Near Real-Time Electric Load Approximation in Low Voltage Cables of Smart Grids with Models@run.time

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ABSTRACT

Micro-generations and future grid usages, such as charging of electric cars, raises major challenges to monitor the electric load in low-voltage cables. Due to the highly interconnected nature, real-time measurements are problematic, both economically and technically. This entails an overload risk in electricity networks when cables must be disconnected for maintenance reasons or are accidentally damaged. Therefore, it is of great interest for electricity grid providers to anticipate the load in networks and quicker detect failures. However, computing the electric load in cables requires computational intensive power flow calculations and live consumption measurements. Today's view of the grid is usually based on on-field documentation of cables, fuses, and measurements by technicians and therefore often outdated. Thus, the electric load is usually only simulated in case of major topology variations. However, live measurements of smart meters provide new opportunities. In this paper we present a novel approach for a near-time electric load approximation by deriving in live the current electric topology and cable loads from smart meter data. We leverage the models@run.time paradigm to combine live measurements with topology characteristics of the grid. Our approach enables to approximate the load in cables, not only for the current grid topology, but also to simulate topology changes for maintenance purposes. We showed that this allows a near real-time approximation while remaining very accurate (average deviation of 1.89% compared to offline power-flow calculation tools). Developed with a grid operator, this approach will be integrated in a monitoring and warning system and as an embeddable solution for on-field simulation.

CCS Concepts

•Computer systems organization → Embedded and cyber-physical systems; •Software and its engineering → Model-driven software engineering; *Real-time systems software; Abstraction, modeling and modularity;*

Keywords

Electric load prediction, smart grid, model-driven engineering, models@run.time, real-time monitoring

1. INTRODUCTION

To keep pace with the ever-increasing demand for energy a modernization of today's electricity grid is inevitable. The vision of such a modernized electricity grid is referred to as the smart grid vision [1]. The smart grid will enable advanced new features like an automated control of devices, remotely collecting consumption data, or demand time pricing [19] to increase the efficiency and reliability of today's electricity grid.

To transform this vision into reality, two major challenges must be addressed: first the seamless integration of renewable energies and distributed micro generations and secondly, the convergence of modern information and communication technology (ICT) with power system engineering [7]. Leveraging this intelligent communication network, smart grids can help to balance the electric load to avoid peaks. For example, in future scenarios, electric vehicles could be forced to delay their charge cycles or even to transfer electricity back to the grid in peak times [10]. However, this leads to a more and more interconnected and complicated electricity grid, which strongly increases its complexity. This motivates the interest of electricity grid operators to predict the electric load in the network —especially when the topology changes— to anticipate overload risks. However, computing the electric load in cables is challenging and requires complex and computational intensive power flow calculations and up-to-date measurements of electric consumption. These are usually based on a static and therefore often outdated view of the physical grid topology. Thus, the electric load in cables is usually only calculated in case of major topology changes. For this reason, such tools are ill-suited for near real-time calculations, as needed *e.g.,* to suggest counter reactions in advance of a potential overload, *e.g.,* restricting the maximum load for customers, scheduling charge cycles of electric vehicles, or for technicians to decide if it is safe to disconnect a cable.

In this paper we present a novel approach for an electric load approximation method, which leverages a dynamic, continuously updated model abstraction of the grid by combining the physical topology and digital live measurements.

