„DEVELOPMENT OF A TOOL FOR SPECIFIC LOAD PROFILE-BASED SELF-CONSUMPTION OPTIMIZATION USING PV POWER FORECASTING“

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Abstract:

The German government's initiative to cover 80% of the gross electricity supply with renewable energies by 2050 brings considerable ecological benefits, but also poses several challenges. One of these challenges is the growing number of photovoltaic systems (PV systems), which, due to their high feed-in power, already pose a risk to the security of the electricity distribution grid during long periods of sunny weather. To counteract this, active research is being carried out in the field of PV power forecasting. This research is primarily aimed at providing the grid operator with a predicted power output, which enables a longer planning horizon and thus increases the operational grid security.

However, the considerable annual electricity consumption of private households and the increasing spread of PV systems for self-consumption show that the energy behavior of households, especially self-consumption, also influences grid security.

Additionally, households have an incentive to boost their self-consumption because the cost of drawing each kilowatt-hour from the grid is substantially higher than the compensation received for injecting an equivalent amount of energy back into the grid. However, as of now, there is no software available that easily enables households to tailor the usage patterns of their electrical appliances according to a photovoltaic (PV) forecast.

The project described here aims to close this gap by creating such software. Various PV forecasting models are used and tested for their suitability for this purpose. A self-generated optimization process is implemented in this project to optimize the consumer configuration based on the PV forecasts. The here-developed tool enables the user to enter parameters for his PV system and the specific load profiles of his electrical appliances. Based on this data, the optimization algorithm determines a consumption plan with a forecast horizon until the end of the next day that maximizes the user's self-consumption.

To validate the tool, the optimization process is carried out over a period of 60 days using a predefined scenario and the results are compared with a scenario in which the electrical appliances are intuitively operated at midday. The analysis of these results ultimately shows the potential impact of such a tool on the economic efficiency of private households and the supply stability.

Keywords: PV power forecast, Self-consumption optimization, Power grid relief

1 Motivation

The German government's goal [1] of increasing the share of renewable energies in the gross electricity supply to 80 % by 2050 requires increased investment in research, development, and promotion of photovoltaic (PV) systems. However, this expansion also brings challenges. In particular, if more energy is generated than required in favorable weather conditions, the increased feed-in power can lead to disruptions in the distribution grid. A notable event that illustrates this problem occurred on September 13, 2023, when the grid operator "Bayernwerk" had to shut down several PV systems due to the endangered grid security [2]. Possible solutions include the further development of energy storage technologies, the expansion of the electricity grid, making consumption patterns more flexible, and improving forecasting methods. The latter should, above all, enable the grid operator to preventively counter critical situations regarding grid security [3,4,5].

Private households also play a significant role in influencing grid security in Germany [6]. At 129 TWh [7], German households will require around 25 % of the total annual electrical energy demand of approx. 491 TWh in 2020 [8]. In addition, around 2.6 million private persons operate PV systems [9], which also influences grid security through the feed-in of renewable energy. The behavior of these households therefore has a direct impact on the utilization of the distribution grid.

An overall view of the above facts makes it clear that the strain on the electricity grid can be relieved not only by improved action on the part of grid operators but also if private households consume their self-generated electricity directly instead of feeding it into the grid. This thesis is supported by [6]. Since private households are only paid around €0.08 for every kWh fed into the grid [10], while every kWh purchased costs around €0.37 [11], it is also the economic aspect that motivates private households to increase their consumption.

While forecasting models, programs, and control algorithms for renewable energy and load management are being actively developed for grid operators, private households have limited opportunities to increase their self-consumption. Although smart home technology is becoming more widespread, many household appliances are still limited to a timer function. Regardless of the technology in place, scheduled, remote, or automated access to household appliances will remain ineffective if it is not specified when they need to be activated for optimal self-consumption.

