

## IMPROVING SHORT-TERM LOAD FORECAST ACCURACY BY UTILIZING SMART METERING

Petri VALTONEN  
Lappeenranta University of  
Technology – Finland  
petri.valtonen@lut.fi

Samuli HONKAPURO  
Lappeenranta University of  
Technology – Finland  
samuli.honkapuro@lut.fi

Jarmo PARTANEN  
Lappeenranta University of  
Technology – Finland  
jarmo.Partanen@lut.fi

### ABSTRACT

*Smart metering is coming: electricity distribution companies in many countries are installing or have already installed new Automatic Meter Reading (AMR) systems as a response to the electricity market reforms and new regulations. AMR systems enable remote connections of customers' energy meters and exchange of information in real time. This provides new opportunities to develop methods that can benefit all the stakeholders in the power markets.*

*This paper describes how smart metering can be utilized in improving the short-term load forecasting (STLF) accuracy. Through sophisticated AMR systems, energy consumers' electricity consumption data can be retrieved in a short time whenever the data is needed. This provides great opportunity to use real-time measurement data to make more reliable and accurate electricity consumption forecasts. These AMR-based load forecasts can be exploited to create a new ancillary service that benefits different electricity market parties and asset owners.*

### INTRODUCTION

New AMR systems make it possible to obtain real-time measurement data from customers' energy meters whenever these data are needed. This opens up opportunities to create new services for electricity retail companies and other electricity market parties. One such service is to use AMR data to produce more accurate load forecasts. This AMR-based load forecasting is based on the idea that energy companies and other electricity market parties can use data from the distribution companies' AMR systems. In practice, this can be realized for instance by using a remote connection, which allows the energy company to access distribution companies' remote reading systems and/or databases and retrieve the required data.

AMR-based load forecasts can help energy producers to control their production more accurately and electricity retailers to manage their procurements more precisely in the spot and after-spot markets. By AMR-based load forecasts, the need for more expensive regulating power decreases, which brings savings to the electricity retailer and the producer. Furthermore, the DSO (Distribution System Operator) benefits from the more accurate STLF for instance in the operation of the network and the procurement of the power losses.

In this paper, it is introduced how AMR systems can be utilized to produce AMR-based load forecasts and how this affects the accuracy of the STLF and profitability of the business. Chapter 2 provides some important background information about AMR system installations in Finland and the utilization of AMR systems. Chapter 3 introduces the basic idea of AMR-based load forecasting and the most important factors that affect its accuracy and profitability. Chapter 4 presents a case example considering the profitability of the AMR-based load forecasting. Finally, conclusions are made in Chapter 5.

### AUTOMATIC METER READING SYSTEMS

A major reform concerning electricity metering regulations in Finland was made in February 2009. As a result, at least 80 percent of all electricity consumers shall be under hourly-based measurements and remote meter reading no later than 1 Jan 2014 [1]. Similar electricity metering reforms have been realized in many countries. Thus, it seems that in the near future, smart metering is coming to replace virtually all traditional energy meters.

Installation of new AMR systems incurs expenses but can also bring savings, open new business opportunities and make many improvements possible. AMR systems enable among other things remote connection of customers' energy meters and exchange of information in real time. This real-time AMR data can be used in monitoring, load forecasting, and in many other applications and services.

#### Utilization of AMR technology

Electricity consumers' consumption data can be retrieved from AMR meters whenever the data are needed. The main application where AMR meters are typically used is the reading of energy consumers' hourly consumption data for invoicing purposes. AMR data can be utilized also in many other applications [2], such as short-term load forecasting.

In Finland, local distribution companies own or have leased their AMR systems. The equipment and characteristics of the AMR systems are typically planned according to the prevailing situation and the needs of the local distribution company. Because of that, AMR systems may differ greatly depending on the area. This is the reason why typically only the distribution companies have utilized AMR systems in their business. New operation models and working methods are under construction and have to be developed further so that different electricity market parties can utilize smart

metering more efficiently in their business. Some improvements, such as national minimum requirements for the functionalities of AMR meters have been announced, but more actions are needed.

Utilization of smart meters in different applications sets different conditions for reliability, bandwidth, and other features of AMR systems. This means that all the needed applications and services may not be realized by using the existing AMR systems. For example, communications may have to be considered in more detail, if there is a need to utilize smart meters for other than invoicing purposes.

