STATE FORECASTING IN SMART DISTRIBUTION GRIDS: A MODULAR APPROACH USING CARMA-ALGORITHM

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ABSTRACT

As an initial paper of the author's research and development results on grid state forecasting, a structural and algorithmic approach with a practical scope of application is proposed. The focus is on a modular bottom-up concept and a smart time series analysis for implementation purposes on a decentralized autarkic grid automation system.

INTRODUCTION

Distribution system operators (DSO) are facing substantial changes in the power supply infrastructure. The increasing amount of renewable energies, which is driven by politics and technical progresses, leads to technical challenges concerning the power supply quality. Changing load and infeed scenarios stress the electrical equipment by load flow situations, which it has never been designated for. The conventional supply structure anticipated a unidirectional power flow from the high voltage (HV) levels in the transmission system over the medium and down to the low voltage (MV, LV) grids in the distribution system for a long time. The ongoing changes already lead to partially inverted power flows with massive impacts on the voltage quality and capacity utilisation, which is especially critical at grid connection points that are powering consumers. DSOs are responsible to handle those highly fluctuating and bidirectional power flow situations by providing the given power quality standards. [1]

Approaches to Cope with the Ongoing Changes

As an economical alternative to the very cost-intensive grid enhancement, smart grid systems represent an innovative solution [2], [3]. Within several research and development projects on smart grid systems, the authors have developed marketable solutions for advanced monitoring and control purposes in distribution networks [4], [5]. Currently the authors are aiming for the development of an integrated and coordinated smart grid system with enhanced operational functions, such as Grid State Forecasting (GSF) as a supportive component [6].

Motivation for State Forecasting in Smart Grids

State prediction is an elementary component of future systems enabling *smart energy markets*, providing an advanced transparency to the DSO and allowing to initiate "one step ahead" grid interactions [7]. Preventive grid operation is necessary to avoid improper grid states (voltage range violations or overloads), caused by decentral power integration. While existing smart grid systems are capable of reacting to an already occurred violation only, the prevision of critical situations ensures a higher power quality in distribution systems with more flexibility concerning the strategical options. [4] The choice of suitable actuators for most efficient and economic control purposes will get more flexibility, since even plants with a higher reaction time can be involved – by manual interventions (DSO) or autarkic operation (automation system).
Besides the advantages in active grid operation, future energy markets will benefit from forecasting systems, as soon as they provide information about grid capacities in advance. This information represents a key component in the development of regional smart markets. In this way, it is presumable that future systems will most likely be able to involve demand side management as an autarkic actuator for power quality purposes, coupling the market with the smart grid unit.

The following chapters will present the modular structural design as a basis of the overall concept with a focus on the load forecast module, realized by a novel algorithm.

BASIC CONDITIONS AND USE CASE

Based on preliminary works, there is a software and hardware architecture given, which defines certain framework conditions and restrictions for the algorithm. As a modular implementation, the forecast algorithm is assumed to run cycle based on a smart remote terminal unit (smart RTU), where several security aspects are limiting the system's capabilities. So, due to the overall system quality and stability, various requirements and demands need to be complied by the design and realization of the GSF:

Stability. The calculation should converge in all cases and oscillation (caused by transient effects, for example) may not occur. It should be always in a defined state.

Robustness. On-line parameter changes (as by expansion of facilities) or fluctuations in the analysed time series should not significantly affect the calculation.

Adaptivity. The dependence on individual parameters for each time series should be minimized to provide a high compatibility without huge effort. The system should be universally applicable with an automated and fast learning process.

Quality. The calculation results need to satisfy a sufficiently high quality for reliable information.

Performance. High efficiency concerning resource requirements (database and runtime) must be given, due to memory and processor limitations and a predefined input data set.

Compared to the application in a simulation environment, the challenging point here is to fulfil all of those requirements simultaneously as far as possible under real conditions. A comprising methodology is needed to reach a sufficiently high precision while strictly avoiding high calculation or parameterisation effort and big data.

