ARTIFICIAL INTELLIGENCE FOR MICROGRID PLANNING

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ABSTRACT

This paper puts forth how artificial intelligence could assist in the intelligent design of microgrid energy systems. The planning of microgrids entails many interacting variables and trade-offs between efficiency, economy and reliability. In order for an artificial intelligence to assist human planners it has to generate optimal designs based on the input and performance criteria. This paper showcases a basic learning neural network to generate a microgrid design for a mid-sized city.

INTRODUCTION

A microgrid is a group of local, interconnected electricity producers (generators) and users (loads) which can operate as a single, self-sufficient entity. Microgrids are usually connected to the centralized grid (macrogrid) but can disconnect and maintain operation autonomously (adaptation from [1] [2]).

This ability of microgrids to operate self-sufficiently and autonomous promises to enable higher reliability, higher penetration rates of renewable energy sources and more effective demand-response. Capturing these benefits is worthwhile for reasons of social, economic and sustainability. Expenditure on the electrical and gas grid combined amounts to ± 1% of GDP, for the Netherlands this amounts to around 6 billion EUR in 2015 [3]. For the electric grid, the current expenditure is set to increase by a factor of 2 to 3 until 2050, mostly due to grid expansion [4]. Poorly designed microgrids could end up raising costs and perform poorly for incorporating renewables.

Incorporating flexibility and optionality is becoming more important as the speed of change in technology and demand patterns is increasing. Grid investments have an economic lifetime of 15 – 50 years. Microgrid designs that design for flexibility and optionality can assist in preventing future surprises, expensive write-downs and unplanned grid enlargements.

Artificial intelligence constitutes the designing and building of intelligent agents that receive input and instructions from the environment and take actions that affect that environment [5]. An intelligent agent is one that acts so as to achieve the best outcome or, in case of uncertainty, the best expected outcome. Due to the rapid development in computational capacity and artificial intelligence, the deployment of intelligent agents is becoming more relevant to intellectual tasks. Authors endeavor to apply artificial intelligence to the task of network planning, architecture and design. This paperapplies a rational agent to the design of a microgrid.

RESEARCH QUESTION

Can we develop tools and techniques that utilize the progress in computational resources and machine learning to allow microgrids to be more optimally designed and operated? How could we apply artificial intelligence to design microgrids with a high level of reliability and integration of renewable resources -while remaining affordable? Both in the short- and long-term.

More broadly, can we apply the findings to create tools to enable the planning of 'mobile electric assets' such as batteries, electrical vehicles and fuel cells. Finally, authors hope the findings prove useful in reframing the future technology possibilities and assist in the preparation for break-through scenario's and strategies for the energy transition and meeting the obligations of the Paris Agreement.

METHOD

The problem is a combination of the classical Unit Allocation Problem and Transmission Problem. The Unit Allocation problem is concerned with optimal geographical location and sizing of the generator unit. The Transmission Problem is concerned with the optimal geographical location and sizing of the transmission and distribution cables. In general, a good design and architecture scores high on efficiency, cost and reliability.

The method of addressing this problem is to test Artificial Intelligence techniques in designing and planning microgrids. The authors work on developing and testing these new techniques for both theoretical problems and real-life grid cases. The method consists of comparing the actual grid with an artificial intelligence generated grid design.

The results and outputs are evaluated compared to the actual grid for grid length and capacity, as no generation is available in the current area. In addition, the usefulness of the artificial intelligence in designing a grid including 'mobile electrical assets' and planning for disruptive scenarios are qualitatively assessed.

Artificial intelligence for network planning

Authors designed an artificial intelligence to assist and optimize for the Unit commitment and the Transmission Problems with the following method:

1. Determine demand (load over time, geographic location)
2. Set performance function (efficiency, costs, reliability)
3. Determine input variables (relevant investment, costs and losses)
4. Design expert systems (generator allocation, connecting, sizing of capacity, dispatching)
5. Design neural network that creates expert systems
6. Train neural network with real-life problems
7. Generate microgrid plan with trained neural network

The following difference are observed compared to classical grid planning:

Table 1: comparing classical planning and artificial intelligence

Classical planning	Artificial Intelligence approach
Supply driven	Demand driven
Optimize for single system element	Optimize for whole system
Heuristics	Learning & feedback loops
Planning rules	Few planning rules
Rule-based	Learning-based
Network specific	Broader application of learning
Detailed plan	Abstract design

The artificial intelligence approach focusses more on demand for two reasons: in order to make it easier for the artificial intelligence to learn how to supply the demand in an optimal manner and to make the artificial intelligence more generally useful as it could assist in different planning problems.

The goal for the artificial intelligence is to optimize total system design. The goal is defined as the performance standard against which the resulting system design is scored. The scope of the system is taken as both supply and transmission to meet the demand. Meeting demand is defined as the demand over time and in space.

The performance standard is determined in the following manner. The efficiency and reliability are given as input stating the required minimum level. The performance is rated as the capacity and operational costs for the generator (supply) and transmission.