### AMR-BASED LOAD FORECASTING

New AMR systems provide an opportunity to obtain real-time information from customers' loads. AMR-based load forecasting is one way to exploit this data. It is based on the idea that energy retail companies or other electricity market parties can get the needed data from distribution companies, for instance by a remote connection.

#### Accuracy of the load forecast

Short-term load forecasting is an important but challenging task. There are many variables that have to be taken into account during the forecasting process. Weather conditions, temperature in particular, have a significant effect on forecasts. Another important factor is the type and number of customers. Besides these, there are a large number of other more or less significant factors, which affect the accuracy of the load forecasts.

Numerous different STLF methods have been developed, which are based on different models such as Knowledge, Neural Networks, Fuzzy Logic, or other hybrid forecasting methodologies [3]. Typically, STLF deals with hourly loads with time intervals from a day to a week ahead [4]. Real-time AMR data can be used in short-term load forecasting or even in more real-time load forecasting such as Very Short Term load Forecasting (VSTLF) or Real-Time Load Forecasting (RTLTF), depending on the delay of data transfer, time used to produce the forecast, and so on. The main principle of the AMR-based load forecasting is anyway the same in all cases. It focuses on extrapolating the recently observed loads to the nearest future.

Based on [4], [5], and [6], some results concerning the forecasting accuracy of different methods are gathered in Table 1. The table provides the methods, the Mean Absolute Percentage Errors (MAPE) of each method, and a short description of each method. The average percentage error (APE) can be calculated by

$$APE = \frac{L_{Forecast} - L_{Actual}}{L_{Actual}} \times 100 \quad (1)$$

and the mean absolute percentage error by

$$MAPE = \frac{1}{N} \sum_{i=1}^N |APE_i| \quad (2),$$

where  $N$  is the number of fitted examination points in time.

Table 1. Load forecasting results based on [4], [5], and [6]

Study	Method	MAPE [%]	Description
<b>VSTLF using Artificial Neural Networks</b>	Artificial Neural Networks	0.4–1.1	Forecasts were made with 20,30,..., 60 minute time leads
<b>Real-Time Load Forecasting in Power Systems</b>	Regression model	3.67 (max)	Predicts loads 30 minutes into the future in 5 minute steps
	ANN Model	1.72 (max)	
<b>Short-Term Hourly Load Forecasting using Abductive Networks</b>	Abductive Networks	1.14	Predicts next-hour loads applying recent hourly load data up to the preceding hour
	Neural Networks	1.41	

According to these studies, we can say that it is possible to achieve a better forecasting accuracy by using real-time load data than by the traditional methods. For example in [5], a 47 % reduction in forecasting error was obtained by the proposed method compared with the traditional forecasting method.

#### The effect of the data transfer delay

The more accurate real-time measurement data are used to make the load forecast, the greater the accuracy of the forecast is. Therefore, it is important to minimize the time used in meter readings. It depends mainly on the communication technology and bandwidth applied, but also the qualities and interferences of the network affect the data transfer times. Consequently, it may be a challenging task to determine specific meter reading times.

A previous study [7] gives some suggestive results about the customers' meter reading times. These times depend on the size of the customer groups, the size of the transferred data series, the data transfer technology, and so on. As a conclusion of this study, it can be said that customers' hourly energy consumption data can typically be obtained in one-hour time interval, which is the minimum requirement if load forecasting is used to predict the next-hour loads. Only in the largest distribution substations the data transfer, which uses low-speed communications, such as PLC, may involve so long delays (one hour or more) that load forecasts cannot be made for the next hour by using the preceding-hour load data.

#### Profitability

The profitability of the AMR-based load forecasting depends on the obtained savings and the implementation costs. The purpose of the AMR-based load forecasting also significantly affects its profitability, which is why the method has to be considered for each case individually. In this chapter, it is proposed how the profitability of AMR-based

load forecasting can be determined when it is used to control the power balance of the energy company.

The costs of the regulating power, in one-hour time interval, can be calculated by

$$c_t = |\mathcal{E}_t| \left( |p_{elbas,t} - p_{reg,t}| + V_{Fee} \right), \quad (3)$$

where the subscript  $t$  denotes the usage hour,  $\mathcal{E}$  is the balance error,  $p_{elbas,t}$  is the price of electricity in after-spot markets,  $p_{reg,t}$  is the price of the regulating power (balance power) and  $V_{Fee}$  is the volume fee of the regulating power. The higher the price of the regulating power is compared with the electricity after-spot price and the larger the error between the actual and forecast load is, the greater the cost of the regulating power is, and the larger saves the AMR-based load forecasting can provide.

