USE CASE APPLYING MACHINE-LEARNING TECHNIQUES FOR IMPROVING OPERATION OF THE DISTRIBUTION NETWORK

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ABSTRACT

This paper discusses the use of machine learning (ML) techniques to improve fault handling in distribution networks. The paper includes a short survey on the use of ML techniques in fault handling and shows that little published work has been done on using weather data and smart metering data as data sources. It can be argued that this is desired to increase the performance and usability of ML in operational support systems. Previous work also focuses almost exclusively on statistical machine learning aiming to replace traditional simulation models, overlooking other ML methods which can support operations. Here it is illustrated that Case based reasoning (CBR) can be used to aid the decision-making for example, when trying to restore service after an outage. The paper also describes the use of experience databases to aid the operator during fault handling. To illustrate potential use of ML and CBR, the paper presents a use case for future fault handling in low voltage distribution network and discusses the usefulness of this approach. This example shows that implementation of ML techniques in daily operation can be expected to contribute to reduction of costs for the network companies and increased security of supply for the customers.

INTRODUCTION

A distribution system operator (DSO) naturally wants to avoid outages in the power supply. Outages can cause large costs for repairs and incur penalties like cost of energy not supplied (CENS). In addition, outages are inconvenient for the customers and might damage the reputation of the DSO. During localisation and repair of the faults, the personnel can suffer injuries, especially during demanding weather conditions such as strong winds and snow. Hence, improving the precision of fault localization is desirable to reduce the outage duration and increase personnel safety.

Localising a fault can at present be time consuming and it is difficult to provide customers with precise and timely information during the outage. All customers connected to the distribution network in Norway must have a smart meter installed by 1.1.2019, and this provides new source of information for the DSOs that can be useful for fault handling, as well as other applications. Smart meters can notify the DSO when power is lost, and this is a large improvement compared to current practice where the DSO rely on customers alerting them. At the same time development of information and communication technologies (ICT) and cost reductions for computing power allows application of advanced techniques such as machine learning (ML) to resolve many operational issues, including fault handling, more efficiently. The planned introduction of CENS for households by 1.1.2020 [1] is expected to increase the focus on fault localization and repair in the low voltage distribution network. According to a white paper [2], analytics is becoming a part of core business processes for an increasing number of utilities. Three high priority areas for analytics are reported to be energy forecasting, smart metering analytics and asset management. In a review paper [3] four analytics areas for smart metering data are highlighted; load analysis, load forecasting, load management and miscellaneous, with the latter including outage management.

This paper starts with a short survey of the application of machine learning techniques in fault handling. The perpetual challenge of outage and fault management for DSOs is then discussed. Finally, the paper presents and discusses a use case for improved future fault handling in low voltage distribution networks utilising ML techniques. The paper constitutes the first results of the activity "Smart Grid Operation", which is a part of the Norwegian program Centre for Intelligent Energy Distribution (CINELDI), which is a Centre for Environmentally-Friendly Energy Research (2016-2024) [4].

MACHINE LEARNING TECHNIQUES IN FAULT HANDLING

Machine learning has been applied within the energy domain to solve several types of problems such as predicting power generation from solar panels [5], detecting cyber-attacks in the grid, optimizing power consumption in large data centres and predicting failures in grid components [6]. Here we focus on the handling of faults in the distribution network from the perspective of the DSO. Thus, we have chosen to specifically identify machine learning techniques previously used for identifying causes and locations of faults. Most ML methods train models to fit a set of data (the training data). The output from the ML method can be seen as a function of the ML method and the training data. Thus, the results from ML methods are very dependent on the data used to train the models. As a result, the current state of the art of applying ML to fault handling has three main features: The machine learning method, the specific problem that is targeted, and the data used to train the model.

A short survey on the use of ML techniques for fault handling in the power system domain has been conducted. In short, the survey (for details see [7]) finds that a multitude of ML methods are being applied within fault handling: Fuzzy systems [8], expert systems [9], artificial neural networks (ANN) [10], support vector machines (SVM) [10] and Q-learning [11]. The most prominent method by a large margin was ANN, see e.g. [10, 12-14] followed by SVM, see e.g. [10, 12, 14, 15]. The most targeted problem was fault location, see e.g. [10, 13, 15].

