A Contribution to the Load Forecast of Price Elastic Consumption Behaviour

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***Abstract*—By influencing the demand side by means of price signals (Demand Response) additional flexibility potential in electric supply systems can be provided. However, by influencing the demand side typical consumption patterns of previously unaffected consumers are changed. This will lead to increasing uncertainty in load forecasting. This paper deals with the forecast of load time series in consideration of price-based consumption influence. Additional requirements for load forecasting methods resulting from the price elastic consumption behaviour are analysed in this paper. Furthermore, the model residuals of established model approaches will be analysed to explain the disturbance characteristic caused by the price elasticity. Finally, the impact of the model residuals on the load forecast was investigated.**

***Index Terms*-- Demand forecasting, demand response, consumer behaviour, time series analysis.**

I. INTRODUCTION

The climate and energy policy objectives and the associated rising percentage of the feed-in from fluctuating generation by renewable energies are significant technical challenges for the future electricity supply systems. To maintain the system stability and the security of supply by the permanent balancing of production and consumption, there is a need to introduce new flexibility potentials. Besides the development of storage technologies or the implementation of production management for fluctuating generation, flexibility for the electric supply system can be provided by adjusting the demand side to the given fluctuating feed-in (consumption follows production). The influence on the consumption is done by exploiting the demand side load shifting potentials and is technically realized via the Demand Side Management (DSM). DSM contains all measures to influence the load on the demand side, whereas indirect DSM and Demand Response (DR), respectively, specifies the influence of time-varying incentive signals (e.g., price signal) on the consumption behaviour. A detailed categorization of DSM measures and related definitions is carried out in [1], [2].

A disadvantage of DSM is that the typical previously unaffected consumption patterns are altered by market and/or generation situational incentive signals. This in turn increases the uncertainty in the load forecast and thus the uncertainty in subsequent processes. In energy supply, load forecasts are an important contribution for the optimal planning and operation of energy and resources.

In section II the rising uncertainty is demonstrated by smart meter data of two field studies. In this paper, the requirements for a load forecasting method considering price-based consumption influence (price elastic consumption behaviour) are analysed. The problem is described and a system technical examination given in Section III. In Sections IV the requirements for new forecasting methods are discussed. The properties of the residuals that occur through price-based consumer influence are explained and a possible contribution for modelling is discussed in Section V. Thereby, the price effect is interpreted as a disturbance. Section VI gives a summary of the investigations and case studies in this paper and an outlook for further researches is conducted.

II. UNCERTAINTY IN FORECAST

In the present paper, time series, forecasts of established method approaches and the resulting forecast errors are evaluated as a measure of uncertainty. The smart meter data sources from the Olympic Peninsula Project (OPP) [3], in which the consumption behaviour of household consumers in response to variable tariffs (Time of Use - TOU consumer group and Real Time Pricing - RTP consumer group) compared to a control group with a constant tariff (FIXED consumer group) were examined. On the basis of established method approaches, such as Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN), different forecasts for the respective consumer groups are generated and compared. The ARIMA model approach (to estimate consumer load changes instead of consumer loads) bases on (1) [5] where $\varepsilon[k]$ is white noise and a_i and b_j are model parameters. The orders p and q of the ARIMA model as

