Bottom-up forecasts for load demand and the grid infeed of renewable energy sources

Dr. Marisa MÄDER
LEM-Software – Germany
marisa.maeder@lem-software.com

Dr. Harald HEINRICH
LEM-Software – Germany
harald.heinrich@lem-software.com

Dr. Ingrid HEINRICH
LEM-Software – Germany
ingrid.heinrich@lem-software.com

Anja RÖDEL
Süwag Energie AG – Germany
Anja.roedel@suewag.de

ABSTRACT

LEM-Software presents a database-supported software solution for bottom-up energy forecasts on various time scales. From the point of view of a large energy supplier, handling the daily business regarding forecasts is a time-consuming challenge. Dealing with thousands of recorded load curves and hundreds of thousands of load profiles, a software is needed that can do as many of the necessary processes automatically. LEM has developed a fully automatic bottom-up feature that starts with importing all required data and ends by doing the forecast. All steps inbetween can be chosen to take place automatically or can be done manually. This way users can choose themselves how much automation they want to have in their daily forecasting business.

INTRODUCTION

Taking part in the German energy market, no matter which role is represented, usually means doing day-ahead or other time scale forecasts of load demand. Where it has mostly been common so far to calculate those forecasts as a sum of consumers, we present a database-supported bottom-up forecast solution, which works fully automatically, if desired.

