adoption of EVs stimulates the demand for CS, therefore it is reasonable to suppose the availability of CSs along with renewable generation in future EHs. Moreover, the availability of CSs contributes to the overall profitability of the EHs investment. Finally, from an electrical point of view, EVs are storage units, therefore the connection of several EVs to an Energy Hub Charging Station (EHCS) enhances the potential control options within the EH to ensure stability and power quality.

For this reason, it is important that, when planning the EH placement, several factors are taken into account:

- The availability of renewable energy sources and power substations capacity, to quantify the potential power infeed in the candidate EH location.
- The energy and power demand. As mentioned above, good coordination between generation and load is fundamental to reducing the impact of transportation electrification, both in terms of energy losses in the distribution grids, power congestion, power flow reverse, etc.

EHs optimal placement is a relatively new problem, especially in the transportation sector. The availability from NRAs of wide areas in which to deploy EHs represents a unicum in this field. For this reason, the literature offers a limited amount of works to refer to and support the development of scientifically recognized methodologies for optimal EHs placement. A comparable work in terms of degrees of freedom in the placement of EHs is represented by (Khardenavis et al., 2021), where a robust optimization approach is presented for the planning of Mobile energy hubs in urban networks.

In this report, it is presented the activity research performed in ENROAD for optimal placement of future energy hubs with renewable generation. The methodology is based on data aggregation from different open-source datasets involving the availability of renewable energy sources, land for generation devices installation, traffic density patterns, electric vehicle charging patterns, road topology, and land destination of use. The problem is formulated in a multi-objective linear programming problem, which can be solved either with linear programming solvers or with meta-heuristic methods. The multiple objectives considered are:

- the minimization of the EH units, to minimize the overall investment;
- the minimization of the distance of the EH from the closest power substation;
- the maximization of the potential energy generation.

An application of the methodology is presented, where an optimal placement of EHs is studied around Trondheim, in Norway. The results show how these single objectives, if analysed singularly, bring different EH placements. The domain of the solutions reproduces a Pareto Front, which has to be analysed by decision-makers to evaluate the best compromise between different contrasting objectives.

The document is organized as follows: in Chapter 2 the problem of EH placement optimization is presented; Chapter 3 explains the methodology proposed; Chapter 4 shows an application of the methodology in a case study based in the urban area of Trondheim; Chapter 5 closes the documents with a discussion over the main results and outcomes of the study, and ideas regarding future expansion of the methodology.

2 OPTIMIZATION AND INPUT DATA

As briefly mentioned in Chapter 1, several factors should be taken into account when planning the placement of Energy Hubs. Most pre-eminently:

- The availability of renewable energy sources potential;
- the availability of land for generation devices installation;
- the assessment of energy and power demand.

Energy and power demand assessment indirectly involve further assessment process on traffic pattern, EV drivers' habits, etc.

In general, the assessment of optimal locations for future energy hubs implies a modelling process, where the system, intended as an interacting group of items forming a unified whole (Merriam-Webster, n.d.), should be described in a mathematical form to formulate the optimal solution.

The modelling process can be described as structured in the following sequential actions:

1. Identify the entities involved in the definition of the optimal placement of energy hubs;
2. Identify the data that best characterizes the dependency of the system on each entity;
3. Describe mathematically the interdependence of the identified entities towards the optimal solution.

These actions will be singularly discussed in the following paragraphs.

2.1 INTERDEPENDENT ENTITIES IDENTIFICATION

The optimal placement of energy hubs is determined by the interaction of two major infrastructures, the power system and the transportation system, and their respective interdependence. The power system represents the main source of energy for a transportation infrastructure fully electrified. Therefore, it is reasonable to assume that the higher density of energy hubs will be in the proximity of power system substations. This assumption is even more reasonable in a short-term time perspective, to minimize capital costs for creating new interconnection lines, in addition to operational cost minimization (e.g., due to power losses) in the daily usage.

Another factor that determines the location of an energy hub is determined by the availability of renewable energy sources. Today's availability of small-sized power generation devices, compatible with the installation both in urban and rural areas, combined with a wide availability of areas managed by NRAs, represents an appealing opportunity to increase the return on investment (ROI) over the electrification of the transport infrastructure.

Another entity to consider is the load pattern. As mentioned in the previous chapter, in this report we are going to consider as load the EV charging demand, which is closely related to the traffic pattern. It is reasonable to assume that higher profitability is obtained with an energy hub/charging station installed where a higher traffic density is measured.

2.2 DATA IDENTIFICATION

Data collection for the entities identified in section 2.1 can represent a challenge, especially if special agreements with Distribution System Operators (DSOs), Charging Operators (COs) and NRAs are not in place for accessing restricted data. In this context, open-source data represents an interesting replacement for official data.

Nowadays, through the web is possible to access a high volume of open-source data: for example, OpenStreetMap (*OpenStreetMap*, n.d.) represents one of the largest repositories of open data on many infrastructures, such as transportation, power system, communication infrastructure, centre-of-interest locations, etc. Nevertheless, the analysis of the accuracy of this data is transferred to the single contributors and voluntary checks of the data.

Another open dataset is represented by open APIs for having access to traffic records. For example, Google provides access to traffic information via the Distance Matrix API (*Distance Matrix API*, n.d.), which nevertheless requires a developer key and imposes usage limits for free subscriptions. As an alternative, most NRAs provide real time information regarding the traffic status in the most relevant motorways.

Among these, it is worth mentioning the Statens Vegvesen API for the traffic records along the inductive loops deployed in Norwegian streets (*Statens Vegvesen*, n.d.), and the feed DATEXII (versions 2 and 3), which provides the real-time traffic information that the Flemish Traffic Center generates on the Flemish highways (*Flemish Traffic Center*, n.d.).

The datasets above mentioned can be enriched by eventual data describing user habits. As example, a significant improvement in modelling the transportation-electrical system can be achieved by EV charging patterns, differentiated by different areas (e.g., rural vs urban, patterns in commercial areas, patterns in public parking, etc.). In general, it can be challenging to obtain this data, which is often available only among charging operators and protected as confidential.

Finally, another important dataset as support of identified entities' descriptions is represented by weather data. Across the web, several data sources can be found in terms of wind speed and duration, solar irradiance, air temperature, etc. This data is fundamental to estimating the generation potential of different areas for the future Energy Hubs.

2.3 A MATHEMATICAL MODEL

The interrelation of the system entities introduced in Section 2.1, supported by the datasets identified in Section 2.2, should be described as a mathematical model, in order to properly estimate the best locations for future energy hubs, based both on technical suitability and potential energy supply at the selected area. The identification of the best location for EHs involves defining an optimization problem. This typically implies specifying an objective function and a set of constraints.

The objective function may be represented by several goals, some of which may be conflicting. For example:

- Minimizing the number of energy hubs, to minimize the capital expenditures;
- Maximizing the energy generation from renewable energy sources;
- Minimizing the distance of energy hubs from available power substations.

These goals can be reached given that a set of constraints are met; for example, the available power (from DG or power substation) should be sufficient to feed the expected load from EV charging, in order not to discourage the adoption of Electric Vehicles.

Different approaches can be used to find a solution to the problem. An advantage is obtained by describing objective functions and constraints as linear, to define a Multi-Objective Linear Programming (MOLP), and make it possible to solve the problems with simple variants of the simplex algorithm, or by using meta-heuristic methods, such as Genetic Algorithm.

In general, with Multi-Objective Optimization (MOO) exist multiple Pareto optimal solutions, therefore it is assigned to the decision-maker the choice of the final solution that better meets the overall strategy of the NRAs.

3 THE PROPOSED METHODOLOGY

With reference to section 2, the methodology has been organized according to the points listed:

- Identification of entities involved in the optimal placement;
- Identification of available data;
- Mathematical model.

It is important to emphasize how these three levels are strictly correlated when proposing a methodology. For example, all entities for which a dependency towards an optimal placement are identified, but have no supporting data, should be ignored, since they cannot be mathematically defined. For this reason, necessarily, only the processes and entities supported by data availability have been modelled.

The methodology is implemented in python programming language. For this reason, along with the methodology description, details about the python libraries used and the specific implementation are given.

3.1 SYSTEM ENTITIES IDENTIFICATION

As mentioned above, the mathematical model has been restricted to the system entities that are supported by available open-source data. For those necessary entities for which no open-source data was found, reasonable assumptions have been taken.

The system entities identified are:

- Traffic time-series
- Power substations location
- Street topology
- Area availability
- Wind measurements
- Land destination of use
- Wind turbines data
- EV charging patterns

3.2 DATASETS IDENTIFICATION

The main open-source datasets have been identified in the following:

- OpenStreetMap
- Statens Vegvesen
- NVE

OpenStreetMap

OpenStreetMap (OSM) is a worldwide project for geographical data gathering, which results in the production of openly available geographical maps. All data made available through OpenStreetMap is released with Creative Commons BY SA license, which means that all the data can be openly used conditional on citation of the OpenStreetMap source in all the works based on their data. One of the most important characteristics of OpenStreetMap is its community-based nature, therefore everyone is invited to collaborate by inserting new data and contributing to the project. The quality of OSM data is constantly monitored by the scientific community through a very wide range set of tools and applications (Mooney & Minghini, 2017; Ramm et al., 2011).

Along with the collaboration of volunteers, the OSM dataset receives the contribution of many institutes and authorities. In the case of Norway, it is possible to mention the Norwegian Mapping Authority (Kartverket), the Norwegian Public Roads Administration (Statens Vegvesen), the Norwegian Directorate for Cultural Heritage (Riksantikvaren), the National Library of Norway (Nasjonalbiblioteket), and many others. This collaboration of public authorities allows for building a set of layers where different pieces of information are mapped in the OSM geographical carts, such as, for example, the location of places of public interest.

The concept of layering different datasets, which are named Map Features, is fundamental for understanding the approach laying behind OSM. The map features represent physical features on the ground (e.g. roads or buildings) and are referred to by using specific tags attached to its basic data structures (*Map Features - OpenStreetMap Wiki*, n.d.). There is a set of 28 primary features included in OSM, among these: highway (which includes roads and footpaths), natural (which is used to describe natural and physical land features), public transport (which is used for features related to public transport, such as bus stops, stations, etc.), waterways (which includes rivers, streams, channels, etc.), etc. Among these features, the *power* tag is used to identify a wide range of facilities and features that relate to the generation, distribution and transmission of electrical power.

