A FLEXIBLE TOOL FOR INTEGRATED PLANNING OF ACTIVE DISTRIBUTION NETWORKS

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ABSTRACT

This paper presents a flexible and integrated planning tool for active distribution network to maximise the benefits of having high levels of renewables, customer engagement, and new technology implementations. The tool has two main processing parts: "optimisation" and "forecast". The "optimization" part is an automated and integrated planning framework to optimize the net present value (NPV) of investment strategy for electric distribution network augmentation over large areas and long planning horizons (e.g. 5 to 20 years) based on a modified particle swarm optimization (MPSO). The "forecast" is a flexible agent-based framework to produce load duration curves (LDCs) of load forecasts for different levels of customer engagement, energy storage controls, and electric vehicles (EVs). In addition, "forecast" connects the existing databases of utility to the proposed tool as well as outputs the load profiles and network plan in Google Earth. This integrated tool enables different divisions within a utility to analyze their programs and options in a single platform using comprehensive information.

INTRODUCTION

Recent electricity price escalation in Queensland (QLD) has put tremendous pressure on distribution network service providers (DNSPs) to explore strategies for avoiding or postponing costly network upgrades. Active distribution networks (ADNs) have high levels of renewables, customer engagement, and new technology implementations. An enormous number of possible scenarios for network investments and operation along with complicated load forecast considering the features of ADNs [1] are the main drivers to develop a flexible and integrated planning tool. In addition, this tool should effectively use the existing databases from the utilities and enhance visualization of the electric distribution network.

This paper presents a flexible tool for integrated planning of ADNs. The main goals for this tool are designing an economical network, which satisfies network and load constraints, and consider operational cost. In addition, this tool has great flexibility to include and model new technologies that might be introduced in the future. Moreover, it can take into account different types of customer engagement for demand management, electric vehicle (EV), and control algorithms for grid-connected and privately-owned energy storage systems (ESSs) as well as corresponding uncertainties. This integrated tool enables different divisions within a utility to examine their particular issues in a single platform using comprehensive information. Figure 1 shows the interaction of different divisions of a utility with the proposed tool.

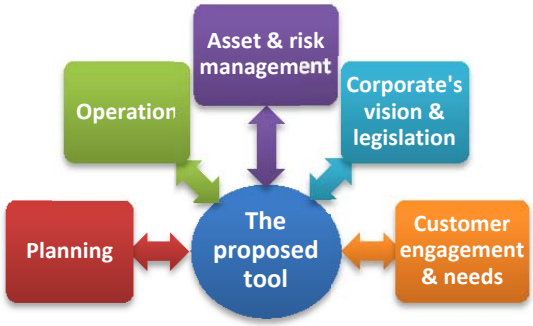

Figure 2. The role of an integrated tool in a utility

This paper, first, explains the "optimization" and "forecast" parts of the tool. Then, the combination of these parts and flow of data between them are examined.

AN INTEGRATED OPTIMIZATION PROGRAM FOR DISTRIBUTION PLANNING

The integrated optimization program is an automated tool that optimizes the net present value (NPV) of the investment strategy for electric distribution network augmentation over large areas and long planning horizons (e.g. 5 to 20 years). The evaluation includes investment costs, operational costs, and salvage values. This integrated planning tool considers all upgrades required in electric distribution networks, simultaneously, to meet load growth and network constraints. The overall features of this optimisation program are presented in Table 1.

Table 1. Features of optimisation program

Optimization Program for Future Energy Grids
Objective is to simultaneously optimize: ✓ Transformer sizing and upgrading, ✓ Conductor sizing and upgrading, ✓ Reactive power compensators sizing & siting, ✓ Voltage regulator (VR) placement, ✓ Energy storage system (ESS) sizing & siting, ✓ Cross connector sizing & siting, ✓ Upgrading of zone substation transformers and network reconfiguration.
Operation and Maintenance (O&M) consideration: ✓ O&M fix cost, emission cost ✓ Reliability cost (SAIDI and SAIFI), ✓ Cost of electric power and energy loss.
Handling constraints: ✓ Bus voltages and thermal limits of conductors and transformers.

Planning approach

To obtain the minimum NPV cost over the planning period, this program uses an efficient forward-backward planning algorithm developed in [2]. In this approach, a year within planning horizon is selected as "Reference Year" ("Ref. Year"). Then, forward fill-in planning from the "Ref. Year" to the final year, and backward pull-out planning from the "Ref. Year" to the first year are performed. This planning procedure is repeated for each "Ref. Year" within the planning horizon. After comparing the NPV of different plans associated with different "Ref. Year", the plan with least NPV is selected. The flowchart of proposed forward-backward approach is shown in Figure 3 [2]. This sequence avoids the massive optimization of considering all options for all years, simultaneously.

