ENABLING AUTONOMOUS RECONFIGURATION OF LOW VOLTAGE NETWORKS

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ABSTRACT

The energy landscape for Low Voltage (LV) networks is changing. Due to embedded renewables, energy flows are increasingly bi-directional and the wider adoption of EVs and electrical heating are predicted to lead to increases in LV network load. These changes increase the burden and risk to LV networks, requiring the need for network reinforcements. Historically, LV networks are reinforced by adding more cables to the network or by manually re-configuring the network when warnings are reported. However, these solutions are likely to be insufficient in the future. A more active approach is required, which includes the ability to autonomously reconfigure the networks according to the local load. This is now feasible for LV networks because of the mass roll out of smart meters and the growing use of Geographical Information Systems (GIS) which collate information about network topology. This paper proposes a framework that enables the autonomous reconfiguration of the LV networks using these two key data sources.

INTRODUCTION

The energy landscape for LV networks is changing. These changes will soon be amplified by the push to minimize dependency on carbon-based fuels, not just to generate electricity using Low Carbon Technologies (LCT), but also to electrify transport and heat. This raises the overall electricity demand on to the networks, increasing their burden and risks, and in turn requiring the need for network reinforcement.

Historical options for LV network reinforcement are to either add more cables to the network or to manually re-configure the network when warnings are reported. The former comes at a high cost, while the latter, if not resolved in time, can lead to faults resulting in loss of connections. Active management of the LV network can be an option to help solve this issue. Active Network Management (ANM), initially developed for Medium Voltage (MV) networks and above, is defined as the real-time management of power producing or consuming devices within the thermal or voltage constraints of the network [1]. Examples of ANM in the context of LV networks are (i) to control renewable export to the grid [2], [3], and (ii) demand side management (DSM), specifically the control strategies for electric vehicle (EV) charging [4], [5]. However, ANM for LV networks, especially for 400V networks and below (domestic networks), need not be limited to these activities. It can also include the ability to autonomously reconfigure the network connectivity based on overall customers' energy requirements, i.e., to automate the opening and/or closing of link boxes and/or fuses to minimize the risk of network constraints violation.

This option, which was historically unfeasible, is now possible because of the broader visibility of the LV network through the use of smart meters and the broader infrastructure initiatives, i.e. for communication and cyber-security. There is also an increasing use of Geographical Information Systems (GIS), which collate and store the LV network topologies and assets data within a single platform.

We propose that to ensure effective autonomous reconfiguration of LV networks, the following 3 key processes are to work in cohesion with each other: (i) Validation of LV network topology (impedance map) information on GIS; (ii) The forecasting of potential voltage violation on the network, and (iii) Simulation and calculation of potential risk of alternative LV network configurations based on their forecasted energy flows. The alternative LV network configuration selected is then the one with the minimal predicted risk. Figure 1 shows our developed framework indicating how the 3 key processes are coordinated. As shown in Fig. 1, these 3 key processes use both smart meter data and the LV network topology and assets data stored in GIS.

The paper is divided into 5 sections. The next section will discuss our motivation for autonomous reconfiguration of LV networks. We define LV networks as a group of LV circuits that are energised by the same transformer. A transformer can have multiple fuses, providing electricity to multiple LV circuits; therefore, an LV circuit is the group of cables that connects all electricity consumers to a common energised fuse on a transformer. The following sections describe the proposed framework and the 3 key processes within the framework. Figure 1 illustrates the use of Power System State Estimation (PSSE) tools used to validate the approximated missing cable(s) data in the

LV network and the simulation of alternative LV network configurations. PSSE is only feasible if the demand power data of all customers in a circuit are available. When this is not the case, we propose the use of a predictive model to estimate the missing data. This is briefly discussed in the second last section. The final section concludes the paper.