OpenStreetMap provides different APIs for downloading data from their database. Through these APIs, the power tag can be used to query the OSM database and download power system elements of a specific geographical area, filter them based on specific elements, etc. Most of these methods return the data in the OSM XML format, which can be used by most of the common tools for database inspection or population. Among these methods, Planet.osm provides a complete copy of the OSM database every week in different formats, such as PBF or OSM XML. Other APIs allow querying selectively specific areas, such as XAPI, GeoFabrik, ProtoMaps and Overpass.

In particular, the Overpass API is exploited by a python tool, called OSMnx. OSMnx is a package that is publicly available on the most common Python package managers (Pip, conda, etc.), which allows downloading data from OSM databases and processing them with the standard python data science tools (Boeing, 2017, 2019). More specifically, two main formats are made available by OSMnx methods:

- NetworkX format, which converts OSM data in graph format compliant with the NetworkX library
- Pandas dataframes.

Based on these features provided by the OSMnx package, a method has been developed which allows processing several features from OSM, more specifically:

- The street map topology, which is converted into a NetworkX graph;
- The power features, which is converted into a synthetic grid model in the pandapower format (Thurner et al., 2018);
- Several additional amenities, such as public on-surface parking areas and land destination of use information.

Statens Vegvesen

Statens Vegvesen is the Norwegian National Public Roads Administration (NPRA), and is responsible for road administration on national and European roads. This means planning, developing, operating and maintaining the roads. As a professional body, Statens Vegvesen contributes to the National Transport Plan with studies and proposals to the Ministry of Transport, research and dissemination of the results and development of guidelines. Statens Vegvesen provides a website (*Statens Vegvesen*, n.d.) with a wide range of datasets freely available through direct download or API. Among these:

- traffic data such as directions, travel times, webcam images and video
- vehicle information
- driver's license information
- environmental data
- parking register
- statistics from traffic data and traffic accidents

Based on the available data, from the Statens Vegvesen API information regarding the vehicle traffic volume is extracted, more specifically:

- Measurement devices (e.g., inductive loops) location;
- Measurement devices recorded data

This data is finally processed and associated with the OSM-based street map graph.

NVE

NVE is the Norwegian Water Resources and Energy Directorate, which is responsible for managing the country’s water and energy resources. It is an organization that is subordinate to the Ministry of Petroleum and Energy, and is actively involved in promoting cost-effective energy systems and contributing to efficient energy use.

NVE's website (*NVE - Norges Vassdrags- Og Energidirektorat*, n.d.) provides a catalogue of open data that is licensed under the Norwegian license for public data (NLOD), which is compatible with the Creative Commons CC BY 3.0, and that are accessible through API.

Among the available datasets in the catalogue:

- Hydrological and meteorological measurements
- Water bodies
- Flood and landslide exposed areas
- Hydropower and Wind resources
- Many others

The NVE data source has been used to have access to Norwegian wind atlas, from which the wind full-load hours t has been extracted. This parameter is a number that reflects the yearly wind energy production. It is defined as the number of hours that, multiplied by the nominal power of the wind turbine, returns the yearly wind energy production available in that site for a turbine with the same power curve shape[1].

Other sources

Additional data is necessary to obtain a complete model of the transportation system - power system interaction. This data cannot be found in open datasets, due to confidentiality agreements with data handlers, therefore reasonable assumptions have been taken based on research group experience in the electric mobility field:

- *Number of EVs out of total vehicles measured by inductive loops*. Statens Vegvesen does not provide a classification of vehicles based on fuelling energy type. For this reason, an assumption must be taken based on the current statistics of Norway, which are assumed as uniform in all

[1] For more details, refer to https://www.nve.no/energi/energisystem/vindkraft/vindressurser/ and to the ENROAD D2.2 deliverable

Norwegian areas. In the case study presented in Chapter 4, a value of 10% EV penetration rate is assumed.

- *EV Charging patterns*. Different behaviours related to charging habits can be observed depending on the hour of the day, the day of the week, the season, the area (rural vs urban), etc. Different time or location conditions have an impact on the EV driver's probability to stop by a charging station and charge his vehicle. In this methodology, a probability of a vehicle stopping by a charging station is defined as shown in Figure 1, for different CS types: Urban area and Suburban area, which refer to charging stations located along motorways inside and outside the city. These curves are specified for weekdays and weekend days.

(a) (b)

Figure 1. Probability of EV charging

3.2.1 DATA PROCESSING

Traffic volume gathered from Statens Vegvesen API and power grid data downloaded from OSM represent a set of information that is uncorrelated. In order to properly describe the power system and traffic states, some post-processing is therefore necessary.

3.2.1.1 Power system

The networkx format is exploited for performing a graph analysis of the network topology. The pandas dataframe is used to gather all the metadata associated with each networkx edge and node, by mapping the correspondent OSM univocal identifiers (osmid). In this way, the power grid components and properties, collected in the pandas dataframe, are merged with the graph topology.

Starting from a slack bus (by default chosen a bus among the ones with the highest voltage identified in the network), the graph is traversed with a breadth-first search (BFS) algorithm.

Initially, a pandapower model is created: an `ext_grid` pandapower element is created in correspondence with the slack bus. Then, the graph traversal is performed with the following procedure:

- Each graph edge (in the networkx format) is associated with the corresponding line properties (from the pandas dataframe): for example power line length and type (overhead/cable);
- The pandapower network is iteratively updated by adding the new buses and lines identified for each networkx edge.

All the buses are defined by geographical coordinates. The voltage reference is assigned based on the voltage property of the line. Based on the voltage property, also the cable sizing is defined, by choosing one of the default line sizes from the pandapower library.

Once the basic power grid topology in pandapower is created, the last step consists of post-processing the data to take into account the voltage transformation within the substations.

3.2.1.2 Transport system

The dataset available, as mentioned above, consists of:

- A graph associated with the streets topology, downloaded from OSM
- Data traffic, downloaded from Statens Vegvesen, recorded by the measurement points located in different streets.

To have a complete picture of the traffic in a given area, a simple algorithm for traffic state estimation is implemented.

The traffic estimation is calculated based on the assumption that the traffic inflow through the inspected area is equal to the traffic that leaves the area. This condition assumes therefore that no cars entering the area will stop in the observed area, for example for parking, and no cars which have previously parked in the area will leave. In other words, we are assuming that those two effects will compensate in the long term. In more other words, we assume that the behaviour of traffic flow through the area is stationary.

The street map can be associated with a directed graph G, which can be represented by an incidence matrix I:

$$\boldsymbol{I} = \begin{bmatrix} \boldsymbol{i_{11}} & \dots & \boldsymbol{i_{1j}} & \dots & \boldsymbol{i_{1M}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \boldsymbol{i_{i1}} & \dots & \boldsymbol{i_{ij}} & \cdots & \boldsymbol{i_{iM}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \boldsymbol{i_{N1}} & \cdots & \boldsymbol{i_{Nj}} & \cdots & \boldsymbol{i_{NM}} \end{bmatrix} \tag{1}$$

where N is the number of the graph nodes n, and M is the number of edges m. i_{ij} is equal to -1 if the edge m_j is leaving the node n_i, +1 if the edge m_j is entering the node n_i, 0 otherwise.

Let’s consider the simple example in Figure 2:

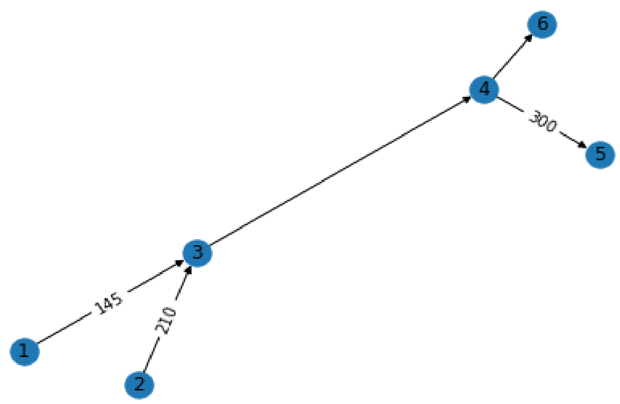

Figure 2. Example of a graph associated with traffic measurement

Typically, the number of measurement points is significantly lower than the street segments, therefore an approximation is necessary to have a state estimation of the traffic for each hour analysed.

It represents a simple street map with 6 nodes and 5 branches. Each street is described by a directed edge, which defines the only way the traffic flow is allowed. 3 out of 5 branches have a traffic measurement defined. The adjacency matrix assumes the following form:

$$\boldsymbol{I_e} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 1 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & -1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

To identify the traffic flow not directly measured, a linear system can be set up. The system assumes that for each node:

$$\sum_j \boldsymbol{a_{ij}\, x_j = 0} \tag{3}$$

where x_j is a non-negative variable that defines the traffic flow through each edge crossing the node, and a_{ij} represent the parameters of the augmented incidence matrix that consider also the traffic in- and out-flows on the graph leaves.

If we call $\bar{x}$ our vector solution defined as

$$\bar{\boldsymbol{x}} = [\bar{\boldsymbol{x}}_{\boldsymbol{M}} \quad \bar{\boldsymbol{x}}_{\boldsymbol{L}}] \tag{4}$$

where L is the number of leaves, and the constant terms vector is defined as:

$$\bar{\boldsymbol{b}} = [\bar{\boldsymbol{b}}_{\boldsymbol{N}} \quad \bar{\boldsymbol{b}}_{\boldsymbol{K}}] \tag{5}$$

where K is the number of edges with known flow values, we can define the augmented matrix that solves the system as:

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{I_e} & \boldsymbol{I_l} \\ \boldsymbol{I_k} & \boldsymbol{0} \end{bmatrix} \tag{6}$$

where I_l is a matrix $[N \times L]$ that represents the adjacency matrix for in- and out-flows through leaves, I_k is a matrix $[K \times M]$ that defines the equivalence of flow for the K flows with known values, 0 is finally a zero-matrix $[K \times L]$.[2]

The vector solution $\bar{x}$ can therefore be calculated by simply solving the linear problem:

$$\bar{\boldsymbol{x}} = \boldsymbol{A}^{-1} \cdot \bar{\boldsymbol{b}} \tag{7}$$

The system of the shown example has been modelled and solved in python language, and the result returned for the vector x is the following:

```
x = array([145., 210., 355., 300.,  55., 145., 210.,
    300.,  55.])
```

Solving undetermined cases

The above-explained solution to the problem works only when certain conditions are set:

- The number of known flows is such as the problem is well-conditioned
- The problem is consistent (e.g., the known values do not set negative flows through a directed positive edge)

In the reality, the number of known flows is far less than the number of street branches. Moreover, due to possible measurement error, or any cars that park within the inspected area along some roads, the principle of continuity of flow may be broken.