SYSTEM ARCHITECTURE

Figure 1 schematically shows the scope of application and the role of the GSF implementation in the decentralized autarkic automation unit, which is located in the HV/MV transformer station. Supported by a communication infrastructure based on IEC 60870-5-104 protocol, the unit is provided with continuous measurements in the monitored grid area and capable of sending commands to actuators (variable transformers, controllable loads or feeders). Just approximately 15 % of all nodes need to be measured for sophisticating results in the state estimation by network partitioning or sensitivity analysis [8]. Together with a parameter set, containing static information on the grid (branches, feeders and topology), the cyclical updated measurement builds up the input data base for the forecast algorithm.

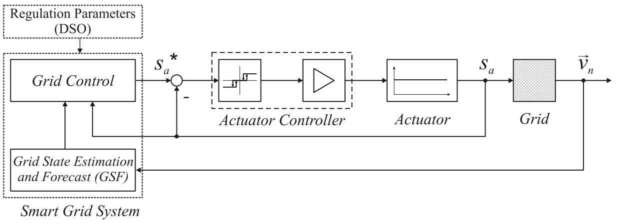

Figure 1: System structure and assignment of the GSF in a decentral Smart Grid System

Quantity of the Time Series Analysis

The smart grid system's main focus remains on the detection of state violations and supporting control operation. Therefore, the grid's nodal voltages and branch currents are the primary quantities in the following examinations. Basically, it is suitable to consider these quantities to be forecasted directly. Thus, the power flow has been chosen as time series for the proposed algorithm as a bottom-up approach for an indirect grid state prediction.
The first important reason for this is a high rate of modularity and flexibility. The consumed power at a substation is independent of other grid elements unlike the voltages for instance that are depending on the overall power flow situation. Therefore, it needs less calculation effort to apply external factors on the time series which can be a big advantage as far as sophisticated real-time inputs are available. New loads and feeders can be directly considered in the power prediction and additionally, time schedules of controllable loads (flexibilities) can be easily integrated. In case of a direct voltage prediction based on historic data, the correlation between the consumption changes and the grid state requires more effort to be determined. It takes less effort to quantify the weather's direct influence on the generated power than on the nodal voltages, for example.
The second important reason for the indirect approach is the relation between the nodal power flow and the nodal voltages. Figure 2 demonstrates the results of an exemplary power flow calculation (Newton-Raphson) in two scenarios. The grid consists of seven consumer nodes with branch parameters (impedance, length) extracted from an anonymised geographical information system (GIS) data set. As reference, a strongly load dominated power flow scenario has been chosen. In a second case, the real power consumption at node 6 P_6 is reduced by 50% while the reactive power remains the same as in the reference scenario.

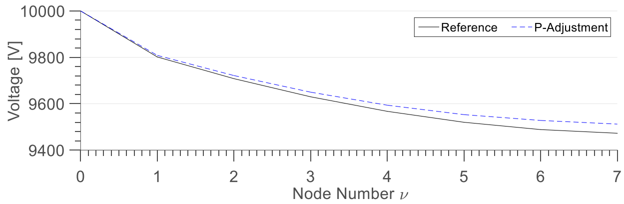

Figure 2: Impact of selective power changes on the grid state (sensitivity)

Table 1 shows the relative voltage changes as a result of the load modification. It is noticeable that the load modification of $\Delta P_6 = -50\%$ only leads to a relative voltage change of $\Delta U_6 = 0.42\%$. The fact, that power fluctuations have only a weak impact on the voltage level, is reasoned by the sensitivity relation which depends on the topology and line parameters [9]. Yet it provides a huge advantage because, considering the relation $\Delta U_\nu \ll \Delta S_\nu$, a greater error tolerance can be accepted in the power forecast to still obtain a high precision in the primary quantities.