By leveraging the digital live measurements available in emerging smart grids, combined with simplified mathematical formulas and modern model-driven software engineering techniques, this enables to approximate the load in cables in near real-time and can therefore be continuously updated, *e.g.,* for every newly measured consumption value or topology change. The model contains the topological entities over time (*e.g.,* smart meters, data concentrators) as well as the physical network topology (electricity cables) and its properties and is continuously updated at runtime to reflect the current state of the grid. In particular, we take advantage of information from *power line communication (PLC)* medias to infer and enrich in live the electric topology from the communication logs. By using a model of state and behaviour of physical smart grid elements, we can simulate actions, *e.g.,* what happens if we disconnect or connect cables. Due to automated meter reading [7], one of the probably most visible smart grid features, customers' consumption data can be automatically collected and stored in regular intervals. We use this data together with the smart grid topology to approximate the electric load in every cable over time. By additionally taking the size of cables into account, we can approximate the maximum capacity of each cable and create alarms if the load reaches a threshold value, *e.g.,* 75% of its capacity. The idea has been developed together with our industrial partner Creos Luxembourg S.A., the main grid operator in Luxembourg, for an electric load monitoring and warning system and for technicians to decide wether it is safe to disconnect a cable for maintenance reasons. We evaluate our system together with Creos, based on real data from the smart grid testbed deployment in Luxembourg. We demonstrate that the performance of our system is compatible with near real-time requirements, while the accuracy of our results remain in average 1.89% compared to the results of the power flow calculation tool[1] currently used by Creos. The advantage of our approach is its near real-time capability.

This paper is structured as follows. Section 2 gives the background of this work, context modeling, models@run.time, and a description of the smart grid topology in Luxembourg. Section 3 presents our approach for electric load prediction in low-voltage cables, which we evaluate in 4. Section 5 discusses related work before this paper concludes in 6.

2. BACKGROUND

In this section we describe the background for this work: the electrical foundations behind our approach, modeling techniques in general and models@run.time in specific, and a description of the smart grid topology in Luxembourg.

[1]http://www.digsilent.de/

2.1 Electrical Foundations

The fundamental physical law on which the approximation of our approach is based on is Kirchhoffs current law [16]. It says that "the sum of all currents around one node is equal to 0". We leverage this law to build an equation system for all cables in the topology and to finally derive the electric load in each cable. The precise rules and ideas behind this approach are detailed in section 3.

2.2 Modeling and Models@run.time

In order to approximate the electric load in cables and to simulate the impacts in case of topology changes (*e.g.,* disconnected cables for maintenance, accidentally damaged cables) we use a model of the smart grid topology. Over time different formalisms to model and reason about systems have been developed and used for different purposes, *e.g.,* [18], [2], [20]. Over the past few years, an emerging paradigm called *models@run.time* [15] proposes to use models both at design and runtime to support intelligent systems. At design time, following the model-driven engineering (MDE) paradigm [14], models support the design and implementation of the system by simplifying the design process, promoting communication between stakeholders, and maximizing compatibility between systems. The same (or similar) models are then embedded at runtime in order to support the reasoning processes of intelligent systems. These models are continuously updated at runtime to represent the current state of a system. Most of these approaches have in common that they describe a system using a set of concepts (classes, types, elements), attributes (or properties), and the relations between them. We refer to the abstraction of a system (set of described elements) as a *model* and to a single element (concept) as *model element*. The concepts of our approach are, in principle, independent of a concrete model representation strategy. However, the implementation of our approach is built with an open source models@run.time framework, the Kevoree Modeling Framework [8] (KMF[2]). KMF is an alternative to EMF [3] and specifically designed to support the models@run.time paradigm in terms of memory usage, runtime performance and especially to mix measured data and extrapolation functions. We decided to leverage a models@run.time based approach for several reasons: First, models provide a semantically rich way to model a system. Second, models can be used to define reasoning activities like electric load approximation. Third, the models@run.time paradigm has been proven to be suitable to model complex cyber-physical systems (like smart grids) during runtime [15].

2.3 The Smart Grid Topology in Luxembourg

This work has been done in collaboration with our industrial partner Creos Luxembourg S.A., the main electricity grid operator in Luxembourg. Therefore, we describe in the following the main characteristics of the smart grid test deployment there. A more detailed description and analysis of the smart grid topology in Luxembourg can be found in [11]. Based on this, we later build an abstract model of this topology and fill it with real data in order to approximate the load.

