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The FlexNett Simulator

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Abstract. This paper documents research conducted in the Norwegian FLEXNETT project. It describes a new tool that was developed to study the future impact of prosumers with PV panels on the grid in Norway and the potential energy flexibility that lies with residential prosumers. Systematic use of energy flexibility can be an important instrument for managing peak loads and voltage problems in weak power grids. The influx of distributed energy resources can amplify this problem, but also help to resolve it. Self-balancing neighborhoods can be very attractive. This implies that loads related to energy demands can be curtailed and leveled out by different controllable devices or managed by using local energy production in the area to reduce the impact on the general distribution grid. The simulation tool is GIS based and can be applied to study the situation related to a single household, a neighborhood or in a specific transformer area. Unlike similar tools that address production yields over a period, the FLEXNETT Simulator addresses production and energy dynamics down to every 10 minutes. Due to the relatively low solar angle in Norway and rapidly changing weather these dynamics can be very prominent and induce local impact that is specific to a house or a neighborhood. The paper further describes how a recurrent neural network has been used as an engine to produce realistic values for the simulator.

1. Introduction

This work was conducted as part of the FLEXNETT project [1] lead by SINTEF Energi and with contribution of more than 20 industrial partners. The overall focus of the project was to investigate the present and future role of prosumers in the distribution grid. In particular, the role of private prosumers as instruments of energy flexibility for the local Distribution System Operator(DSO) was investigated. Energy flexibility relates to the possibility of reducing and leveling loads in order to avoid congestions in the electricity infrastructure and to maintain a high quality electricity supply. One of the central research questions specified was how prosumers with roof top based photovoltaic (PV) panels, with and without batteries, can help reduce peak loads in the grid. The grid was never designed to handle a two-way flow of energy with production facilities at its terminal points. The advent of distributed, renewable energy sources has called for research to understand how production at the grid's terminal points best should be catered for. As the use of PVs are still in its infancy in Norway it was considered important to determine new policies and methods early and be proactive to avoid situations that can cause problems for the operation of the grid. Experiences from southern Germany, where certain parts of the distribution grid have suffered uncontrolled and rapid peak accumulations of feeds, alternated by significant aggregated consumption loads triggered part of the research in FLEXNETT. High loads and rapid peak shifts can be a challenge. Congestions and voltage problems related to the influx of distributed resources are not uncommon. Besides it has been shown that rapid peak shifts can cause life degradation on transformers. One important cause for these problems are related to the intermittency of solar and wind production. Another is that PV based production typically tops when consumption is low. This is quite common for residential areas where people spend time away from their house when the sun is at its highest and PV based production reaches its maximum.

A proactive investigation of PV based production and the role of prosumers in a Norwegian context was therefore called for. Some of the challenges experienced in southern Europe could be amplified further north due to geographical latitude and the low azimuth levels of the sun during larger parts of the year. The impact of local topography, vegetation and house architecture could cause greater local variations and together with cloud conditions cause even a higher frequency of alternating, aggregated loads in the distribution grid. At the same time opportunities were spotted. If local production could be organized so that local load balance could be maintained this could benefit the grid operations. Demand-response programs where loads are moved to periods of sunshine have been introduced and tested [2]. As the quality and price levels of batteries are improving they could also make a difference. Finally, pro-active planning could help to eliminate or alleviate the load issues, especially for new residential areas to be built where solar power is considered as an integral part of the construction project. But the same procedure could also be used to for existing residential areas in combination with a distributed set of batteries [3]. All of these issues were embraced by the FLEXNETT project. To answer part of this it was decided to create a novel simulation tool. Members of UiT tied up with Smart Innovation Norway to produce a solution that will be presented here. In the next paragraphs we will first explain some prerequisites for the work undertaken.

Then we will describe the tool created and how it was applied to produce relevant results. Finally, we will discuss the benefits and how we see the way forward.