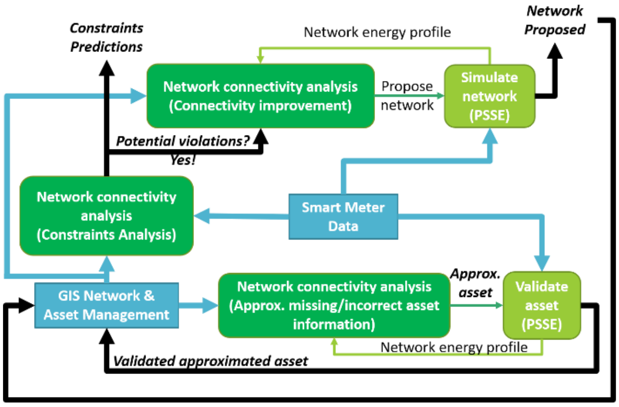


Fig. 1. The framework for autonomous reconfiguration of LV networks.

MOTIVATION

Restricting ANM to just the management of power producing or consuming devices [1] has some limitations and disadvantages. For example, a DSM for EV charging requires the buy-in of EV consumers in order to allow the distribution network operator (DNO) to control how their EVs are charged [4], [5]. DNOs must perform DSM not only to meet the voltage constraints limits, but charging must also satisfy the customers' needs. Hence, customers' loss of control on when to charge or run their loads can be an issue. For example, consider the case of a customer who requires his/her vehicle, but the vehicle is in the queue and is yet to be charged; this can result in customer dissatisfaction, causing the customer to potentially leave the scheme. At present, EV penetration is low, so this problem is not yet pronounced. However, there are several countries aiming to stop the sales of new diesel and petrol-fuel cars in the near future [6]. The UK, for example, has a target of 2040 [7]. In practice, there will be a maximum EV charging level that DSM can successfully manage before constraints violations occur. If the maximum limit is reached, it would be beneficial for the DSM to operate together with autonomous LV network reconfiguration to ensure that constraints can be met despite the increase in electricity demand. This solution would also reduce the need to add more cables to the ground, which can be disruptive to the consumer and expensive to the DNO.

Excessive renewable export to the network is also an issue, especially on short LV circuits and/or circuits with a small number of loads. Voltage out of bound excursions can occur if curtailment of excessive energy export is not in place. This can cause customer dissatisfaction because of the potential loss of income. If autonomous LV network reconfiguration is in place, curtailment can be prevented if the short circuit has the option to be part of a larger circuit capable of accepting more generation export into the network without causing constraint violation.

ANM FRAMEWORK FOR LV NETWORKS

As mentioned, autonomous reconfiguration of the LV networks requires 3 key processes to work in collaboration with each other.

Validation of network topology

Before any reinforcement can be proposed, an accurate understanding of risks to the network is required. Risk can be measured based on the network capacity. We propose that the circuit capacity is approximated based on the total line impedance of the circuit I_N, calculated using the circuit topology and its cables connectivity. The lower the I_N value, the higher the circuit capacity.

Typically, (mains) cables with small cross-section area (XSA) have high resistance and reactance values and low ratings and capacities, in turn resulting in higher risks in comparison those with larger XSA. Because of this, if I_N is low, the circuit has higher capacity to fulfil more demand (and generation), with lower risk of exceeding the constraint limits. Therefore, low risk circuits are circuits with low I_N.

Calculating the LV circuit total line impedance I_N

To calculate the total line impedance of an LV circuit I_N, we first transformed the LV circuit into its equivalent electronic circuit, with each cable segment in the circuit appearing as a resistor. An example of this is shown in Fig. 2. I_N is then calculated using Thevenin's Theorem, using the cables' resistance Rm^{-1} and reactance Xm^{-1} values provided by the cable manufacturer and the cable segment length reported in GIS.