The survey found that most of the research done on applying ML to fault handling has been done on transmission networks, as is also seen in the survey done by Ferreira et al. [16]. Some of that knowledge is transferrable to distribution networks, which is the main focus of this paper. In terms of sources for training data, mainly simulated data has been used, and very little data collected from the real world. This is probably because the number of real outages is limited. Surprisingly, we found little research done on using smart meters as a data source for fault handling.

Fault handling is in general comprised of four phases; detection, location and diagnosis, and finally repair/response. Most of the research found in our survey was focused on detecting, locating and classifying (diagnosing) the faults. Very little work has been done on applying ML to suggest responses to faults. This contributes to explaining the absence of some ML methods such as case-based reasoning (CBR)[17]. CBR is well suited for mapping similar problems (or cases) to similar solutions, especially when solutions are best described with text and not numbers. CBR is inspired by psychological models, as humans use past experiences (cases) to solve new problems. Presented with a new problem (case) a CBR system will search it is case-base (a repository of stored cases) for similar cases, then present the user with the solution to the most similar case adapted to the new case. The new solution will be stored in the case-base along with the original case description.

Based on the survey, we propose a new general architecture for fault handling in distribution networks that takes advantage of several data sources, such as smart meter data and weather data, and state-of-the-art machine learning techniques including CBR. The architecture is shown in Figure 1.

OUTAGE AND FAULT MANAGEMENT – AN EXAMPLE FOR APPLICATION OF NEW TECHNIQUES

Managing an outage in distribution networks and restoration of power supply are important tasks for a DSO. Different ways of doing this have been described in numerous use cases. A use case is commonly defined as a list of steps defining interactions between different actors in order to achieve a certain goal. Therefore, considering changes in operation of distribution networks in the future, e.g. for the time horizon 2030-2040, it is reasonable to expect that the triggering event (outage for one or several customers) and the final result or goal (restoration of the power supply) will remain unchanged. The composition of interactions among the involved actors from the initiating event to the goal is however going to be modified in the future by applying the most up-to-date technologies.

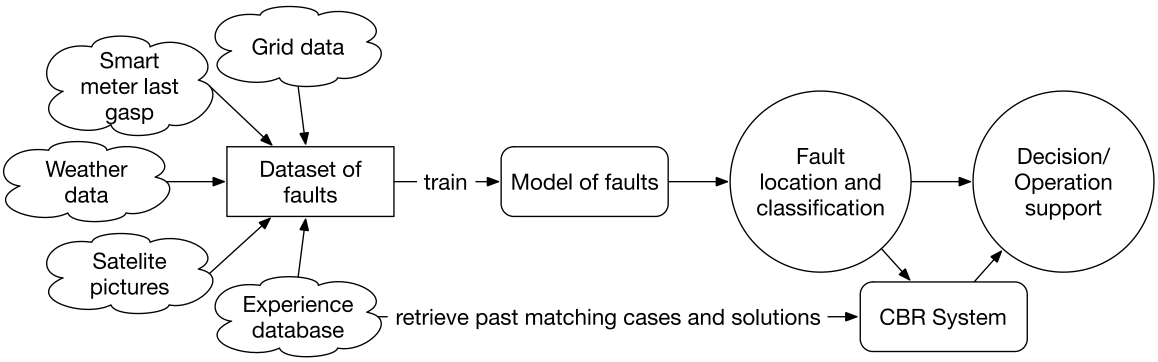

Figure 1: A proposed architecture for fault handling in distribution networks based on machine learning techniques.

The way of dealing with faults and outages has certain limitations at present, which can be improved:

Fault handling:

- Localisation of the fault can be very demanding, especially in rural areas and in bad weather conditions
- Prioritisation of customers for reconnection during restoration of power supply can be necessary in case there are multiple faults involving many customers, such as during severe weather conditions

Work processes:

- Mobilisation and dispatching of working crews can be significantly improved if the fault localisation and fault type are well predicted. This may be especially relevant during for example bad weather and holiday periods with high electric loads
- Automation of (the mandatory) registration of faults. Today this requires manual work that is time consuming and potentially error prone.