AMR-based load forecasting is assumed to be an ancillary service, and therefore no meter installation or maintenance costs are allocated to it, only the meter reading costs. In this case, the costs of this service come from meter readings and depend mainly on the communications used. Data transfer costs are difficult to specify exactly, since the distribution networks and organization of meter readings vary greatly depending on the area. If meter readings are carried out by using a GPRS network, data transfer costs depend mainly on the particular distribution network or the local network operator. In the next chapter, a case study is presented, where the effect of meter reading cost on the profitability of the AMR-based load forecasting is considered in more detail.

## CASE STUDY

In this example case, AMR-based load forecasting is used to decrease the regulating power costs of the energy (retail) company during a regulating power price peak. The profitability calculations are based on actual consumption and power balance data of one local energy company in Finland. The data consists of forecast and actual hourly consumption and procurement data in the time interval between 1 Jan 2009 and 30 April 2009. These data are first used to calculate the energy company's average power balance errors within the chosen time interval. When these errors and the electricity price in the regulating power and spot markets are known, the savings obtained in the regulating power markets are calculated. With this information, it can be calculated which are the maximum allowed meter reading costs in order for the load forecasting to be a profitable ancillary service.

Some assumptions had to be made in the calculations since it was not possible to obtain all the required data. It is supposed that the average MAPE of the energy company's load forecast is reduced by 3 percentage units from the

original 6 % of the total by using real-time AMR data in the load forecasts. These assumptions are made according to the information from different studies and the energy company's balance information. It is also supposed that the AMR-based load forecasting is an ancillary service and only the meter reading costs are allocated to it. The customer volume of the energy company is 80 000.

These calculations are made by using the Nordpool Elspot prices instead of the Nordpool Elbas prices since it was not possible to get the required Elbas price data for the corresponding time interval. The effect of using the Elspot price instead of the Elbas price is quite significant since the difference between the Elspot and Elbas price is typically very small compared with the difference between Elspot/Elbas and regulating power prices.

## Profitability calculations

The largest costs from the regulating power come typically during the regulating power price peaks. This is why the case examination is made on 5 Jan 2009 during a regulating power price peak. Figure 1 illustrates the price of the regulating power in Finland on 5 Jan 2009.

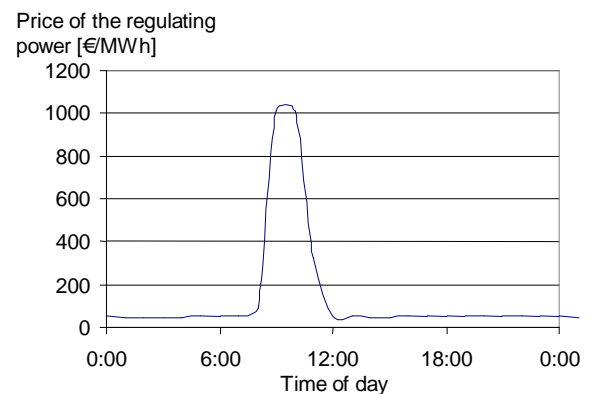


Figure 1. Price of the regulating power on 5 Jan.2009

As can be seen in Figure 1, the price of the regulating power rises above 1000 €/MWh during the price peak. Table 3 presents the more exact Elspot and regulating power prices during the price peak, which are used in the calculations.

Table 3. Elspot and regulating power prices on 5 Jan 2009, 07:00–14:00

Hour	07–08	08–09	09–10	10–11	11–12	12–13	13–14
Regulating power price [€/MWh]	53	93	1007	1007	325	51	51
Elspot-price [€/MWh]	43	44	47	47	47	47	47

The regulating power price started to increase between the hours 7 and 8. It is supposed that after 7 o'clock the energy company noticed the beginning rise in the regulating power. They decided to start the AMR-based load forecasting and began to read the latest consumption data from the

customers' meters. This continued until 13 o'clock when the price peak seemed to end.