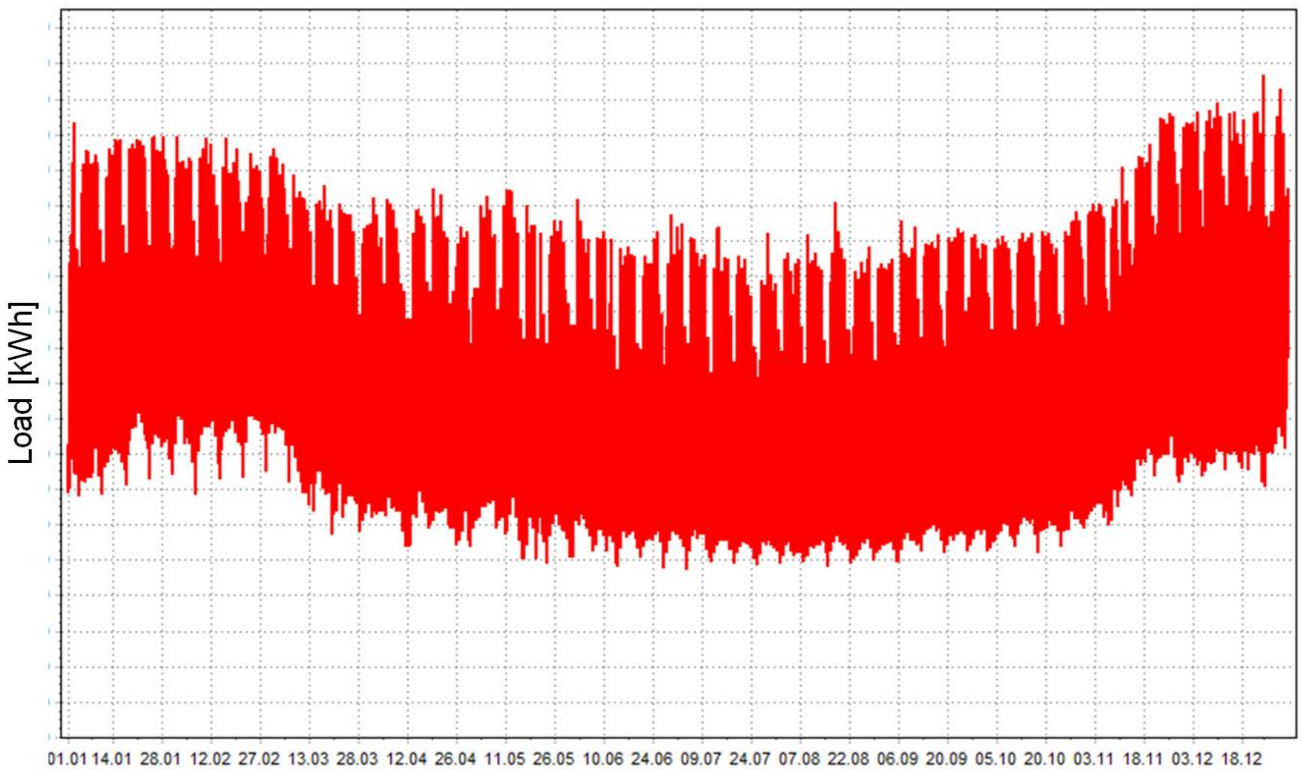

Figure 1: A database object that represents a load curve

BOTTOM-UP FORECASTS

The LoadManager is a database-supported software solution that is able to forecast load demand (and other time series based energy data curves) for various time scales. The basic idea of the program is to work with database objects whose configuration of parameters can be chosen freely. Figure 1 shows an example of a time-series-based database object that can include load data. The data can be visualized, edited, analyzed, and much more.

Method

Every task in the LoadManager is implemented in so-called topologies. A topology is a tree-like structure that can include an unlimited number of database objects. Special topology objects help to solve given tasks, such as making forecasts for example. A typical simple structure of a forecast topology is shown in Fig. 2.

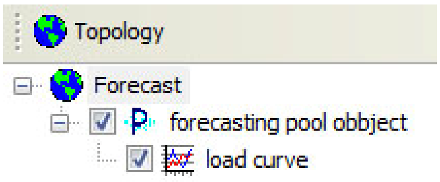

Figure 2: Typical structure of a forecasting topology

Large companies involved in the trading of energy often have to deal with some thousands of recorded load curves and hundreds of thousands of load profiles. The first challenge is therefore to build up the topology that represents the amount and structure of the curves. Mostly, one individual curve is associated with one customer, if the task is seen from the point of an energy supplier. The load profiles, representing households and smaller industrial customers, can be accumulated to profile groups. Even though this reduces the number of database objects in the program, it would still be a time-consuming task to build up a forecasting topology in the LoadManager by hand.
This is why LEM created an opportunity to let the LoadManager do as many steps as desired by the user automatically. This way, it is possible to initially import a file (for instance a `csv` file; other formats common in the German energy market like EDIFACT formats are also possible) representing the customer master data. According to this data, the topology can be organized in specified ways. It is useful and common to follow regional criteria when building up the topology structure. Handling an electricity forecasting topology, its structure is mostly organized by transmission system operator (TSO) control area, balancing group, distribution network operator, and sometimes calendar.
Usually it is also useful to further distinguish between load curves influenced by weather and such that aren't. Influencing factors like calendar, production (for industrial customers), temperature, speed and direction of wind, as well as solar radiation, can be taken into account by the mathematical models that produce the forecasts.
The automatic process can also test whether load curves depend on various influencing factors like weather. The load curves will then be included into the respective branch of the topology tree.
Position changes of objects within the topology are done automatically as well. This can occur when customers move. The case of ending contracts and new customers is also considered by the program.

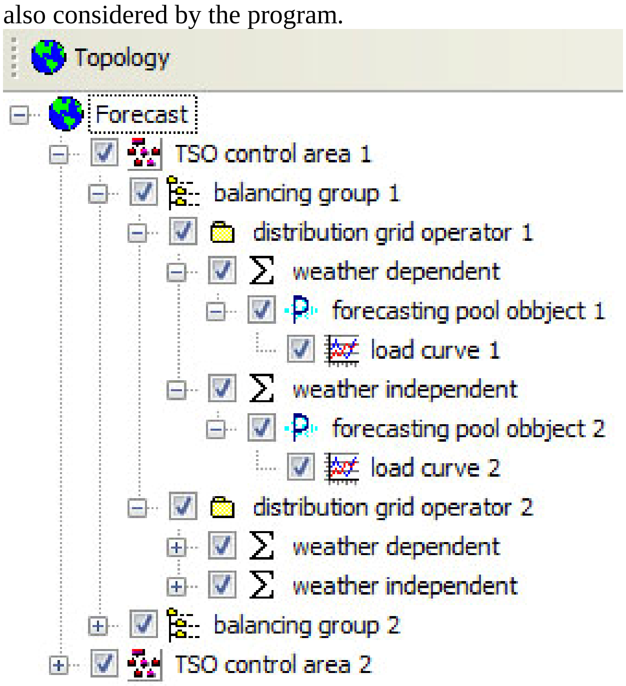

Figure 3: Automatically built up forecasting topology organized by regional aspects and weather influences.