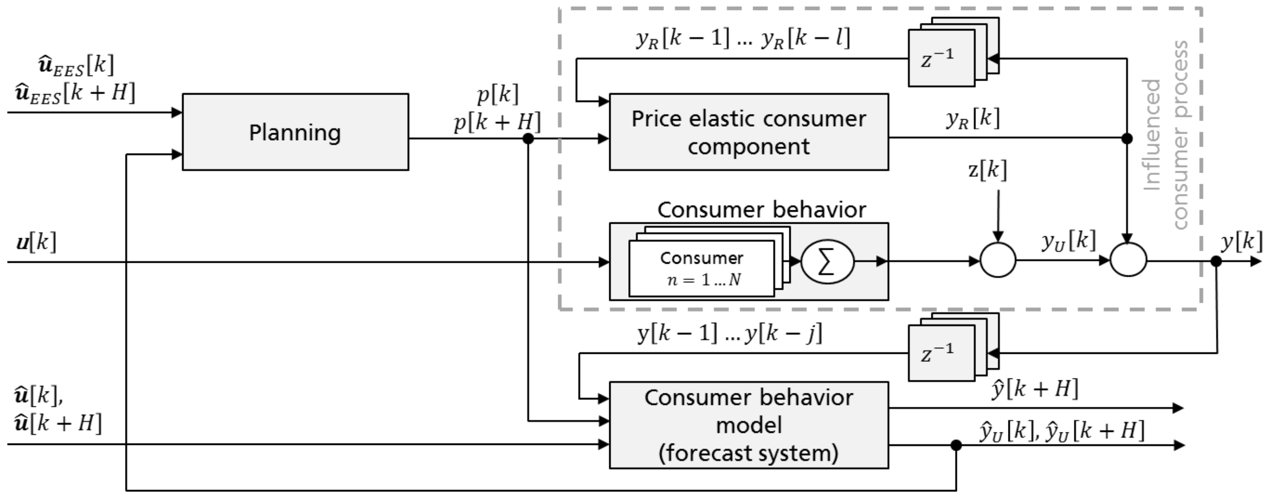

Fig. 1. Price elastic consumption process with consumer behavior model and planning [4]: k - index of time (sampling time 15 minutes); H - forecast horizon, $p[k]$ - price signal, $\hat{x}$ - estimation of x, $\boldsymbol{u}[k]$ - exogenous influencing values, $u_{EES}[k]$ - exogenous influencing values of electric energy system, $y[k]$ - price elastic consumer load, $y_U[k]$ - unaffected component of consumer load, $y_R[k]$ - affected component of consumer load, $z[k]$ - disturbance value

well as the difference filters ∇^d are determined in advance as a result of a data analysis. By including the tariff as an exogenous variable, the ARIMA approach is extended to ARIMAX (ARIMA with exogenous variable).

$$\nabla^d x[k] = \sum_{i=1}^{p} \left[a_i \nabla^d x[k-i]\right] + \varepsilon[k] + \sum_{j=1}^{q} b_j \varepsilon[k-j] \qquad (1)$$

In the context of signal models, the ANN approach can be attributed to nonlinear stochastic models. ANN approaches are also widely used in energy economics and literature concerning forecast time series [6]-[9]. The ANN approach used in this paper is a simple feed forward neuronal network with three layers, hyperbolic tangent activation function and a backpropagation algorithm for the training [10], [11].

TABLE I. RESULTS BASED ON OLYMPIC PENINSULA PROJECT DATA

Consumer group	Forecast results for different methods			
	ARIMA	ANN	ARIMAX+ tariff	ANN+ tariff
Forecast error MAPE [%]				
FIXED	15,26	15,04	-	-
RTP	17,53	17,39	17,49	17,27
TOU	19,48	19,04	19,52	19,37
Increase of the forecast error compared to the control group [%]				
RTP	14,87	15,63	14,61	14,83
TOU	27,65	28,99	27,92	28,79

ARIMA – Autoregressive integrated moving average, ARIMAX – Autoregressive integrated moving average with exogenous variable, ANN - Artificial Neural Network

The OPP dataset was split for the investigations. Two-thirds of the data are used to train the ANN and one-third are used as test data. The investigations indicate an increasing forecast error for price elastic load. The results of the investigations based on OPP dataset are summarized in Table I. The error is measured as the mean absolute percentage error (MAPE) defined in (2). Here x are the measured values, $\hat{x}$ are the forecast values and N stand for the number of forecasts values.

$$MAPE = \left(\frac{1}{N} \cdot \sum_{k=1}^{N} \frac{\left| x[k] - \hat{x}[k] \right|}{x[k]} \right) \cdot 100\% \qquad (2)$$

In [12], the impact of load shifting as a response to a price signals is analysed. Different forecast methods, approved and commonly used by the German energy industry, are used to forecast the consumption of a price influenced consumer group (groups for house owners and tenants) in comparison to a control group with a constant tariff. The investigations are based on smart meter data from a field study called RESIDENS. The investigation in [12] indicates results analogous to those based on the OPP dataset in this paper. The results from [12] are summarized in Table II.

