CLASSIFICATION OF LOW VOLTAGE DISTRIBUTION NETWORKS BASED ON FIXED DATA

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ABSTRACT

The limited visibility of Low voltage (LV) networks brings significant knowledge gaps in understanding its capability to accommodate low carbon technologies (LCTs). LV network classification is a feasible and cost-effective solution that increase visibility of large scale LV networks with substantially reduced monitoring. This paper introduces a novel LV distribution substation classification method aiming to group LV networks with easily obtained fixed data. By using multi-criteria decision making techniques, specifically, the fuzzy inference system, key fixed data are linked to target typical LV network types. The proposed method is validated and compared with the postcode based locational classification on 938 substations in South Wales of the UK. Through this novel fixed data classification approach, a new LV substation with known fixed data can be directly assigned into one of the target LV network types and its load characteristic can be estimated based on characteristics of the existing substation group.

INTRODUCTION

The anticipated high penetration of low carbon technologies (LCTs), such as electric vehicles (EVs), heat pumps (HPs), photovoltaics (PVs) will largely be connected at customer properties. There would be unprecedented impact brought by these LCTs on LV distribution networks. However, a large part of LV networks were constructed half century ago [1] and the operating framework within LV networks was not conceived with LCTs in mind. As a consequence, integrating LCTs would change power and voltage behaviors in the LV networks. It may also bring unpredictable adverse effects to the existing networks, such as voltage and thermal overload, serious voltage unbalance etc.

Currently, there are significant knowledge gaps in understanding the capability of LV distribution networks to accommodate LCTs. The real time power and voltage status at LV network are hardly known, since the networks have not previously been designed to carry on large scale of monitoring. There are numerous substations and branches: 230,000 HV/LV substations, including 580,000 transformers and 376,000 km overhead lines and underground cables in LV distribution networks [2] in the UK. It is neither economic nor practical to collect large scale of real time data of transformers' and feeders' power and voltage to check the quality of supply.

However, with the penetration of LCTs, it is necessary to increase the visibility of LV distribution networks, i.e. gain the knowledge of voltage and power to understand the network conditions. Since monitoring a large amount of substations and feeders cannot be realized practically, the challenge lies in how to get information from LV networks with minimum monitoring devices.

LV network classification is a feasible and cost-effective solution that reduces the dimensionality to investigate large-scale LV networks with substantially reduced monitoring. A proper LV network classification could achieve two aims: 1) using limited substation types to represent large-scale LV networks; 2) grouping LV networks with similar characteristics. The first aim ensures monitoring limited number of LV networks in each type has similar results with monitoring large scale of LV networks. The second aim guarantees a new LV substation can be assigned into the existing LV network types, i.e. the new LV substations' characteristic can be inferred from existing LV network characteristics. Therefore network operators can monitor reduced number of LV substations in each LV networks type. By analyzing and comparing the patterns of monitored power and voltage profiles in each group, the characteristics of the whole LV distribution networks can be identified.

Previously, instead of LV network classification, many of earlier studies are focused on the classification of end customers only to support the development of tariff selection and market strategies. In [3-5], customers are predefined based on customer type such as domestic or commercial using the results acquired by questionnaires. In the UK, customers are classified to 8 types determined by customer types, load factors and meter types indicating in Metering Point Administration Number (MPAN)[6]. However, classification of LV networks is more complicated because: 1) there is no explicit target type of LV networks like "domestic" or "commercial" in the case of customer classification; 2) the classification criteria are diversed because not only the customers served but also the properties of transformers and feeders need to be considered; 3) the direct link between the classification criteria and possible LV network type is hard to find because of the uncertain and vague relationship between classification criteria and target LV network types.

So far, there has not been many works done on LV network classification. Work [7] proposes a "bottom up" LV network classification by aggregating and summarizing all customer types and location information connected on the LV network. However, this method is time- and cost-consuming and impractical to classify large scale of LV networks.

The work is sponsored by Western Power Distribution in the UK under 'LV Network Templates' project.