Table 1: Relative changes of voltage and current after power reduction

Node ν	1	2	3	4	5	6	7
ΔP_ν [%]	*0*	*0*	*0*	*0*	*0*	*-50*	*0*
ΔS_ν [%]	*0*	*0*	*0*	*0*	*0*	*-36.75*	*0*
ΔU_ν [%]	*0.07*	*0.14*	*0.21*	*0.28*	*0.35*	*0.42*	*0.42*
$\Delta I_{\nu\mu}$ [%]	*-6.06*	*-7.03*	*-8.36*	*-10.35*	*-13.55*	*-19.99*	*-0.41*

Modular Approach of the GSF Module

The bottom-up approach allows to create a generic, expandable and specifically optimisable model for real-time grid state forecasts.
Figure 3 presents its schematic structure. Coordinated by a central monitoring component, there are two modules intended for time series analysis, which in this case is destined for a separated handling of loads and feeders. This structure makes the implementation more flexible since different parameters can be set or different algorithms can be implemented, each optimised for a specific kind of time series. The instantaneous power values as a measured real-time input data are allocated by the monitoring module and processed by the algorithms, whose output data is a time series for each value. This output represents a power forecast for a specified time in the future, up to 24 hours. All calculations are based on a slim database and can be either monitored themselves or run through a state estimation, which delivers a forecast of the entire grid state, including all measured and unmeasured nodal voltages and branch currents.

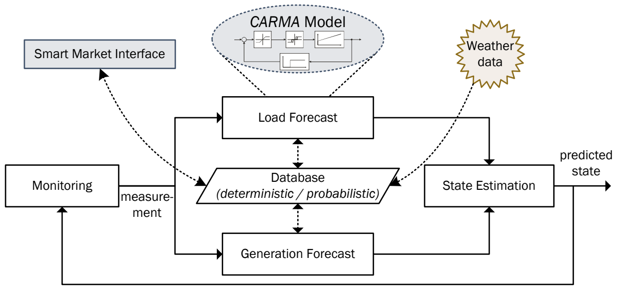

Figure 3: Modular bottom-up approach of the GSF structure

Considering the external data interface, it is also provided to use weather data, external power generation forecasts (solar or wind) or market based information as real-time input to achieve a higher precision. For these purposes, a separation in a *deterministic* and a *probabilistic* component is intended. Timetables, provided by market actions and external power forecasts, will be assumed as a deterministic component, while the probabilistic component is calculated by the internal algorithms.

CARMA MODEL FOR LOAD FORECASTING

In the first step towards the predictive state estimation and as a central component of the GSF algorithm the authors developed a short-time load forecasting method, the Controlled Autoregressive Moving Average model (CARMA). The choice of the right methodology is strongly affected by the given system conditions and the defined use case. Models for time series analysis usually imply increased complexity concerning parameterisation and calculation effort with a growing desired precision. Simple methods provide a forecast consisting for example of the last day or last week data with a minimal effort. This provides a high adaptivity, though the results are very static and can lead to relatively high errors. Moreover, it is necessary to save a high amount of preceding data, especially when considering specifically classified day-types for example. In several studies artificial neural networks are the method of choice. They provide a very high quality with the possibility of training the algorithm for different time series, yet for small deviations a very particularised database is needed. Autoregressive Moving Average (ARMA) models represent an adaptable method that has been modified and optimised over time. Seasonal Autoregressive Integrated Moving Average (SARIMA) or Autoregressive Integrated Moving Average with exogenous influence (ARIMAX) are often applied on forecasts of generated power for example. [10], [11] In the described research project, an alternative modification has been designed.

In contrast to the conventional ARMA model, the modification is slightly simplified, basing on a weighted moving average method. The available cyclic input is described by a data vector $\vec{u}$, containing the nodal measurements of a reduced set of n sensors installed in a x-node distribution grid ($n < x$). Depending on the resolution of the forecast, a step width between two values Δt_m (in minutes) needs to be defined. The 24-hour-prediction then contains $\tau = \frac{1440}{\Delta t_m}$ values ($\tau = 288$, considering a 5-minute resolution for example). It is remarkable, that a conversion from the real time step of a day t_m (in continuous minutes from 1 to 1440) to the specific cycle time is necessary for a correct assignment of values regarding the resolution. In the following, the time variable t is assumed to be the related time step after converting the continuous time t_m by

$$t = \frac{(t_m - 1) - [(t_m - 1) \bmod \Delta t_m]}{\Delta t_m} + 1, \qquad t_m \in [1{,}1440]$$