TABLE II. RESULTS BASED ON RESIDENS DATA

Consumer group	Forecast results for different methods				
	AR	ANN	RNN	ANN+ tariff	RNN+ tariff
Forecast error MAPE [%]					
Control	14,63	13,2	12,93	-	-
House	18,93	16,61	15,96	16,56	16,04
Tenant	20,38	17,74	17,09	17,55	17,09
Increase of the forecast error compared to the control group [%]					
House	29,39	25,83	23,43	25,45	24,05
Tenant	39,30	34,39	32,17	32,96	32,17

Abstract of results from [12]: AR – Autoregressive, ANN - Artificial Neural Network, RNN – Recurrent Neural Network

III. PROBLEM DESCRIPTION

The emphasis of this paper is the indirect influence of the consumption behaviour by price signals in an electrical power system (Fig. 1). The result of the complex planning in DSM is the price signal $p[k]$ at sampling time k. The planning and thus the price building mechanism are taking into account various factors influencing the electric energy system $\boldsymbol{u}_{EES}[k]$, e.g. existing network restrictions, market criteria or current generation and load forecasts. With the distinction between market-oriented or net-oriented use of DSM measures [2],

[13], forecast and planning methods are needed to influence the electrical load optimally with consideration of energy market and technical aspects. For certain cases of generation feed-in situation, the need and the range of a load influence for a future planning horizon H can also be measured meaningfully based on the forecast of the unaffected load $\hat{y}_U[k+H]$. The unaffected consumption behaviour is the starting point of the planning. Therefore, the used forecast methods must be able to predict the unaffected component of the total consumption. These methods must be able to conclude from the influenced historic consumption data $y[k-1]\ldots y[k-j]$ and other available input variables $\boldsymbol{u}[k]$ to the unaffected load behaviour using reverse-calculation. The result is a corresponding forecast. The price signal, as a result of the planning, influences the consumption behaviour in return. The influenced load curve $y[k]$ is obtained from the unknown unaffected and affected signal components $y_U[k]$ and $y_R[k]$ respectively. There is a system feedback due to the forecast of the unaffected load curve introduced as an input of the planning. The resulting system structure is discussed in detail in [4].

IV. Requirements for load forecasts regarding price elastic consumption behaviour

For the modelling of the price-based consumption behaviour, various approaches can be found in the literature. The price elasticity as a measure of the change in demand in response to a price change is the basis of various approaches [13]-[17]. The price elasticity is often explained as a time-variant function, depending on month, day, hour, seasonal influences or even specific type days [15]-[17]. The predictability of consumers to adjust to price changes and thus the price elasticity also depends on lead time (planning horizon) for which prices are known in advance. The effects occurring by the price-based consumption influence not necessarily have to occur directly in response to price changes. Rather, the reactions are also expected a priori or a posteriori time-shifted, potentially leading to “non-causal load reactions” to existing or estimated future price changes. Furthermore, the own signal past of influenced signals is an important impact (autoregressive behaviour), because the percentage of already exploited influence potential can be derived which is currently not available. Assuming the influence on the consumption behaviour is a measure for load shifting (only the time of the power consumption is changed), an energy storage like behaviour is obtained. However, there are special properties and degrees of freedom by the storage behaviour of influenced consumers. Thus, in [18] the consumer behaviour is modelled as a virtual storage. Furthermore, regression models [19], fuzzy systems [16] or optimization models [17] are used or different DR scenarios are determined stochastically using Monte Carlo simulations [20]. As a summary of system analysis in Section III and the modelling approaches used in the literature, different requirements for forecast methods of price elastic consumption signals can be determined:

- The forecast of the unaffected load component for price elastic consumption behaviour is needed for the planning.
- Type day and seasonal price elasticity
- Autoregressive behaviour of estimated load
- Storage behaviour at load shifting
- Consideration of the planning horizon (lead time)
- Dynamics of consumer reactions depending on price forecast horizon (causal and non-causal behaviour)

V. Model residuals

If a model explicitly takes into account all systematic factors of the consumption behaviour, the model residuals (model error $e[k]$) will only include randomly occurring deviations between the measured values and the estimated model outputs. In this case, the model error $e[k]$ is white noise [5], [21], [22]. In the literature, a variety of modelling approaches can be found for the load forecast of the consumption behaviour (without price elastic consumption behaviour). An overview of established model approaches for load forecasts offer among others [6] and [7]. For the following discussion (see Fig. 2), it is assumed that an established approach for load forecasting exists, assuming white noise $\varepsilon[k]$ as an error signal. By demonstrating that the error signal corresponds to white noise, the optimal forecast method is modelled (assumption of optimal forecast) [5], [22]. The periodogram test is used to demonstrate the existence of white noise [5]. The periodogram test is a null hypothesis test with consideration of the significance level *alpha* and is based on the cumulative periodogram.