2. Empirical Studies

Prior to the development of the FLEXNETT simulator empirical studies were conducted. The data used were harvested from the municipality of Hvaler in the county of Østfold in Norway. Hvaler was the first municipality in Norway where every residence was equipped with a smart meter connected to an AMS infrastructure deployed by Norgesnett, the local DSO. This happened in 2011. A substantial data history with a fair resolution was therefore available. This data allowed us to study the hourly load profiles of many different residences across the municipality. The double hump consumption profiles were quite uniform around the year with a distinct morning peak and a similar one in the late afternoon or early evening. However, there were certain differences with respect to when these peaks appeared. On the level of the principal substation these differences tended to even out, suggesting non-uniform behavior across areas and individual residences. However, within a single neighborhood the opposite seemed to be the case. Here, acute peaks were more common since the origin of the data received was not disclosed for the study we could only compare with consumption profiles of people we were able to get closer too. These were residential owners who took a special interest in the project. A statistical analysis showed, not surprisingly, that there was a relationship between demographic parameters and the type of consumption profile obtained. But we also found that many of the neighborhoods represented in the area were populated by people in the same age group and with matching daily routines. This could be related to the fact that many of these neighborhoods, mostly single residences and chained houses, were established at distinct points in time as the needs for housing emerged. Thus, older neighborhoods were typically inhabited by older and retired people, while recent property developments were dominated by families with smaller children. Hvaler was also the first municipality in Norway with a distinct population of residences with roof top panels. An active and facilitating policy introduced in

2015 created a set of incentives for residents to invest in panels. A small subset of these shared their production data with the project from the start, thus making it possible to create a history on local production, albeit not more than records for 20 units. To determine the conditions for production we studied the local topography and weather conditions for each one. For half of these we were allowed to inspect the property physically to specify features like height and angle of the roof and its orientation with respect to vegetation and other structures. The records harvested, and the observations made were used for a wider set of project purposes, some of which have been published elsewhere [4, 5]. One important conclusion from these studies was that production varied significantly for different neighbors in the same area and with the same type and size of roof top PV panels. It was apparent that local conditions causing shadows, both permanent, arbitrary and periodic made an impact. On an aggregated level this increased the intermittency, although much of this could be considered periodic.

One of the objectives of FLEXNETT was to carry out analyses to create the basis for the FLEXNETT simulation tool. The basic task was to examine empirical data and to use it to develop a tool to study the non-observed and the non-existent. In other words, we would use the tool to study what would happen if whole new areas were equipped with rooftop panels. What impact would a high-density deployment of PVs cause and how can it potentially be exploited for the benefit of the grid? A simulation tool was an obvious answer, if not the sole option. There was enough time series to power the generation of records for the simulations. But the set with production data was significantly leaner. These records represented far less households, despite significant histories for each of them. Standard statistical methods were considered but were rejected in favor of machine learning techniques based on a form of recurrent neural networks called the Long Short Term Method (LSTM).

3. Tool Making

One reason that standard statistical methods were rejected for the simulation was the inclusion of circumstantial data such as local weather and contextual elements representing causes for non-permanent shadows. All of this influence the rate of production and thus the degree of intermittency. Hence, the current state of production may, in the general case, not honor the Markov assumption. In other words, the current input does not hold all the information needed to compute the next event. LSTMs represent a type of deep learning techniques [6] that have proven useful for different applications, including time series and text analysis. Like most regression techniques these type of neural networks are typically used for prediction. And as such they can also be used for generating series of data based on the history [7]. The FLEXNETT problem was treated as a Partially Observable Markov Decision Process (POMDP). Each house in the municipality and their future production history could be considered the full state space were only part of it could be observed. Like other vanilla flavor neural networks, a recurrent network can be seen as a function approximator for such a universe. But a recurrent network like LSTM produces a dense state specification as a function of the entire history. This is due to their ability to carry out operations over sequences of vectors. In addition, it combines the vector containing the input with a state vector that in addition to the output vector creates a new state vector. Hence neural networks like the LSTM can be effectively used as a world model generator. The LSTM in FLEXNETT was constructed accordingly. The output $y(t, R)$, representing the production at any given time of the year, **t**, of any residence **R**, equipped with a solar panel would then be approximated with the LSTM representing the function $\mathbf{f}(P_1, P_2, P_3, P_4, ..., P_n, R(PV, x_1, x_2, ..., x_n))$. Here, P_i, PV, x_i represent historic production at specific times, peak panel production and a vector of geographical and topographical parameters x_i, respectively. Different versions of the part vector $R(PV, x_1, x_2, ..., x_n))$ were attempted, but problems with convergence was experienced. The final version of R was limited to PV panel size and physical orientation in 3 dimensions. The LSTM was trained on the time series collected