This study introduces a new approach to classifying LV networks into locations and customer types based groups by readily available fixed data. It aims to find the relationship between various criteria and LV network types through decision making techniques. The proposed approach solves the problems by: 1) setting the target LV network types consisting of location and customer dominant type information, which indicates population, economic condition and customer energy use. These factors can be used to estimate the penetration of LCTs [7]. 2) selecting the key fixed data to represent LV substation characteristics and generating a hierarchy way of utilizing fixed data as classification criteria. 3) building the relationship between the criteria and target LV network types by multi-criteria decision making process consisting expert rules and fuzzy inference system. Consequently, typical LV networks are generated. A new LV substation with known fixed data can be directly assigned into one of the target LV network types. The method is validated on the LV substations in the South Wales of the UK with the help of limited real-time power data and the results are compared with postcode classification.

The main contributions of the work are: i) it proposes a new multi-criteria decision making approach to classifying LV network considering both customer and network physical characteristics; ii) it transfers different types of fixed data into reasonable and effective classification criteria; iii) it links fixed data and LV substations' geographic information, which proves to be more representative of power characteristics than postcode classification; iv) the work increases the visibility of LV distribution networks and helps DNOs set planning and operation strategies at scale.

The rest of the paper is organized as follows: Section II introduces classification criteria and target types. Section III detailed illustrates LV network classification method. Section IV conducts case study on the South Wales substations. Section V summaries the paper and future work.

CLASSIFICATION CRITERIA AND TARGET TYPES

Fixed data

The "fixed information/data" of the substations represents the information that does not change or changes very slightly during a long period. The fixed data generally contains: construction condition, i.e. the ground mounted transformer or the pole mounted transformer, transformer rating/capacity, out-going LV feeder number, serving customer number and type and the customer energy consumption.

These key fixed data can be transferred to classification criteria in LV network classification: 1) The pole-mounted transformers and overhead lines are generally used in rural areas, while ground-mounted transformers and underground cables are installed more frequently in urban areas [8]. 2) The pole-mounted transformers are usually rated from 5 to 315KVA, while the ground-mounted transformer size tends to be between 200 to 1000KVA. 3) The out-going LV feeder number reflects customer density: high customer density areas require more LV feeders. Additionally, LV feeder number depends on the type of customers connected. Domestic customers are connected to one feeder with single phase services. Commercial and industrial customers connected at LV networks can either connect to one feeder or several feeders with three phase services [9]. If the customers (often commercial and industrial customers) need high reliability and quality services, their connecting feeder number will be doubled. 4) the customer number and energy consumption directly show the load density and connected customer types.

Target LV network types

The variability of LCTs and diverse characteristics of existing LV networks pose different pressures to LV networks [7]. The variability of LCTs lies in following aspects: 1) the penetration level is relating to population and economic factors, which differ from dense central urban and dispersed rural areas; 2) the type and operation time vary between customer types and energy use. Additionally, the physical construction characteristics of LV networks, such as transformer rating and feeder number, are fundamentally different between urban, suburban and rural areas. Therefore, the capacity or headroom available on existing networks to accommodate LCTs differs. As a result, the types of LV network are defined based on: 1) locations: urban, suburban and rural; and 2) dominant customer types: domestic dominant, "industrial and commercial" dominant and mixed dominant.

METHODOLOGY

Given the fixed data of a substation, the challenge is how to link the fixed data with target LV network types. A hierarchy method is shown in Fig. 1. The proposed multi-criteria decision making process is also shown in the figure. Firstly, expert rules using the electrical engineers' experience initially develop four groups of substations. Then, if-then rule based Mamdani fuzzy systems is used to deal with the uncertain relationship between fixed data and target LV network types.

Expert rules

Expert rules are set up based on substation properties.

Substations with and without half-hourly metered load

Firstly, the groups are divided into substations with and without half-hourly metered load. Half-hourly metered substations indicate the served customers with larger energy consumption usually with a peak above 100kW or with special demand. In this type of substations, the case of high energy consumption by small number of customers and out-going LV feeders frequently appears. Thus, customer number and out-going LV feeder number cannot truly

reflect the load density, which is different from that in substations without half-hourly metered load. Therefore, it is essential to treat the substations with and without half-hourly metered load separately. Then, the customer number and out-going LV feeder number will not be considered as criteria in the "With half-hourly metered load" group.

Construction type

After being divided into with and without half-hourly metered load groups, substations are further classified according to their construction types. According to network planning and design manuals [8, 9], the choice of ground-mounted and pole-mounted transformers is based on the geographic characteristics. This property can be used as a straightforward way to distinguish most rural substations. Therefore, substations are divided into ground and pole-mounted types accordingly in this step.