For this reason, this project aims to develop a software tool that enables every user to plan the use of household appliances in such a way that self-consumption is maximized. For this purpose, various methods for PV power forecasting are to be tested for their quality, compared, and integrated into the software. Based on the predicted power data, the previously analyzed energy load behavior of various household appliances, and with the help of numerical optimization algorithms, a recommendation for action is created. This provides the users of the software with the optimum consumer constellation in terms of time and can be implemented with smart home devices as well as with time-controlled or manually operated devices. Finally, the effects that the use of this software could have on electricity consumption, electricity feed-in, the electricity grid, and the economic efficiency of households are analyzed.

2 PV power forecasting

2.1 Methods and properties of PV forecasting models

There are various approaches to predicting PV yields or solar irradiation, which can be divided into three types of models.

On the one hand, these are *physical models*, i.e. models that use mathematical and physical principles together with meteorological parameters from measuring equipment or other models to calculate the output of a specific PV system. Although these models have sensitivities due to volatile weather behavior [12], they have the advantage that they can be used without an underlying collection of historical data.

Statistical models refer to historical data and other input parameters to produce a PV power forecast by matching and probabilities. According to [13], this methodology has proven to be superior to physical models as it offers the possibility to ignore measurement errors in the determination of input parameters. However, to create statistical models with a corresponding accuracy, an appropriate data basis and knowledge in the field of machine learning are required.

Hybrid models are a combination of physical and statistical models, whereby the result values of one model are often used as the basis or parameters for the subsequent model.

The selection of a forecast model also requires consideration of the forecast horizon, which is defined as the difference between the forecast time and the prediction time. The accuracy of a forecast varies depending on the forecast horizon, with reference [14] showing that forecast errors correlate positively with the time horizon. However, suitable planning requires a sufficient time frame for implementation. An appropriate forecasting horizon is therefore 24 hours regarding the use case.

In addition to the forecasting horizon, the temporal resolution of the forecast power profiles also influences the accuracy of forecasting models. Electrical power changes can take place within seconds, but such resolutions can hardly be realized in PV forecasts. The choice of a resolution of 30 minutes is a sensible compromise due to the computing time and susceptibility to errors, particularly given the different power profiles of different consumers.

2.2 Accuracy and quality of PV forecast models

The accuracy of a forecast model is determined by the deviations of the forecast results from the actual values. These deviations are quantified using error metrics, which include RSME (Root Square Mean Error), MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error). RMSE is most used in the evaluation of PV forecasts [15], as this error metric is particularly sensitive to extreme values, which is advantageous for models with a short forecasting horizon, as is the case for most PV forecasts.

The application of error metrics always refers to the output of the systems under consideration. A comparison of systems with different outputs can therefore only be made using normalized values. For this purpose, average or installed outputs are often used for PV systems [14]. A corresponding calculation is made using the predicted power $\hat{P}_t$, the real power P_t, the number of measured values M and the installed power $P_{install}$, as the equation described

$$RMSE_{normalized} = \frac{\sqrt{\frac{1}{M} \cdot \sum_{t=1}^{M} \left(\hat{P}_t - P_t\right)^2}}{P_{install}}. \tag{1}$$

In principle, the better the values of the error metric, the greater the accuracy of a forecasting model. However, different models are based on different objectives, and these objectives can also diverge [5]. This is illustrated by the fact that models with the same error metric value can have fundamentally different forecasting behavior [5]. For example, in situations where economic and energy loads are controlled, a model that tends to forecast more power would be less suitable. The quality of a model therefore varies depending on the application, which is why the results of the comparative methods should be considered but not used as the sole basis for decision-making.

2.3 Comparison of different PV forecasting models

To realize this project, three different PV forecasting models are used and examined for their suitability for the software in terms of accuracy and quality. Table 1 shows the models used, their type and determination approaches. With the help of these models, a daily PV power forecast was carried out over a period of 60 days, based on the specifications of the two real PV systems in Table 2. The resulting hourly power values are then compared with the real data using the RSME error metric. The result of this analysis can be seen in Table 3.