The training of the artificial intelligence is done by providing different loads and to allow it to generate a design containing sufficient generators and transmission at minimum cost. To achieve the training of the artificial intelligence the authors put forth the following approach: a neural network that generates expert systems. An expert system is an algorithm that emulates the decision-making ability of a human expert. The neural network generates expert systems by setting the key variables. The expert system in turn executes the various planning steps, being: location of generators, location of transmission, sizing of capacity for generators and transmission and dispatching in time.

The learning set-up allows the artificial intelligence to assist in different network planning problems. Examples are hydrogen, direct current, water or other networks. The trade-off is a loss in specificity and detail of the output as well as having less design parameters to plan for. Authors estimate that these hurdles can be overcome in future generations and with more elaborate learning examples. The results of this learning set-up are relatively abstract network designs compared to more specific, more detailed plans which are achievable with existing systems. An example of such a system is DER-CAM [5].

The problem is simplified by applying a rectilinear grid. This reduces the search space for the transmission problem. The learning of the artificial intelligence is achieved by applying a standard gradient descent method to arrive at the global minimum. The optimum has been proved mathematically for 40x40 microgrid size per generator. Larger subproblems can be solved but are not yet proven to yield optimal solutions.

Besides the different expert systems, the artificial intelligence can apply one or multiple layers in the network design. This layering is also applied in current grids (380 kV to 10 kV) and the agents also utilize this layering as will be shown.

Data for the artificial intelligence

To train the artificial intelligence, the data contains descriptions of demand locations in coordinates, load size (demand). In addition, the input variables are efficiency, reliability, investment and operational costs. Finally, some basic input is provided to guide the construction of the expert systems and learning method.

The data used is from the DSO Enexis (The Netherlands) and constitutes aggregated data for street level (postal code level 6). The data corresponds to electricity usage by small- and mid-sized users in postal code areas 9711, 9712, 9713 and 9714 [6]. There are 24.202 grid connections in the area serving a total of 37.895 residents living in 28.200 households [7]. Total yearly electricity demand is 76.7 mln kWh.

The data describes aggregated connection size of 10 to 120 individual homes and small- to medium-sized businesses. It excludes large loads (users). In the test 846 demand locations are identified for which the electricity demand is rated from 1 to 160, representing yearly average usage of electricity per demand location. The scaling is done to enable faster convergence for the individual expert systems and decrease computational time.

Designing a microgrid for a medium-sized city

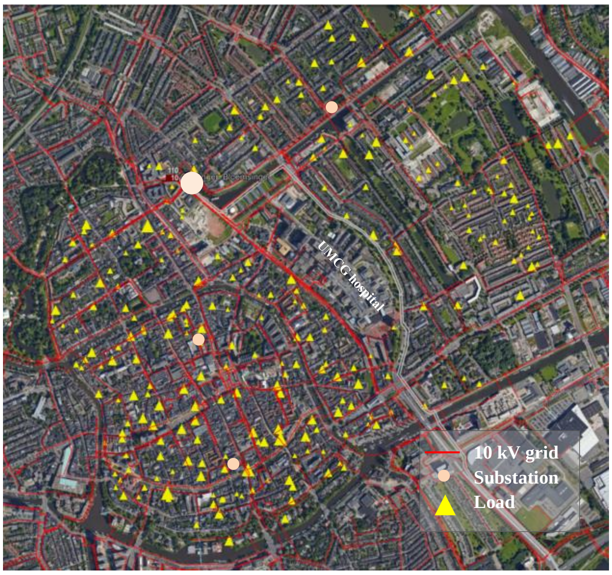
In order to test the artificial intelligence, the following problem statement is used: design a new microgrid for a medium-sized city, on the scale of street level and based on open data. New in this case means a plan in which existing generators and transmission are not taken into account. The reason for this design problem is to identify how the artificial intelligence designs a new grid and to be able to compare it to the existing grid.

The city is Groningen, located in the north of The Netherlands. The city is used since a lot of local data is available and there is an interesting spacing of load, both geographically and load size (see data sources in [6]).

RESULTS

The current 10 kV grid length is estimated at 105 km ± 25 km (see red lines). The orange area in schematic 1 is the 110 kV connection. Below, the current situation is illustrated:

Schematic 1: current grid in Groningen (in red)



The smaller orange dots are the transformer substations. The load/demand is described in 260 load points which are visualized in the yellow triangles. The load is based on the 846 data points from the open data. No load appears in the parks, city squares and the hospital area. The hospital does not appear as it is classified as a large user and is not within the dataset.