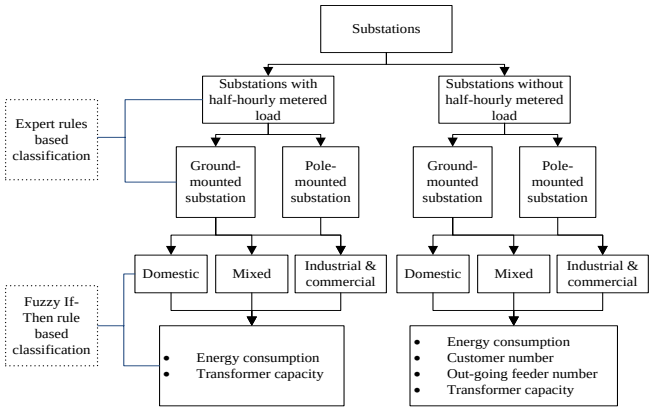

Fig. 1 Flowchart of fixed data classification method

Fuzzy inference system

In order to further classify substations into subgroups, the rest fixed data, including the customer type, energy consumption, customer number, out-going LV feeder number and transformer capacity are used.

However, there is uncertainty in relationship between rest fixed data and target LV network types. It is not possible to set clear quantity boundaries inside each type of fixed data to achieve one-to-one correspondence with target types. Taking transformer capacity as an example, generally rural substations tend to have the smallest capacity, while urban ones usually have the biggest; yet it has to be acknowledged that there are no clear quantified capacity boundaries between each two groups. In other words, a 500KVA transformer could belong to both suburban and urban substation. Therefore, the fuzzy theory, in particularly, fuzzy inference system (FIS) is appropriate for approximating system behaviors [10].

Fuzzy inference system is a rule-based model that can provide a mechanism to link linguistic description of the system with their computational realizations. There are three main fuzzy inference systems: Mamdani systems [11], Takagi-Sugeno(T-S) [12] and Tsukamoto models. In the proposed classification method, Mamdani systems [11] has been chosen. It has a better linguistically interpretative characteristic than its counterparts. In addition, the results of Takagi-Sugeno and Tsukamoto system are non-fuzzy equation, but results of substation classification are hard to transfer to a non-fuzzy equation. This shows Takagi-Sugeno system is not suitable here.

The fuzzy inference system mainly consists of three steps: fuzzification, inference mechanism and defuzzification. The first fuzzification step is to convert the crisp inputs, i.e. the fixed data into fuzzy sets. In the location model, 150 substations located at rural, suburban and urban areas are chosen as samples to get typical energy consumption, customer number, out-going LV feeder number and transformer capacity distribution. The mean and standard deviation numbers are directly used to develop Gaussian input membership functions for the system, which is shown in Fig. 2. The "low", "medium" and "high" fuzzy variables are assigned to each input parameter according to its effect on location characteristics. The "urban", "suburban" and "rural" fuzzy variables are assigned to output of the system. In customer dominance model, inference criterion is "industrial and commercial" energy consumption percentage and is represented by "low", "medium" and "high" fuzzy variables. The membership function is shown in Fig. 3. Outputs are represented by "domestic"," mixed" and "industrial and commercial" fuzzy membership function. In the model, the output employs singleton membership function, which is much easier and clearer to illustrate the results. In a singleton system, the membership value is 1 for only one particular linguistic input variable and 0 for others.

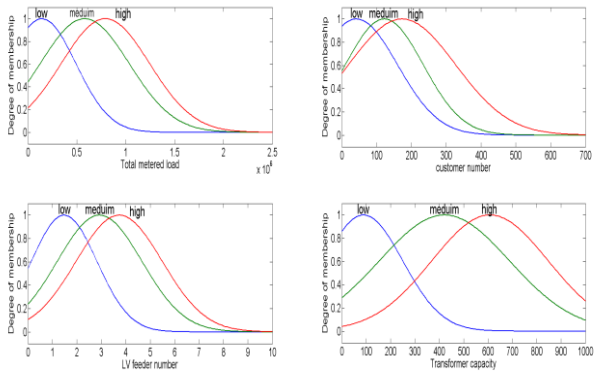

Fig. 2 Location input membership function

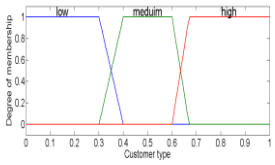

Fig. 3 Customer dominance input membership function

The second step, i.e. inference mechanism is the application process of "If-Then" rules with linguistic level of each input considered. In the location model, more "high" fuzzy inputs lead to more possibility of "urban" output. On the contrary, more "low" inputs give more chance of "rural". About 81 "If-Then" inference rules are created for the decision

process of this fuzzy model. The customer dominance model is a single-input-single-output system. Therefore, the if-then rule is direct one-to-one correspondence. At last, in the third step, the mean of max method [13] is used to defuzzify the linguistic output.

