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Modelling Future Prosumer Nodes and their Impact on Network Planning – a Case Study

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***Abstract*—This paper presents a pair of reasonably likely scenarios for low voltage (LV) electricity consumption and distributed generation and investigates how these scenarios will impact a realistic approximation of an existing section of LV network generated by a distribution network-planning algorithm using falsified but realistic existing load data. Some simplifying assumptions are made due to the difficulty of modelling the consumption of individual customers, but general methodology is set up and illustrated that will suit a more fine-grained analysis as data becomes available. The scenario loading uses simulated consumption time series data for two heating scenarios: EV consumption using uncontrolled and sensible charging scenarios, and photovoltaic rooftop generation time series data from earlier research at Aalto University. The results clearly illustrate that smart EV charging can alleviate the need for network reinforcements but the network upgrade costs imposed by the most pessimistic uncontrolled EV charging are also quantified.**

Keywords—Distributed Generation; EV charging; Expansion Planning; Load scenarios

I. Introduction

Some claim that distributed generation is the power system's answer to the climate crisis and some claim that centralized large scale renewable and nuclear is the answer. Finland may be seen to favour the latter alternative, but really, everything will be required: centralized production, distributed production and intelligent consumption and storage, with active networks connecting it all. This paper studies the LV side of the puzzle, establishing whether at least the primary components of an existing LV network are capable of handling the load magnitudes and profiles they will experience in the near-to-medium future.

Rooftops are perhaps the least controversial place to put photovoltaics (PV), and while the private-car paradigm might not be the best way forward in a sustainable future, suburbs in Finland are already seeing a rapid increase in electric vehicles (EV). Accordingly, this paper puts these two likely phenomena together with consumption profiles for two likely heating scenarios, district heating and ground-source heat pumps, and checks the impact of these radically different and increased loading scenarios on existing network, using a 40-year planning horizon. A more complete account of this study including Matlab coding used for the analysis can be found in [1].

While this paper simply presents a locally-relevant case study, there has been considerable work in recent years regarding the hosting capacity of LV feeders, particularly in cases where reverse power flows from distributed generation impose voltage rise violations. Reference [2] addresses hosting capacity both in terms of a literature review, consideration of reactive power support from the PV converters and arrives at a categorisation of feeders in terms of parameters such as various line length and customer proximity data, the ratio of total line length to number of loads, kWm and kWΩ, line impedance (resistance being the most significant contributor in LV), etc. Considerable work on the topic specific to Finland has been carried out. For example, [3] considers active and reactive power control to increase the hosting capacity of PV in LV networks, at least in terms of voltage. The topic of this paper is to case-specifically assess the impact of both EV and PV on LV feeders, and to this end [4] draws the conclusion that smart charging helps EV hosting, but does not help PV hosting much.

Our case study will investigate a typical suburban case in Finland, and discuss the topic more generally in the discussion. The aim is to assess a specific realistic existing section of LV network in terms of voltage and thermal constraints when subject to significant installations of PV and EV charging.

II. Methodology

The LV implementation of a distribution network planning algorithm [5], Optimizer, which works as an optional module in the commercial network information system software TrimbleNIS, was used to produce a realistic present-day low voltage network using actual LV customer locations around a fictitious secondary (MV/LV) substation, node 0 in the centre of Fig. 1.

Fig. 1 is taken to be a present-day existing network, and the scenario simulations in the paper are checked to see if this existing network can cope with them. Nodes 1 to 55 are LV customer connection points and 56 to 87 are mostly cable boxes, from which each LV connection point is connected via a spur feeder. The numbering and feeder layout is clearer in the topological depiction of the existing network in Fig. 2.