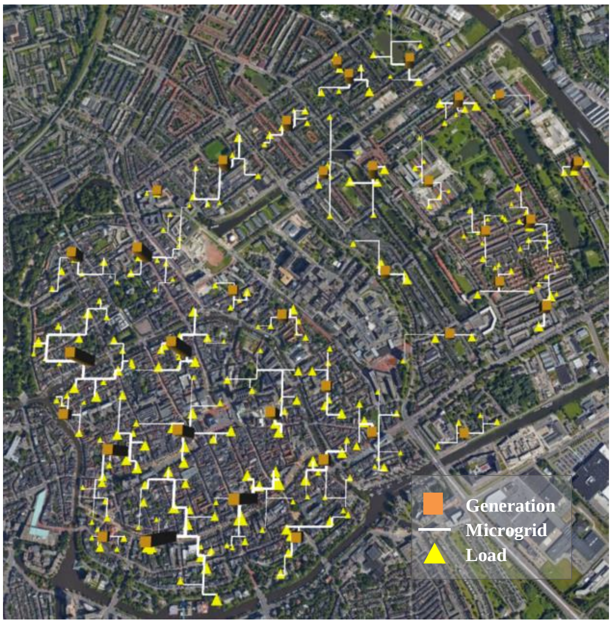
Schematic 2: current grid in Groningen (zoom-in)

A closer look at the map reveals more detail about the grid and how the demand is aggregated to street level. The reason the demand is not evenly distributed has to do with the input data which is anonymized and aggregated to postal code level. Basically, we're looking at postal code-based demand.

Microgrid design by an artificial intelligence

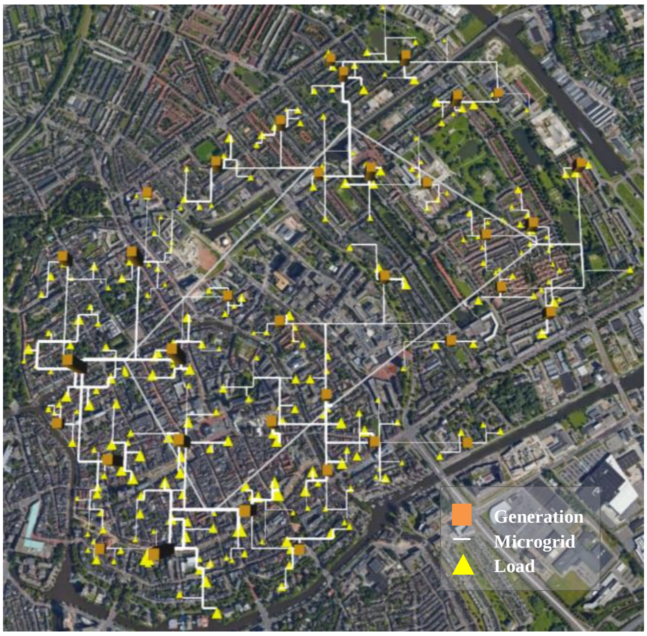
The artificial intelligence output is a two-level design for the microgrid. The higher level consists of five different demand clusters. The lower level consists of forty demand clusters each with its own generator.

Schematic 3: artificial intelligence generated design (lower-level grid design)



The roughly forty smaller microgrids are connected in two manners: first to each other, and second to the macrogrid (grey line).

Schematic 4: artificial intelligence generated design (lower level and higher-level grid design)



The design uses many small-scale generators/suppliers at the lower level with each supplying 300 – 3000 people and small businesses. The output contains a relatively large amount of generators/supply to minimize transmission.

The output contains four reliabilities improving design elements:

1. each subgrid can be supplied by near subgrids within the larger microgrid they are a part of,
2. a larger microgrid can be supplied by the other microgrids together,
3. the two largest generators could go down without loss of supply.
4. each grid can run in self-sufficiency mode,

The length of the microgrid is 45 kilometers, 20 kilometers at the lower level and 15 km at the higher level. This is about 60% less than the estimated 105 km ± 25 km of the current grid. These findings are in line with similar findings using artificial intelligence to generate grid designs for a country as a whole [8].

Artificial intelligence performance

Authors assess that the artificial intelligence would be able to plan with a higher level of detail: load per connection and potentially even per application/device. In addition, the planning could in theory be made once a day and even once an hour if enough computational capacity is available. This would allow for the theoretical planning of mobile assets such as cars, batteries, generators and fuel cells with a dispatch timeframe of days or hours. Authors will pursue this reasoning over the coming months with a real-life testcase.

More generally, the combination of classical planning tools and artificial intelligence appears attractive. The artificial intelligence can generate a whole-system network designs with novel layouts. This more abstracts design layout can be fleshed out into more practical plans with classical planning tools.

Finally, given the uncertain future developments in technology and demand, the usage of artificial intelligence provides a new tool to assist in devising out-of-the-box and even radical scenarios and designs to assist the energy transition and in meeting the obligations of the Paris Climate Agreement.

DISCUSSION

Authors observe that the current BUS standardized testcases are too narrow to test a whole system design against. Over the coming period, a concentrated effort is made to generate a dataset and problem definition to assist the development (and competition) of artificial intelligence applications. The capability to plan mobile assets could lead to lower total overall system cost and higher reliability, however this requires more studies and the usage f the aforementioned standardized test datasets.

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