[2] The system can be optimized by studying the spanning tree and fundamental cycles and cutsets. The number of equations and variables would be reduced. Yet, this represents a first, working, model of the problem.

For this reason, a least-squares solver is used to solve the problem. More specifically, since the constraint of non-negativeness applies to traffic flows through directed edges, a non-negative least squares (**nnls**) solver is used, which solves the following problem:

$$\min_{\boldsymbol{x}} \|\boldsymbol{Ax} - \boldsymbol{b}\|, \text{s.t. } \boldsymbol{x} \geq \boldsymbol{0} \qquad (8)$$

Let's consider the example shown in the following figure:

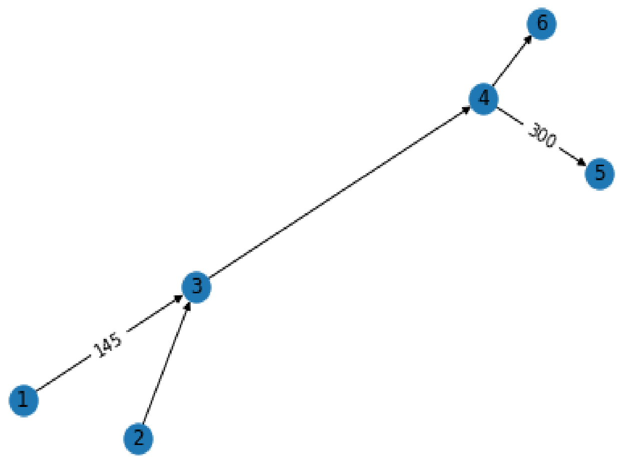

Figure 3. Graph associated with undetermined measurements

As can be observed, this is an undetermined problem: there are infinite solutions that can match the given set of flows.

The nnls solver returns the following solution:

```
x = array([1.45000000e+02, 1.55000000e+02, 3.00000000e+02,
    3.00000000e+02, 1.42108547e-14, 1.45000000e+02,
    1.55000000e+02, 3.00000000e+02, 0.00000000e+00])
```

This represents one of the infinite viable solutions.

EV traffic consumption

Given the knowledge of the overall traffic and the probability of EV vehicles stopping by a charging station (see Figure 1), it is possible to have an estimation of the power consumption $P(v, l, h)$, which is calculated as follows:

$$P(l,h) = \sum_{v \in V} K(v,l) \cdot \vartheta^{-1}(v) \cdot C(\mathrm{v}) \cdot D(v,l,h) \cdot p(v,l,h) \qquad (9)$$

Where $K(v,l)$ expresses the penetration rate of EVs of class v (e.g., short EVs, heavy-duty vehicles, etc.) in a given location l, $D(v,l,h)$ indicates the density of vehicles v traffic $\left[\frac{N.vehicles}{hour}\right]$ in a given location l and for a given hour h, C is the average consumption power for the EV class v, $\vartheta(v)$ is the time (in hours) required on average for charging EVs of class v, whereas $p(l,h)$ expresses the probability of a vehicle of class v stopping by a charging station.

Another assessment of traffic consumption is calculated in terms of energy, through the following equation:

$$L(l) = \sum_{h=1}^{8760} \sum_{v \in V} K(v,l) \cdot \vartheta^{-1}(v) \cdot C(\mathrm{v}) \cdot D(v,l,h) \cdot p(v,l,h) \qquad (10)$$

where $L(l)$ represents the total energy consumption in a given location l in one year.

3.2.1.3 Rasterization of information

With the methodology expressed in the previous section, it is possible to obtain an estimation of the power consumption for each street, as a function of the traffic density obtained with the state estimation method.

The problem of identifying an optimal energy hub location is a problem that, given the infinite number of possible placements, necessarily requires a discretization and simplification of the domain of the solution space.

For this reason, a raster-based method has been used to simplify the vectorial representation of traffic information. The method used is described in Figure 4.

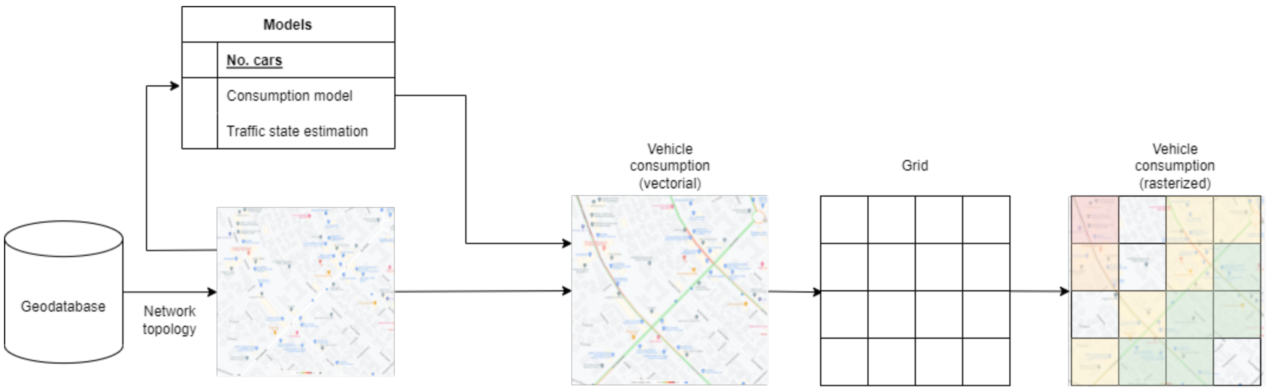

Figure 4. Rasterization of power consumption information

An overlapping grid to the street map is defined, and characteristic power consumption (equation 9) and energy consumption (equation 10) are calculated for each cell. The characteristic power and energy consumption are discretized by associating to each cell the **maximum** consumption calculated for all the streets that cross the given cell.

3.3 THE MATHEMATICAL MODEL

The optimal location of charging stations is performed according to a customized version of the bin packing problem. A bin packing problem is an optimization problem in which a set of objects, each of a given size, have to be assigned to a set of bins with given capacity using as few bins as possible (Bernhard Korte & Jens Vygen, 2006).

Given n items and m bins, with w_j as weight of item j and c as capacity of each bin i, the classical bin packing problem assigns the item according to the following minimization problem:

$$min\ \mathrm{OF} = \sum_{i=1}^{m} y_i \tag{11}$$

Subject to:

$$\sum_{j=1}^{n} \boldsymbol{w_j x_{ij} \leq c y_j} \qquad \boldsymbol{i \in M} \tag{12}$$

$$\sum_{i=1}^{m} \boldsymbol{x_{ij} = 1} \qquad \boldsymbol{j \in N} \tag{13}$$

$$\boldsymbol{y_i = \{0, 1\}} \qquad \boldsymbol{i \in M} \tag{14}$$

$$\boldsymbol{x_{ij} = \{0, 1\}} \qquad \boldsymbol{i \in M, j \in N} \tag{15}$$

Where:

$$y_i = \begin{cases} 0, \text{if bin i is used} \\ 1, \text{otherwise} \end{cases}$$

$$x_{ij} = \begin{cases} 0, \text{if item j is assigned to bin i} \\ 1, \text{otherwise} \end{cases}$$

The optimization problem is represented by the objective function (11), which aims at minimizing the number of bins hosting the set of items. The set of constraints is given by equations (12 - 15), where (12) represents the capacity constraints: for each bin i in the set of bins M the sum of weights of the items j assigned to the bin j should never exceed the capacity c; (13) assigns each item j from the set of items N only to a single bin i; finally, the decision variables y_i and x_{ij} are defined as binary variables in equations (14) and (15), respectively.

In the case of energy hubs location, the bin i represent the potential energy hub located in the discrete area i, whereas the item j weight represents the load demand associated with the vehicle's consumption within a discrete area j.

Nevertheless, minimizing the number of energy hubs only partially fulfils the necessities for an optimal placement. In fact, topological constraints should be taken into account, which assign to each energy hub the load demands due to EV charging covered in the neighbouring discrete areas. Moreover, the distance of each candidate location for energy hubs from the closest power substation should also be considered. Finally, also the availability of renewable energy should be taken into account. All these factors do not always concur with the same placement decision. In fact, some EH locations may be advantageous for the proximity of high vehicle traffic density, whereas other locations may be more interesting in terms of renewable energy availability. Therefore, the mathematical problem is set as a multi-objective optimization, which assumes the following form:

$$\boldsymbol{min}\ \mathbf{OF_1} = \sum_{\mathrm{i=1}}^{\mathrm{m}} \mathbf{y_i} \tag{16}$$

$$\boldsymbol{min}\ \mathbf{OF_2} = \sum_{\mathrm{i=1}}^{\mathrm{m}} \boldsymbol{\phi_i} \tag{17}$$

$$\boldsymbol{min}\ \mathbf{OF_3} = \sum_{\mathrm{i=1}}^{\mathrm{m}} \left[-\boldsymbol{G_i y_i} + \sum_{j=1}^{n} \boldsymbol{L_j x_{ij}} \right] \tag{18}$$