DEMONSTRATION

In this section, the proposed classification methodology is tested on 938 substations in South Wales of UK, spanning from Newport to Swansea.

Results of fixed data classification

By analyzing the fixed data from all LV substations with the proposed classification, these examined substations are grouped into 9 categories. The classification results are in Table I and Fig.4. As seen, 59% (558) of the substations are in urban area, 14% (128) and 27% (252) in suburban and rural areas. According to customer type, domestic customer dominant substations are majority in the three areas, accounting for 63% (592), while mixed load substations are the least, taking up only 6% (59).

TABLE I. SUBSTATION CLASSIFICATION RESULTS

Location/Type	Rural	Suburban	Urban
Domestic	172	58	362
Mixed	7	14	38
Industrial & Commercial	73	56	158

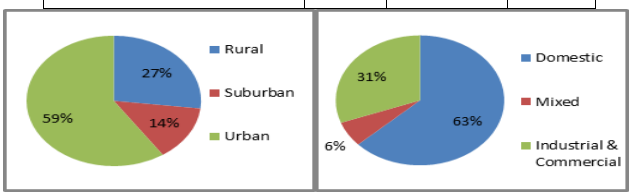

Fig. 4 Substation classification location and customer dominance

Results validation by load profiles

In this study area, limited monitors have been installed to collect LV substations data to increase the visibility of LV networks. Further more accurate LV network types can be generated based on measured substation load patterns[14].

The classification results are proved effective to represent large scale of LV networks with various characteristics. The LV network classification results are validated by limited monitoring data. The load characteristic of each type of LV network is shown in Fig. 5. The customer dominance results can be validated by load profiles. Urban, suburban and rural LV networks are discriminated by the amplitude of demand. The power consumption in urban area is the largest with the average about 100KW. The suburban and rural areas have less and least average power consumption of 50KW and 20KW respectively. In urban and suburban area, load patterns clearly vary between domestic, mix and industrial and commercial dominant LV networks. The different load characteristics display that "industrial and commercial" substations have the peak load during working time. The mixed load substations have two respective peaks in the morning and evening. By comparison, the domestic substations have higher load in the evening and a lower load in the morning. While, in rural area, load patterns do not vary obviously, which is due to the lower and dispersed demand.

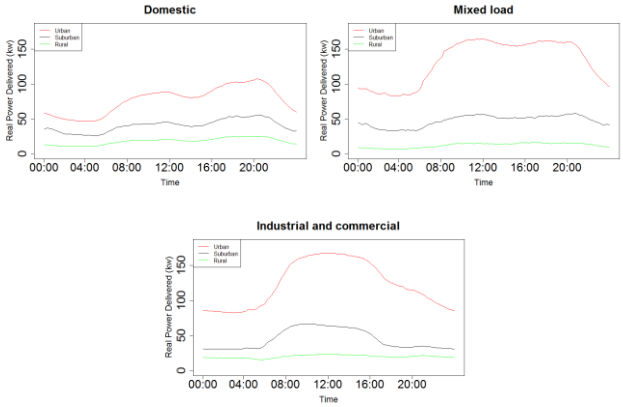

Fig. 5 Load profile validation of LV network types

Results comparison with postcode classification

In this section, a comparison between proposed classification and postcode classification is demonstrated. The result of comparison proves that proposed method is more accurate to group LV networks with similar characteristics.

The most straightforward approach to LV substation classification is by its locational postcode, which has been adopted in [7]. But such approach has many disadvantages. Firstly, there is no postcode on LV substation. To get the geographic information of LV network, postcodes of the connecting customers need to be gathered. It is hugely time- and labor-consuming to collect large scale of customer postcodes. Additionally, this location information alone cannot fully reflect the electric properties of the local area, as they do not relate to other key indicators such as consumptions.