At the same time, there is an emerging desire at DSOs to utilise the smart metering infrastructure as much as possible in order to improve planning and operation of the distribution network. Until recently, observability of the low voltage (LV) distribution network was minimal, and DSOs were normally informed about outages directly by the affected customers. Installation of smart meters brings an opportunity to modify the process by utilising the meters so-called last gasp function. This function sends an alarm to the DSO in case the voltage drops below a pre-defined threshold or in case of an outage. Combining signals from several smart meters can allow the DSO to identify the affected area and the actual fault location more accurately [18].

The working hypothesis for this paper is that ML techniques, together with improved data availability from e.g. smart meters, can substantially improve fault handling in the future. The following use case tries to address how the above-mentioned limitations can be resolved by deploying the new techniques and data.

Use Case: Fault handling in low voltage distribution network in 2030/2040

The use case is inspired by the proposed architecture in Figure 1 and focuses on fault handling in the low voltage distribution network in the coming decades. In Figure 2 a flow chart for the use case is provided. The triggering event for the use case is an outage, that may be detected in three possible ways: By smart meters, by breaker operation at the secondary substation, or by a customer. The number of outage reports/complaints from customers is expected to decrease in the future, as the use case will enable DSOs to rapidly inform the customers about an outage and how it is being handled.

Additionally, the use case will enable automatic and precise fault localization and fault handling. The ultimate objective of the use case is to improve the security of supply in low voltage networks by reducing the time to restoration after an outage.

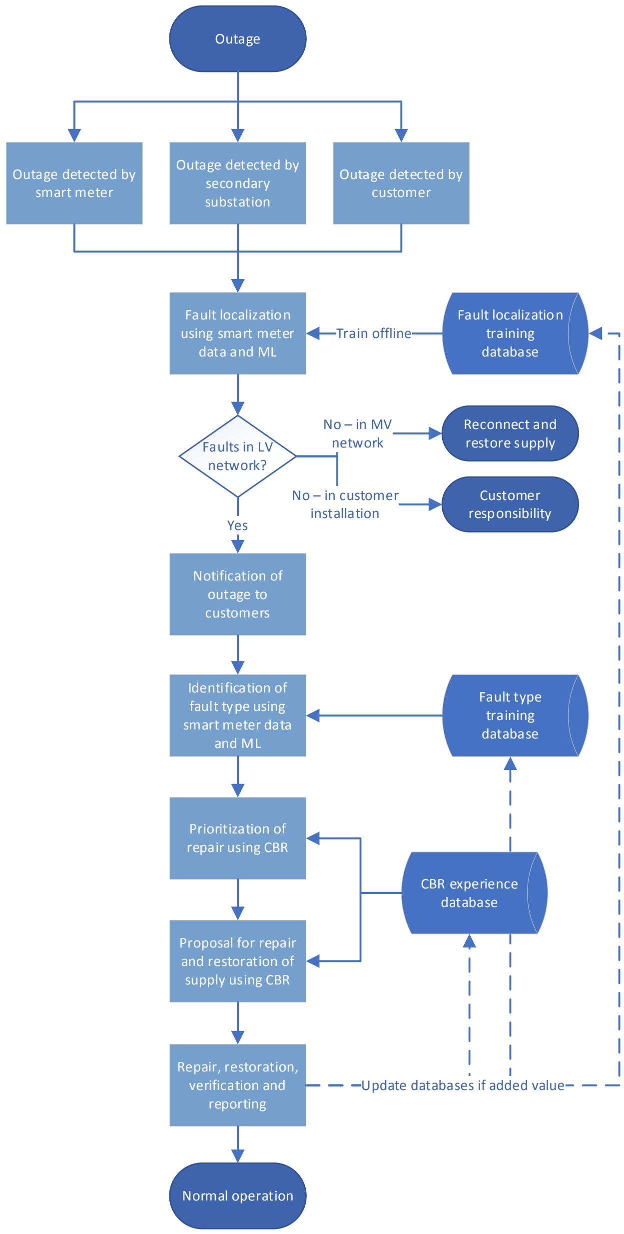

Figure 2: Flow chart for fault handling in low voltage distribution networks in 2030/2040 utilising ML

Description of the Use Case

After receiving the alarm, fault localization occurs automatically by analyzing data from smart meters using machine learning algorithms. Although focus here is on machine learning, other methods may also be relevant for fault localization. With the large number of smart meters, both redundancy and missing or bad data is important to be properly handled [19]. Another concern is that training of the ML model may pose a challenge due to limited number of experienced outages. This problem may be mitigated by utilising simulated data as discussed in the above ML survey.