Subject to:

$$\boldsymbol{w_i x_{ii}} + \sum_{j=1}^{n} \frac{\boldsymbol{w_j}}{\ln \boldsymbol{d_{ij}}} \boldsymbol{x_{ij}} \leq \boldsymbol{c y_j} \qquad \boldsymbol{i \in M} \tag{19}$$

$$\boldsymbol{\phi_i} = \left\| \overline{\boldsymbol{d}}_{ij} \circ \overline{\boldsymbol{x}}_{ij} \right\| \qquad \boldsymbol{i \in M} \tag{20}$$

$$\sum_{i=1}^{m} \boldsymbol{x_{ij}} = \mathbf{1} \qquad \boldsymbol{j \in N} \tag{21}$$

$$\boldsymbol{y_i} = \{\mathbf{0}, \mathbf{1}\} \qquad \boldsymbol{i \in M} \tag{22}$$

$$\boldsymbol{x_{ij}} = \{\mathbf{0}, \mathbf{1}\} \qquad \boldsymbol{i \in M, j \in N} \tag{23}$$

OF_1, with equation (16), establishes the minimization of the number of energy hubs, as in the previous single-objective formulation. Equation (17) introduces a new objective, OF_2, that aims at minimizing the range of coverage of each EH. $\boldsymbol{\phi}_i$ is a quantity that expresses the covered radius in meters. The intention of this objective is to avoid that the charging station of an energy hub is assigned the load of an area far from its location and to keep a geographical association of each energy hub to its local traffic ($\boldsymbol{\phi}_i$ further explained down, where a full definition of this quantity is given). The third objective OF_3, described in equation (18), aims at minimizing the difference between supplied energy load due to vehicles charging

($\boldsymbol{L_j}$) and the locally produced energy from renewable energy sources generation ($\boldsymbol{G_i}$). Differently from $\mathrm{OF_1}$ and $\mathrm{OF_2}$, that can only be positive, $\mathrm{OF_3}$ can also be negative. The minimization of $\mathrm{OF_3}$ prioritizes solutions where the generation is higher than the load, i.e. higher profitability of the energy hubs.

Equation (19) replaces equation (12), to add a distance-based behaviour in the capacity constraint formulation. In this equation, the overall weight for each EH $\boldsymbol{i}$ is determined by the weight related to the local traffic in the item/raster $\boldsymbol{w_i}$ plus a weight component $\boldsymbol{w_j}$ for all the rasters $\boldsymbol{j}$ assigned to the EH $\boldsymbol{i}$, which decreases proportionally to the inverse of the logarithm of $\boldsymbol{d_{ij}}$, where $\boldsymbol{d_{ij}}$ is the distance of the raster $\boldsymbol{j}$ to the raster $\boldsymbol{i}$ (see Figure 5). Both weights $\boldsymbol{w}$ and capacities $\boldsymbol{c}$ express in this case power: power demand for $\boldsymbol{w}$, and power capacity for $\boldsymbol{c}$.

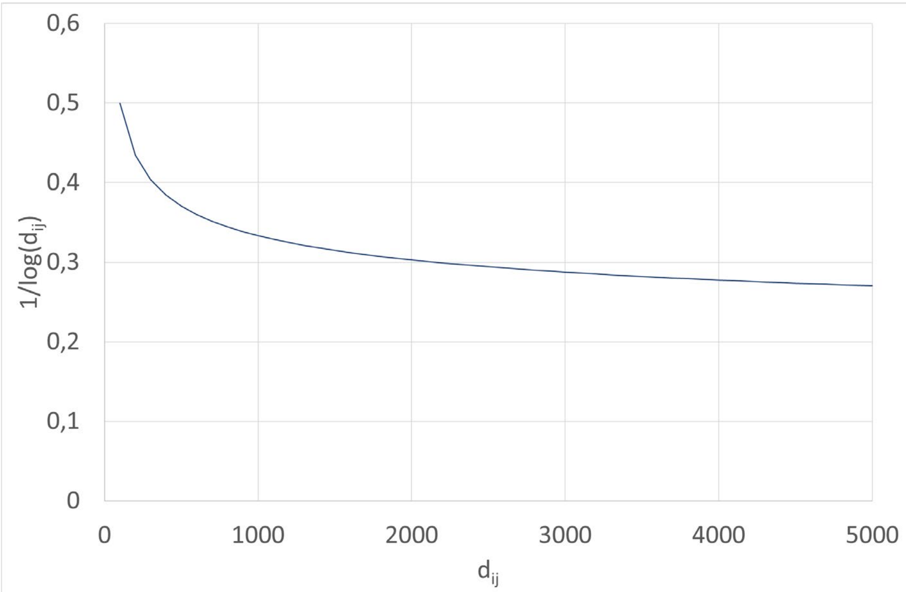

Figure 5. Multiplicative factor of weights based on distance

The scope of this version of the capacity constraint is to take into account the following points:

- the further is the traffic from the EH, the lower is the probability that the traffic will stop by the energy hub;
- the traffic is discretized in an hourly time frame, therefore the vehicles in neighbouring rasters will, with some probability, coincide.

Moreover, Equation (20) defines the radius $\boldsymbol{\phi}_i$ as the norm of the vector $\|\overline{d}_{ij} \circ \overline{x}_{ij}\|$. The set of constraints (21-23) is identical to (13-15) previously discussed.

The set of equations (16-23) is linear; therefore, it can be solved with any MILP solver (provided that it is able to handle multiple objectives). Another option is represented by heuristic solvers.

Having multiple objectives, the solution to the problem is not represented by a unique point, but by a set of optimal choices placed on a Pareto Front. Then it is up to the decision-maker to choose the solution that better suits the decision-maker strategy.

In the following chapter an example is provided, related to an optimal placement of EHs in the area of Trondheim. In this case, the solution is obtained with a Genetic Algorithm.

4 CASE STUDY

The overall method has been inspected by considering an optimal energy hub placement in the area of Trondheim (Norway), focusing on main motorways and trunks.

4.1 DATA ACQUISITION

21 inductive loop measurement devices were identified through the Statens Vegvesen API as installed along the inspected roads. The inductive loop names and locations are listed in Table 1 and shown in Figure 6, where the streets belonging to highway and motorway class, which are represented by a total of 265 road stretches, are highlighted in blue. For each of these measurement points, the traffic data records for the whole year 2021 were downloaded through the same API.

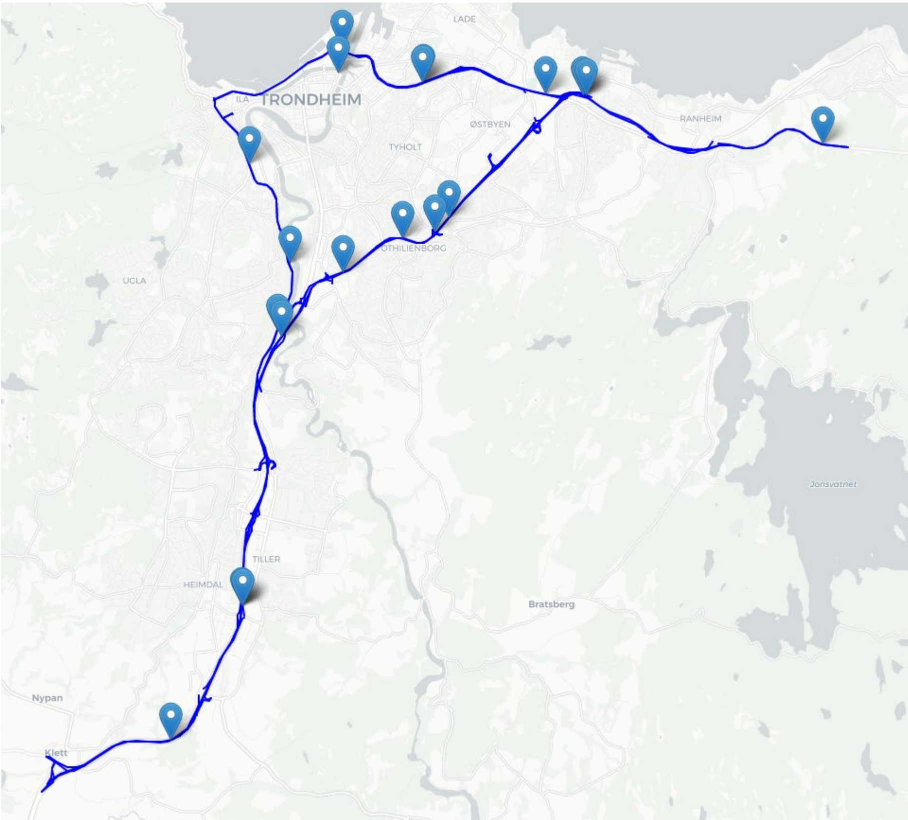

Figure 6. Location of traffic measurement points in the Trondheim area

Table 1. Location of traffic measurement points in the Trondheim area

id	name	lat	lon
44210V2411509	Grillstadtunnelen til Rotvoll	63.431343	10.493692
81077V72158	Havnegata	63.438910	10.406326
41020V3128088	Heimdalsmyra rampe fra Isdamvegen til E6	63.348200	10.370416
66126V3112188	Storlersbakken ved viltovergang	63.326318	10.344227
21571V2394246	Strindheimtunnelen mot Nyhavna	63.433297	10.435812
20570V72811	Sundland	63.402320	10.406869
60797V2801059	Heimdalsmyra E6 mellom ramper	63.348348	10.370178
36935V72359	Selsbakk	63.392779	10.383003
40649V2411511	Grillstadtunnelen fra Rotvoll	63.430977	10.494072
35002V72811	Moholtlia	63.407889	10.428456
77022V72359	Oslovegen	63.403845	10.387464
06970V72811	Kroppanbrua	63.391793	10.384529
78492V2394249	Rotvollekra	63.431276	10.480316
21801V72158	Brattørbrua	63.434645	10.405040
46684V1842951	Marienborgtunnelen	63.419949	10.372672
73951V2394243	Strindheimtunnelen mot Rotvoll	63.433090	10.435691
55570V3128090	Heimdalsmyra rampe fra E6 til Isdamvegen	63.348309	10.369918
63028V72219	Moholt rampe til Moholt	63.408842	10.440246
94210V2411536	Grillstadtunnelen vest	63.430956	10.494996
44660V72811	Moholt ved Vegamot	63.411130	10.445121
32375V72155	Væretunnelen	63.423255	10.580731

4.1.1 TRAFFIC AND CONSUMPTION ESTIMATION

As the first step, a state estimation problem is set up. This system results in 21 known traffic values out of 265 unknown traffic states. The system is strongly underestimated, therefore the nnls solver is used. Since each inductive loop records 8760 measurements, ideally the nnls solver should be applied for 8760 states.

