APPLICATION OF TIME-RESOLVED INPUT DATA FOR SMART GRID SIMULATION

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ABSTRACT

Grid control algorithms need to be tested in a simulation before adapting to the real network operation. Typical simulation techniques are load flow-based. Thus, an appropriate network model and realistic input data are needed. Varying feed-in and load data may lead to considerably differing loading scenarios. The quality and plausibility of data is therefore highly important.
Usually distribution system operators don't possess time-resolved data for all grid elements. This makes a realistic simulation of large networks complicated. Standard load profiles and historical data may be used.
One alternative possibility for generating time resolved behaviour of all network participants is an agent-based approach. In the project Agent.GridPlan[1] a multi-agent system for distribution network planning is being developed. The system provides active and reactive power time series based on weather data and individual parameters of loads and generators. Using this simulation technique a forecast-based network reconfiguration algorithm is tested in the scope of a one-year-simulation.

INTRODUCTION

The increasing integration of distributed renewable energy sources (RES) into the distribution grid level leads to a more volatile power flow and thus fluctuating nodal voltages and higher loading of network branches. Hence, a necessity for new operational control concepts to be considered in the planning process evolves. Network control allows for keeping the network state in a permissible range and optimising the operation. Therefore, the necessary sophisticated control algorithm simulations require time-resolved input data like nodal active and reactive power time series.

In the collaborative demonstration project Grid4EU [1] TU Dortmund University and Westnetz developed a multi-module control system which rearranges the power flow by means of the network topology reconfiguration. In this manner grid voltages and currents can be controlled to avoid violations of operational limits. Further, the system also enables the reduction of active power losses. The principle is based on adopting the network topology during the course of the day according to the forecasts of the network's loading state.

This paper highlights the difference between two data generation approaches and their impact to the results of the Grid4EU control system simulation. The paper's overall concept is depicted in Figure 1.

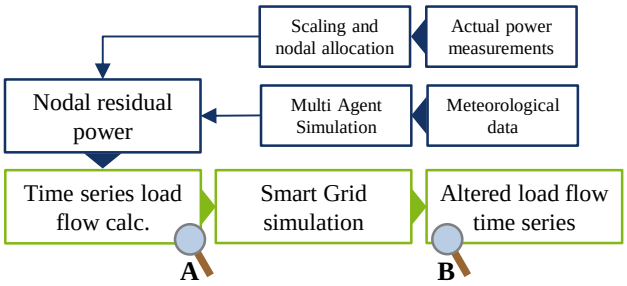

Figure 1: Overall examination concept

Two input data generation methods are considered to provide nodal residual power time series:

- **S**caled **T**ime series (ST) approach involves few real power measurements for different types of RES. These curves are normalized and scaled regarding to the installed capacity.
- **M**ulti-**A**gent **S**imulation (MAS) based approach offers individual generation and load curves. These are generated during a MAS which requires weather data and specific load and RES parameters.

The first examination A evaluates the differences induced by the different input data. The load flow results are processed further to the Grid4EU control system simulation. Here, different input data would lead to different control behaviour. During the simulation network topology is altered for loss reduction. Finally the load flow results are analysed in examination B and are compared with the results from uncontrolled grid operation in examination A.

1 The project "Agent.GridPlan" (agent-gridplan.net) is funded by the European fund for regional development

DESCRIPTION OF INPUT DATA SOURCES

Electrical network under testing

For the examinations of this paper part of a real medium voltage (MV) grid of Reken, a city situated in western Germany, is provided by Westnetz. It is the same network used in Grid4EU project [1], as of March 2016.
The considered MV grid includes an intermeshed loop, which is operated in radial mode, so that in practice three feeders do exist (see Figure 2). It covers around 7.1 MW load and has an installed RES capacity of 10.8 MW. Because of the high share of RES, the grid's compliance with common voltage limits is challenging, especially in future scenarios.