If only one smart meter reports an outage, the fault is probably in that installation, and it is then the customers' responsibility to rectify this. If the fault is located to the medium voltage (MV) distribution network, it is for simplicity assumed that automatic reconnection and restoration is possible. The remainder of the use case hence applies to the LV distribution network.

After notification of customers, the fault type is identified using ML techniques. Here several data sources may be relevant, including grid data, weather data, satellite pictures, and smart meter data. Machine learning algorithms are well suited to take into account data from several data sources. Identification of fault type includes identifying the component (cable, overhead line, substation) and phases (one phase, multiple phases, grounding) involved, as well as the cause of the fault.

Following identification of fault location and fault type, the operator needs to identify appropriate actions. For multiple faults, this may include prioritization of repairs. A CBR system can use the predicted location and cause of a fault as a new problem description to search within an experience database for similar problem descriptions. If one is found, the previous solution can be retrieved, adapted and presented to the user of the system. If the retrieved solution is straightforward and recognized as identical to the current problem it can lead to automatic actions such as resource allocation, prediction of type of repair needed, and issuing of work orders. Prioritization of repairs may be especially relevant in the future, when high penetration of renewables (PVs etc.) may enable customers to be self-sufficient for a while during the outage such that they can be given a lower priority.

Finally, it is verified that normal supply has been restored and the resolved outage case is documented in the experience database if it provides added value compared to the data already stored in the database. The fault location and fault type are also stored in the ML training databases.

DISCUSSION AND LIMITATIONS

Being set in the years 2030 – 2040, the use case relies on a number of assumptions and prerequisites. Smart meters must be installed with data reporting capabilities of enough resolution, including last gasp-functionality. This requires that the meters have sufficient battery supply to send data also during an outage. Time stamping of data must be well-synchronized between all smart meters (e.g. using GPS) in order to be enough for improved fault localisation. There must be communication between systems that enables transmission of data at sufficiently high frequency, speed, bandwidth, and with sufficiently low latency to conduct outage analysis timely. (E.g., today's radio mesh technology for communication from smart meters is replaced by other technology, such as 5G).

It is in the use case assumed that all outage handling takes place centrally, i.e. in the DSO control centre. Alternatively, part of this functionality may be decentralized. The system responsible for collecting smart meter data, e.g. located in the secondary substation, could also include functionality for localizing the fault and identifying the fault type. The present study does not consider complete automation of the LV distribution network e.g. using remotely-operated breakers. Such breakers may allow to combine the use case with self-healing techniques and corresponding analytics.

The functionality included in the present use case may also be useful in similar use cases for improving the operation of the distribution network. An example is anomaly detection. Such a use case can benefit from the same machine learning algorithms and data, with the objective to identify unnormal conditions by comparing with normal behaviour. An advantage is that in such a scheme, the ML algorithm can be trained with data from normal operation, of which there is an abundance. The challenge then becomes to evaluate the severity of the anomalies, i.e. what constitutes an anomaly severe enough that some action needs to be taken. CBR techniques can be a nice fit for this decision-making challenge.

CONCLUSIONS AND FURTHER WORK

ML appears to be a viable tool for improving the most common processes in fault handling, such as decision support and fault type classification. Deployment of ML will require that certain technological prerequisites are met, such as availability of smart metering with required functionality, availability of sufficient ICT infrastructure, and computational power.

Further work may include integration of other technologies such as self-healing and new types of customers as for example prosumers into the use case. The ML- and CBR-based support can provide probabilities of potential faults and causes of these, and hence thus give input to long term planning of required manpower and materials. The presented use case does not include exceptions from the steps in Figure 2, such as missing data from smart meters, but these exceptions are important to identify in further work.

The use case has not been tested. An option for testing is simulated tests of the last gasp functionality for fault localization. For testing of ML functionality, a first step is to prepare an appropriate data set for simulation of outages or increase the number of outages by sharing information among different DSOs. The sharing of information can also increase the number of cases in the databases of Figure 2.

Deployment of new techniques will probably require substantial efforts and investments and is unlikely to happen without sufficient incentives for the network operators, such as e.g. CENS.

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