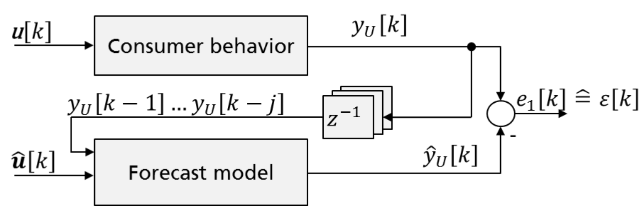

Figure 2. Optimal forecast model: $e_1[k]$ - residuals/ forecast error, $\varepsilon[k]$ - white noise

If the consumption behaviour is additionally influenced by price signals, the influences of the price signal can be interpreted as a disturbance (Fig. 3). Without the knowing of the price signal, the forecast model is unable to consider the price effects on the load signal.

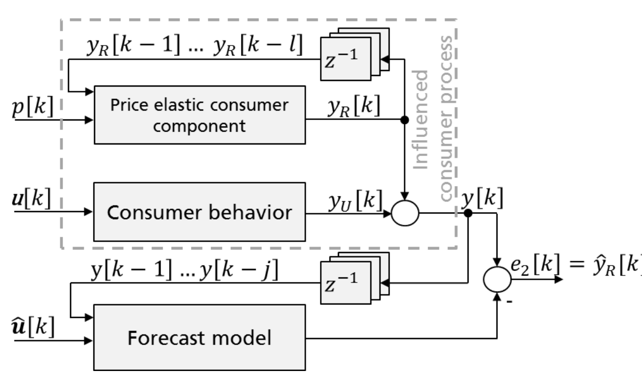

Figure 3. Forecast model without price consideration and model residuals: $e_2[k]$ – residuals/ forecast error

Consequently, relevant price changes increase the model error, and thus, price and model error are correlated with each other. The functional relationship between price and load change is transmitted to the error signal. In practice not all systematic factors can be included in consideration, because the data logging is technically impossible, too costly or some relevant factors are unknown. In such cases, the error signal cannot be characterized as white noise, because the values still contain functional relationships to unknown factors or are correlated with each other. To forecast the unaffected load component in consumption processes with price elastic consumption behaviour (described in Section II), in this paper investigations focus on whether and how the discussed error signal can be used for the modelling. With an exact approximation of the affected load component $y_R[k]$, the unaffected load component $y_U[k]$ can be calculated as follows.

$$y_U[k]=y[k]-y_R[k]. \tag{3}$$

Based on the unaffected load component, calculated for a historic time domain, conventional and established forecast methods [6], [7] can be used to forecast the unaffected load component. In the following subsections, the disturbance characteristic, that occurs with the price elasticity, is investigated with the help of two case studies.

A. *Case Study 1: synthetic smart meter data*

To validate the postulated proceeding (Fig. 2 and Fig. 3), a synthetic dataset is used in Case Study 1. With the aid of the synthetic dataset, the investigation can be executed under controlled conditions by knowing all signal components. The load time series $y_U[k]$ is a standard load profile (SLP) superimposed with a random disturbance and represents the unaffected consumer (FIXED) group. The influenced load time series $y[k]$ represents the RTP consumer group and is affected by a dynamic tariff with several price levels. Thereby the simulated price elasticity of the affected load component $y_R[k]$ varies with type day and with time of day and is known for Case Study 1. An ANN method is used to forecast the load time series of the FIXED group for the forecast horizon of 24 hours (96 samples by a sampling interval of 15 minutes).

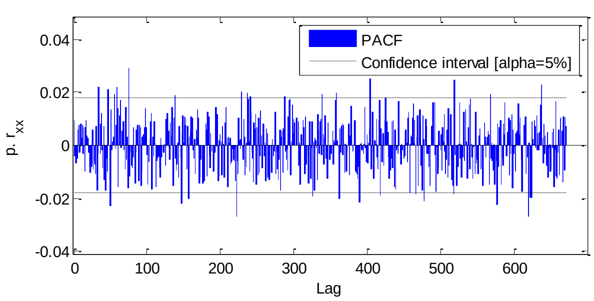

Figure 4. Partial autocorrelation function of the forecast error $e_1[k]$ and confidence interval and a lag up to one week (672 samples by a sampling interval of 15 minutes) for Case Study 1