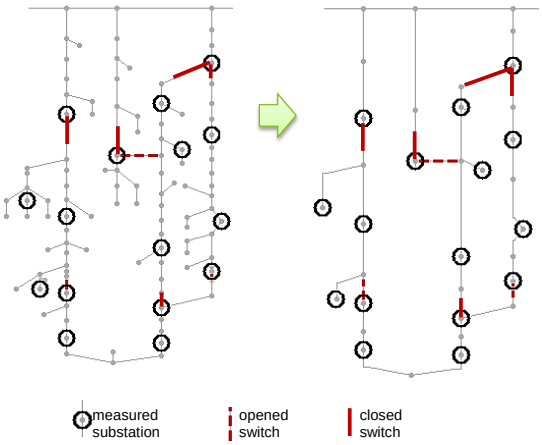

Figure 2: Grid4EU network and its reduced equivalent [5]

In order to provide a certain degree of comparability, for both data generation methods data from the same geographical region have been gathered. For the ST approach RES feed-in measurements are used. In contrast, the MAS requires weather data records. All RES units are modelled with $cos\varphi = 1$, hence, their reactive power contribution is zero. Loads are assumed to have the power factor of $cos\varphi = 0.9$. The primary substation is modelled as a slack bus with the constant voltage of 10.3 kV.

Scenarios for future grid loading

For both input data generation approaches two scenarios are used. The base case scenario refers to the situation in 2016 and in the future scenario the RES development in 2035 is considered.

The assumed forecast of energy conversion systems has already been published in [1]. Due to the fact, that the given installed capacity is of 2016, the forecast data was adopted and extrapolated, as shown in Table 1.

Table 1: RES development forecast for the test grid area [1]

Year	PV	WG	CHP
2016	1.000	1.000	1.000
2035	1.552	1.170	0.235

In order to achieve a more realistic constellation of a possible future grid load, today's DGs are not simply scaled up. For photovoltaic (PV) plants it is assumed, that the growth in capacity will allocate in the voltage levels, like today's capacity is distributed (MV: 76.9 %, low voltage (LV) level: 23.1 %). Justified by the small plant size in LV level, the current aggregated models are scaled up. The remaining capacity is built by MV level plants with a nominal power of 250 kW each and only located at category II and III nodes. The wind generation (WG) capacity will only rise marginally, what can be interpreted as repowering of today's older WGs. The decrease in Biomass and combined heat and power (CHP) plants is assumed to take place only in the medium voltage level, whereas at first the smaller plants are getting deconstructed.

Scaled time series approach

A pragmatic way to generate nodal power data is by using historical records or standard load profiles (SLP). Generation and load curves are needed to be scaled to the installed capacity of the corresponding load or generator.

Three different types of generation units are considered for the test grid. CHP units are supposed to provide a constant feed-in. For wind and photovoltaic generation active power records are used. Because of only few wind generators a single wind turbine time series is applied for all units. Photovoltaic generators are subdivided in three power categories (0-42 kW, 42-123 kW and over 123 kW), which are assigned to three associated measurements.

All loads are modelled with the same scaled mixed SLP. This profile takes into account weekly and seasonal variations of the load.

Multi-Agent Simulation

Another possibility to obtain input data for Smart Grid simulations, especially for investigations in the future, is to utilize a simulation framework. In this paper the MAS "SIMONA" is used. It is developed by TU Dortmund University [2]-[3], and under further development as part of Agent.GridPlan, a collaborative project with Westnetz. The multi-agent modelling paradigm allows for detailed bottom up modelling of complex entities, which pursue their own goals and interact with the environment, they are situated in [4]. The SIMONA tool is not only able to convert non-electric data, e.g. weather and economic information, into power feed-in and consumption, but is also able to analyse the system state by time series load flow calculation. Moreover SIMONA assists in evaluating the impact of novel market-oriented approaches.
Although the MAS has more possibilities, in this paper the simulated feed-in of RES and power consumption of loads is utilized. The load flow calculation and later simulation is carried out externally.

Input data for the Multi-Agent Simulation

Unlike with static load flow calculation, a time series based load flow calculation needs a wider input data basis. In consequence the information about network topology and grid participants has to be enhanced. The MAS acquires the RES feed-in with detailed plant models and environmental information, such as solar irradiance. As the required plant parameters are not necessarily known by the distribution system operator (DSO), some assumptions have to be made. For every PV plant random parameters of panel orientation and inverter efficiency are considered. The characteristics of WG are given by exemplary reference WG, whose characteristic curves have to be scaled to fit the nominal power to the WG units situated in the grid. The CHP and biomass plants are modelled with constant power output.