The first step of postcode classification is find the postcode of the LV substations. The substation postcodes are determined by the postcodes of the associated customers appearing most frequently. Then the postcodes can be mapped to Lower Level Super Output Area (LLSOA) code. Finally, the LLSOA code and rural/urban indicators [15] are matched to find their geographical locations. By using the same test data set, the 938 LV substations can be divided to urban, town and fringe, village and hamlet and isolated dwelling according to their postcodes. Town and Fringe area is taken as suburban area, Village and Hamlet and Isolated Dwelling areas are regarded as rural area. About 10% substations location information is missing either from the DNO's record or from the LLSOA code, which is represented by "not available".

The comparison results are shown in Fig.6. The overall distributions of urban, suburban and rural area are similar. But the LV substations in each LV network type are different. The coincidence factor is shown in Table II. By comparison, the largest controversy is in classification of

suburban area substations, where only 4.7% substations are coincident. It could be explained as 25% of the substations in this type are without available postcodes. Besides, difference in rural area is larger than 50%. The difference comes from majority of rural substations in fixed data classification are assigned in urban and suburban areas in postcode matching method.

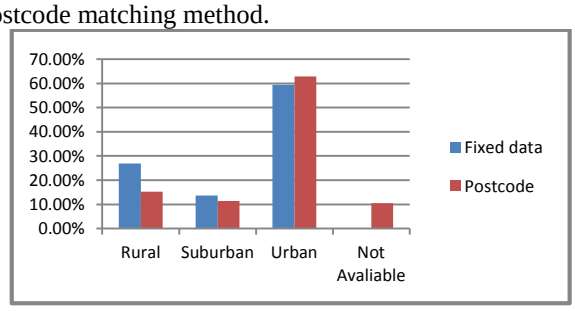

Fig. 6 Comparison between fixed data and postcode classification

TABLE II. RESULT COMPARISON BETWEEN CLASSIFICATIONS

Type	Coincidence percentage	Percentage of N/A postcode
Rural	45.2%	6.8%
Suburban	4.7%	25%
Urban	74.2%	13.6%

More detailed comparison results show the fixed data classification can better reflect the load characteristics of the LV distribution network. As illustrated before, the classification results in rural and suburbia have larger difference. Therefore detailed comparison results of the two locations are demonstrated. Standard deviations of substations' load profiles in each type are compared in table III. The mean, maximum and minimum standard deviation values of fixed data classification in both rural and suburban areas are nearly half of postcodes classification. In Fig.7, "industrial and commercial" groups' standard deviations in suburbia and rural are plotted. Noticeably, the standard deviation of fixed data classification (red) is lower than that of the postcode classification (black) during the whole day.

TABLE III. LOAD PROFILE STANDARD DEVIATION COMPARISON

Location	Method	S.D. Mean	S.D. Max	S.D. Min
Rural	Fixed data	10.85	19.30	0.16
	Postcodes	27.04	47.5	11.84
Suburban	Fixed data	24.36	59.78	8.12
	Postcodes	49.72	92.44	21.37

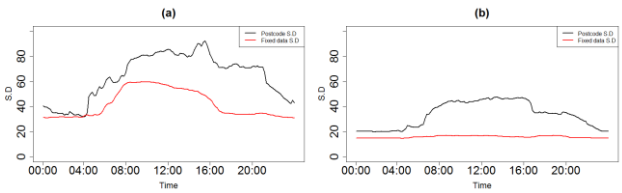

Fig. 7 I &C standard deviation comparison in suburbia (a) and rural (b)

CONCLUSION

This paper has presented the principle and implementation results of a novel LV distribution substation classification method based on readily available fixed data. By using multi-criteria decision making model, key fixed data are linked to target typical LV network types. It cost-effectively classifies the LV network to different location and customer dominant types without the need to collect large scale of connecting customer information. The performance of the proposed classification method is firstly validated with limited real time data. The classification results are effective to represent large scale of LV networks with various characteristics. Besides, proposed classification is compared with postcode classification and proved to be more accurate to group LV networks with similar characteristics. The results from the method can be used by network operators to assist the estimation of LCT penetration, evaluation of investment options and conduct similar planning and operation strategies for LV distribution substations in the same group. Based on the classification result, future work could be carried out to achieve further accurate LV networks visibility with the help of substantially reduced monitoring devices.

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