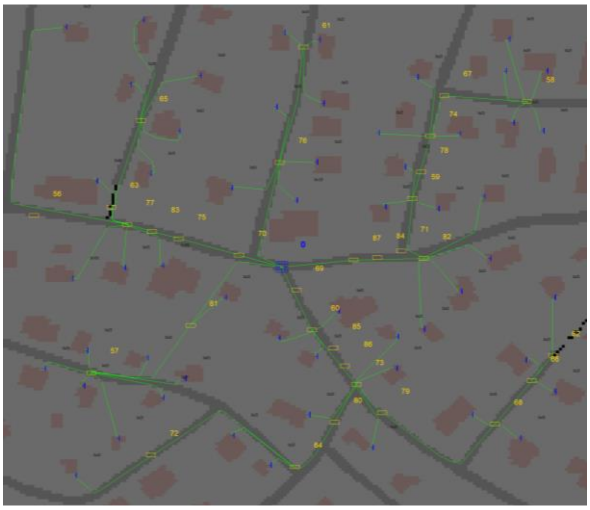

Fig. 1. The simulated LV network, which forms a close approximation to a real existing LV network

Matlab® was used for the scenario modelling in this paper, which involved handling hourly-resolution time-series data behind every LV connection point, and Excel was used for handling smaller amounts of data and for the load summation analysis. To estimate the heating load of housing, the Finnish National Geoportal (*Paikkatietoikkuna*) was used, as it can calculate the area of user-selected sections from the map interface.

A. Heating Scenarios

The first scenario corresponds to the suburban LV customers keeping their existing heating system, which is District Heating, assuming that a way is found to decarbonise this technology. The second scenario assumes that all the customers change to Ground Source Heating Pumps (GSHP). The profiles for the consumption of LV customers based on the two heating types were taken from Monte Carlo simulations produced in [6].

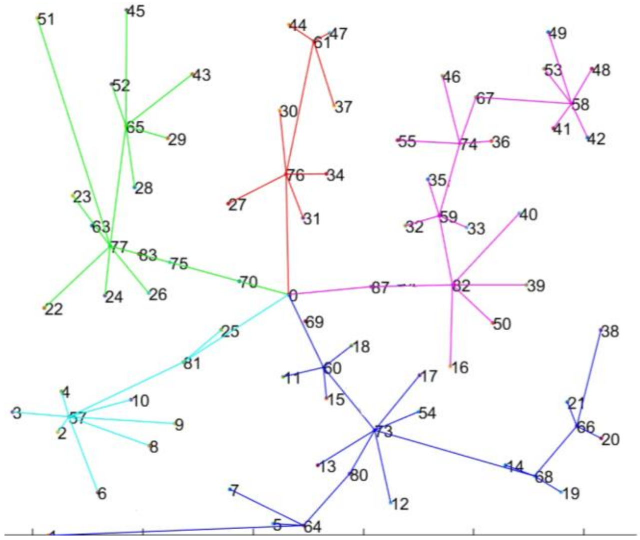

Fig. 2. A topological view of the “existing” LV network

In order to appropriately scale these profiles to each LV customer, we used some Direct Electric Heating (DE) data as a guideline, assuming that, for example, District Heating houses of the same size would have 25% of the annual electricity demand (0% for heating) of DE houses. GSHP houses were assumed to require 10% of the electrical energy for heating and 20% for other electrical demand (excluding EV charging), making a total energy demand of 30% of a DE house. These rather crude empirical assumptions were checked with reference to a commercial website [7]. Using such an approach gives us reasonably realistic consumption profiles for houses taken from a map, relieving us of concerns about infringing data protection legislation. The profiles themselves are taken from rigorous statistical modelling used to generate 100s of years of Monte Carlo simulated data based on real measurements.

Similar to the consumption, the challenge with PV modelling is to obtain suitable time-series profiles and to scale those profiles suitably to reflect the inclination of the panels. Time series data close to the geographic location of the LV network under investigation was taken from [8], where the nominal value is 100 kW and the panels are assumed to face south (i.e., Azimuth angle = 0°). While it is true that such Monte Carlo simulated time series are only as good as the years of measured data they are statistically based on, and therefore may not capture extreme behaviour, the extremes of significance for dimensioning the lines are peak PV generation, which are adequately captured in such simulations. Fig. 3 shows one such simulated year of PV data.