[2]http://kevoree.org/kmf

The smart grid topology in Luxembourg is built upon a power line communication [9] (PLC) network. A major advantage of PLC is that the same media that is used for electric power transmission can be used for establishing the communication network and transmitting data. On the other hand, a major concern with PLC is the amount of electric noise and disturbances that may be encountered, which requires advanced error detection techniques. The main devices in the topology, for the context of this work, are:

Smart meters are the cornerstones of the smart grid infrastructure. Installed at customers houses they continuously measure electric consumption and quality of power supply and regularly report these values to utilities for monitoring and billing purposes. Another major task of smart meters is load management, as they are able to trigger relays to connect/disconnect specific loads. Smart meters are either directly, or via other smart meters (repeaters), connected to a data concentrator. In regular intervals, in Luxembourg every 15 minutes, smart meters report their consumption data to their associated data concentrators.

Data concentrators collect and store consumption data from a number of associated meters. In regular intervals (several times a day, immediately) they send this data, usually via IP connections, to a central control system. Concentrators have the ability to send commands, like requesting consumption data or to shut down electricity. Physically, data concentrators are located at power substations. In case of bigger housing complexes a concentrator can also be located directly in the housing complex itself.

Central system all data concentrators send their data to a central system where all data are stored, aggregated and analyzed. Because of legal regulations these data must be deleted in regular intervals (*e.g.,* cannot be stored longer than x month).

Cabinets and cables: cabinets are electric enclosures which connect cables. With the help of fuses it can be controlled, which of the cables should be connected. Cables, cabinets, and the state of fuses (open/closed) are an important part of our model to approximate the electric load in cables.

The grid in Luxembourg is organized in multiple graphs. This means, that fuses in cabinets are configured in a way that cables starting at a transformer substation, are connected to several other cables in cabinets but usually never end in another transformer substation (no cycles)[3]. Instead, cables always end in a *dead end* (not connected to another cable). Figure 1 shows an example of how such a topology looks like. In our approach we leverage this topology characteristic to analyse every transformer subgraph independently from others. This makes it possible to easily parallelize the electric load approximation and simulation for the whole grid.

[3]There exist some cases where two transformers are operated in parallel mode and then they are interconnected (mostly not by purpose but when technicians forget to open the fuse after an intervention)

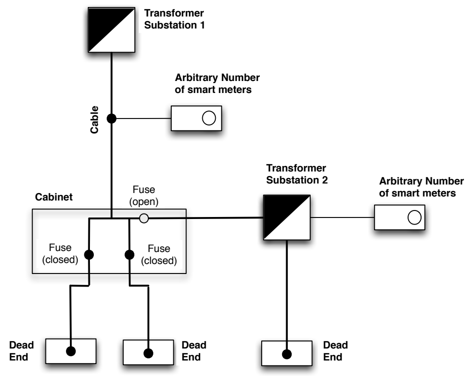

Figure 1: Example based on the smart grid topology structure in Luxembourg

3. ELECTRIC LOAD APPROXIMATION

In this section we describe how we approximate the electric load in cables and how we simulate the impacts on the load in case of topology changes (*e.g.,* cable disconnection). The goal is an electric load monitoring and warning system as well as a decision support system for technicians.

3.1 General Considerations

To solve the problem of a dynamic anticipation of the electrical load in the grid under certain planned/unplanned events we combine a topology abstraction (model) and active data (continuously updated at runtime). Based on this abstraction we analyze the state of the grid and apply electrical formulas, based on a simplified electrical model, in relation with reactive/active aspects that are beyond the scope of common simulation tools. This enables to consider dynamic changes, (*e.g.,* in the physical grid topology but also in the measured values like consumption data. Figure 2 shows an overview of our approach. In a first step, we derive the current topology from our model-based abstraction of the grid. The model is continuously updated from the live measurements of the smart grid. Then, based on the derived topology we apply the electrical formulas for the load approximation. In a final step we solve the formulas and calculate the electric load. In the following we describe these steps in more detail.