Table 1 - PV forecasting models used

Name	Model Type	Determination of solar radiation	Weather forecast	Consideration of cloud cover	Determination of PV power
Forecast.Solar	Statistical	Historical data from PV-GIS [16]	Various forecasting tools [16]	Not evident	Not evident
KM_physical_V1	Physical	Based on [17,18,19]	OpenMeteo-API	Based on [20]	Based on [21]
KM_OpenM_V1	Physical	OpenMeteo - API	OpenMeteo-API	Not evident	Based on [21]

Table 2 - Locations and properties of the PV systems

No.	Longitude / °	Latitude / °	Slope / °	Azimuth / °	Installed power / W
1	51.8	11.6	30	180	800
2	52.3	12.9	5	90	425
			5	270	425

Table 3 - Results of the accuracy determination of the individual forecast models in relation to the individual PV systems and in total

	RMSE-Forecast.Solar / %	RMSE-KM_OpenM_V1 / %	RMSE-KM_physical_V1 / %
System 1 - S, 30°, 800 W	13.18	11.63	13.48
System 2 - OW, 5°, 850 W	11.98	16.12	13.55
Total	12.59	14.09	13.51

In addition to the accuracy values, the quality of the forecasting models for use in the software was also examined. For this purpose, the course of the forecast power and that of the real power was graphically displayed and then evaluated. This is shown as an example for 07.07.2023 and 14.07.2023 in Figure 1.

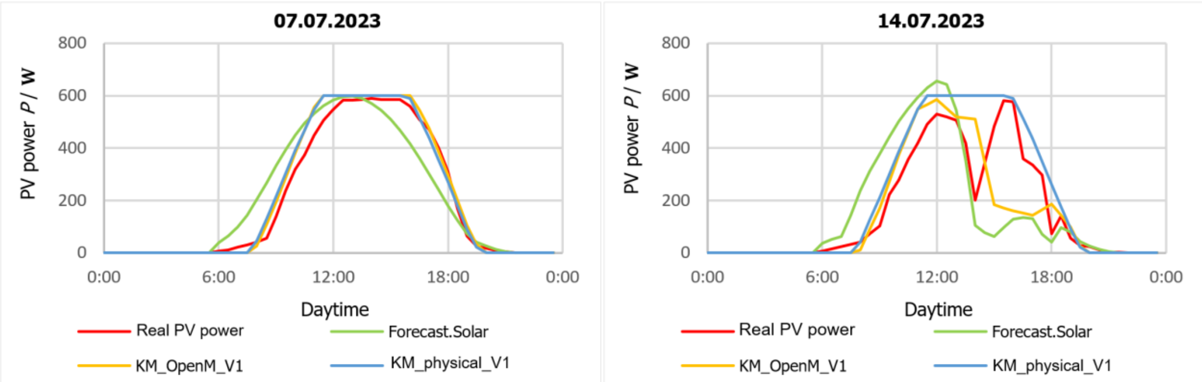

Figure 1 - Presentation of the forecast models for the PV system S, 30°, 800 W on 07.07.2023 and 14.07.2023

The data analysis shows that the forecasting program "Forecast.Solar" has the lowest error value overall for both PV systems and therefore offers the highest forecasting accuracy. The visual comparative analysis of the representations does not reveal any significant peculiarities of this model. Consequently, the forecast model can be characterized as average and robust.

Despite the finding of the highest error rate for the "KM-OpenM_V1" forecasting model in the overall analysis, this does not necessarily imply its inadequacy as a forecasting method. In addition to a high accuracy for PV system 1, the graphical representations indicate that the power curve of this model is often similar to the real power. Furthermore, the error values are due to underestimated power values. Optimization based on this forecasting model therefore results in an increase in self-consumption.

Although the forecasting model "KM-physical_V1" is positioned in the middle range in terms of accuracy, the analysis of the behavior indicates that errors are often due to over-predicted power. Optimization using this model could therefore lead to a significant portion of the required energy being needed precisely when no PV power is available. As a result, this model appears to be the least suitable for the intended use case based on the available data.