The houses in the LV network area (using a more detailed map interface than shown in Fig. 1) were analysed to establish their most likely Azimuth angles, assuming a given tilt angle of about 45° [9]. The relationship of the energy lost when the azimuth angle deviates from 0° has been derived from [5] by interpolating between data points, see Fig. 4. The energy loss percentage for South-East and South-West is 5% which was taken directly from [5]. For the East and West, the article did not mention a specific value. It did explain how azimuth angle deviations of up to 23º have little to no influence on the energy losses. However, when azimuth deviation angles increase so do the energy losses. With this information, a first approximation can be calculated, by representing the known values, and estimating the value at the desired angle. 250 W 60 cell solar panels were chosen, which have a surface area of 1.66 m^2. Using the appropriate area for each house and the respective energy loss due to Azimuth angle (i.e., when the panels do not face south) to appropriately scale the time series data in [8] yields one year of hourly resolution solar data for each rooftop installation.

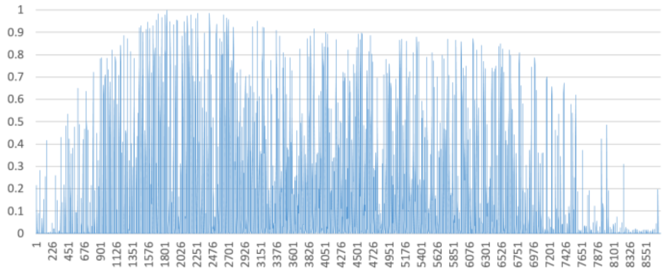

Fig. 3. 8760 hours of simulated photovoltaic output (p.u.) at study case location.

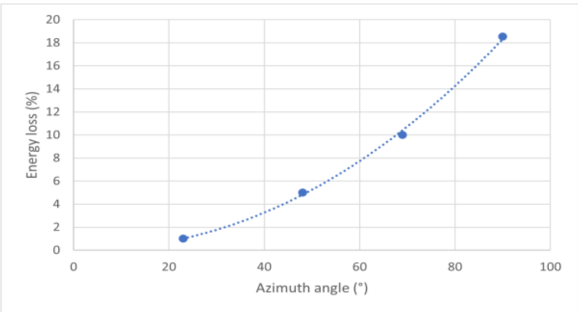

Fig. 4. Energy loss vs. Azimuth angle at the relevant latitude.

This approach lacks a more detailed investigation of shading and so is somewhat idealised. The typical PV power rating varies from 1 to 4 kVA per rooftop installation, noting that at southern Finnish latitudes, the capacity factor for solar panels is about 10%.

B. *EV charging*

Two options for home EV charging are explored. The first is to assume that a significant number of residents plug their car in when they get home from work and that the EV load is split evenly between level 1 charging (3.7 kW) and level 2 charging (11 kW, noting that Finnish households usually have 3-phase power available). The second option assumes some *smart* coordination of EV charging in a given LV region, by dividing the night into five 3-hour periods: 17-20, 20-23, 23-2, 2-5 and 5-8. Customers fed by the same cable box are given different charging periods to lower the summation of loading onto the trunk feeders. The assumptions behind the previous parametrisation are an assumed average travelling distance per work-day of 60 km (noting that we are analysing a suburban location, the average distance travelled by car each day is 40 km in Tampere [10]), and an average battery capacity of 40 kWh.