To simplify the computation, eight average values have been calculated for the representative days in Table 2.

Each representative day is a sequence of 24 traffic states for 24 hours, which must be weighted for the number of occurrences in a year.

In Figure 7 the 0.6 quantile of the traffic states is represented. The colourmap shows the street segments where a higher density of traffic is detected along the motorways in the inspected year.

Table 2. Representative traffic states analysed

No.	Season	Day	# occurrences / year
1	Spring	Weekday	65
2	Spring	Weekend	26
3	Summer	Weekday	65
4	Summer	Weekend	26
5	Autumn	Weekday	65
6	Autumn	Weekend	26
7	Winter	Weekday	65
8	Winter	Weekend	26

By assumption, it has been decided that the overall dimensioning of the charging station infrastructure would be designed over the 60th percentile. That is, for 40% of the cases it is accepted that a vehicle would have to wait in queue or have to redirect to other charging stations.

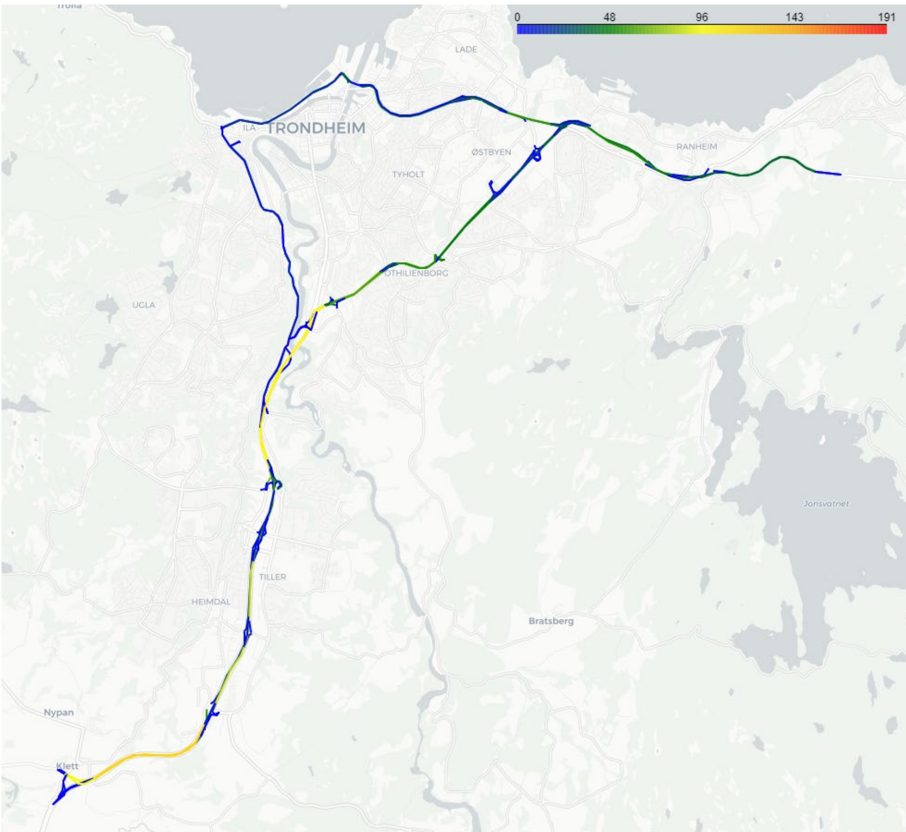

Figure 7. Traffic estimation results

The street map has then been rasterized over a grid 50x50, to reduce the problem into a set of discrete squares. Each square (795 m latitude, 727 m longitude) is assigned its power consumption value, according to the approach described in Chapter 3 (Rasterization of information (3.2.1.3), EV traffic consumption (3.2.1.2)).

On equations (9) and (10), respectively for power and energy load consumption calculation, the data assumed is:

- All vehicles are assumed short vehicles, with average charging power consumption *C(v)* of 40 kW
- Penetration rate $K(v, l)$ = 0.1
- $\vartheta(v)$ = 0.5, which means that in average two EVs will in average be fully charged in a single hour.
- $p(v, l, h)$: four probability curves are assumed, as shown in Figure 1. Rasters are divided into urban and suburban according to the properties obtained from the OpenStreetMap geolocalized database entries.

The result of the rasterization and power consumption assignation is shown in Figure 8. The scale is expressed in terms of kW of power consumption at the 60th percentile.

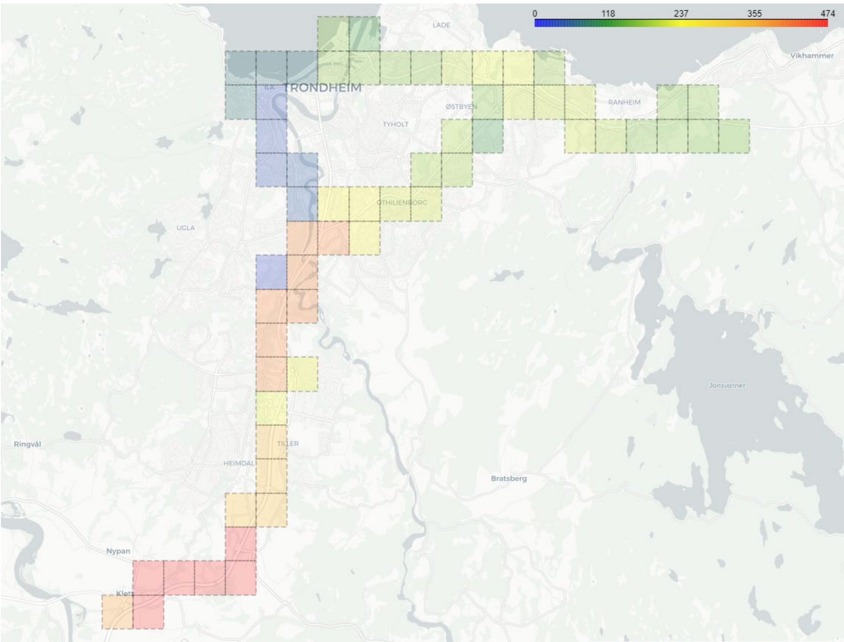

Figure 8. Traffic estimation rasterization and power consumption assignation

What can be observed is that a higher traffic density is located on the highway that leaves Trondheim in the southern direction. The higher consumption in the 60th percentile is lower than 500 kW, therefore it is assumed that charging stations within energy hubs should be able to supply at least 600 kW, which is assumed as CS nominal power (i.e., the parameter *c* in equation 19).

4.1.2 POWER SYSTEM AND GENERATION DATA

Final data processing is represented by the power system model acquisition. As described in section 3.2, OpenStreetMap data has been used to gather information regarding power system topology. In Figure 9 the power network topology for Trondheim is shown.

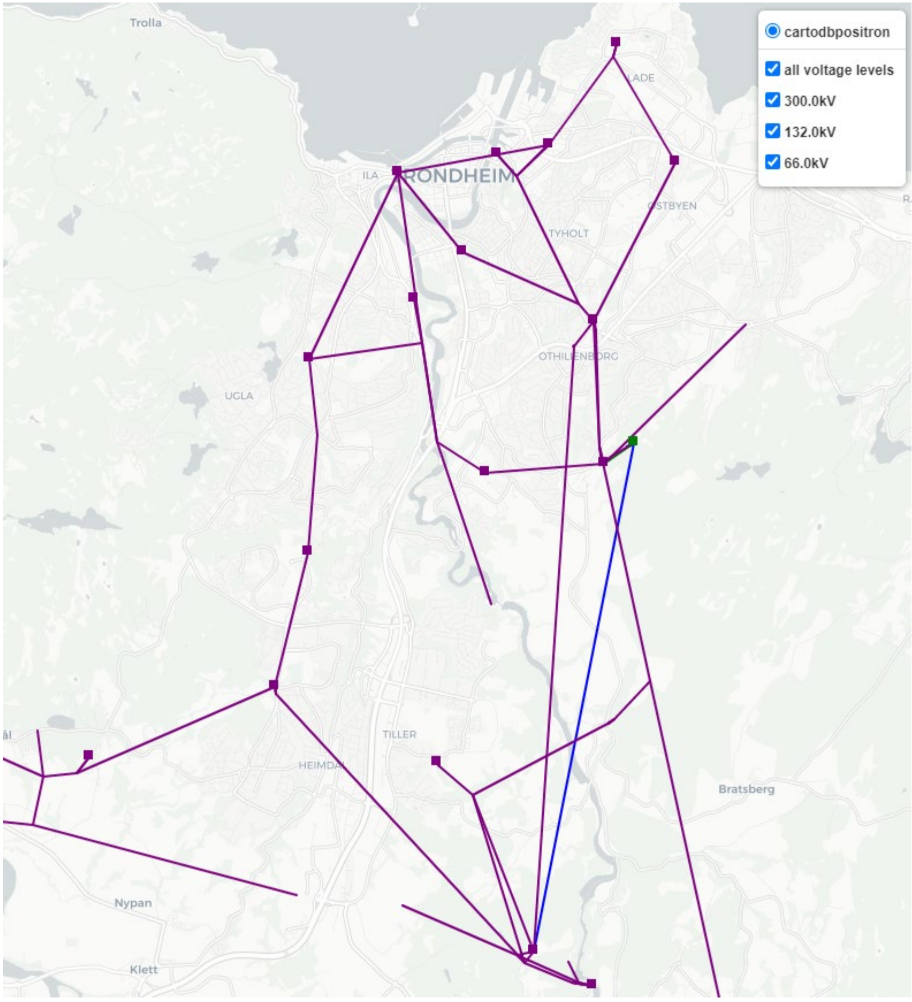

Figure 9. Power system map in Trondheim

What can be observed is a higher density of substations in the proximity of the city centre, whereas in the suburban area substations are in general more distant from the motorway.

For determining the generation potential from renewable energy sources, the inspection has focused on wind power. The wind atlas from NVE, through the APIs made available by NVE, has been used to determine the number of full-load hours ***t*** (see section 3.2 for reference).