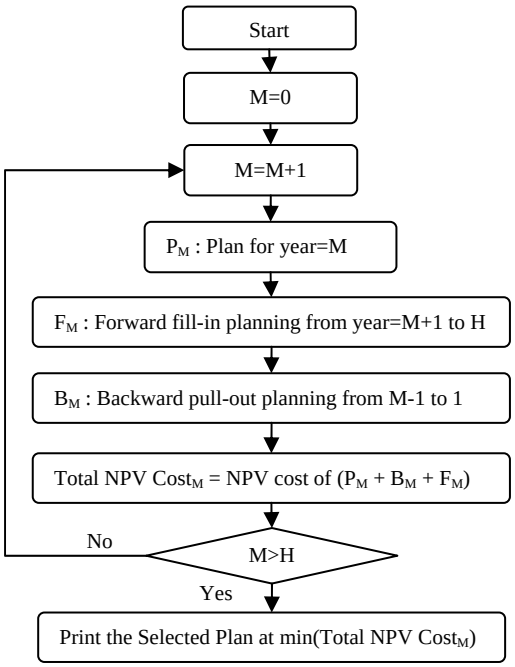

Figure 3. The flowchart of proposed forward-backward approach.

Optimization method

As seen, the proposed approach is able to perform planning up to horizon year (H) based on only forward fill-in (M=1), or backward pull-out (M=H), or forward-backward planning (M=1…H). Each of these planning strategies includes a set of one-year planning. In this tool, this one-year planning is carried out based on a modified version of PSO (MPSO) by adding the idea of mutation from genetic algorithm as in [3] into standard PSO particle update rules. This hybrid algorithm increases the diversity of variables to avoid local minima. In addition, the constriction factor approach for PSO is applied in this algorithm because it has better performance compared to the inertia weight approach [3]. The objective function of optimization method for one-year planning at year y is as:

$$J^y = C^y_{Net,fix} + C^y_{Net,var} + C^y_{O\&M} - C^y_{salvage}$$

$$Task: \ min\, J^y$$

$$subject\ to: \begin{cases} 0.95 \le |v_i| \le 1.05 \\ |I_i| \le 1.1\ ,\ \ i = 1 \dots n-1 \\ discrete\ equipment\ sizes \end{cases} \quad (1)$$

where $C^y_{Net,fix}$ and $C^y_{Net,var}$ are NPV of fix and variable investment cost including all upgrades at year y, respectively, $C^y_{O\&M}$ is NPV of O&M cost as mentioned in Table 1, $C^y_{salvage}$ is the salvage NPV of $C^y_{Net,var}$, v_i and I_i are the voltage at i^{th} bus and current of ith branch in pu, respectively, and n is the number of buses.

The decision variables in each particle of MPSO for electric distribution planning of active distribution networks include the location and the size of batteries, capacitors, conductors, voltage regulators, and new zone substation as presented in Figure **4**.

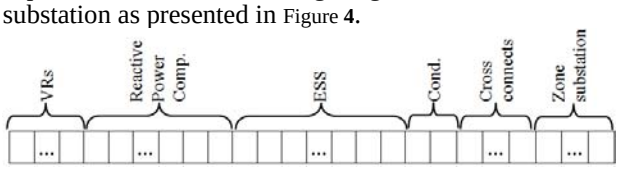

Figure 4. Particle structure in MPSO.

In the initialization process, a population of particles is randomly generated. Each particle represents a candidate solution for expansion planning. The J^y calculation involves two steps in our problem. First we calculate the total capital and operating cost for each given particle, then we carry out AC load flow based on the direct method [4] for the network configuration given by the particle to check if all constraints are met. If a constraint is violated, we penalize the particle by adding a high cost value to the objective. In addition, the load flow gives all necessary information for calculating the total loss associated with each particle. The required transformer upgrades for both, distribution transformers and sub-transmission/zone substation transformer, are calculated for each corresponding particle after finding the loading of transformers by including the new upgrades given in the particle. In addition, network reconfiguration is examined [5], considering new upgrades proposed in the particle, to find the economic location of new zone substation among a proposed set. Moreover, the reliability cost is the cost of system average interruption duration index (SAIDI) and cost of system average interruption frequency index (SAIFI), which are individually calculated for each particle. The SAIFI cost per failure-customer and SAIDI cost per customer-minute are provided from the utility. The estimated objective function value of each particle is used to locate the individual best particle and global best particle. Then we proceed to the next iteration, where a new population is generated by updating the velocity of each particle based on the best solution seen so far by that particle and on the global best particle. This procedure is continued until convergence. The detailed optimal upgrades for 20-year plan and the cost minimization progress for a planning in a year for realistic 747-bus distribution network is shown in Figure 5.