3 Obtaining and adjusting load profiles of electrical consumers

In addition to the expected PV outputs, self-consumption optimization requires the load profiles of electrical consumers to be considered. Due to a lack of data sources, load profiles from various appliances and manufacturers were recorded independently as part of the project. However, the load profiles obtained in this way cannot be used directly for the optimization program in their original form. This is due to the standard form of data recording, which takes place both in one-minute periods and whenever the load changes. To use the consumption data, it must first be broken down into a standardized temporal distribution, which is also adapted to the temporal resolution of the PV power forecast. The procedure described in the dissertation [4] is used here. Because power peaks are only of short duration for most household appliances, the time- and energy-accurate method [4] for adjusting the load profiles is selected for this project. Figure 2 illustrates the real and the adjusted load profile of a dishwasher. Although the power peaks in moments of scarce PV power are not completely covered, the method considers the total energy demand over 30-minute periods. It is therefore assumed that this methodology covers most of the required energy demand according to the optimization when viewed holistically. To make the program in its basic form usable for all users, profiles of some household appliances have been stored in the software, including washing machines, dishwashers, and dryers.

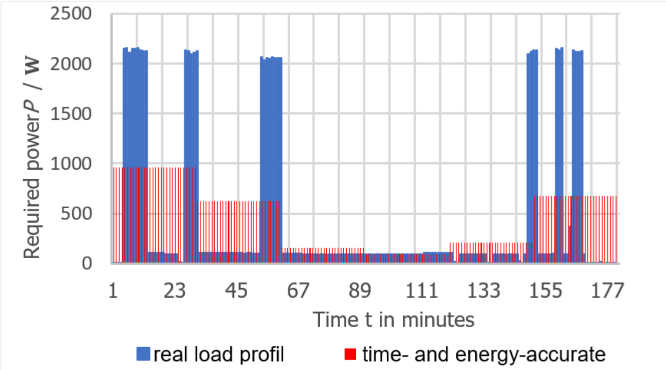

Figure 2 - Comparison of a real load profile with a time- and energy-accurate load profile with 30-minute resolution

The standard load profiles provided are representative of equivalent appliances from different manufacturers. In addition, the application enables all users to integrate the load profiles of their individual household appliances into the existing data by means of a simple import. This allows the consumer constellation to be optimized for the coming day to be mapped as a digital twin within the software if desired.

4 Optimization algorithm

An optimization algorithm is required to create a consumer constellation with maximum self-consumption. This must vary the starting times of the loads in relation to the predicted PV power to minimize the need for external electrical energy. In addition, various ancillary conditions that are decisive for the real operation and economic efficiency of private households must be considered within the optimization process. These include, among others:

- a possible parallel operation of consumers,
- specific start and end times based on user behavior,
- as well as the economic value of grid electricity compared to PV electricity.

To achieve these goals, an optimization algorithm based on the enumeration method is being used. This algorithm checks each temporal constellation of consumers to identify the one with the lowest demand for grid-related energy. It should be noted that the number of consumers directly influences the computational effort, as the enumeration method is not considered to be particularly efficient. Nevertheless, the total computing effort does not exceed the requirements, as the computing operations to be processed are limited to subtractions. The main advantage of the enumeration method is that it is an integer optimization method that determines the global optimum or one of the local optima with a certainty of 100% under the given parameters, as it has no termination criterion.

5 Creating the software tool

Based on the PV forecast models, recorded load profiles and the optimization algorithm, a software tool is developed that meets the defined requirements. The "BeeWare" framework for cross-platform application development is used for this. The choice of this framework not only enables programming in the Python language, but also the execution of the program code once written, without additional work on different operating systems such as Windows, macOS, Linux and on mobile platforms such as iOS and Android. This ensures that a wide range of users can use the developed software to increase their own consumption right from the tool creation stage.