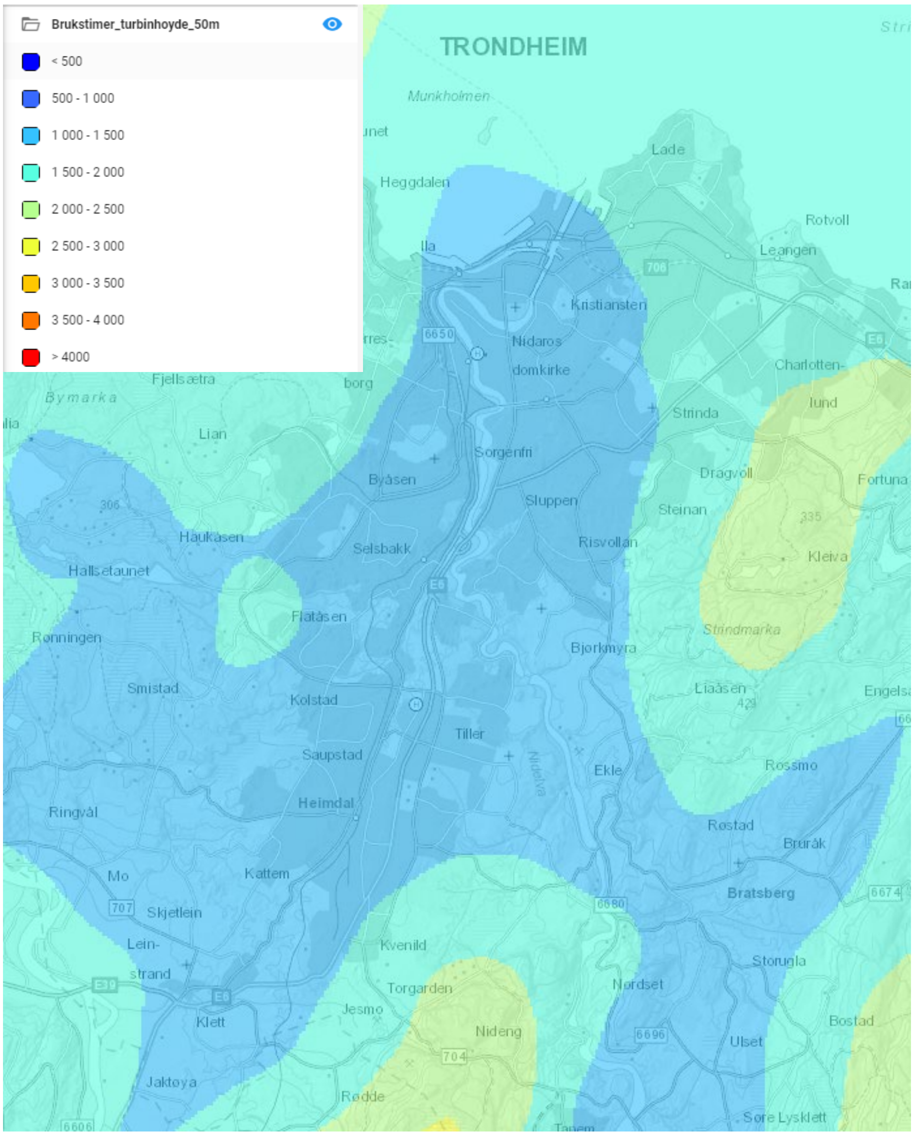

Figure 10. Wind potential full-load hours for the area of Trondheim (source: NVE)

Nevertheless, the potential generation from wind power is function of further aspects, such as the power curve shape of the wind turbine, and the available area for installing the wind turbine/wind farms.

Regarding the wind turbines, the ENROAD Deliverable D2.2 has been used as the main source of the different technologies available. Based on this inspection, the Turbine Bornay 6000 has been adopted. In Table 3 the main characteristics of the adopted technology for renewable generation in the energy hubs are reported from the turbine datasheet.

Table 3. Characteristics of Bornay 6000 turbine

Item	Unit	
Reference turbine		Bornay 6000
Rotor Architecture		HAWT
Manufacturer		BORNAY
Nominal Power	**kW**	6
Peak Power	**kW**	6,2
Rotor Diameter	**m**	4
Nominal Wind Speed	**m/s**	12
Cut-in Wind speed	**m/s**	3,5
Cut-out Wind speed	**m/s**	20
Survival wind speed	**m/s**	60
Weight	**kg**	107
Cost	**EUR**	9069
Minimum separation between turbines - parallel to prevalent wind	**number of rotor diameters**	9
Minimum separation between turbines - perpendicular to prevalent wind	**number of rotor diameters**	4
Warranty	**years**	3
Expected lifetime	**years**	20

Regarding the available area, OpenStreetMap has been used as main data source. The available on-surface parking areas in the different rasters have been identified as possible installation areas of the selected wind turbines. By crossing the wind turbine characteristics from the turbine datasheet, the available parking areas from OSM and the wind measurements from the NVE atlas, the potential wind generation for the specific area inspected is calculated.

$$G(l) = T \cdot \frac{A(l)}{a} \cdot \tau \tag{24}$$

Where T is the nominal power of the wind turbine, $A(l)$ is the available parking area in the given raster l, a is the area surrounding the turbine to keep the necessary distances from neighbouring turbines or objects, and τ is the full-load hours obtained from the NVE wind atlas.

The result of the calculation for each raster is reported in Figure 11, where the colour scale is defined in terms of yearly energy potential in kWh for the single raster.

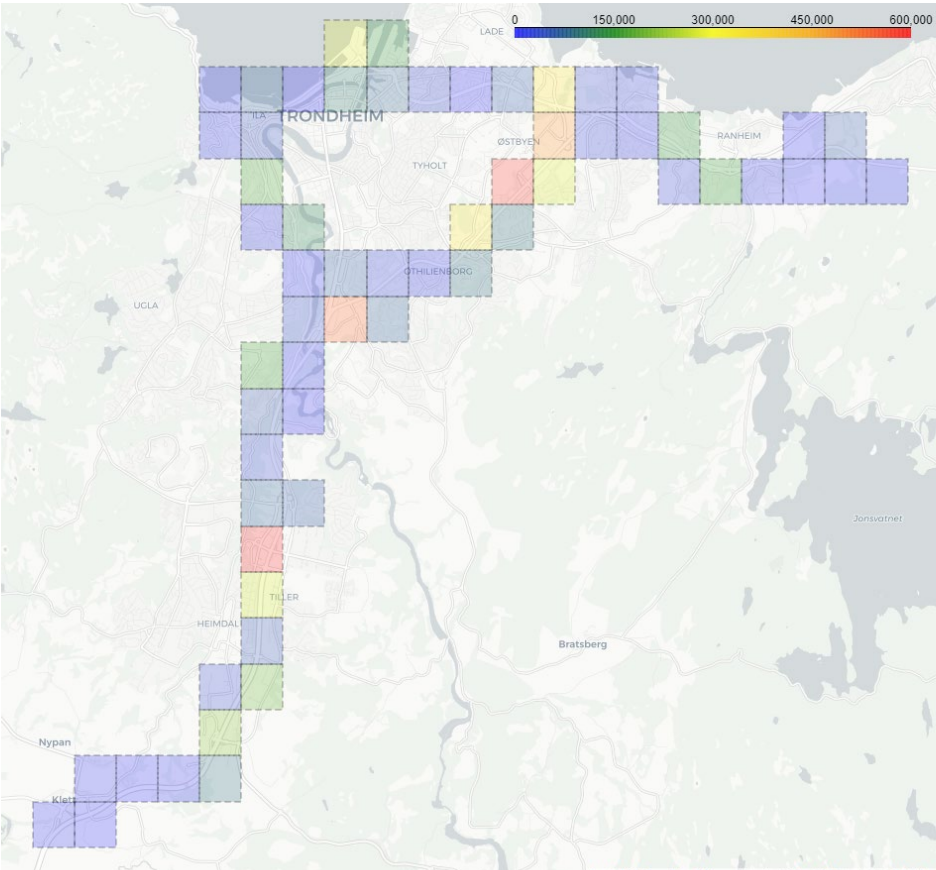

Figure 11. Energy potential from wind generation in the area of Trondheim [kWh]

What can be observed from Figure 11, compared with the wind atlas in Figure 10, is that there is not a perfect correspondence of energy density between wind availability and productivity of the area. This is due to the different available surfaces for installing wind turbines in the different rasters.

4.2 SOLVING THE OPTIMIZATION PROBLEM

Given the input data defined in section 4.1, the system of equations (16) to (23) is implemented. As mentioned in section 3.3, the system represents a set of linear equations, therefore it can be solved with several approaches, both analytical, e.g., with a MILP solver, or with meta-heuristic methods.

For this specific case study, the solution is sought through the algorithm NSGA-II (Non-dominated sorting genetic algorithm II), a variant of genetic algorithm that emphasizes the non-dominated solutions and that uses an elitist principle to generate the offspring of a population (Deb, 2001; Deb et al., 2002). The implementation of the optimization problem is done in python language (release 3.9), with the library Pymoo (Blank & Deb, 2020), which provides several algorithms to solve multi-objective optimization problems.

As the main parameters of the NSGA-II, the following have been assumed:

- Population size: 1200
- Number of offsprings: 1000
- Number of generations: 1000

The problem was solved in a Laptop DELL, Intel Core i7 2.1 GHz, 32 GB of RAM, with Ubuntu 20.04 Operating System.

In total, the solution to the problem with the given settings required 34 hours. Nevertheless, it has to be pointed out that no efforts have been made to improve the computational efficiency of the computing architecture, for example by allowing the parallelization of the computation among the different processor cores.

4.3 RESULTS

As mentioned in section 3.3, the results of the MO problem do not produce a unique solution, but are placed in a Pareto front. In Figure 12 the solutions are placed in a three-dimensional space, where the axes are represented by the solutions for the objective functions OF_1 (*f1*), OF_2 (*f2*) and OF_3 (*f3*) described in (16) – (18), respectively.