Figure 3 shows an example for a forecasting topology organized by regional and weather aspects.
When dealing with as much load data as is the case for most large energy suppliers, incomplete or incorrect data always has to be taken into account. Voids or completely missing datapoints in the load curves occur more often than one would think. LEM presents different solutions for this problem. In the automation process for a bottom-up forecast, which means every load curve is forecasted individually, the data is checked every day. Objects with incomplete or incorrect data are left out by the forecast and are moved into a tree branch where the user can easily identify them. Alternatively, voids can be filled with comparable data. If new, i.e. more complete and correct data arrives over the interface, old data will be overwritten. The next time the complete topology is checked, objects with now complete and correct data are moved back into the branch where they can be forecasted. The program does not check data again that has already been found to be complete and correct. This way high performance is guaranteed.
If the forecasting process is wished to be less automatic, the

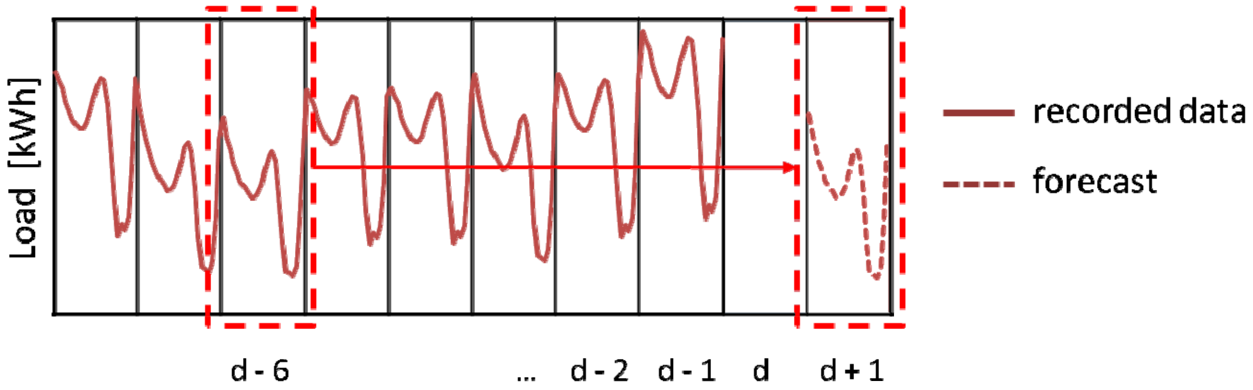

Figure 4: Simple day-ahead forecast. The forecast for day d+1 represents a copy of the day d-6 and is done on day d.

user can also check specified data objects in the LoadManager by starting the function manually.

Once all the data objects have been tested for whether they depend on influencing factors, and if the data is correct and complete, the actual forecast can be done by the program. The LoadManager includes many different mathematical forecasting models. Some of the simpler ones copy the respective day from the last week or calculate the average of the same day over the last six weeks. Calendar effects like public holiday are always taken into account. More complex models are based on artificial neural networks.

In general, forecasting models use historical load data and other factors mentioned above to find out the influence on the temporal behavior of the load. Based on this information, the models create a forecast of the load demand over different time scales. The LoadManager can do day-ahead-forecasts, forecasts for the rest of the current day, monthly forecasts and annual forecasts.

Fig. 4 shows an example for a simple day-ahead forecast model. A forecast for day d+1 is done on the current day d by copying day d-6. More complex models learn the correlation between the load curve and influencing factors. On this basis and with influencing factors like weather, the forecast is calculated.

During the automatic bottom-up process the best-fitting model is chosen automatically by the program. After all processes of data clearing and choosing the correct parameters, the forecasts are done automatically as well. All of the automatic steps can be done manually as well. Users can choose how much automation they want in their daily forecasting business.