6 Potential of the software tool

The aim of investigating the potential is to use a representative scenario to determine the difference in terms of energy fed into and drawn from the grid when using the software tool compared to intuitive consumer use. In this way, a statement can also be made as to whether and how the software affects the economic efficiency of private households and the security of the grid. The scenario, based on an imaginary household of a family of three, determines which electrical consumers are used on each day of the week. Although the pool pump used would practically only be used in the summer months of the year, it can be considered representative of other consumers. The following scenario is considered to analyze the potential of the software:

- Monday: Base load (100 W), Pool pump (5 h continuous), dishwasher
- Tuesday: Base load (100 W), Pool pump (5 h continuous), Washing machine
- Wednesday: Base load (100 W), Pool pump (5 h continuous), Vacuum cleaning (1 h), Laptop charging
- Thursday: Base load (100 W), Pool pump (5 h continuous), dishwasher
- Friday: Base load (100 W), Pool pump (5 h continuous), Charging the tool battery, Laptop charging
- Saturday: Base load (100 W), Pool pump (5 h continuous), Washing machine, Oven (1 h)
- Sonntag: Base load (100 W), Pool pump (5 h continuous), Vacuum cleaning (1 h), Laptop charging

Consumption patterns of all appliances used in this scenario were simulated with recorded load profiles. The analysis is carried out by applying the program to the 60 data sets of PV system 1 "South, 30°, 800 W". Thus, for each day it is determined which consumer constellation is the result of the optimization of the program and which energy feed-in and grid consumption this results in daily and over the entire period. This is then compared with a simulation without using the program, in which it is assumed that people would intuitively operate their appliances at midday, i.e. when the sun is at its highest position. Figure 3 serves to illustrate these two methods. The results of the 60-day test series are shown in Table 4.

Table 4 - Results of the 60-day test series of optimized and intuitive usage according to the defined scenario

	Energy fed into the grid in optimized scenario / kWh (percentage difference to intuitive operation)	Energy consumed from grid in optimized scenario / kWh (percentage difference to intuitive operation)	Energy fed into the grid in intuitive scenario / kWh	Energy consumed from grid in intuitive scenario / kWh
PV system 1 - S, 30°, 800 W	39.2 (-9.7 %)	149.5 (-2.8 %)	43.4	153.8

The potential analysis confirms that the use of the program leads to an increase in self-consumption over the period under consideration. In the 60 days of the optimized scenario, less electrical energy is drawn from the grid and fed in. However, the difference between the scenarios is less than expected. Extrapolating this to one year and assuming an energy price of around 0.37 €/kWh results in annual savings of around 10 €. The energy fed into the grid is only marginally lower at around 25 kWh.