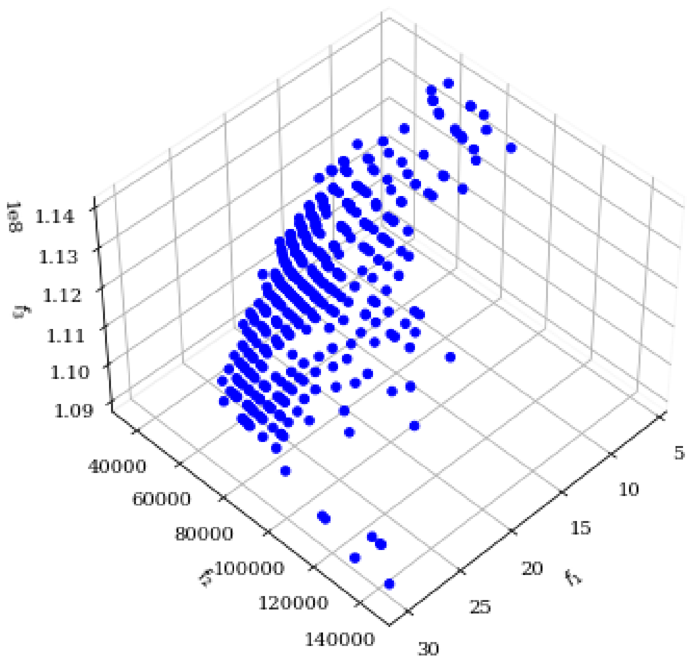

Figure 12. Pareto front of the Multi-Objective Optimization problem solutions

A flattened version of the plot is given in Figure 13, where diagrams are plotted in a bi-dimensional space.

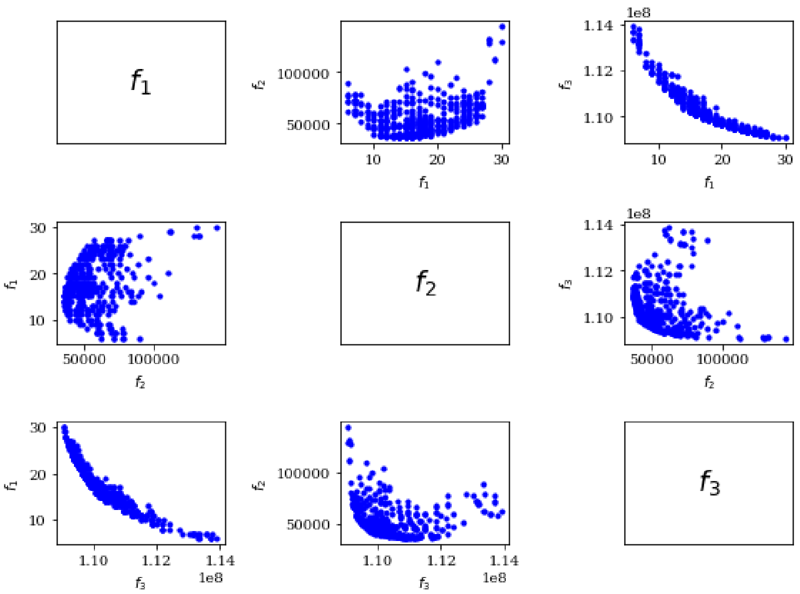

Figure 13. Flattened representation of the Pareto front

Figure 13 helps to understand what the main trends in the solution space are. In general, what can be observed is that the minimization of f1 corresponds to a worse solution for f3. In fact, in order to optimize f3 (i.e., increasing the overall energy generated by the EHs), a higher number of EHs should be installed. A more complex trend is observed for f2. Remind that f2 minimizes the overall radius covered by the EH and the distance from the closest power substation. Increasing the number of EHs from the minimum (6 EHs, calculated by the optimal solution for f1) results in an improving solution for f2: in fact, a higher number of substations results in a smaller coverage radius for the single EH; over a certain threshold, f2 Pareto front increases. This is due to the fact that the remaining rasters for additional installation of EHs are locations far from the available substations. f3 general trends are represented by a straightforward advantage in increasing the number of EHs: any incremental number of EHs installed results in a smaller difference between the overall energy demand from EV charging and the yearly energy generated by the wind turbines.

In total, 440 non-dominated solutions were found. In Figure 14 a distribution of the optimal number of EHs placed in Trondheim is plotted in a bar chart.

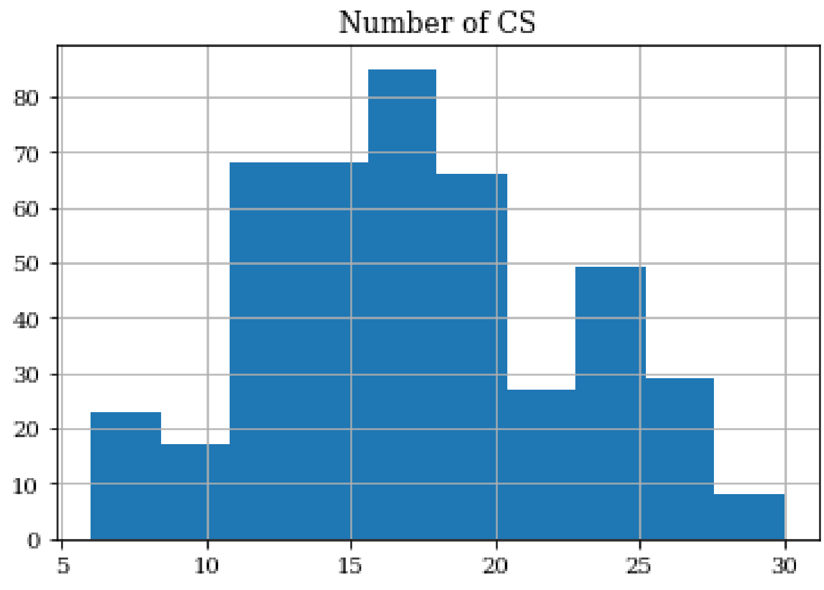

Figure 14. Distribution of number of EHs placed in the Trondheim area

Six solutions identify the minimum number of EHs installed. These solutions are highlighted in Figure 15 with red dots.

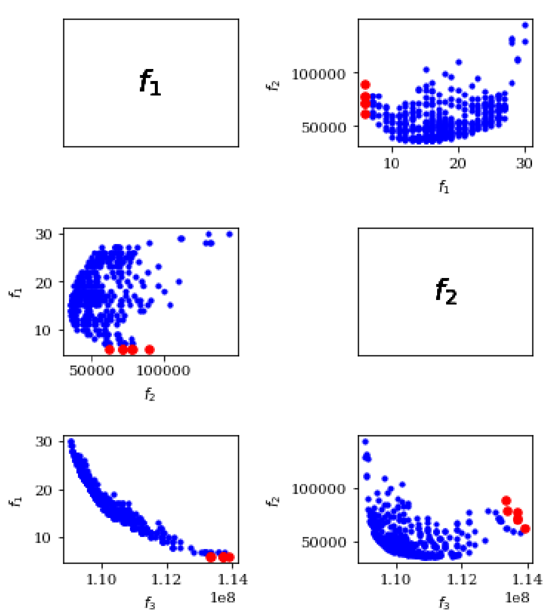

Figure 15. Minimum OF_1 solution points

A sample of this optimal solution points for OF_1 is reported in the following figure:

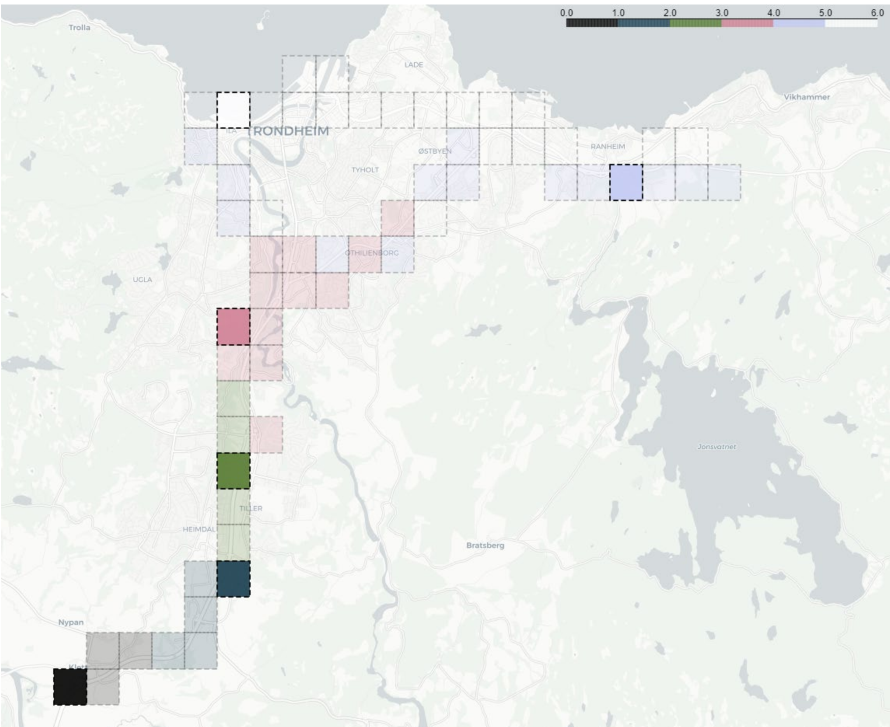

Figure 16. OF_1 non dominated solution

What can be observed is a higher density of the solutions in areas that are densely characterized by high traffic, according to Statens Vegvesen statistics (ref. to Figure 7). What can further be observed is that there is no optimization of the EH coverage radius in the assignation (e.g., some rasters in the North-West area of Trondheim are assigned to the purple EH placed at North-East).