Each analysed time series is being allocated to a specific database, consisting of a vector $\overrightarrow{y_v}$ with the length of one day's number of time steps τ.

$$\vec{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix}, \qquad \overrightarrow{y_v} = \begin{bmatrix} y_{v,1} \\ y_{v,2} \\ \vdots \\ y_{v,\tau} \end{bmatrix}, \qquad v \in [1, n]$$

The entire database can be expressed as a $n \times \tau$-matrix $\boldsymbol{D}$ where the elements $y_{v,i}(t)$ represent the predicted value for time step i at node v, as an output at time t.

$$\boldsymbol{D} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,\tau} \\ \vdots & \ddots & \vdots \\ y_{n,1} & \cdots & y_{n,\tau} \end{bmatrix}$$

During the initialisation in the first τ cycles, the measurement is adopted by the database. After this period, it is updated in each cycle, calculating a weighted average value of the actual measurement $u_v(t)$ and the related database element $y_{v,t}$ by exponential smoothing.

$$y_{v,t}(t) = \alpha_y \cdot u_v(t) + (1 - \alpha_y) \cdot y_{v,t}(t-1)$$

Obviously, the database directly contains the real-time forecast for the next 24 hours. As output function, the array elements just need to be shifted, starting at $y_{v,t+1}$ to receive the predicted values beginning at the following time step.

$$y_v{}'(t) = \begin{bmatrix} y_{v,t+1} \\ y_{v,t+2} \\ \vdots \\ y_{v,t} \end{bmatrix}$$

The proposed method reasonably provides a higher precision with more periodic inputs as they can be considered in large and load dominated low voltage networks with a consumption close to the standard load profile. Therefore, it is more efficient to use measurements of MV/LV substations rather than branch measurements in a MV grid.

For an increased and dynamic adaptivity, an ex post error analysis has been integrated in the calculation model for an on-line evaluation of the results. In each time step, an exponential smoothing of the forecasted value's residual deviation $\bar{e}_v(t)$ provides a real-time quality validation.

$$\bar{e}_v(t) = \alpha_e \cdot \frac{y_{v,t}(t) - u_v(t)}{u_v(t)} + (1 - \alpha_e) \cdot \bar{e}_v(t-1)$$

This estimation leads to a valuation, using $|\bar{e}_v| > \epsilon$ as criterion for the necessity of a recalibration. In case of fulfilling this condition, a dynamic ex ante error compensation is triggered. The adjustment vector $\vec{c}_v$ contains τ elements, resulting in a straight falling line with an amplification factor k_c and adjustment horizon t_h (see Figure 4).

$$c_{v,i}(t) = \begin{cases} k_c\, \bar{e}_v(t) \cdot \left(1 + \frac{1-i}{t_h - 1}\right), & 1 \le i \le t_h \\ 0, & otherwise \end{cases},$$