IOP Conf. Series: Earth and Environmental Science **352** (2019) 012005 doi:10.1088/1755-1315/352/1/012005

and tested on a part of the collected data history separated from the training set.

Since PV production follows the sunlight, it has an inherent Sin Wave-like property. As such, variations in production would come as a consequence of physical objects existing between the sun rays and the PV panel. Such objects could come in the form of weather, such as clouds, and stationary or mobile ground objects. The LSTM should be able to account for ground objects simply from the recurring change in production. For the weather, including data from nearby PV panels should include information about changing weather conditions. A multi-dimensional training data consisting of production times series from multiple PVs was tested to see if it could provide better predictions than using only the time series from one single PV. For any given installation P_i, its training data consisted of time series $P_{i_1}, P_{i_2}, P_{i_3}, ...$ as well as time series from other PVs P_j, P_k, P_l in the area. The training data was organized in sliding windows(batches) of 36 time steps (6 hours X 6 values per hour), where the first (35 x number of PVs) values were input. The sliding windows was shifted by 1. The output then, was a single floating point value that represents the predicted next production value.

Real consumption data was applied. The rich data set made available to the project permitted this. Time series from the complete data set was chosen at random. Bias was further reduced by introducing multiple replications for the simulations. One issue was the difference in time resolution. As the training data was sampled on a 10-minute interval this became the standard for the simulations too. Since the meters provide on hourly data for the consumption we used that. For the purpose at hand it sufficed to use average data across the hour. In the future higher resolution consumption data is desired. A graphical interface was developed to control the simulation. It included a Geographical Information System (GIS) section that also provided information to the simulation engine (see Figure 1). By selecting a house or a group of houses linked to the same part of the grid the tool would generate the dynamics of loads for a single household as well as a neighborhood or a larger area. Similarly, it would be possible to choose simulations for a particular period i.e. day, month, season or a full year and the results could be shown in real time or produced as a batch.