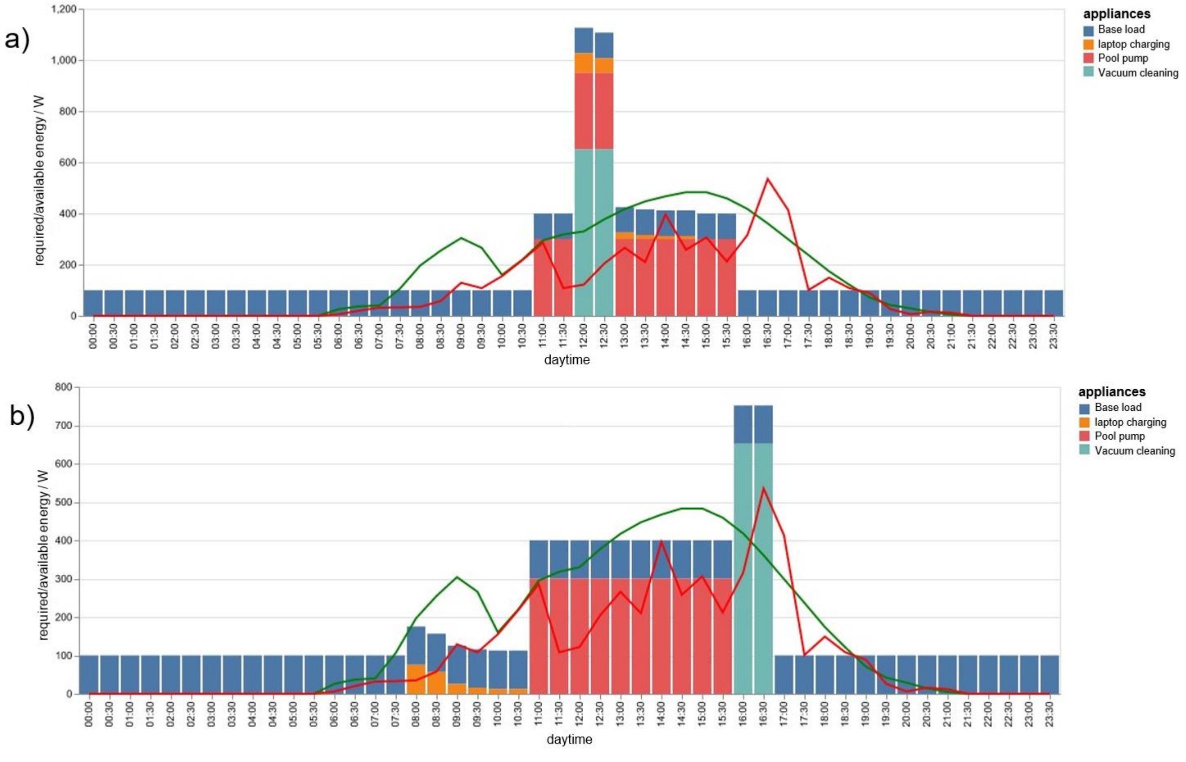

Figure 3 - Illustration from the software tool comparing intuitive (a) and optimized (b) operation of the loads, where the green curve represents the predicted power and the red curve the real power

The limited effect of the optimized appliance constellation can have various causes. The PV system under consideration has a purely south-facing orientation, which means that the output is often highest at midday. This supports intuitive operation and reduces the difference between the operating modes. The forecast quality also influences the potential, as it occurred within the test series that deviating power forecasts of intuitive consumer use led to higher self-consumption. As no model has 100% accuracy, the potential for improvement here is not foreseeable. Nevertheless, a more suitable forecasting model can increase the overall potential. The size of the PV system and the power consumption of the loads can also influence the potential of the software.

7 Summary and Outlook

The developed software tool enables the creation of a PV power forecast for the coming day in connection with specified photovoltaic systems. Considering the available energy and the planned electrical household appliances, the tool generates time-based recommendations for action to maximize self-consumption. This recommended consumer constellation is not exclusively limited to the use of smart home technology but can also be implemented using time-controlled or manually operated devices. By using cross-platform development, the software tool can be used on all common operating systems. The result of the project is an application that is easily accessible, runs stably and offers people without the need for complete automation the opportunity to maximize their consumption.

The determination of potential based on an example scenario shows that it is possible to increase self-consumption using the software. Although the effects on economic efficiency and grid security are small in individual cases, the cumulative effect of many households increasing their self-consumption can have a positive effect, particularly in terms of grid stability. If the program is used in companies with larger PV systems and higher energy requirements, the potential of the software can be further increased. An in-depth investigation in this context is recommended.

From a scientific and technical perspective, advances in forecasting models in particular offer opportunities for improvement. The further development of PV forecasting models is not only a potential continuation of this work but also represents an important field of research in general. In addition, the software can be further developed for use in larger companies. This will allow the potential of the software to be increased and its effects on the electricity grid to be researched in more detail.

To be able to make more detailed conclusion on the potential of the software in terms of reducing CO2 emissions and costs as well as relieving the distribution grid, further potential analyses should be carried out which, in addition to other PV systems, also consider different consumer scenarios and different local environmental conditions.

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