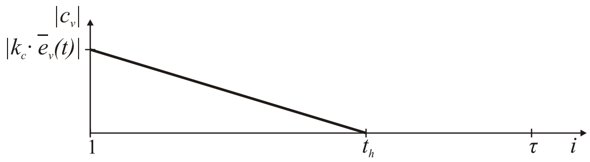

Figure 4: Adjustment function for dynamic error compensation

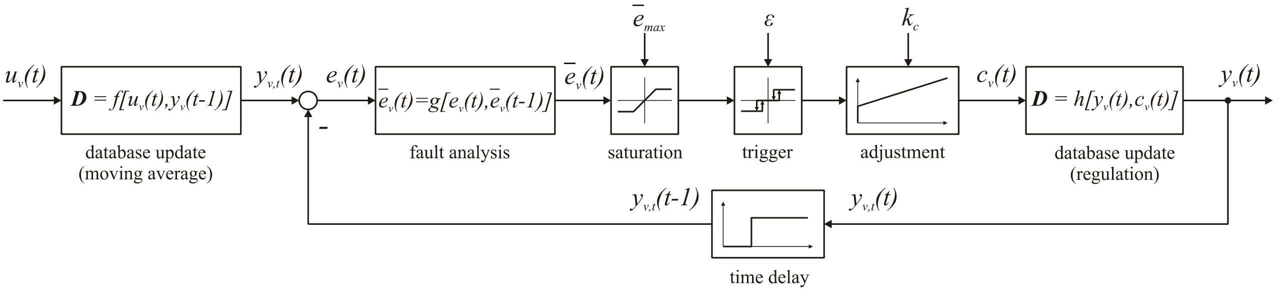

Figure 5: Schematic structure of the proposed CARMA model

A saturation of the fault analysis result by $|\bar{e}_v| < \bar{e}_{max}$ provides a damped regulation of occurring transient high deviations and prevents the outputs from oscillation. The multiplication of this curve with the actual specific nodal database represents the new adjusted database. Again, as in the generation of the output, the vector element's shift must be regarded.

$$y_{v,i}(t+1) = \begin{cases} c_{v,i-t} \cdot y_{v,i}(t), & t < i \le \tau \\ c_{v,\tau-t+i} \cdot y_{v,i}(t), & 1 \le i \le t \end{cases}$$

In sum, the methodology is simply based on historic measured data (autoregressive), while the memory usage is optimised as the database simultaneously represents the output. The fact that in medium voltage levels power consumption at most of the nodes can be assumed to be nearly periodic over the days, allows to use an efficient exponential smoothing method that is improved by a weighted error analysis. The overall constellation of all components behaves like a closed loop control of the calculated time series, as it is illustrated in Figure 5.

SIMULATION RESULTS

For testing and validation purposes, the load forecasting model has been programmed in MATLAB and analyzed in different specific simulation environments.

Load Forecast

In the first step, the pure behaviour of the CARMA model is evaluated on a nodal load curve as time series over 25 days. An exemplary daily curve with the related forecast in steady state is depicted in Figure 6. Setting the parameters to $\Delta t_m = 5, \alpha_y = 0.5,\ \alpha_e = 0.6,\ k_c = 0.3,\ t_h = 50,$ $\epsilon = 0.2$, the mean absolute percentage error (MAPE) over all forecasted values rapidly drops from 100 to below 20 percent during the first 1.5 days (see Figure 7).

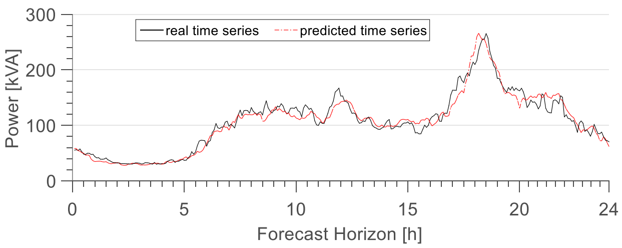

Figure 6: Load curve and CARMA forecast for one exemplary day

In its following progression, a weekly periodic increase is noticeable, which is reasoned by changed load situations on weekends. The dynamic error compensation's effect can be observed in the calculation's precision curve over the forecast horizon. Figure 8 shows the daily mean errors of four different days, evaluated in relation to the prediction horizon. A remarkable improvement in the short term forecast, evolving through the adjustment horizon is apparent. Indeed, the intensity of this effect, as well as of the qualitative outliers (as a reaction to differing load situations), depends on the choice of parameters. They can be adjusted and optimized according to the field of application.

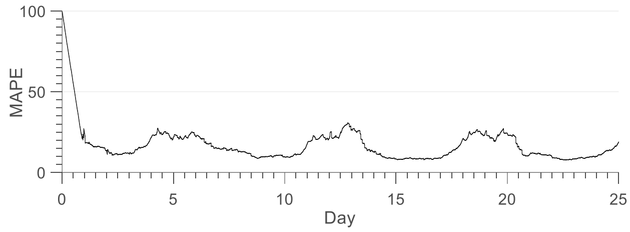

Figure 7: Evolution of the MAPE over 25 simulated days

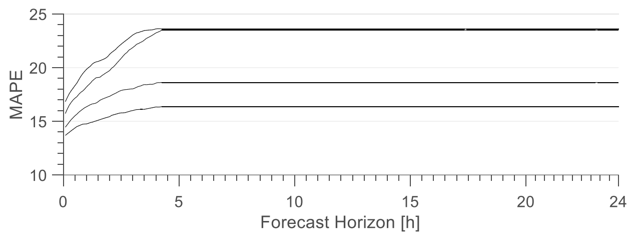

Figure 8: MAPE of the power forecast related to the forecast horizon on 4 random days