The energy company read the customers' hourly consumption data from the usage hours 8–13. Based on these data, the company made new load forecasts for the hours 9–14. Thanks to these, the average decrease in the MAPE was assumed to be 3 percentage units from the original 6 percent total value. The hourly costs of the regulating power are calculated by equation 3. According to these results, the hourly savings from the AMR-based load forecasting are calculated and presented in Table 4.

Table 4. Hourly savings obtained by the AMR-based balance control

Hour	09–10	10–11	11–12	12–13	13–14
Savings by the AMR-based load forecasting [€]	3948	3948	1145	19	19

The total savings from the hours from 9 to 14 are 9079 €. It is supposed that every customer's load data is read once in an hour during this time interval. This means that the use of the AMR-based load forecasting was profitable if the meter reading costs were less than (9079 € / (5\*80 000 customers)) = 2.2 cent/reading.

It is important to notice that the new more accurate load forecasts can usually be made without reading every consumer's load data at every hour. Reading of the most important customers' load data, such as large industrial companies and other consumers with highly and rapidly varying loads, usually provides enough information to obtain more accurate load forecasts. This would help to decrease the meter reading costs, which in turn would increase the profitability and lead to higher allowed meter reading costs per customer. Further, the usage hours when meter readings are carried out could have been chosen more optimally. In this case, the most optimal meter reading time would have been the hours 8–11. Since the measurement data were already read from the usage hours 11–13, it was advisable to make a more accurate forecast also for the usage hours 12–14.

Many variables affect the meter reading costs. In the case of GPRS, the costs are dependent on the network operator. On the other hand, the total number of meters also affects these costs. In the case of PLC, meter reading costs vary depending on the number of meters under one concentrator and the data transfer connection used between the concentrator and the reading system. PLC data transfer costs are smaller than those of GPRS, if the number of meters under one concentrator is high, and the costs are about the same or higher if the number of meters per concentrator is small. In general, we can estimate that the cost of reading the customer's meter once is roughly the same as the cost of a SMS message, which can be as low as 0.5–1.0 cent/message (in Finland). According to this information and the calculated maximum meter reading cost (2.2 cent/reading),

we can say that in this case, the use of AMR-based load forecasts was profitable.

## CONCLUSIONS

It was shown by a case example that AMR-based load forecasting can be a profitable ancillary service. In general, we can say that AMR-based load forecasting can be a profitable service for many electricity market parties if it is appropriately planned and allocated.

As shown in the case example, an energy retail company can obtain savings in regulating power markets by AMR-based load forecasting. Also other electricity market parties can exploit this ancillary service to improve their business. Development of new smart-metering-based ancillary services, such as AMR-based load forecasting, opens new business opportunities also to the asset owner, who organizes the metering. Profitable ancillary services benefit all electricity market parties and asset owners as well as improve the functionality of the electricity markets.

## REFERENCES

- [1] *Valtioneuvoston asetus sähkötoimitusten selvityksestä ja mittauksesta 66/2009* [Government Decree on settlement and measurement of electricity transactions], given on 5 February 2009.
- [2.] H. Sui, H.Wang, M-S. Lu, and W-J. Lee, 2007, "An AMI System for the Deregulated Electricity Markets," *Power Tech Conference*, Lausanne, Switzerland
- [3] S. Tzafestas, E. Tzafestas, 2001, "Computational Intelligence Techniques for Short-Term Load Forecasting," *Journal of Intelligent and Robotic Systems*, 31, pp. 7–68
- [4] H. Daneshi, and A. Daneshi, 2008, "Real Time Load Forecast in Power System," in *Third International Conference on Electric Utility and Restructuring and Power Technologies*, Nanjing, China
- [5] W. Charytoniuk, M.-S. Chen, 2000, "Very short Term Load Forecasting Using Artificial Neural Networks," *IEEE transactions on Power Systems*, Vol. 15, No.1, pp. 363–268
- [6] R.E.Abdel-Aal, 2004, "Short Term Hourly Load Forecasting using Abductive Networks," *IEEE Transactions on Power Systems*, Vol. 19, No.1, pp. 164–173
- [7] P.Valtonen, 2008, *Interaktiivisen asiakasrajapinnan mahdollistamat energiatehokkuutta tukevat toiminnot ja niiden kannattavuus* [Interactive customer gateway in improving energy efficiency – consideration of new functions and their profitability], Master's thesis, Lappeenranta University of technology, Lappeenranta, Finland (in Finnish).