Loads are modelled with an individually mixed SLP characteristic. Because of the missing knowledge about the secondary substations' load composition, the load type can be classified by its location. The assumed categories are listed in Table 2 and adapted to local specificities. The assumed apparent power of the static load flow model is split as specified by the secondary substation's category and used to scale the SLPs, so that it marks the highest power consumption.

As well as the inherent network parameters, the environmental input data has to be prepared. Because there is no economic interaction investigated, the only environmental information used is weather information. These measurements are captured at the primary substation.

Table 2: Categorisation of secondary substations

Cat.	Description	H0	G0	L0
I	Residential	75 %	25 %	0 %
II	Mixed	50 %	25 %	25 %
III	Agricultural	25 %	0 %	75 %
IV	Commercial	25 %	50 %	25 %

Measurements from 2013 in a quarter hourly resolution are utilized here. Due to missing data occurrence and faulty measurement the corrupted data has to be filled up. The missing values are replaced by typical values for the affected time interval. Those are obtained by averaging all given values of the quarter hour over the given month and scaling to fit neighboured time frames.

FORECAST-BASED CONTROL ALGORITHM

The presented control system makes decisions about the change of network's topology based on few measurements from the MV grid. When overvoltages or line overloads occur, a spontaneous reconfiguration takes place. The other reason for the network topology reconfiguration is loss-optimal operation. Based on the residual load forecast, future switching times and corresponding target topologies are obtained as shown in [5]. A simplified control flow is illustrated in Figure 3.

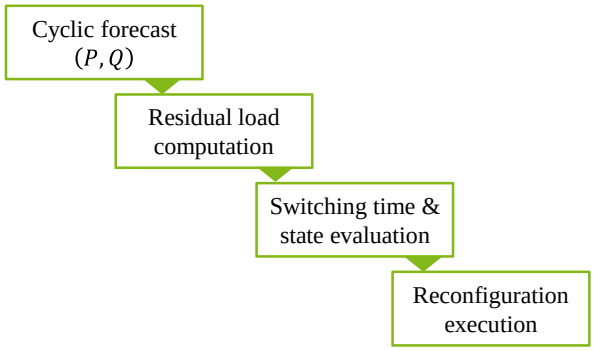

Figure 3: Basic principle of the loss reduction algorithm

Active and reactive nodal power forecast is calculated for every automated secondary substation of the system. The forecast resolution is quarter hourly; it is updated with every new time step. Because of not fully monitored grid forecast values of few secondary substations are mapped onto a reduced network model (see Figure 2). This enables load flow computation for the later optimization. Next, the residual load curve is computed from the sum of the active power forecasts. This curve provides information for possible future switching times. Here inflection points of the residual curve are supposed to be near-optimal times for topology reconfiguration. Target switching state is being evaluated by a heuristic-based method. In case the topology needs to be reconfigured, the target topology state is put on the switching action list. Switching actions are carried out at the scheduled time. With every new 15 minutes interval forecasts, switching time and target topologies are updated in a cyclic manner.

Forecast technique

The nodal power measurements are characterized by multiple seasonal components and high volatility. Especially, the photovoltaic share of the active power time series shows its day and time variation, whereas load curves indicate a distinctive weekly seasonality (e.g. workday and weekend). Due to these facts and also with respect to limited substation automation hardware (considering field implementation) an adapted version of the double seasonal exponential smoothing method, developed in [6], is used as forecasting model. The forecasting model is defined by the following difference equation, where Y_t denotes the observed time-series and $\hat{Y}_t$ denotes the one step ahead forecast at time t:

$$\hat{Y}_t = L_t \cdot D_{t-s_D} \cdot W_{t-s_w}$$

Within the model three separate components are estimated: the level L_t, the daily cycle D_t and the weekly cycle W_t. The cycle lengths are denoted by s_w (week

cycle) and s_D (daily cycle) and t indicates the actual time index. L, D and W are functions of the measured time series value Y_t at the time t and are updated with every new measurement. The computational burden of this approach is very low. Each update is based on simple linear transformations and after the initialization only few values have to be stored.

Heuristic-based network reconfiguration

For obtaining the target topology a simple heuristic-based algorithm is chosen [5]. The algorithm is based on the switch exchange principle and shows good performance for radial networks with several loops.