Validation of approximated cables

The impedance calculation therefore requires full knowledge of all the cables in the network and their topologies to be correct. Incomplete and erroneous cable information, however, are identifiable issues that result from human errors during the process of digitising LV networks within the GIS and/or on-site operators failing to follow rigorous data management steps during the asset and network connectivity updates. Because of this, the first steps for autonomous LV network reconfiguration is the need to validate the network topologies. This is to ensure the correct indication of the network capacity and risk.

The tree-based search algorithm we have described in [8] can be used to approximate any missing cable information in the LV circuit. This algorithm introduced the term *asset path*, defined as the list of cables that connects the source to an endpoint (or the unknown cable). Any unknown cable can be approximated with a specific cable value if the two cables have similar asset paths.

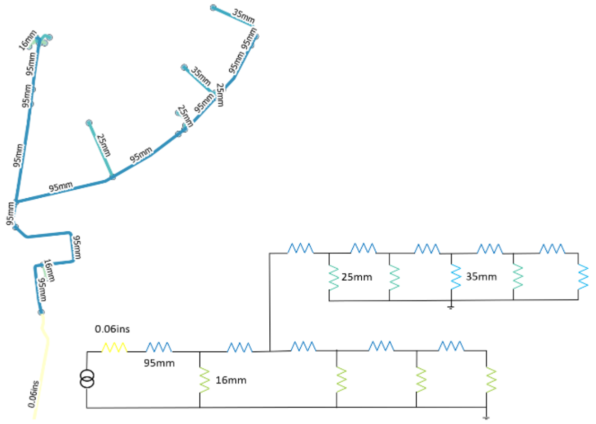


Fig. 2. The equivalent circuit (right) of the LV circuit (left), if the 0.06ins cable is connected to the source.

Multiple choices can be suggested, and as shown in Fig. 1, the value selected to approximate the unknown cable data has to be validated. Validation can be performed using either (i) the PSSE tool, if the circuit has sufficient smart meter coverage to enable the tool to replicate the voltage distribution for the circuit; or (ii) the predictive model indicated by (1), which predicts the voltage distribution in a circuit. $\widehat{V_{SM}}(t+\Delta\tau)$ is the predicted voltage at future time $\Delta\tau$ for customer with the distance d_{SM} from the source (energized fuse in the substation). $V_1, \dots, V_m, \dots, V_M$ and $P_1, \dots, P_m, \dots, P_M$ are the voltages and customers power demand provided by all or selected M smart meters in the circuit at time $(t - x\Delta\tau)$, with d_m the distance of smart meter $m \in M$ from the source. x is the number of historical data required for prediction. I_N is the total line impedance of the circuit. The closer $\widehat{V_{SM}}(t+\Delta\tau)$ is to the actual voltage value reported by the smart meter SM, the higher the likelihood that the approximated cable included in the calculation of I_N is the unknown cable.

Understanding of the correct network topology is also necessary to guide how best to reinforce the network. This is to ensure that the new suggested topology has a lower risk in comparison to the previous configuration.

Modelling and prediction of constraints violations

Prediction of potential constraint violation is essential and should be provided in time for the network reinforcement to be in place before constraints are violated. Equation (1) predicts the voltage distribution on the network.

We use deep learning to create the predictive model $\widehat{V_{SM}}(t+\Delta\tau) = f(.)$ in (1). Deep learning is a form of machine learning and it is chosen because it maps the correlations between the multi-dimensional input data to the required output value. It is a type of artificial neural network (ANN) composed of multiple processing layers, each layer consisting of linear or non-linear modules called neurons that transform the input data presented at the first input layer to its required correlation by hidden layers, which then leads to the output value provided by the output layer [9]. The closer $\widehat{V_{SM}}(t+\Delta\tau)$ is to either voltage limits and the faster $\widehat{V_{SM}}(t+\Delta\tau)$ reaches the limit ($|\widehat{V_{SM}}|$ is high), the higher the likelihood of voltage constraint violation. Further details on the predictive model are described in the following section.