C. *Deriving the Relevant Network Parameters*

The time-series PV, relevant load and EV charging data must be summed for each node (LV customer connection point) and combination of fed nodes at common nodes upstream (e.g., cable boxes, branch points and the secondary substation). Refer to Fig.2. From the summed time-series data at each node, the following parameters are derived: P_{max}, P_{min}, Q_{max}, Q_{min}, and T_{losses}. The latter parameter T_{losses} is used to multiply the loss power based on peak loading to approximate the annual I^2R losses of the relevant line or component n, where

$$T_{losses,n} = \frac{\sum_{t=1}^{8760} P_n^2(t)+Q_n^2(t)}{\left(max(S_n(t))\right)^2}. \tag{1}$$

Note that in (1), P_n and Q_n are themselves summations (for every hour of the simulated year) of everything node n feeds. For example, node 75 in Fig. 2 feeds nodes 83, 77, 26, 24, 2, 63, 23, 51, 65, 28, 29, 43, 45 and 52. S_n is calculated from the active and reactive power flows in each line section. A power factor of 0.95 lagging was assumed when calculating the reactive powers at the LV connection points.

Referring to Fig. 2, the relevant demand, EV and PV time series data need to be summed to derive the parameters listed above for each of the 55 LV nodes. The time series data from all fed nodes then need to be summed when working upstream to calculate the parameters in common nodes, such as the cable boxes, branch points and ultimately the secondary substation.

The Excel analysis consists of an active and reactive load summation rather than a full load flow, which of course the commercial NIS does perform. The maximum currents can be derived from the maximum apparent power flowing in each line section, and voltages can be calculated from these currents. This crude backward-forward sweep converges quickly, but it should be noted that if distributed generation is significant, then P_{min} and Q_{min} (representing minimum demand, maximum generation) should be checked as well, for both thermal loading and voltage rise. It should also be mentioned that a 40 year time horizon was used for costing, coupled with low load growth of 0.12 %/annum (the scenarios imply large step-changes in growth), and an interest rate of 3 %/annum.

III. Results

The results are presented in terms of the two main scenarios, GSHP and District Heating. Each scenario entails summing the data for each of the 8760 hours of the simulated year. Only typical mid-winter day and mid-summer day results will be shown. It turns out that although the consumption profiles vary considerably between the two heating types, the EV charging and summer PV generation dominate the profiles, rendering similar results for the two scenarios.

A. *Ground Source Heat Pump Scenario*

Fig. 5 shows the load profiles of the LV customer (prosumer) at node 6 in Fig. 2 for a random day in the winter and a random day in the summer. This is the profile of only one prosumer node and so the positive peak is dominated by the EV charging, with its temporal position dictated by which charging period the customer is allocated. It can be seen that even with EV charging, the PV generation in the summer can match or even exceed the demand when the sun is shining, indicated by the demand becoming negative, which implies net generation.

The impact of distributing the prosumers fed by the same cable box to different EV charging periods is shown in Fig. 6-8. Although we use the term smart, this is not really what the term means, as *smart* would imply active control of charging, other consumption and DG, taking into account a lot more than this paper covers.

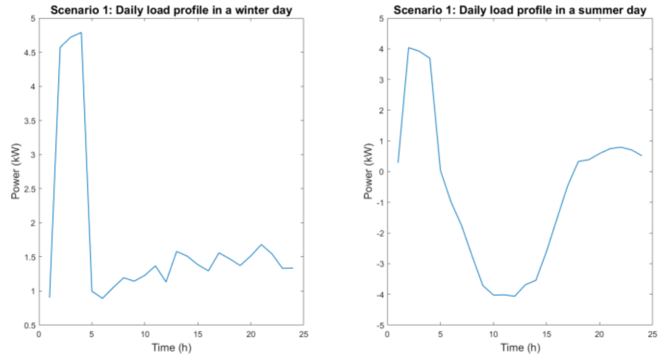

Fig. 5. Daily profile for one LV prosumer in the GSHP scenario (node 6)

To better represent the different possibilities three aggregation nodes are shown. Fig. 6 represents a node which only has customers with type 1 charging (3.7 kW), Fig. 7 shows customers with type 2 charging (11 kW) and Fig. 8 represents customers of both types. The uncontrolled EV charging stops charging when the battery is full. This is simulated to capture the worst load conditions in the network. This means that in customers with type 1 charging, it takes 11 hours to charge the battery, and with customer type 2 charging it takes 4 hours. On the other hand, the smart charging only charges the vehicles sufficiently for their prospective use, 60 km/day, which explains why the area under the plots (i.e., energy) is not the same.