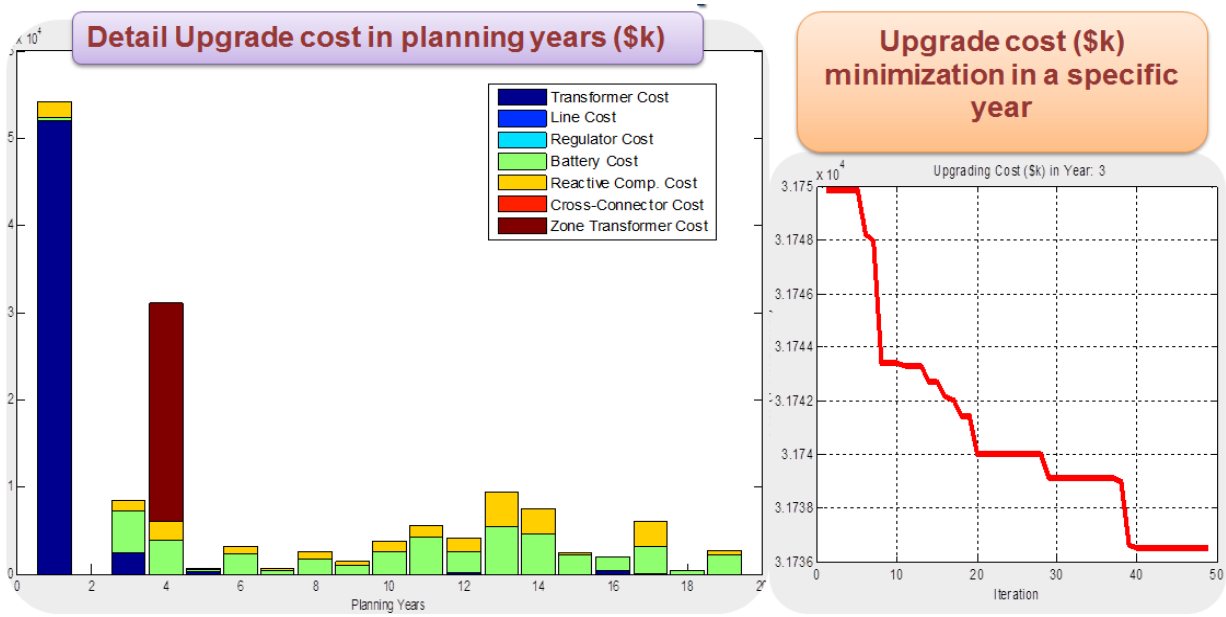

Figure 5. The detailed upgrades for 20-year plan and the cost minimization progress in a realistic 747-bus distribution network.