The fundamental physical law on which the following calculations are based on is Kirchhoff's current law [16]. It says that *"the sum of all currents flowing into a node is equal to the sum of the currents flowing out of this node"*, or more formal:

$\sum_{k=1}^{n} I_k = 0$, *where n is the total number of currents flowing towards or away from the node.*

If we apply this on our topology model we can derive four basic rules for the electric load approximation:

1) For every cable we need one current calculation for the ends of the cable, i_1 and i_2. Since we only have the consumption values of all smart meters and our topology model,

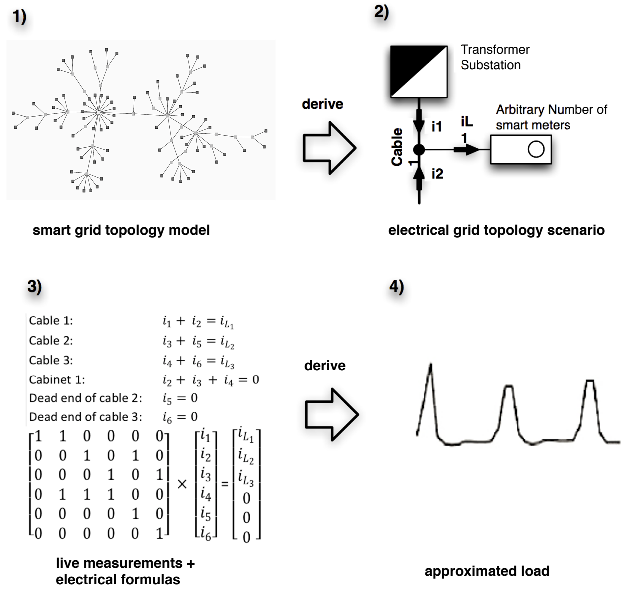

Figure 2: From the current smart grid communication topology (1) we first derive the electrical topology scenario (2), then combine it with live measurements and apply the appropriate electrical formulas (3) to finally derive the load approximation (4)

which specifies —among other things— which smart meter is connected to which physical cable, all loads of a cable can be summed up as: $I_L = \sum_j i_{load_j}$ (neglecting the active and reactive impact form the cable, *e.g.,* losses, generation). These loads can be considered as a current flow out of the cable (to the consumer) and according to Kirchhoffs current law we can derive following equation: $i_1 + i_2 = I_L$. i_1 and i_2 are the dominating values for the electric load considerations since they determine the cable loads.

2) We can apply Kirchhoff's current law for all cabinets, meaning that all currents of cables j connected to a cabinet will sum up: $\sum_j i_{cabinet_j} = 0$.

3) For a dead end cable the current at one end is 0.

4) For each circle (cables are directly or indirectly connected in a circular way) the point that is from a physical point of view the nearest to the transformer substation has to be determined. On this point the two cables that are part of the circle must carry the same current: $i_1 = i_2$.

Those rules allow us to calculate the currents at both ends of every cable independently of the grid structure. In any topology with n cables we implicitly have $2 * n$ unknowns (current at the start and end of each cable) and we therefore need $2 * n$ equations to solve the system. Since we have as many equations as unknowns the system to solve will be a square matrix and have always one solution. For example, if we consider the three cables in Figure 5a, the equation system to solve would look like the following example:

$$\begin{array}{l} \textbf{Cable equations} \left\{ \begin{array}{l} \\ \\ \\ \end{array} \right. \\ \textbf{Cabinet equation} \; \{ \\ \textbf{Dead end of cable} \; \{ \\ \textbf{Circle equation} \; \{ \end{array} \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & -1 & 0 & 0 & 0 \end{bmatrix} \times \underbrace{\begin{bmatrix} i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5 \\ i_6 \end{bmatrix}}_{\textbf{End points of cables}} = \begin{bmatrix} i_{L_1} \\ i_{L_2} \\ i_{L_3} \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{array}{l} \left.\begin{array}{l} \\ \\ \\ \end{array}\right\} \textbf{Loads} \\ \\ \\ \\ \end{array}$$

Each row corresponds to one equation. The columns of the matrix represent for each cable the loads i_1 and i_2 for the ends of the cable. This means that the first two columns belong to cable 1, the next two to cable 2 and so forth.