Evaluation of alternative networks

The example LV circuit shown in Fig. 3 can have two possible circuit configurations by changing the opening and closing of fuses at its end-to-end transformers. This long circuit can also be split into 2 shorter circuits by opening the fuse at the link box and closing the fuses at both ends of the circuit(s) at the transformers.

If constraint violation is predicted, for example, resulting from the increase in EV charging closer to the source (Circuit A in Fig. 3), reinforcement should be performed, in which case the selected network topology should be the option with the minimal risk of constraints violation. As previously indicated, the evaluation of risk can be performed using the PSSE tool if sufficient demand power data is provided to enable the analysis. We are currently evaluating our methods using simulated smart meter data; therefore, we can simulate the full smart meter coverage for the network, enabling us to generate the voltage distribution shown in Fig. 3. If the likelihood of full smart meter coverage is low, a predictive model $\widehat{V_{SM}}(t+\Delta\tau) = f(.)$ (1) is used instead to predict the risk of network constraint violation. I_N in (1) is the total line impedance value calculated for the alternative LV circuit and d_{SM} is the distance of customer SM from its potential new source.

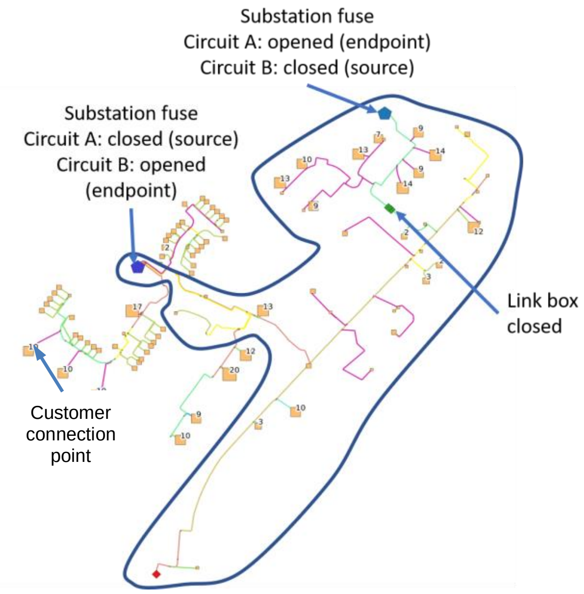
PREDICTIVE MODEL $\widehat{V_{SM}}(t+\Delta\tau) = f(.)$

As indicated in the previous section, we use Deep Learning to create a predictive model $\widehat{V_{SM}}(t+\Delta\tau) = f(.)$, which aims to predict the voltage V_{SM} for the customer at distance d_{SM} from the source at $\Delta\tau = 30\text{min}$ in the future. $\Delta\tau = 30\text{min}$ is chosen as this is the default sample interval used by all smart meters in the UK.

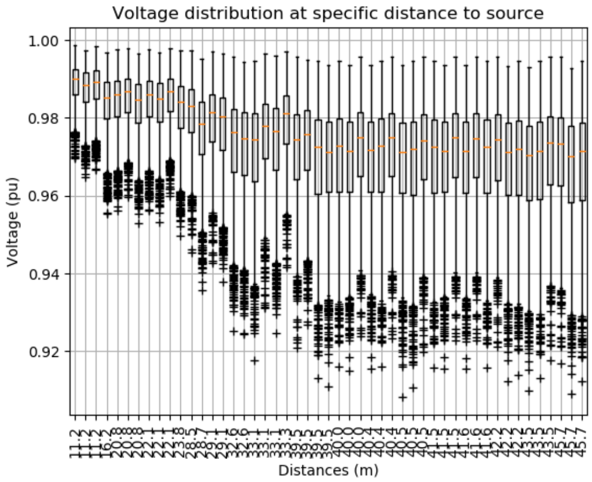
Selective monitoring of constraint violations