Results

Exemplarily, results from a bottom-up forecast project that works completely automatically are shown here. Since customers can move, their contracts can end, or new customers can be included, the corresponding objects in the topology are not fixed in their position. They can move as

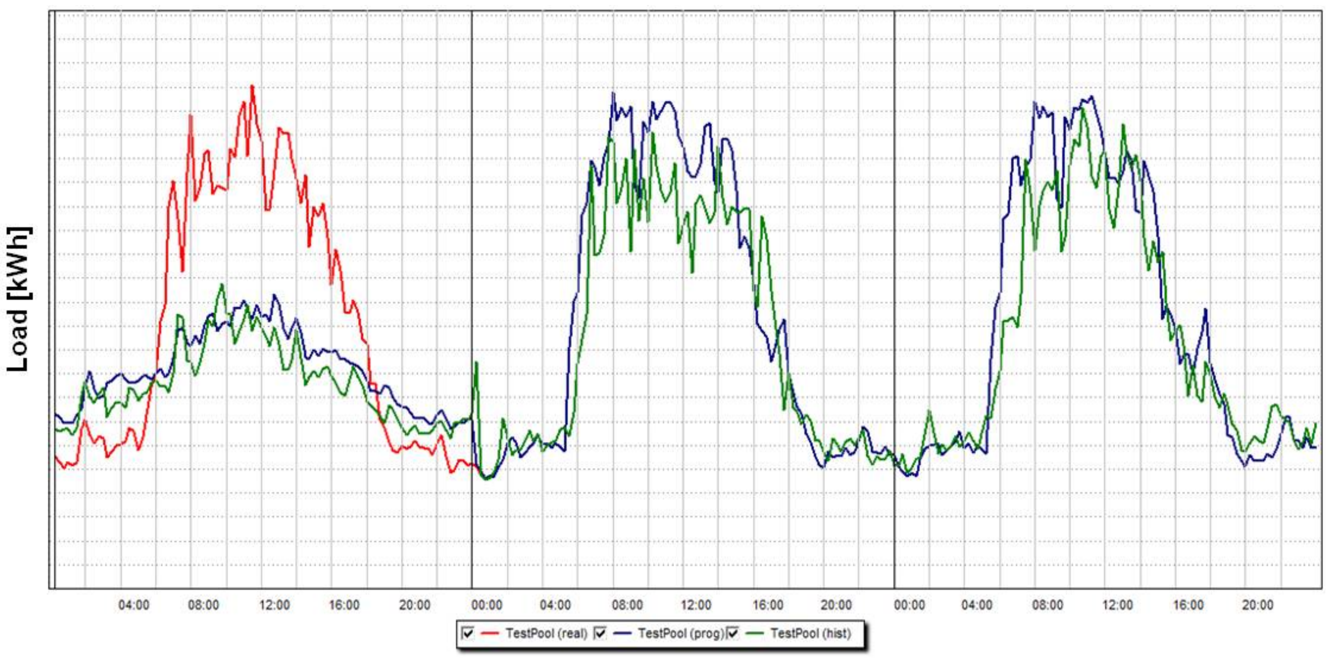

Figure 5: Three days where forecasts have been calculated with the same forecasting pool object. The number of contributing costumers changed between the first and the second day. The graph shows the actual recorded data, the historical recorded data, and the forecast.