In order to approximate the electric load of all cables we have to traverse the topology model, detect the different scenarios regarding the above described four rules, and build and solve the equation system. In the following subsections we describe the different scenarios in more detail and show how we derive the necessary equations. We assume that the smart grid topology in Luxembourg consists of multiple subgraphs and transformer substations are not interconnected. In special cases, where this is not true, our load approximation will yield wrong results. This will be investigated in future work. We can reduce the complexity of the equation system by deriving one equation system per transformer substation. This can be parallelized so that all equation systems can be independently calculated at the same time. By changing the state of fuses and/or cables in our topology model we can simulate how the electric load in all cables will be effected.

3.2 Topology Scenarios

3.2.1 Single Cable

The first topology scenario we look at is a single cable on a cabinet or transformer substation. Figure 3 shows the corresponding topology excerpt. The arrows on cable 1 indicate the conceptual flow of the loads i_1 and i_2. The Figure shows an arbitrary number of smart meters connected to cable 1. The sum of all loads of the smart meters are indicated by load I_{L_1}. We are only interested in the load of the low-voltage cable (cable 1), not in cables connecting meters to the low-voltage cables. We can derive following equations:

Cable 1: $i_1 + i_2 = i_{L_1}$
Dead end of cable 1: $i_2 = 0$

System to be solved:

$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \times \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} = \begin{bmatrix} i_{L_1} \\ 0 \end{bmatrix}$$

3.2.2 Cabinet Connecting Several Cables

The next scenario is a cabinet connecting several cables. Figure 4 illustrates an excerpt of a corresponding topology to clarify this scenario. We assume that all fuses in cabinet 1 are closed, so that cables 1, 2, and 3 are connected. For each cable we have again two loads for both cable ends. On

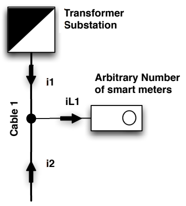

Figure 3: Single cable on a substation

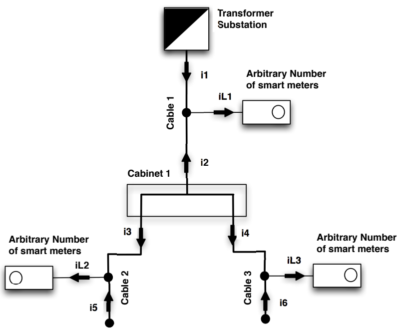

Figure 4: A cabinet connecting several cables

each cable an arbitrary number of smart meters is connected, which individual loads are summed up in one load value for each cable. Cable 2 and 3 have dead ends (no other cable is connected to this cable end). Therefore, we can derive the equations below:

Cable 1:	$i_1 + i_2 = i_{L_1}$
Cable 2:	$i_3 + i_5 = i_{L_2}$
Cable 3:	$i_4 + i_6 = i_{L_3}$
Cabinet 1:	$i_2 + i_3 + i_4 = 0$
DE cable 2:	$i_5 = 0$
DE cable 3:	$i_6 = 0$

DE: dead end

$$\Rightarrow \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5 \\ i_6 \end{bmatrix} = \begin{bmatrix} i_{L_1} \\ i_{L_2} \\ i_{L_3} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

3.2.3 *Parallel Cables*

The most complicated scenario are parallel cables, which can appear in different types. First, several cables can start at the same transformer and end at the same cabinet. Second, parallel cables can appear between two cabinets. This means that several cables start at the same cabinet and all of them end at the same cabinet. Last but not least, we have to consider "indirect parallel cables". These start at the same substation but not necessarily end immediately at the same cabinet. If a cable ends at a cabinet and is there connected to another cable, which ends at the cabinet where other cables starting at the substation ends, they indirectly form a circle. These three scenarios are sown in Figure 5. Figure 5a shows parallel cables at a transformer, 5b parallel cables at a cabinet, and 5c indirect parallel cables. For 5c we can derive following equations:

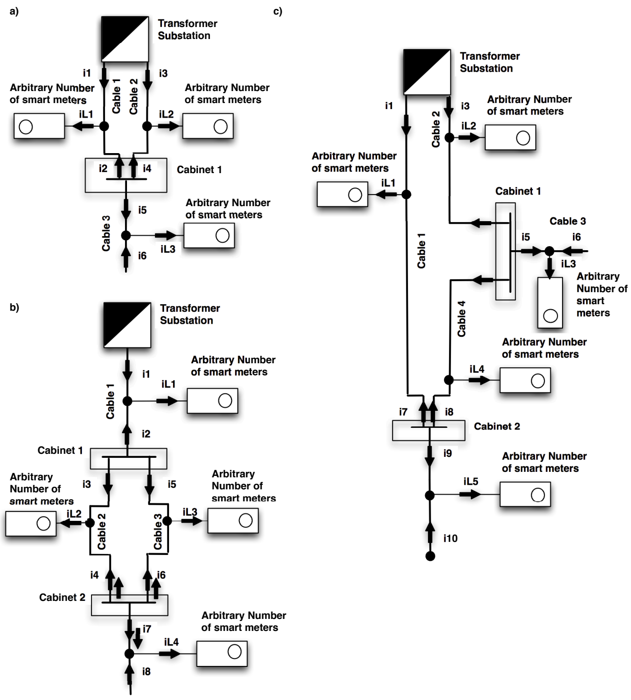

Figure 5: Parallel cables: a) at a transformer substation, b) at cabinets, c) indirect parallel cables

Cable 1:	$i_1 + i_2 = i_{L_1}$
Cable 2:	$i_3 + i_4 = i_{L_2}$
Cable 3:	$i_5 + i_6 = i_{L_3}$
Cable 4:	$i_7 + i_8 = i_{L_4}$
Cable 5:	$i_9 + i_{10} = i_{L_5}$
Cabinet 1:	$i_4 + i_5 + i_7 = 0$
Cabinet 2:	$i_2 + i_8 + i_9 = 0$
DE cable 3:	$i_6 = 0$
DE cable 5:	$i_{10} = 0$
Circle at Transformer:	$i_1 - i_3 = 0$

DE: dead end

System to be solved:

$$\Rightarrow \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5 \\ i_6 \\ i_7 \\ i_8 \\ i_9 \\ i_{10} \end{bmatrix} = \begin{bmatrix} i_{L_1} \\ i_{L_2} \\ i_{L_3} \\ i_{L_4} \\ i_{L_5} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

3.3 Considering Active and Reactive Energy

The calculations so far are only valid for purely resistive loads (only active power). However, in a real grid the current always has a reactive component. To take this fact into account we apply complex numbers: $i_1 = i1_{active} + j * i1_{reactive}$ where j is the complex number. To simplify the approximations we assume that the voltage at each point is equal to 230 V. Since we have the active and reactive energy from the smart meter measurements (customers' consumption data), we can simplify the calculation by taking the active power P and reactive power Q into account, instead of calculating first the current and divide it into an active and reactive part: $S_1 = P_{1_{active}} + j * Q_{1_{reactive}}$ where j is the complex number. The principal to establish the equations stays the same. On the first topology example (see Figure 3) this looks like below:

System to be solved:

$$\begin{bmatrix}1&1\\0&1\end{bmatrix}\times\begin{bmatrix}P_1&Q_1\\P_2&Q_2\end{bmatrix}=\begin{bmatrix}P_{L_1}&Q_{L_1}\\0&0\end{bmatrix} \xrightarrow{yields} \begin{bmatrix}P_1&Q_1\\P_2&Q_2\end{bmatrix}=\begin{bmatrix}1&1\\0&1\end{bmatrix}^{-1}\times\begin{bmatrix}P_{L_1}&Q_{L_1}\\0&0\end{bmatrix}$$

3.4 Electric Load Approximation

To approximate the load in cables, we first create all necessary equations. After this step, we solve the matrix equations and calculate for every cable the components P_1, Q_1, P_2, and Q_2 (the two ends of a cable). With this it is possible to calculate the electric load i_1 and i_2 for every cable:

$$i_1 = \frac{\sqrt{P_1^2+Q_1^2}}{\sqrt{3}*230},\ i_2 = \frac{\sqrt{P_2^2+Q_2^2}}{\sqrt{3}*230}$$

In order to simulate the impacts on the electric load if, for example, a cable would be disconnected we can simply update the topology model with the disconnected cable and trigger the load approximation. Therefore, the concerned equations are recreated and the load in the cables is updated accordingly.