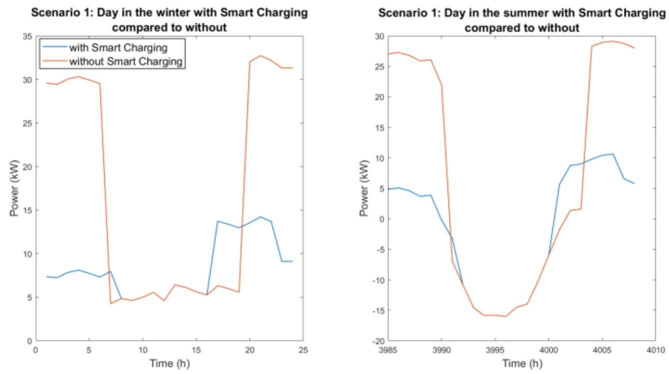

Fig. 6. Comparison between uncontrolled charging and *smart* charging at a cable box feedeing several prosumers (node 57) in the GSHP scenari

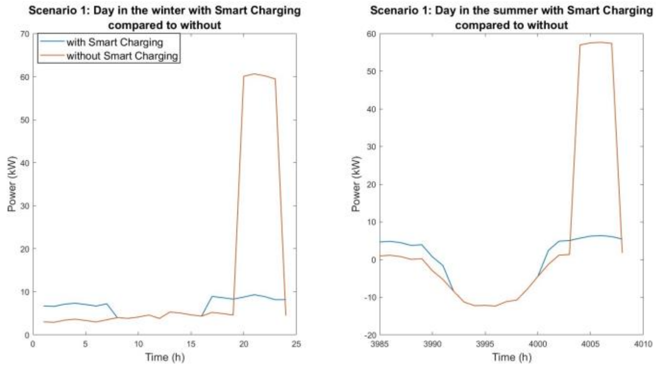

Fig. 7. Comparison between uncontrolled charging and *smart* charging at a cable box feedeing several prosumers (node 65) in the GSHP scenario.

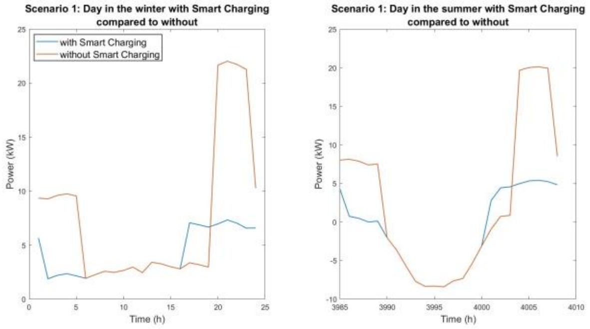

Fig. 8. Comparison between uncontrolled charging and *smart* charging at a cable box feedeing several prosumers (node 65) in the GSHP scenario.

It can be seen how distributing the EV charging in different slots in an aggregation node has a big impact on the power load. While it remains outside the scope of this paper, the means to invest in smart charging (smarter than the five EV charging periods used in this paper) would seem to be worth considering.

B. *District Heating Scenario*

Only the daily profile for node 6 is shown for this scenario, in Fig. 9, where the non-EV demand can be seen to vary somewhat, due to the different heating scenario, but once again, the peaks caused by EV charging and PV dominate the profile. The next subsection looks at the impact on network loading, voltage and upgrade investments for the specific but typical suburban LV network depicted in Figs. 1 and 2.

C. *Impact of the Scenarios on Loading and Voltage*

To contain the results and avoid too much repetition in this paper, we will focus on the north-west (green) feeder in Fig. 2 under the loading imposed by the District Heating scenario. First, as a reference, we give the base case in Table 1, without any EV or PV, just the feeder section with District Heating and the nominal load growth of 0.12 %/annum.