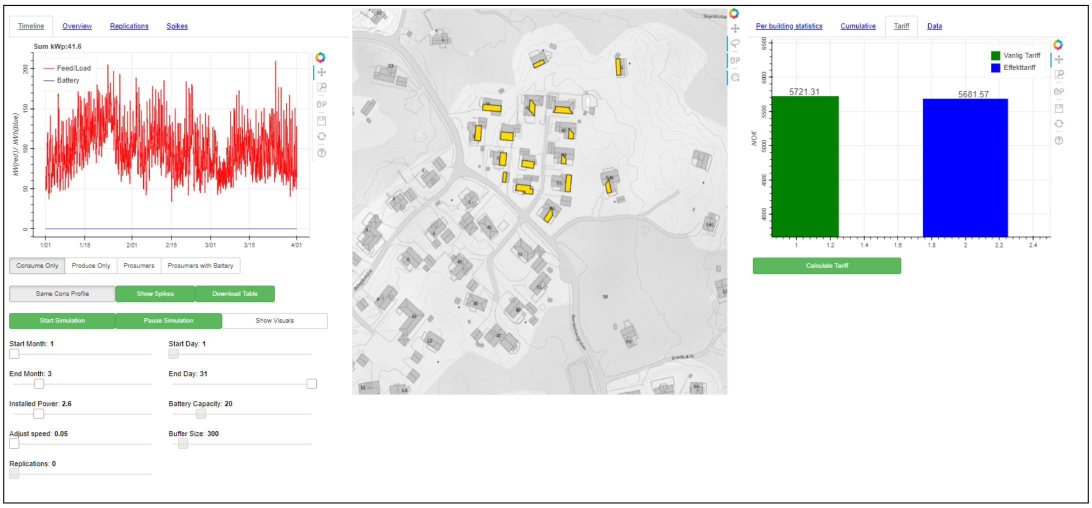

Figure 1. The FLEXNETT user panel showing time series for consumption and production on the left, the GIS panel in the middle where a selection of houses belonging to the same grid connection is investigated. Right a set of tabs can display aggregated power and cost data for the group and per building.

A selection of houses could also be equipped with batteries. For the economic calculations, battery degradation was taken into account, but the battery management was held very simple.

Battery would always have priority to surplus when fully or partly discharged. Degradation was based on the rainfall method [8]. Beyond this we applied a Coloumb Counting [9] method to monitor the state of charge. Economic calculations used the principal grid tariff at Hvaler introduced by Norgesnett as default. This includes a power part [kW]. The tariff for regular households is shown in Table 1 below. But the tool can be also used to analyze economic impacts due to tariffs with fixed and energy related fees only.

Table 1. Tariffs introduced by Norgesnett at Hvaler. Note the power related part

Fixed fee(NOK/year)	Period	Energy part NOK/100*kWh	Power part NOK pr. max hour per month [NOK/100*kW]
625	May-Oct	26.36	61.25
0	Nov-April	28.23	61.25

4. Results

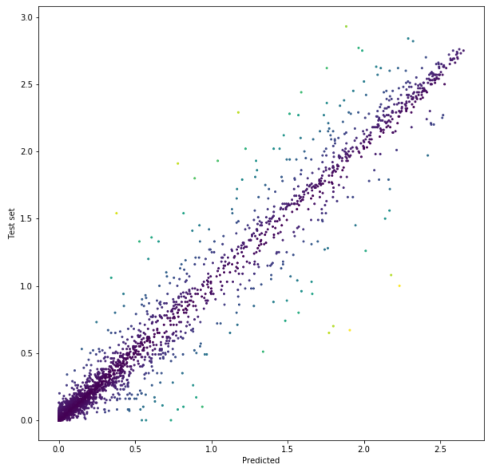

Figure 2. Scatter plot shows predicted values (x-axis) vs. actual values in test set (y-axis).

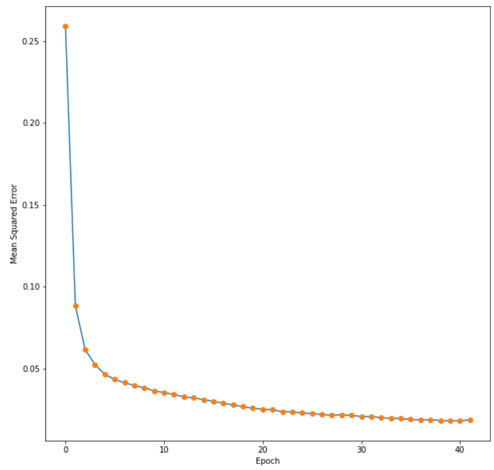

Figure 3. : Learning rate- showing the reduction of the Mean Square Error (y-axis) per training epoch (x-axis).

Figure 2 and Figure 3 shows the result of the training of the LSTM. The method showed good fit and acceptable error rates (MSE). It should be noted that the potential for overfit was present due to the limited sample size available. The network was trained until standard overfitting cutoff measures kicked in. Figure 4 shows the graphs produced for aggregated loads across time for a group of houses connected to the same point of coupling.