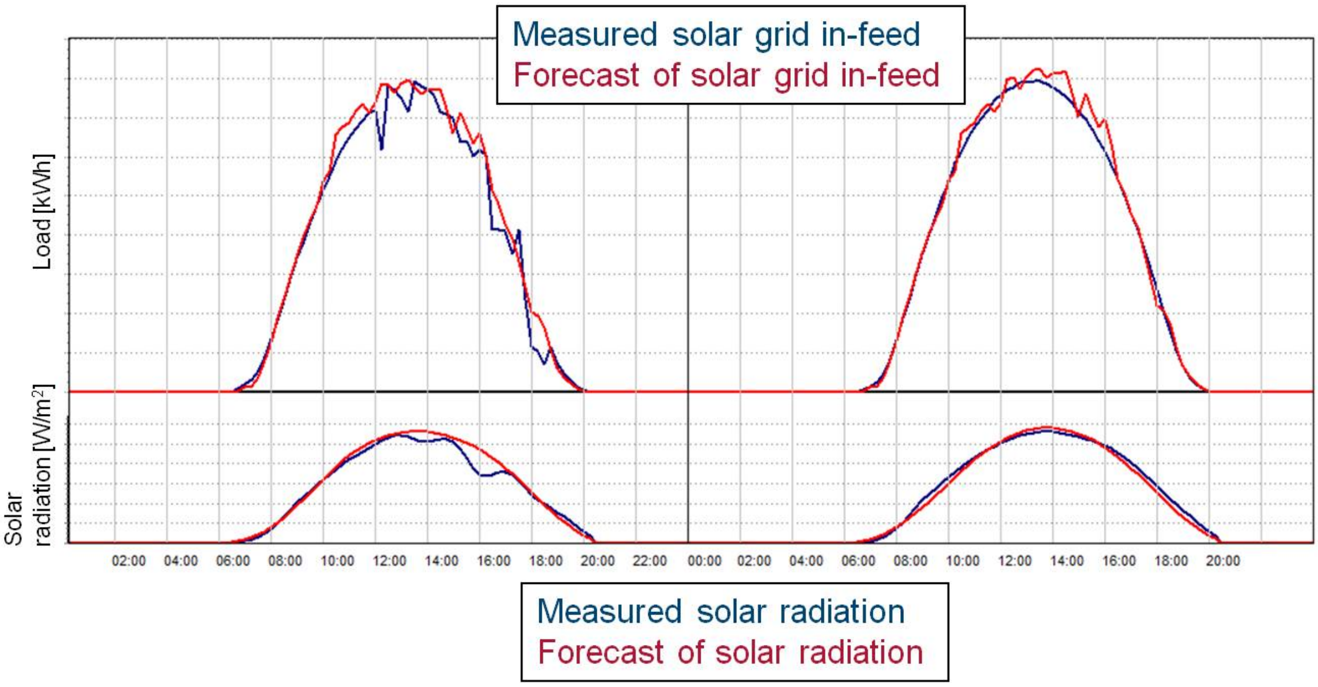

Figure 6: Grid infeed and forecast of the grid infeed of a solar power plant. The global radiation and the forecast of global radiation is shown as well.

well. For an analysis of the predicted load curve this is a challenge, since the data on the forecasting object does not necessarily represent the same amount of customers that can be found in the forecasting pool on the day the analysis is made. LEM therefore developed an overview for every forecasting pool that shows its historical development. This means every pool has a table showing which customer contributed to the forecast on which day. Additionally when visualizing the forecast and the recorded data together, the user can choose between seeing the currently present recorded data or the historical data, meaning the customers that were in the pool on the day the load demand was predicted.

Fig. 5 shows three days for which forecasts have been calculated. The number of customers in the forecasting pool, however, changed between the first and the second day. The red curve represents the recorded data of the customers that can currently be found in the pool, while the green line shows the historical data of the customers that contributed to the relevant forecast. The forecast itself is shown in blue.

FORECASTS FOR THE GRID INFEED OF RENEWABLE ENERGY SOURCES

The importance of renewable energy sources is growing fast at the moment. One of the big challenges dealing with renewable energy sources is their strong dependence on weather. Simply said, a solar panel only produces electricity when the sun is shining, while a wind power plant only works when wind is blowing. Network operators or energy suppliers thus do not know how much energy is going to be fed into the grids. This fact makes forecasts for the grid infeed of renewable energy sources indispensable.

The LoadManager takes the weather into account for forecasts. It is therefore possible to predict the grid infeed of renewable energy sources in a comfortable way. For wind farms the forecast and historical data of wind speed and direction is needed, while the global solar radiation is required to forecast the solar grid infeed.

An example for a forecast of the grid infeed produced by a solar power plant in the spring is shown in fig. 6. As can be seen directly from the diagram, the grid infeed strongly depends on the global radiation.

CONCLUSION AND OUTLOOK

A fully automatic process for bottom-up forecasts of load curves and profiles was presented. Every step, from importing the data to the actual forecast, can be done automatically by the LoadManager. Processes like moving customers, incomplete data, or weather and calendar dependencies are considered. It was also shown that the grid infeed of renewable energy sources can be forecast with the LoadManager.

Looking ahead, LEM is implementing balancing group management processes at the moment. The new rules for communication and billing processes on the German electricity market (Marktregeln für die Durchführung der Bilanzkreisabrechnung im Strom: MaBiS) can comfortably be realized with the LoadManager. Of course, this is also true for the gas market.