To create the predictive model for each individual customer in a circuit is unnecessary and would require high computational overheads. Furthermore, smart meter installation in the UK, as of 2018, is voluntary. As a result,

$$\widehat{V_{SM}}(t+\Delta\tau) = f(I_N, d_{SM}, V_1(t), \dots, V_1(t-x\Delta\tau), P_1(t), \dots, P_1(t-x\Delta\tau), d_1, \dots, V_m(t), \dots, V_m(t-x\Delta\tau), P_m(t), \dots, P_m(t-x\Delta\tau), d_m, \dots, V_M(t), \dots, V_M(t-x\Delta\tau), P_M(t), \dots, P_M(t-x\Delta\tau), d_M) \quad (1)$$



Circuit A



Circuit B

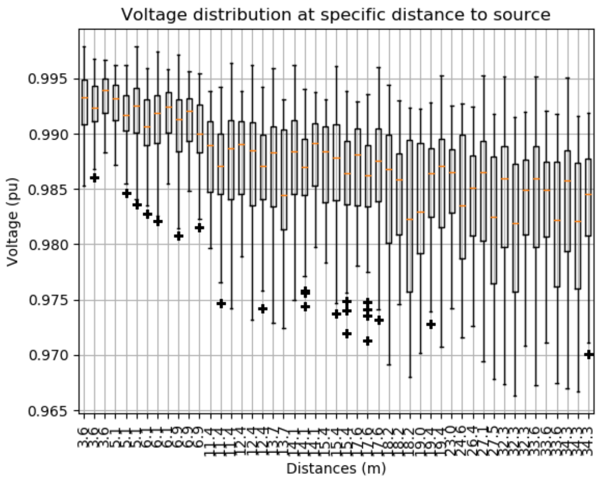


Fig. 3. Voltage distribution (one-month data) at each customer connection point when the source for the circuit is switched.

some parts on the circuit will not be monitored and there will be no data to create the model for that customer.

Circuit theory indicates that the voltage at a specific customer in circuit, V_{SM} at d_{SM}, is a function of the voltages of all the customers; therefore, one model $f(.)$ (1) can be shared by all customers on the same circuit, if the inputs to $f(.)$ are (i) the queried customer location d_{SM}, (ii) total line impedance of the circuit, I_N, common to all customers, and (iii) the voltages $V_1, \dots, V_m, \dots, V_M$, demand power data $P_1, \dots, P_m, \dots, P_M$ and their distances $d_1, \dots, d_m, \dots, d_M$ are sourced from either:

1. if the number of available smart meters is low, all available smart meters in the circuit,
2. otherwise, at the key locations, i.e. first customer on the circuit; first and last customers on each branch; and the customers before each branch point.

This is advantageous, as it also provides the ability to predict voltages at locations without smart meters. Deep Learning therefore creates the $f(.)$ map between available smart meter data in a circuit and the circuit's impedance, akin to Ohm's Law.

Figure 4 shows the predicted voltages $\widehat{V_{SM}}(t + 30\text{min})$ for the customers in Fig. 3 Circuit A. In this analysis, a smart meter provides the voltage and the aggregated power at the customer connection point to the circuit. $f(.)$ is created using 10 customer connection points only, simulating partial smart meter coverage of the circuit. Each line in the figure is the $\widehat{V_{SM}}$ for a specific customer connection point for a specific half hour. The figure shows that between 16:00 to 18:30, $\widehat{V_{SM}}$ is decreasing towards and beyond the voltage constraint limit of 0.94pu (the voltage sag limit for UK). The gradient or $|\Delta\widehat{V_{SM}}|$ is also consistently high during this period. This trend is shown by $> 1/2$ of the customers in the circuit. If early indication of this trend signalled the change to the circuit configuration to Circuit B in Fig. 3, i.e. at $(t + \Delta\tau)$ = 16:30, the constraint violation between 17:00 to 22:30 in Fig. 4 can be mitigated.