As expected, a very low load growth imposed on an existing network does not cause any problems, with voltage or thermal loading. We next explore the case with controlled (*smart*) charging, depicted in Table II. It can be seen that demand dominates generation in most of the line sections, and that voltage drop is acceptable. The main outgoing feeder section from the secondary substation, 0-77 has a 70 mm^2 conductor cross-section with a steady-state rating of 205 A, so the line ampacity is well within limits.

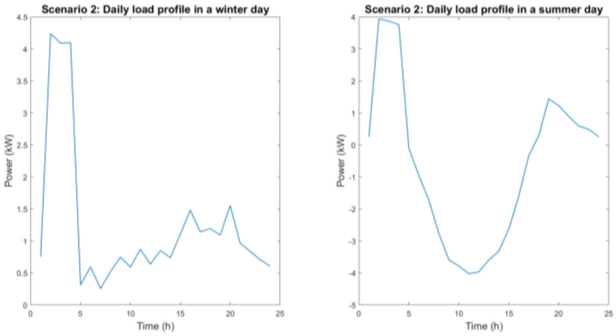

Fig. 9. Daily profile for one LV prosumer (node 6) in the District Heating scenario

TABLE I. BASE SCENARIO (NO EV OR PV)

Up-stream node	Down-stream node	$P_{line,max}$ (kW)	$P_{line,min}$ (kW)	$Q_{line,max}$ (kvar)	$Q_{line,min}$ (kvar)	I_{max} (A)	U_2 (V)
0	77	17.63304	1.770646	5.801271	0.582542	26.7931493	398.1299
77	**22**	1.050976	0.105535	0.345771	0.034721	1.59694267	397.8647
77	**23**	2.522343	0.253284	0.829851	0.083331	3.83266242	397.6071
77	**24**	1.599819	0.160648	0.526341	0.052853	2.43090163	397.927
77	**26**	1.673777	0.168075	0.550673	0.055297	2.54327908	397.8197
77	**51**	1.739949	0.174719	0.572443	0.057483	2.64382732	396.477
77	**65**	9.046179	0.908384	2.976193	0.298858	13.7455362	397.3994
65	**28**	2.06692	0.207552	0.680017	0.068285	3.14065393	397.005
65	**29**	2.101952	0.21107	0.691542	0.069442	3.19388535	397.03
65	**43**	1.802229	0.180973	0.592933	0.05954	2.73846096	396.971
65	**45**	1.576464	0.158303	0.518657	0.052082	2.39541401	396.877
65	**52**	1.498614	0.150485	0.493044	0.04951	2.27712196	397.1851
						Udrop,max = 0.880761	

TABLE II. DISRICT HEATING SCENARIO WITH CONTROLLED EV CHARGING AND ROOF-TOP PHOTOVOLTAICS

Up-stream node	Down-stream node	$P_{line,max}$ (kW)	$P_{line,min}$ (kW)	$Q_{line,max}$ (kvar)	$Q_{line,min}$ (kvar)	I_{max} (A)	U_2 (V)
0	77	49.72513	-39.9322	16.35957	-13.1377	75.5566051	394.6804
77	**22**	4.500316	-2.54629	1.480604	-0.83773	6.83816442	393.5322
77	**23**	6.131739	-6.21516	2.017342	-2.04479	9.31708689	393.3957
77	**24**	4.308031	-3.81436	1.417342	-1.25493	6.545989	394.1287
77	**26**	4.484515	-3.35558	1.475405	-1.10399	6.8141538	393.8406
77	**51**	5.621769	-4.13074	1.849562	-1.35901	8.54219511	389.2403
77	**65**	24.67876	-19.8701	8.119313	-6.53726	37.4990159	392.6635
65	**28**	4.626078	-4.16279	1.52198	-1.36956	7.02925702	391.7689
65	**29**	4.441805	-5.09259	1.461354	-1.67546	6.74925696	391.8725
65	**43**	4.942427	-4.29063	1.626058	-1.41162	7.50994497	391.472
65	**45**	5.288019	-3.22796	1.739758	-1.062	8.03506723	390.884
65	**52**	5.380434	-3.09611	1.770163	-1.01862	8.17548975	391.8835
						Udrop,max = 2.689936	