The tool was used to determine the impact of PV size on the grid and the potential role of the battery. The orientation of PV-panels on self-consumption was also investigated with the tool

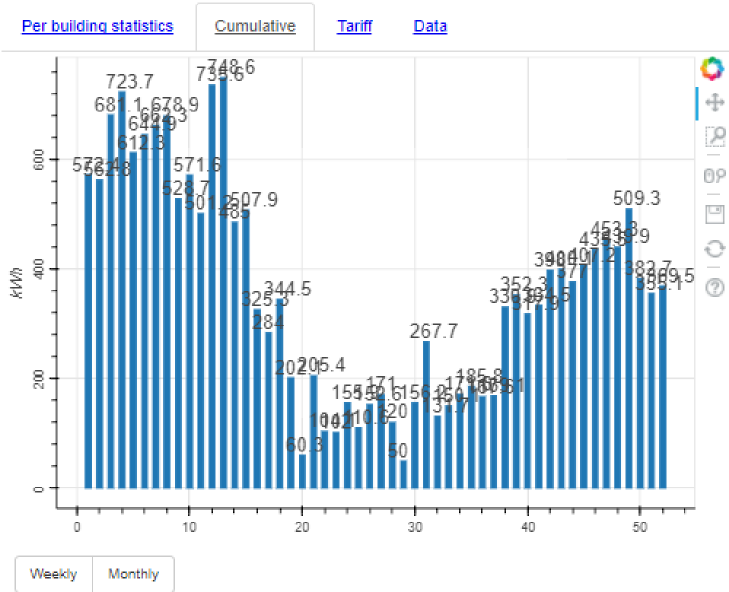

Figure 4. The cumulative net loads (kWh/h) for different hours for a period of app. 50 hours.

[3]. For the selection of households shown in Figure 2 the maximum loads on the neighboring transformer was calculated. Examples are given for three cases: No production facility, all houses equipped with 3,1kWp and 9,3kWp panels.

Table 2. Aggregated net loads for a selection of houses (kWh/h) (see Figure 1) equipped with roof top panels. Min specifies the minimum net load. Max the hour during the year with highest accumulated consumption.

Panel Size	0 kWp	3.1 kWp	9.3 kWp
Min	-9.94	31.58	86.61
Max	-118.93	119.43	-129.45

As can be observed from Table 2, the panel sizes need to be large in order to reach the magnitude of negative loads typically during the month of January with no production. During the warm and sunny part of the year the simulations also showed huge differences in max and min from minute to minute. The tool thus provided evidence that the local infrastructure for the grid areas studied at Hvaler were robust enough to handle a high density of large rooftop panels. Another issue studied was the impact of house orientation. Figure 5 shows the production profiles based on actual metering in the month of June for three different houses in the same neighborhood at Hvaler with PV panels oriented at 106, 182 and 200 degrees. In addition, and arbitrary consumption profile is shown for comparison in order to highlight self-consumption issues and the possibility of self-balancing by design. As can be observed, the easterly oriented panel meet the morning peak of the consumption better than the other two. But the westerly and southerly oriented profile meets the afternoon/evening peak better. The westerly oriented panel could have better absorbed the consumption if it was not cutoff as the curve in Figure 5 shows. This illustrates the susceptibility to local topography and vegetation that obstruct the sun at early and late hours during the summer. Using the tool to investigate the degree of

IOP Conf. Series: Earth and Environmental Science **352** (2019) 012005 doi:10.1088/1755-1315/352/1/012005

self-consumption related to PV orientation the easterly or westerly evening peaks did not match the consumption as well as expected. One explanation is that the neighborhoods investigated was inhabited by a several retired couples. (See Table 3). The dominant morning and evening peaks in the pilot areas at Hvaler came later than expected compared to the average records for the country and that generally show an earlier morning peak and a a more distinct afternoon peak. This fact favored the panels facing south. With the power tariffs introduced the economic benefit of the PV panels increased significantly for the prosumers. The tool further highlighted the need for diversity in orientation. An average neighborhood in Norway with a high density of panels facing south are more likely to accumulate high peaks at noon than areas with roof tops pointing slightly different ways. Moreover, with power tariffs it makes economic sense to adjust panels according to the households consumption profile. But it is important that production does curb the consumption at the hour with the highest energy use. For more on the economic part of FLEXNETT see [10].