The periodogram test with *alpha* = 5% demonstrated that the forecast error corresponds to the white noise ($e_1[k]\triangleq\varepsilon[k]$) in Case Study 1, which confirms the assumption of an optimal forecast. Fig. 4 shows the partial autocorrelation function of the error signal. The dashed line represents the confidence interval with a significance level of *alpha* = 5%. No significant frequencies or autocorrelations occur. In the next step, the identical ANN method is used to forecast the RTP group without the price signal as an input variable (see Fig. 3). In Table III, the correlation coefficients r_{yx} between $p[k]$ and $e_2[k]$ and $p[k]$ and $y_R[k]$, respectively, is calculated.

TABLE III. CORRELATION COEFFICIENTS FOR CASE STUDY 1

Correlation coefficient r_{xy} to the price signal $p[k]$	Affected load component $y_R[k]$	Forecast error $e_2[k]$
	-0,66	-0,59

The negative correlation coefficients, shown in Table III, are obtained by the inverse proportional relationship between a price change and load change (price elasticity). In Fig. 5, the correlation coefficients are presented for separate time intervals for the time of day. The varying correlation coefficients for the time intervals of a day can be explained by the time dependent price elasticity.

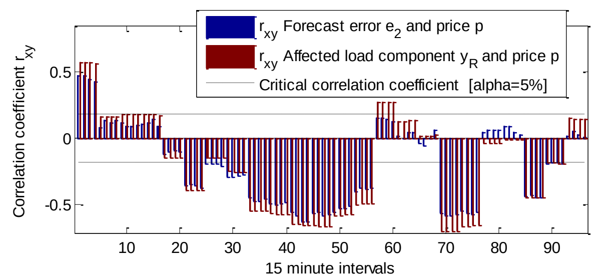

Figure 5. Correlation coefficient r_{xy} of forecast error $e_2[k]$ and price signal $p[k]$ depending on time of day for Case Study 1

The day time dependent correlations between the forecast error $e_2[k]$ and the price signal $p[k]$ conform to the correlations between the affected load component $y_R[k]$ and the price signal $p[k]$. The average daily curves of $e_2[k]$ and $y_R[k]$ are shown in Fig. 6 with a nearly exact approximation. The influencing price signal is shown as the green line.

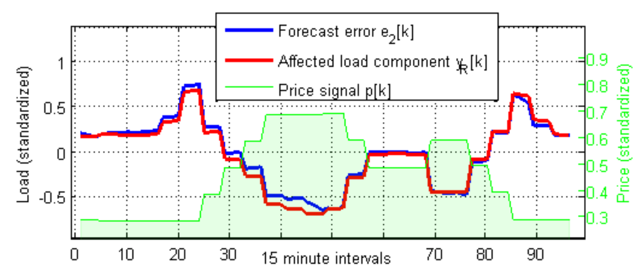

Figure 6. Comparing affected load component $y_R[k]$ and residuals/ forecast error $e_2[k]$ for Case Study 1 (average daily curves)

By confirming the assumption of an optimal forecast and executing the proceeding according to Fig. 3, the functional relationship between price signal and load change can be transmitted to the error signal. The error signal extensively corresponds to the affected load component only superimposed with a random variance. Thus in Case Study 1, the performance of the postulated proceeding could be demonstrated under controlled conditions based on synthetic data.

B. *Case Study 2: real smart meter data*

For Case Study 2, the postulated proceeding (Fig. 2 and Fig. 3) is executed again and the OPP dataset are used for the investigation. An ANN method was used to forecast the consumption behaviour of the FIXED group with a constant tariff and a forecast horizon of 24 hours. The forecast error $e_1[k]$ is tested for white noise. The result of the periodogram test (*alpha*=5%) did not confirm that the forecast error corresponds to white noise. The partial autocorrelation function of $e_1[k]$ (Fig.7) shows that the used forecast method does not generate a forecast with a resulting ideal white noise error signal. The error signal is auto-correlated and a marginal day frequency is present. One reason for the non-optimal forecast is the non-optimal modelling of the input-output relationship by the used ANN method. Another reason is the imperfect knowledge of all systematic factors in terms of building the forecast model. Potential exogenous factors, which influence the behaviour of the OPP dataset, are not available for the investigation in this paper. Furthermore, potential influences caused by specific calendar days are not known either. Additional investigations aimed to enhance the model quality, e.g. by introducing an error model to map the autoregressive error properties of $e_1[k]$, are planned.