It remains to check the health of the existing network if it is subject to uncontrolled EV charging. The results for this are shown in Table III. Table III implies that ampacity (thermal rating) is acceptable, but the voltage drop is of concern. Remembering that the LV network shown in Figs. 1 and 2 only goes to the LV connection point, we must allow for voltage drop in the customer's property, sometimes known as the service network.

If we follow some guidelines, e.g. [11], voltage drop in the utility LV network should be kept below 5%, and therefore the existing network would have to be stiffened to cope with this technical parameter. This is especially the case if one considers voltage rise during times of maximum sunlight. The change in voltage between maximum load and maximum DG is likely to be around 8%.

The final result to relate in this simple but illustrative case study is the likely cost of making this network robust enough to cope with uncontrolled EV charging at every prosumer location.

D. *Extent of Network Upgrade Required to Cope with Uncontrolled EV Charing and the Associated Costs*

Fig. 10 shows that when the entire network area is analysed (corroborated by TrimbleNIS), 4 out of the 5 main outgoing feeders need to be stiffened (increasing their conductor size from 70 mm^2 to 120 mm^2). The most common transformer size in the network region this simulation was based on is 315 kVA. The total demand of the worst-case uncontrolled charging for the district heating scenario is 540 kVA, whereas for the controlled charging it is 272 kVA.

TABLE III. DISRICT HEATING SCENARIO WITH UNCONTROLLED EV CHARGING AND ROOF-TOP PHOTOVOLTAICS

Up-stream node	Down-stream node	$P_{line,max}$ (kW)	$P_{line,min}$ (kW)	$Q_{line,max}$ (kvar)	$Q_{line,min}$ (kvar)	I_{max} (A)	U_2 (V)
0	77	95.79189	-38.0618	31.51553	-12.5223	145.554369	389.619
77	**22**	4.593557	-2.42703	1.51128	-0.79849	6.97984144	388.4317
77	**23**	5.844536	-5.92405	1.922852	-1.94901	8.88068586	388.3787
77	**24**	5.060192	-3.6357	1.664803	-1.19615	7.68888658	388.9624
77	**26**	5.123072	-3.19841	1.685491	-1.05228	7.78443167	388.6469
77	**51**	12.47933	-3.93727	4.1057	-1.29536	18.9621617	377.156
77	**65**	62.69121	-18.9394	20.62541	-6.23106	95.2583618	384.3851
65	**28**	12.75733	-3.96781	4.197161	-1.30541	19.3845716	381.8542
65	**29**	12.78711	-4.85406	4.20696	-1.59698	19.4298298	382.0495
65	**43**	12.53228	-4.08966	4.123121	-1.3455	19.0426207	381.2832
65	**45**	12.34033	-3.07677	4.05997	-1.01226	18.7509568	380.1149
65	**52**	12.27415	-2.95109	4.038194	-0.97091	18.650383	382.5624
						Udrop,max = 5.711006	