State Forecast

Initial simulative tests of the implementation in combination with the smart grid monitoring unit have been applied on a grid model, equating a real medium voltage grid that consists of 104 nodes and 105 branches. 23 measurements were determined to be installed for the state estimation by network partitioning [8]. Only the apparent powers at measured points are considered as forecasted quantities, while there is no differentiation either it is a branch or feeder measurement. Also, the same CARMA parameters are used for each time series, no matter if it is a load or feed-in connection point, which of course is strongly optimizable in practical applications. Including a Newton-Raphson power flow calculation in the state estimation, based on the estimated values, 30 days in 1 minute resolution were simulated in an environment, which was specifically developed for smart grid system evaluation purposes. According to $\Delta t_m = 1$ a shorter absolute adjustment horizon results in this case.

Figure 9 and Figure 10 represent the resulting MAPE in relation to the forecast horizon of the calculated grid state, basing on all forecasted values over a number of measured and unmeasured nodes. It is remarkable that these results represent calculations of an underestimated system, including the plain estimation error. For comparison, in case of an estimation by actual measurements (neglecting errors caused by the forecast), the average absolute deviations amount approximately 0.5V (max 0.41%) and 1A (max 18.1%).

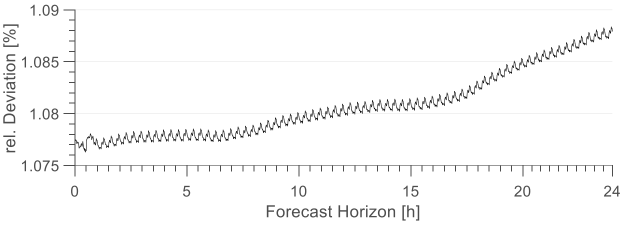

Figure 9: Relative deviation of the predicted voltage related to the forecast horizon (including state estimation error)

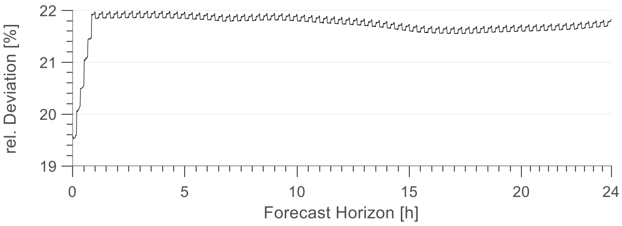

Figure 10: Relative deviation of the predicted branch currents related to the forecast horizon (including state estimation error)

CONCLUSION

The forecast algorithm as an outcome is a useful solution to detect critical grid states in advance, enabling more preventive grid interactions. Generally, this information can be integrated in SCADA systems for monitoring and manual operation purposes or - in smart distribution grids - be used for autonomous control processes. Even though research and development work on this topic is still proceeding, the presented outcome provides a practicable solution that could already be implemented in its current status.
In the next steps, the overall GSF system will be evolved successively in a modular manner. The state estimation, as it was used for analytic purposes in this paper, will be replaced by a more innovative and efficient algorithm to reduce the calculation effort. Additionally, the proposed method provides a data base to determine "free" grid capacities in advance – the knowledge of short-time future capacities turns the system into a *smart market enabler*. First practical results are expected from a forthcoming intensive field testing phase in a real distribution grid.

Acknowledgments

The presented work in this publication is based on research activities, supported by the Federal Ministry for Economic Affairs and Energy. The described topics are included in the project *"Grid Commander"*.

Supported by:

STROMNETZE
Forschungsinitiative der Bundesregierung

Federal Ministry for Economic Affairs and Energy

on the basis of a decision by the German Bundestag

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