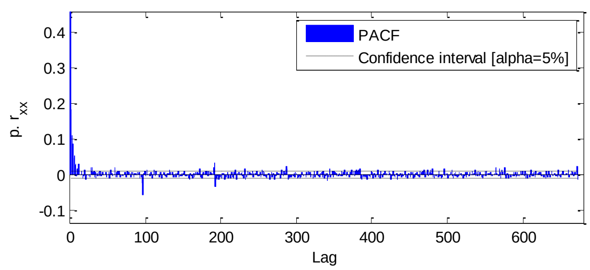

Figure 7. Partial autocorrelation function of the forecast error $e_1[k]$ and confidence interval and a lag up to one week (672 samples by a sampling interval of 15 minutes) for Case Study 2

The previously utilized ANN method is used to forecast the RTP and TOU group without the price signal as an input variable (see Fig. 3). The real affected load component $y_R[k]$ is no measurable time series and not available for the OPP dataset. To substitute the real affected load component, the difference of the consumption time series of the FIXED and the RTP group is used ($y_{R,RTP}[k] = y_{FIXED}[k] - y_{RTP}[k]$ and $y_{R,TOU}[k] = y_{FIXED}[k] - y_{TOU}[k]$). The substituted affected load component $y_R[k]$ is used as benchmark. Note that the difference between the FIXED and RTP group and FIXED and TOU group, respectively, does not have to be a result of variable tariffs outright. Principled differences of the consumer groups in terms of consumption behaviour (independent to the price changes) cannot be excluded. So the substituted affected load component $y_R[k]$ does not have to represent the real consumer response to price changes. Table IV includes the calculated correlation coefficients.

TABLE IV. CORRELATION COEFFICIENTS FOR CASE STUDY 2

Correlation coefficient r_{xy} to the price signal $p[k]$	$y_{R,RTP}[k]$ (FIXED – RTP)	$y_{R,TOU}[k]$ (FIXED – TOU)	Forecast error $e_2[k]$
	0,09	-0,18	0,07

A significant correlation between the forecast error $e_2[k]$ and substituted affected load component $y_R[k]$ to the price signal $p[k]$ cannot be demonstrated. In Fig. 8, the correlation coefficients are presented for separate time intervals of the time of day for the RTP group. Correlation coefficients of separate time intervals cannot be calculated for the TOU tariff because fluctuating prices for the same time intervals do not exist. Significant correlation can be determined for several time intervals of the RTP group. But there are striking disagreements for several time intervals which can be a result of fundamental differences in the consumer groups or the non-optimal forecast model.

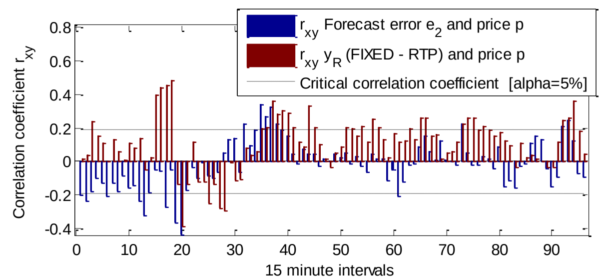

Figure 8. Correlation coefficient r_{xy} of forecast error $e[k]$ and price signal $p[k]$ depending on time of day for Case Study 2

Figs. 9 and 10 present the average daily curves of the forecast error $e_2[k]$ and the substituted affected load component $y_R[k]$. The difference of the curves shown in Figs. 9 and 10 arise from the error of the non-optimal forecast model and from the different consumption behaviour of the consumer groups. The curves of $e_2[k]$ and $y_R[k]$ have similar patterns in each case. However, it is striking that the correlation (Table IV and Fig. 8) between the substituted affected load component and the price signal has a positive sign and thus positive price elasticity is present for RTP group. This generally an increasing price leads to an increasing load. Besides a market mechanism that leads to high tariffs in peak demand times, a possible reason is that RTP tariffs (without lead time for the consumers) do not lead to the desired load shifting responses with OPP dataset in either case [21]. This would also explain the marginal correlations in Table IV. For the TOU group, a negative correlation is present so that increasing price leads to a decreasing load. A reason for the offset between $e_2[k]$ and $y_R[k]$ in Fig. 10 is a difference in energy consumption detected between the FIXED and the TOU groups. Even if the assumption of optimal forecast cannot be confirmed, it is possible, that the postulated proceeding still performs a realistic approximation of the affected load component based on the forecast error. However, the following aspects should be noted:

- The uncertainty resulting from the non-optimal forecast increases the uncertainty in the results.
- By transmitting the relationship between price and load change to the error signal, the characteristics of the uncertainty resulting from the non-optimal forecast, is also transmitted to the error signal.
- For an exact validation of the results, the OPP dataset are unsuitable because of systematic differences between the consumption behaviour and characteristics of the tariff groups.

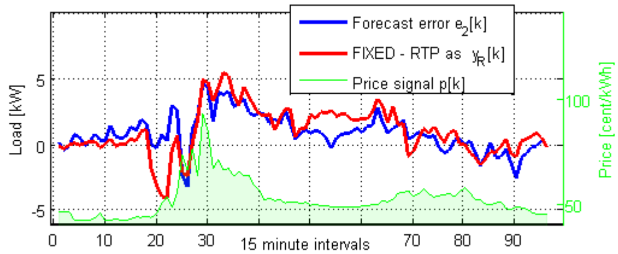

Figure 9. Comparing affected load component $y_{R,RTP}[k]$ and residuals/ forecast error $e_2[k]$ for Case Study 2 (RTP) (average daily curves)

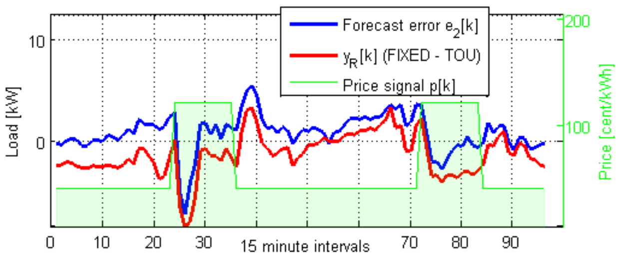

Figure 10. Comparing affected load component $y_{R,TOU}[k]$ and residuals/ forecast error $e_2[k]$ for Case Study 2 (TOU) (average daily curves)

VI. Summary and Outlook

By influencing the demand side by price signals the forecast error for load forecasting and thus the uncertainty increases. In this paper, investigations with established forecast methods (based on real smart meter data from two field studies) demonstrate the increasing uncertainty which amounts 14,61% up to 39,3% in comparison to consumption with a constant tariff. Furthermore, the requirements for load forecasting methods regarding price elastic consumption behaviour are summarized. In this context, the forecast of the unaffected load component of the price elastic consumption is discussed as a necessary asset for further planning. By confirming the assumption of an optimal forecast, the functional relationship between price signal and load change can be transmitted to the error signal. In this case, the error signal provides an exact approximation to the affected load component only perturbed with a random variance. In the present paper, a Case Study based on synthetic data demonstrates the performance of the postulated proceeding. In Case Study 2, real smart meter data are used for the investigations. The used dataset is however not completely suitable for the carried out investigations. The careful selection of the consumer groups in terms of smart meter data is required to prevent systematic errors. Further investigations are needed to enhance the model quality to confirm the assumption of an optimal forecast.

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References

[1] M.H. Albadi, E.F. El-Saadany: "A summary of demand response in electricity markets", *Electric Power Systems Research* vol. 78, pp. 1989-1996, 2008.

[2] J. Aghaei, M.-I. Alizadeh: "Demand response in smart electricity grids equipped with renewable energy sources: A review", *Renewable and Sustainable Energy Reviews* Vol. 18, February 2013, Pages 64–72, 2013.

[3] D. Hammerstrom, R. Ambrosio, J. Brous, T. Carlon, D. Chassin, J. DeSteese, R. Guttromson, G. Horst, O. Jarvegren, R. Kajfasz, et al., "Pacific Northwest GridWise Testbed Demonstration Projects. Part I. Olympic Peninsula Project," Tech. Rep., 2007.

[4] S. Klaiber, P. Bretschneider, S. Waczowicz, R. Mikut, I. Konotop, D. Westermann: „Intelligente Prognoseverfahren für beeinflusstes Verbrauchsverhalten in Energiesystemen". *23. Workshop Computational Intelligence*, Dortmund, 2013.