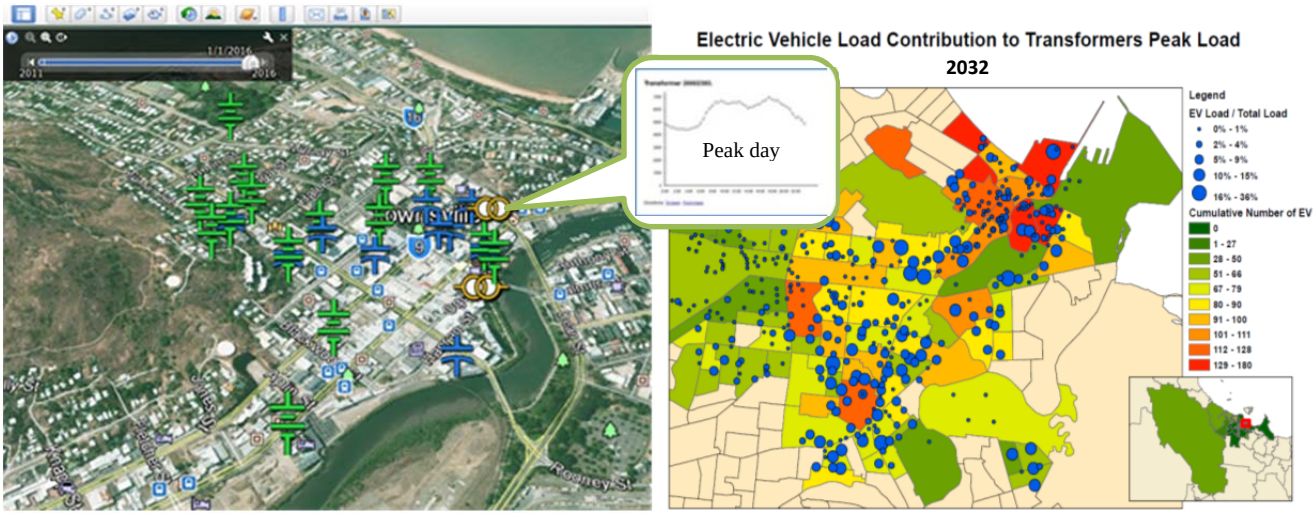

Figure 6. Example of Google Earth visualization.

AN AGENT-BASED MODEL FOR LOAD FORECASTING

The agent-based model allows assessing the impact of different trajectories of consumption at different locations of the electricity distribution grid over many years. For this, the model captures the static characteristics and the dynamic behaviours of the entities impacting the flow of electricity on the network. The simulations outputs are load profiles and various load duration curves (LDCs) that can be assessed for each node on the network using statistical methods, or visualisation tools such as Google earth, see Figure 6. The various LDCs associated with different load forecast including ESSs and EVs pass into the optimisation framework presented in the previous section. The proposed forecast framework outputs network and loading data into a PostgreSQL database, and then uses PostGIS to generate KML files, that can be visualised in Google Earth. For example, overloaded transformers are highlighted in red, and clicking on any transformer brings up a graph of the peak day of that transformer, plus other information about the transformer, as shown in Figure 6.

Agent-based modelling is a bottom-up modelling technique used to model complex systems comprised of autonomous and interacting agents [6-8]. By describing the characteristics and behaviours of entities at the individual level and their relationship to one another, it is possible to assess the behavior of the system as a whole.

This modelling technique was chosen for its capacity to capture complex information in a relatively simple manner, where agents have a spatial component to their behaviours and interactions. In addition, it does not presuppose knowledge about the functioning of the system, only an understanding of the way each individual is likely to behave in relation to another or a stimulus is sufficient. This is especially important for us, as the

processes of growth at the system level are unknown. Indeed with the installations of renewable decentralized generators as well as new technologies such as ESSs, it is not known what will happen as their percentages increase to high values. The same is true when EVs will become more popular. Understanding how, when and where their usage will impact the grid, in terms of loads, voltages and current, is important for decision-makers to better plan it.

Modelling approach

The agent-based model was developed using an in-house modelling and simulation environment, implemented in Java. This software uses a compositional approach to build the model incrementally so that as more entities are to be represented, the model can be extended easily. In addition, this approach facilitates setting up simulations for non-programmers who can simply call on building blocks of agents which will automatically bring the agents in relationship with one another at runtime to create the model. The overall features of this model are presented in Table 2.

Modelling method

The proposed agent-based model captures the static characteristics of the entities described in Table 2, and for each of them, one or more behaviours are available for the user to choose from. These behaviours, described by simple rules or sub-models, can vary according to the way the asset is expected to be used. Their usage can be influenced by different factors: the environment, cultural practices, policy settings, etc.

For example, an ESS can have different control algorithms: they can aim at clipping the peak at a certain location on the network (e.g. a chosen bus), or covering the load over a certain period of the day for a premise (e.g. when the price is high) and recharge when the PV is generating energy. For each of these possibilities, a sub model is implemented in the agent and the user chooses the one at setup.

A user will implement these agents, which can be populated by data extracted from corporate databases. For example, that will describe the structure of the network (i.e. the relationship between the entities) or some of the characteristics of the assets (e.g. ratings of assets) or behaviours (e.g. when based on probability curves).

Once the model is set up, the simulation proceeds in half-hourly time steps meaning that each agent will perform an action, if needed, every half hour. The state variables (i.e. load, current or voltage) of the model will then be updated accordingly. This will finally result in the calculation of an expected load at each node of the network.