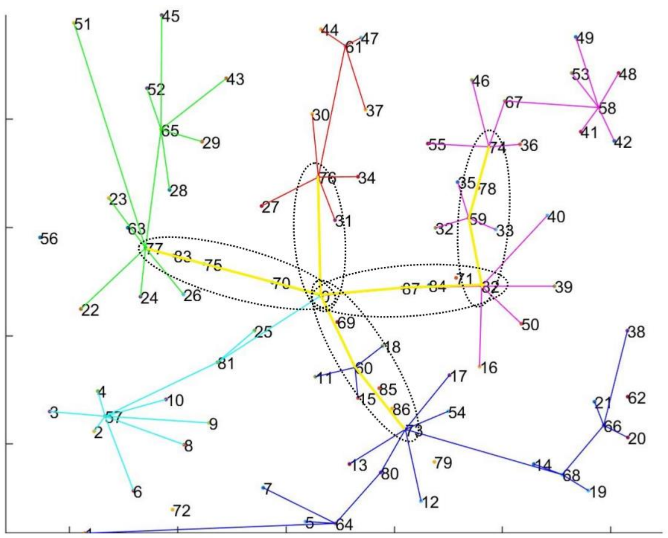

Fig. 10. The yellow feeder sections (encircled with the dotted lines) have to be upgraded to contain the voltage if the network is subjected to 100% of uncontrolled EV charging (the District Heating scenario)

The northeast network section has the most severe voltage problems (Tables I to III covered the northwest section). Upgrading these sections would cost between 24 k€ and 45 k€.

If the cables are located in composite plastic tubes, it may be that they can be pulled out and the new cables pulled in. This seldom goes 100% smoothly. However, if they directly buried the line routes will have to be excavated and the costs will come close to the upper limit. The MV/LV transformer would also require upgrading. A 633 kVA unit costs about 10 k€. This would account to a 30 to 40 €/annum increase in tariff for the customer base in this LV network area, and might be worth the flexibility and unpredictability of how loads will change over the next 20 years or so.

IV. Discussion

This paper relates a study that takes the first step in making a transparent tool for analysing time series data of the various consumption, generation and storage components implicit in tomorrow's LV prosumer. The results portrayed in this paper are specific to a somewhat simplified treatment of specific case studies, but they are somewhat believable if Finland really is serious about becoming carbon neutral by 2035. There will be considerable electrification, and checking whether the infrastructure is up to the job is of critical importance in the energy transition.

As far as the scenario quantified in this paper is concerned, the incremental cost of stiffening the main LV feeders and upgrading the feeding transformer does not seem too punitive. However, the distribution tariff of LV customers does not just cover the LV network. How all these incremental increases aggregate to the MV and HV levels will presumably also entail costs, as will changes in protection to handle power flows in the reverse direction during times of peak distributed generation. These are not hypothetical but real occurrences already in many countries. The scenarios illustrated amount to Brownfied planning on a mature network that has undergone radical changes in loading. An alternative to stiffening the main trunk feeders would be to implement a more nuanced control of the EV charging and coordination with other loads.

What is the answer to the main aim expressed in the introduction; can the case-studied existing network cope with a high penetration of PV and EV in Finnish suburban conditions? The answer is almost! The network is thermally adequate (in terms of the steady-state current limits of the lines, with room for some contingency operation, i.e., backup, which is not shown). However, there are problems with voltage if the rather punitive limit of 5% voltage drop is enforced. Smart charging will alleviate these problems.

Taking a rather wider survey of suburban LV (utilising NIS data), quite often 185 mm^2 conductor sections are used for the trunk feeders, and so it is expected that the Finnish suburban LV networks are mostly up to the job of coping with the likely impact of EV charging and rooftop PV in the near to medium future. Of course this is a general statement and needs to be checked case by case. And, our load data did not show the impact of, e.g., a 5 kW sauna. Care should be taken that the evening sauna does not coincide en masse with the uncontrolled charging of a neighbourhood full of high performance EVs! Presumably electric saunas and the winter (electric) heating of internal combustion engine cars are in part responsible for the relative stiffness of Finnish LV networks.

Dealing with one year of hourly-resolution data is probably computationally manageable for LV planning, but the thesis this paper is derived from also took a look at how deterministic parameters such as coincidence factors (made very much higher by both EV and PV) and loss times are affected and whether they are useful parameters going into the more stochastic future in MV planning, where there are typically hundreds rather than 10s of nodes.

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