In Figure 17 a bar chart representing the distribution of the EH representative radius ($\mathrm{OF_2}$) is shown. The minimum is identified in 36.2 km. The corresponding solution is shown in Figure 18

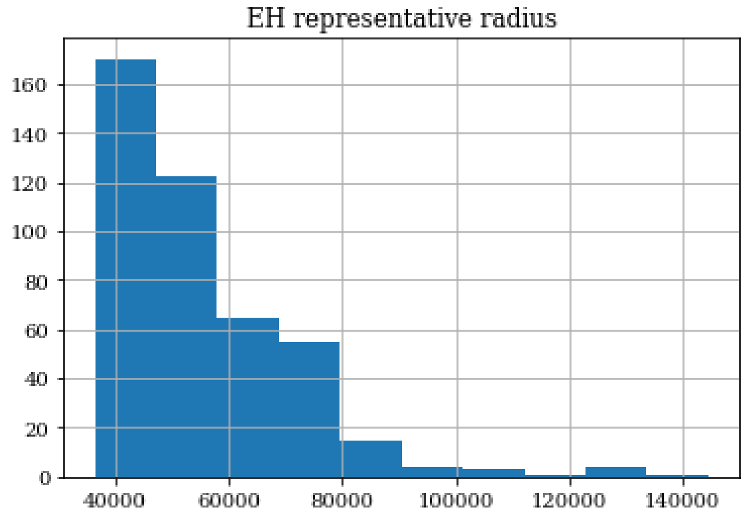

Figure 17. Distribution of coverage radius of EH placed in the Trondheim area

What can be observed is the increased number of EHs installed according to this OF optimization, in order to minimize the coverage radius. Moreover, it can be observed how the higher density of EH location is identified in the rasters that are closer to the available power substations (ref. to Figure 9), due to the dependency of the representative radius on the distance to the closest substation.

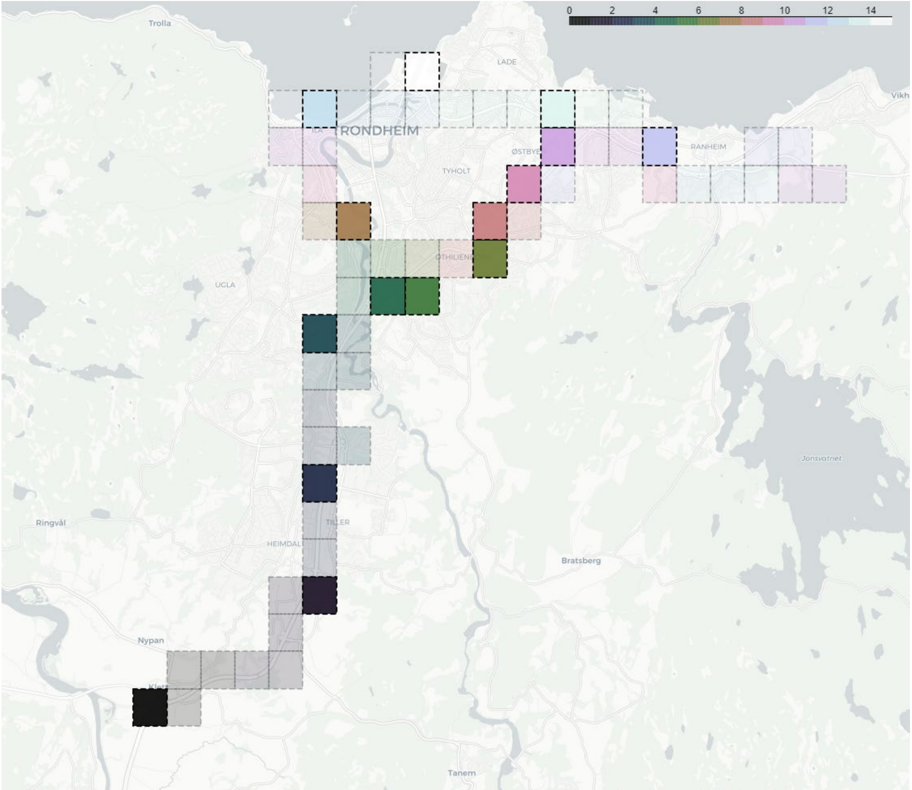

Figure 18. OF_2 non-dominated solution

The final analysis is conducted on OF_3 results. A bar chart of non-dominated solutions for OF_3 is shown in Figure 19. The minimum is identified in 109 MWh/year of EV charging load uncovered by the EH wind generation. The corresponding solution is shown in Figure 20. After an inspection of the results, what is observed is that EHs are installed throughout the whole area, except for those areas where there are no available areas for the installation of wind turbines. A fair correspondence can be observed between results in Figure 20 and the map of wind generation potential in Figure 11 (the linear scale of the colour map does not allow to appreciate the granularity for low values of generation potential – blue colours).

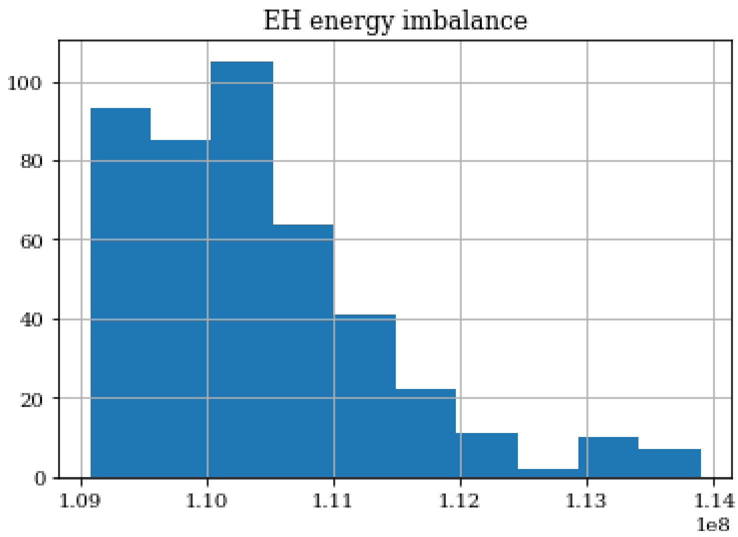

Figure 19. Distribution of energy imbalance for different non-dominated solutions in EH placement in the Trondheim area

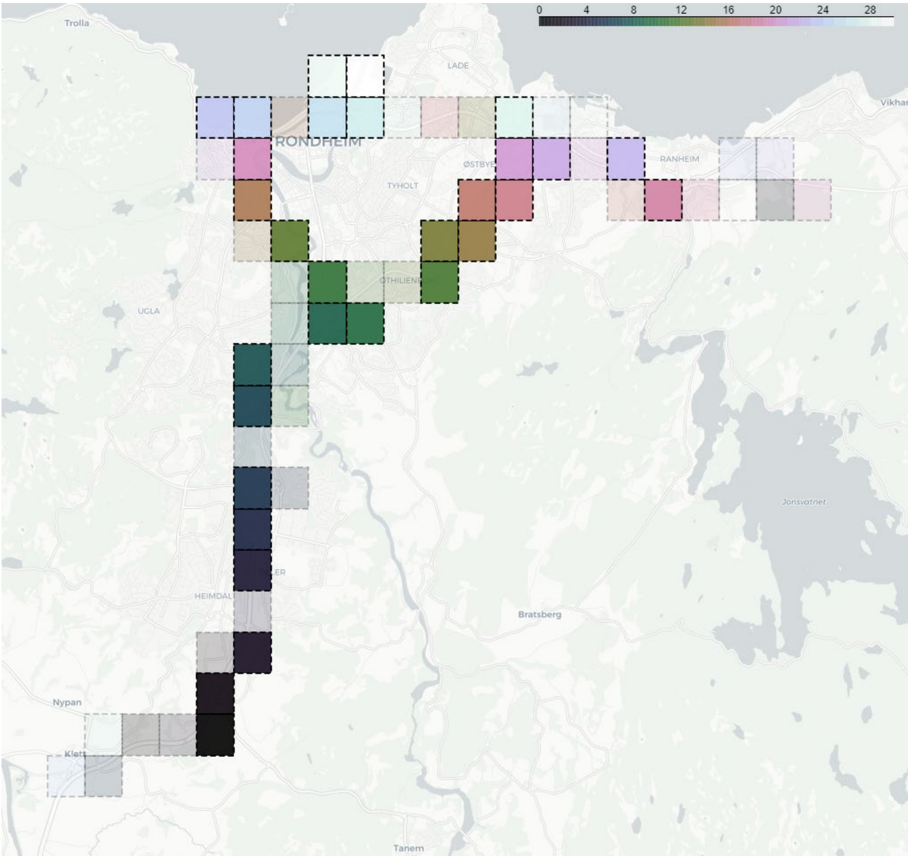

Figure 20. OF_3 non-dominated solution

5 CONCLUSION

In this report, the activity research performed in ENROAD for optimal placement of future energy hubs with renewable generation is presented. The methodology is based on data aggregation from different open-source datasets involving the availability of renewable energy sources, land for generation devices installation, traffic density patterns, electric vehicle charging patterns, road topology, and land destination of use. The optimization problem is formulated in a multi-objective linear programming problem, where the multiple objectives considered are: the minimization of the EH units, to minimize the overall investment; the minimization of the EV charging radius coverage and the distance of the EH from the closest power substation; the maximization of the potential energy generation.

An application of the methodology is presented, where an optimal placement of EHs is studied around Trondheim, in Norway. The domain of the solutions reproduces a Pareto Front, which has to be analysed by decision-makers to evaluate the best compromise between different contrasting objectives.

The case study allows observing different aspects related to the applicability of the methodology and its potential in a real-case study of optimal placement of energy hubs.

When trying to combine different single objectives, these objectives, if analysed singularly, bring different EH placements. The methodology returns the overall space of solutions in a Pareto Front, therefore it is up to decision-makers to select the single solution that is better aligned with the planner overall strategy. This aspect is one of the strengths of the approach proposed, since there cannot be a single optimal solution, due to the several counteracting objectives that contribute to a placement choice. This does not hinder the possibility to apply to each single objective proper weights, and converging the multiple objectives to a single objective through a weighted sum.

The flexibility in the formulation of the methodology allows to further extend the set of constraints and objectives without compromising the generality of the approach.

It has to be noted that the formulation and the example presented in this report are strongly tied, since they are both influenced by the data available for the specific modelling process of the area of Trondheim. A wider availability of data would further enhance the potential of the methodology, e.g. through:

- a better description of the traffic model; as an example, Origin-Destination matrices are not analysed in the model proposed in this report, despite the awareness of a stronger potential than the traffic state estimation proposed;
- a better description of the charging patterns; EH planners can reach agreements with the Charging Operators, and better tune the correlation factor between the traffic on different classes of streets and the probability of vehicles stopping by the energy hub for charging;
- the example has presented only a single technology for renewable generation in the energy hub; a wider analysis could involve several technologies, where the selection of the technology mix to be installed on a single energy hub can be related to economic and regulatory factors, which have not been analysed in this report.

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