4. EVALUATION

In order to evaluate our approach we built a model of the smart grid testbed in Luxembourg. It contains three transformer substations, around 250 smart meters, 30 cables, 27 cabinets, and consumption data of smart meters over a time window of six weeks (one value per meter every 15 minutes). The number of 10 cables and 100 smart meters per substation is representative for three phase grids like the ones in Germany, Switzerland, Austria, or Luxembourg. Furthermore, cables of different substations are usually not interconnected. Therefore, the electric load in cables can be independently approximated for the cables of each transformer and can be parallelized. We used this model to evaluate our approach in terms of performance and accuracy to validate its suitability to be used in a near real-time simulation system for electric load prediction in low-voltage cables.

4.1 Performance of Electric Load Prediction

In order to evaluate the performance of our approach we changed the topology several times and recalculated the electric load in all cables. We divided the calculation in two steps: *i)* traversing the smart grid graph, finding the topology scenarios and building the equations, and *ii)* solving the matrix equation system. For the latter we use the efficient-java-matrix library (EJML)[4]. For each of the three scenarios (every transformer substation) we randomly changed the topology (cable connections) 100 times and measured the average times for the recalculation. We performed the experiments on an Intel Core i7 2620M CPU with 16 GB of RAM. We neglected I/O operations as far as possible by caching all data instead of reading it from a database. The results of this evaluation are shown in Table 1. As can be seen, the costly part is the creation of the equations. This is not a surprise, since our algorithms have to traverse the

Scenario	Overall	Creating	Solving
Transformer Substation 1 (103 meters, 12 cables)	191 ms	190 ms (99.95%)	$\leq$ 1 ms (0.05%)
Transformer Substation 2 (71 meters, 10 cables)	157 ms	156 ms (99.94%)	$\leq$ 1 ms (0.06%)
Transformer Substation 3 (56 meters, 8 cables)	143 ms	142 ms (99.93%)	$\leq$ 1 ms (0.07%)

Table 1: Performance evaluation

topology graph, detect the scenarios, resolve the appropriate consumption data (right time and customers), and derive the equations. In order to optimize this process we built on the work of [13], [12], [11] for building topology models and reason about them. We then gradually increased the complexity of the grid topology (number of cables) in order to evaluate the scalability of our approach and found that the time to approximate the electric load is about linear. This is shown in Figure 6. Since our approach allows to independently build and solve the equation systems for every transformer substation, the overall time is determined by the number of cores (to parallelize) and the most complex subgraph. The recalculation time of less than 2 ms, in average, is what we call near real-time. This shows that our approach is fast enough to be used in a near real-time what-if simulation system for electric load approximation.

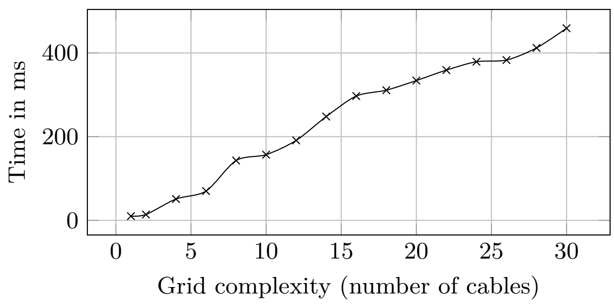

Figure 6: Scalability of electric load approximation

4.2 Accuracy of Electric Load Prediction

In order to evaluate the accuracy of our model-based approach we compared our results with the results of the power flow calculation tool (DIgSILENT), which is currently used by Creos. Therefore, the power flow calculation department of Creos took a snapshot of the smart grid topology and consumption data, created a static configuration for the power flow calculation tool, and calculated the exact loadings. We analyzed the results for several different scenarios and cables and compared it to our approximation approach. For each cable we compared the calculated values for the active as well as reactive energy at the beginning and ending of the cables and the cable loading. We found that our approximation approach is very accurate with deviations below 5%. The biggest discrepancy we found is 5.77% and the smallest 0.07%. In average, we got an deviation of only 1.89%. This shows that our approach is able to dynamically recalculate the electric load in cables in near real-time while still is very accurate.