[5] R. Schlittgen, B. Streitberg, „*Zeitreihenanalyse*" 9th ed.: Oldenbourg Wissenschaftsverlag München Wien, 2001.

[6] H. Hahn, S. Meyer-Nieberg, S. Pickl: "Electric load forecasting methods: Tools for decision making", *European Journal of Operational Research*, Vol. 199, No. 3, pp. 902-907, 2009.

[7] L. Suganthi and Anand A. Samuel, " Energy models for demand forecasting-A review," *Renewable and Sustainable Energy Reviews*, vol. 16, pp. 1223-1240, 2012.

[8] M. A. Hamid und T. A. Rahman, „Short Term Load Forecasting Using an Artificial Neural Network Trained by Artificial Immune System Learning Algorithm," *IEEE 12th International Conference on Computer Modelling and Simulation*, 2010, pp. 408-413.

[9] C. Guan, P. B. Luh, L. D. Michel, Y. Wang und P. B. Friedland, „Very Short-Term Load Forecasting: Wavelet Neural Networks With Data Pre-Filtering," *IEEE Transactions on Power Systems*, p. 1, 2012.

[10] P. Braspenning, F. Thuijsman, A. Weijters: *„Artificial Neural Networks*", Springer-Verlag Berlin Heidelberg, 1995.

[11] D. Pham, X. Liu, "*Neural Networks for Identification, Prediction and Control*" Springer-Verlag London, 1995.

[12] O. Warweg, A. Arnoldt, C. Troitzsch, S. Frenzel, M. Werner, P. Bretschneider, "Analysis of the Effects of Demand Response to the Integration of Renewable Energy into the Distribution Grid" *International Workshop on Integration of Solar Power into Power Systems*, Langen, Energynautics, pp.181-186, 2011.

[13] A. Abdollahi, M.P. Moghaddam, M. Rashidinejad, M.K. Sheikh-El-Eslami: "Investigation of Economic and Environmental-Driven Demand Response Measures Incorporating UC", *IEEE Transactions on Smart Grid*, Vol. 3 No. 1, 2012.

[14] M.A. Bernstein; J. Griffin: "Regional Differences in the Price-Elasticity of Demand for Energy", *National Renewable Energy Laboratory* 2006.

[15] M. Hayn, P. Ringler, M. Ruppert, J. Schmid, V. Bertsch, D. Keles, W. Fichtner: "A residential price elasticity model for agent-based simulation of decentralised energy systems". *E-World energy & water* 2014.

[16] T. Holtschneider, I. Erlich: "Modeling demand response of consumers to incentives using fuzzy systems". *IEEE power and energy society general meeting - conversion and delivery of electrical energy in the 21th century*, 2012.

[17] S. Pflugradt, A. Arnoldt, O. Warweg, P. Bretschneider: „Customer behavior model for load adjustment and tariff forming", *International Workshop on Integration of Solar Power into Power Systems*. 2013.

[18] S. Waczowicz, R. Mikut, S. Klaiber, P. Bretschneider, I. Konotop, D. Westermann: „Virtuelle Speicher als adaptierbare Verbrauchermodelle zur Lastprognose und Betriebsführung in Verteilnetzen", *23. Workshop Computational Intelligence*, Dortmund, 2013.

[19] O. Corradi, H. Ochsenfeld, H. Madsen, P. Pinson: "Controlling Electricity Consumption by Forecasting its Response to Varying Prices", *IEEE Transactions on Power Systems.* Vol. 28, Iss. 1, 2013.

[20] Q. Wang, J. Wang, Y. Guan: "Stochastic Unit Commitment With Uncertain Demand Response", *IEEE Transaction on Power Systems*, Vol. 28 No. 1, 2013.

[21] J.D. Jobson.: „*Applied Multivariate Data Analysis*", Vol. 1, Springer Verlag, pp.290-302, 1991.

[22] J. Wernstedt : „*Experimentelle Prozessanalyse*", VEB Verlag Technik, Berlin 1989.

[23] S. Waczowicz, S. Klaiber, P. Bretschneider, I. Konotop, D. Westermann, M. Reischl, R. Mikut: „Data mining to analyse the effects of price signals on household electricity customers", *at – Automatisierungstechnik*, Vol. 62, No. 10, pp. 740–752, 2014.