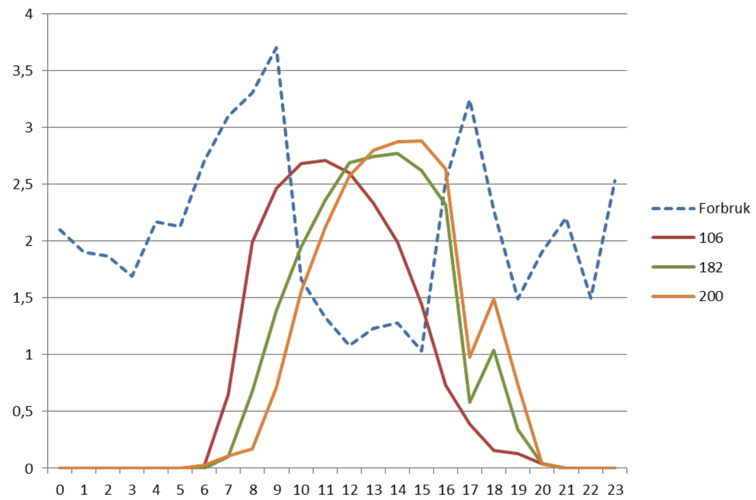

Figure 5. Shows production profiles for an easterly oriented rooftop PV (106), a panel pointing south (182) and a westerly oriented one (200). A consumption profile is shown for comparison.

Table 3. Max and min power for the average household equipped with a 3.1kWp panel. Max net consumption is obviously experienced during winter time. Max net consumption is positive during the summer.

Compass direction of PV	Max power consumption[kW]	Month	Min power (feed-in) [kW]	Month
South	-12.82	january	2.41	june
East	-12.82	january	2.06	june
Southeast	-12.82	january	1.99	june
West	-12.82	january	1.91	june

5. Conclusive Remarks

The FLEXNETT tool for analysis of load dynamics imposed by consumption and rooftop solar panels have been explained. UiT is currently maintaining the software. The simulation tool created applies a machine learning approach for the purposes. A LSTM neural network was trained and applied to simulate the consequences of high-density deployment of solar panels in different areas at Hvaler. The primary idea was to use the tool to investigate the impact of prosumers on the local distribution grid. The tool proved to be useful to determine the magnitude of peaks caused by local feeds and consumption and how rapidly changes in loads can occur. Local conditions play an important role on the production profile and yield at all hours of the day. The tool accommodates this by means of the GIS. The tool developed made it possible to analyse and conclude that the grid sections investigated would be able to absorb a high number of prosumers. However, the tool also showed its strengths in exposing potential vulnerabilities where grid weaknesses can be a reality. The tool can help analyses where collective self-consumption is sought. This would be a kind of self-balancing "by design" where residential areas can be planned to minimize the impact on the grid and to avoid potential congestions. The results from the simulations combined with the empirical studies, suggest that local demography can impact the aggregated, net profiles for sections of the grid. When time of production does not match consumption well demographic homogenity may be an important reason for this. The tool was also useful to determine the cost for single households exposed to Norgesnetts power tariff. The benefit of rooftop PVs that meet hours with maximum consumption can be economically significant if power tariffs are introduced. The tool includes options where batteries can be deployed, and their effects studied. This part has not yet been fully developed and validated. But UiT is currently addressing the issue. Furthermore, the tool is considered as an engine for future studies of local energy markets. The plan is also to extend it to be able to address other areas in Norway. It is believed that the tool will be especially important for studies in the northern parts of the country where the average azimuth is even lower.

6. Acknowledgements

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