[4]https://code.google.com/p/efficient-java-matrix-library/

5. RELATED WORK

Electric load forecasting is an important field for electricity providers to decide early wether extra generation must be provided. Most of recent approaches are based on load profiling, possible through automated meter reading. Park *et al.,* present in [17] an approach for load forecasting based on an artificial neural network (ANN). The ANN is used to learn the relationship among past, current, and future temperatures and loads. Espinoza *et al.,* [6] present an advanced short-term load forecasting approach using kernel-based modeling for nonlinear system identification. They create consumption profiles of customers by applying machine learning techniques to predict hourly loads as well as daily peak loads. An interesting aspect of this work is that they discuss the need to take different context parameters, like weather conditions or the date into account. The work of Espinoza [4] *et al.,* aims at providing a unified framework for electrical consumption forecasting and clustering by creating daily profiles of customers. They first generate short-term models that can produce accurate forecasts, extract temperature and seasonal effects and identify the type of customer under scrutiny. Then, they partition the set of time series, using clustering algorithms, based on the customer profiles. In [5] Espinoza *et al.,* present results from a project in cooperation with the Belgian national grid operator ELIA. They analyze a set of 245 time series, each one corresponding to four years of measurements from a HV-LV substation and apply individual modeling using periodic time series to forecast the electrical load. They use the stationarity properties of the estimated models to identify typical daily customer profiles.

These approaches have in common that they use machine learning techniques to cluster customers based on their consumption and predict the electrical load based on this. Since they ignore the underlying smart grid topology these approaches don't target the approximation of the electrical load in cables. In contrary, we focus on the approximation of the electric load in cables to simulate the impacts of topology changes to create a load monitoring and warning system and for technicians to decide wether it is safe or not to disconnect a cable for maintenance. To the best of our knowledge, there is no other approach combining a continuously updated model of smart grid topology characteristics together with customers' consumption data to approximate the electric load in cables in near real-time and to simulate the impacts of topology changes. However, we can combine electric load forecasting with our approach to extend our system to an early-warning system. If we forecast the load for all customers connected to a cable, we can feed our system with the forecasted values, instead of using the measured ones to check if we expect critical loads in cables.

6. CONCLUSION AND FUTURE WORK

To cover the ever-increasing energy demand the electricity grid becomes more and more complex, *e.g.,* due to the integration of renewable energies. This entails a high overload risk in the electricity network, which becomes even more challenging when cables must be disconnected for maintenance reasons or are accidentally damaged. Therefore, it is of great interest for grid providers to anticipate the load in the network when the topology changes. Computing the electric load in cables requires complex and computational intensive power flow calculations and up-to-date measurements, which are usually based on a static and therefore often outdated view of the grid topology. In this paper we presented a novel approach for an electric load approximation method, which leverages a dynamic, continuously updated model abstraction of the grid by combining the physical topology and digital live measurements. We showed that this approach is able to approximate the load in cables with a high accuracy and is able to simulate the impacts of topology changes in near real-time.

The novelty of this approach lies in the combination of a model-based grid abstraction, leveraging live measurements such as consumption data available in smart grids, and the usage of simplified electrical formulas. The presented idea, which has been developed in cooperation with our industrial partner Creos, has been implemented as a prototype monitoring system to detect potential overloads in cables as well as for technicians to decide wether it is safe to disconnect a cable for maintenance. In our evaluation we showed that our approach is able to recalculate the electric load in cables after topology or data changes in near real-time, while the accuracy is close to the results from power flow calculation tools (average deviation 1.89%). The near real-time capability is the main advantage of our approach.

In future work, we plan to apply electric load forecasting to extend our approach to an early-warning system. For example, if we forecast the electric load for all customers connected to a cable, we could feed our system with the forecasted values, instead of using the measured ones to check if we expect critical loads in cables. This would open the door to enable a dynamic system, able to suggest counter reactions in advance of a potential overload situation, such as automatically restricting the maximum load for customers, or delaying charge cycles of electric vehicles.

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