Prediction of risk of alternative circuits

As indicated in the previous section, we propose that the total line impedance of the circuit I_N indicates for its capacity and $f(.)$ in (1) predicts how voltages are distributed across the circuit. We assume that circuits with similar I_N values will have similar capacity and topology, and therefore may result in similar voltage distributions across the circuit. Because of this, the model created for one circuit $f(.)$ can be shared by another if they have similar I_N values and customers distributions. Figure 5 shows the differences between the actual voltage and the output produced by $f(.)$ created from another circuit with similar I_N and customers distribution (in pu). The inputs to $f(.)$ are (i) the customer location d_{SM} from the source in the alternative circuit, (ii) I_N of the alternative circuit and (iii) the available voltages, power data and their distances from source from the circuit from which $f(.)$ was created for. The figure shows small differences (≤0.02pu), indicating the potential sharing of $f(.)$ between circuits, to enable the prediction of risk of alternative circuit topology and/or the validation of approximated missing cables.

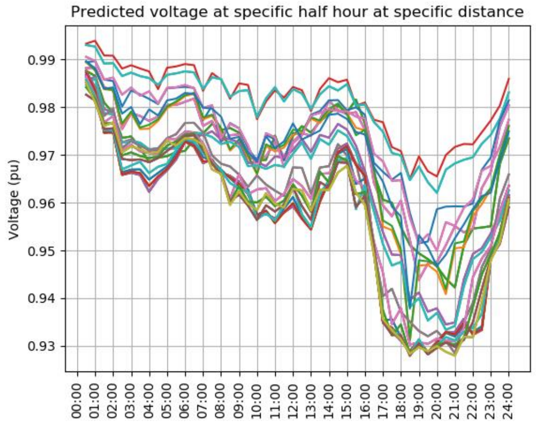


Fig. 4. $\widehat{V_{SM}}$ for customers in Circuit A in Fig. 3. Each line is for a specific customer connection point.

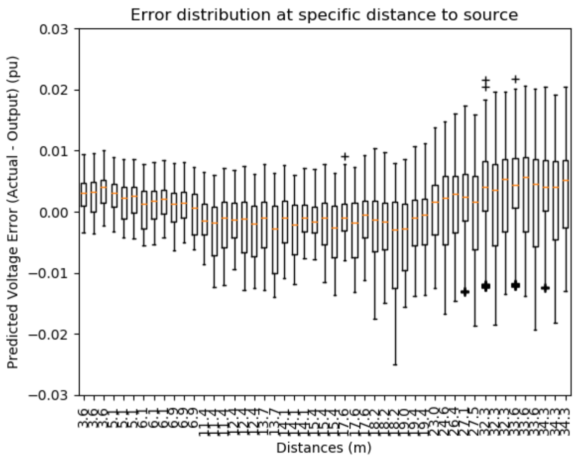


Fig. 5. The model error (actual vs. model $f(.)$ output) for Circuit B in Fig. 3 using $f(.)$ created for another circuit with similar I_N and customers distribution.

CONCLUSION

Autonomous network reconfiguration is a key technology to allow LV networks to cope with the changing energy landscape. Enabling the change to the LV network connectivity based on the energy demand and generation output minimises the risk of constraint violation, as well as reducing the risk of customer dissatisfaction. It also minimises the need to add more cables to the ground, which is expensive and disruptive.

Autonomous LV network reconfiguration is now feasible because of the increasing visibility of the LV networks, resulting from the mass roll out of smart meters and the growing use of GIS that collates and stores LV network assets and topologies. This paper presents a framework developed to enable such autonomous reconfiguration. The framework consists of three 3 key processes that work in cohesion with each other: (i) validation of the LV network topology on GIS; (ii) the forecasting of potential voltage violation on the network, and (iii) evaluation of potential risk of alternative LV networks based on the forecasted energy flow in the new network configuration. When a constraint violation is predicted, a new network configuration that has the lowest forecasted risk according to the customer demand can be selected, among the available options. This framework is under development for its use as part of the LV network management system.

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