Table 2. Features of agent-based model

Agent-based model for Future Energy Grids

Objective is to capture static and dynamic characteristics of:
✓ Entity composing the distribution network
  ✓ Feeders
  ✓ Lines
  ✓ Transformers
  ✓ Switches
  ✓ Buses …
✓ Consumers of different types (residential, commercial, industrial) in terms of load patterns
✓ New technologies introduced on the market
  ✓ Renewable generators (solar panels)
  ✓ Energy storage systems
  ✓ Electric vehicles

Operation consideration:
✓ Use of rules to describe the behaviours, vary depending on
  ✓ Asset modelled
  ✓ Policy requirements
✓ Agents' behaviours are informed by
  ✓ Other agents' behaviours
  ✓ Environment they are in (weather, network characteristics, ...)
✓ Behaviours can use
  ✓ Raw data from historical records
  ✓ Sub models that inform the behaviour (e.g. statistical models)
  ✓ A combination of those methods

INTEGRATION OF THE OPTIMISATION AND FORECAST COMPONENTS IN A SINGLE TOOL

Figure 7 shows the flow of data between the optimization and forecast frameworks. As seen, the network data, load forecast, and possible LDCs are processed by agent-based forecast framework using utility's databases, user input, and component specifications.

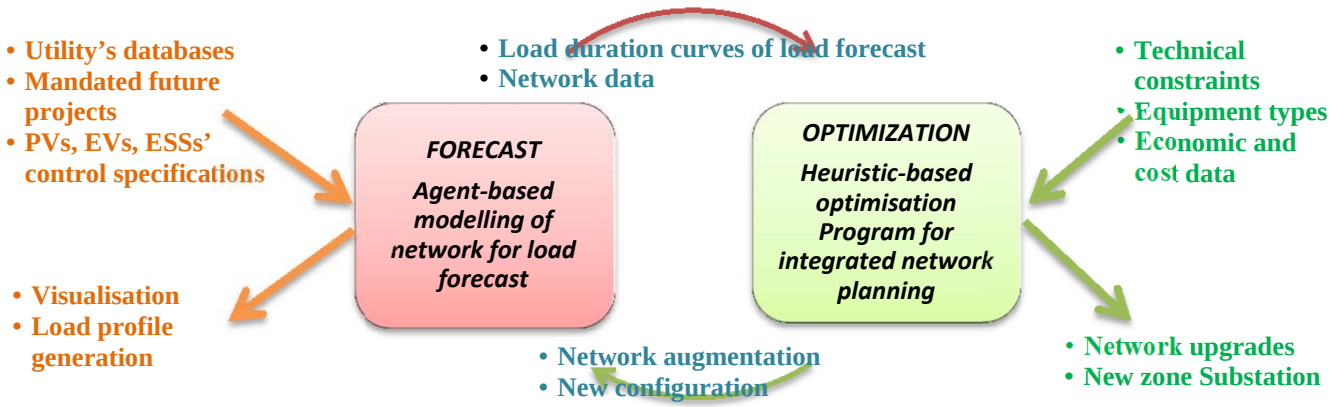

Figure 7. The integration of the developed tool

Therefore, the optimization framework uses load and network data over planning horizon to find optimal augmentation of distribution network based on a heuristic approach. Different type and capacity of equipment including price as well as network constraints such as voltage and thermal limit are taken into account by the optimisation program. After finding the optimal upgrades, these data including new equipment and new network configuration for each selected year over planning years are passed to the forecast framework to be visualised in Google Earth and recorded in the database.

Twenty year planning of a realistic 747-bus distribution network is performed using proposed integrated tool as shown in Figure 5 and Figure 6. This area has been planned for development and facing to the potential of high load growth, featuring up to 1,100 residential dwellings, retail space and an office and entertainment precinct. This development is reflected in the output of forecast tool, showing substantial load growth in future years for this area. Therefore, the optimization tool proposes a high investment in distribution transformers in the early years of the planning period. Since there is not any limitation on high variability in cash flow in the optimization tool, the number of distribution transformer selected at year 1 is very high. In fact, the optimization tool addresses the multiple issues in a distribution network such as demand, voltage and thermal constraints with the cost-effective and least number of solutions. In this case, in year 1, the capacity of batteries, selected through optimization, is not very high, because the life time of distribution transformers is much higher than batteries. However, for the later years, installations of batteries in combination with reactive power compensators are more beneficial. The main difference from conventional planning is that rather than one project to fix one constraint the optimization may propose a few upgrades to fix multiple constraints.

CONCLUSION

A flexible tool for integrated planning of distribution network is presented in this paper. The proposed tool has good flexibility to consider various kinds of new technologies, loads, and customer engagement to forecast the load in future years. In addition, the presented tool provides an integrated optimal augmentation selected from wide range of solutions over planning years.

This tool creates an efficient framework within a utility to fulfil the requirements of network vision and customer satisfaction.

Future works include detailed modelling for full probabilistic forecast and optimisation tool to consider uncertainties of loads and generations.

Acknowledgments

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