The idea of the switch exchange method consists in virtual permutation of the open switch position within a loop. First, a random opened switch is closed. After calculating the load flow, a new opened switch is obtained. The heuristic rule says that the closed switch with the lowest current is the optimal switch to be opened. This process is repeated several times until the calculated objective function (here: network losses) doesn't change anymore. In this way a new optimal topology is calculated.

In order to reduce network losses over periods of time, the forecasted switching times are considered to build the optimizing interval. Average values of the nodal power forecast over the suggested interval and the current topology state are used as input for the reconfiguration algorithm. Before executing the reconfiguration at the forecasted time, the target topology is checked with regard to the updated forecast. In this way possibly unnecessary switching actions are avoided, which saves the lifetime of switching devices.

EXAMINATION A: BASE CASE LOAD FLOW

A first examination of different input data sets is carried out by comparing the feed-in and load time series, respectively the load flow results induced by them.

Differences in feed-in time series are depicted in Figure 4. The duration curve of the cumulative PV feed-in reveals only minor differences between both input data sets. However, it has to be mentioned, that the peak cumulative feed-in calculated by the MAS SIMONA is around 13.4 % higher than that of the scaled measurement time series. This can be traced back to the PV plant model. The PV overproduction is explained by the model's reaction to low sun elevation angles, especially during the winter period, whereby the output values become abnormally high. Further model development should focus on an improved trade-off between simulation accuracy and modelling simplicity.

Whilst the maximum cumulative and simultaneous WG feed-in is nearly equal (MAS approach is 1.82 % smaller), the overall feed-in is apparently smaller than assumed by scaled time series. This can be traced back to specifics of the input data preparation. The wind velocity has to be given at hub height (around 55 m above ground), while the available measurement took place at around 4 m above ground. The measured values have been transferred to hub height with the logarithmic wind velocity formula. The measurement is heavily influenced by micro structural effects like shadowing by trees or buildings, so that the near surrounding cannot be sufficiently represented by an averaged roughness used by the logarithmic formula. Thus, the wind velocity and consequently the WG feed-in are underestimated.

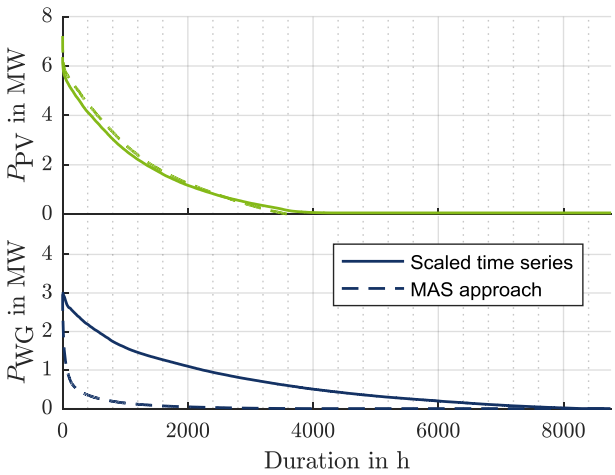

Figure 4: Total PV and WG feed-in duration curve (2016)

For the load it is assumed, that the apparent power provided by the static load flow model marks the maximum power consumption of each load over a whole year. The load composition in ST and MAS approach differ. Figure 5 shows a difference in maximum simultaneous power consumption. Whilst the MAS predicts a maximum value around 5.9 % point smaller than the maximum value obtained with ST, the consumed energy is almost the same (+1,324 MWh, +0.23 %).

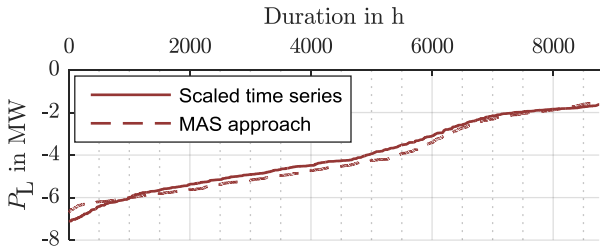

Figure 5: Total load duration curve (2016)

Regarding the voltage characteristics, the underestimated wind energy feed-in by MAS leads to lower maximum voltage magnitudes. The minimum voltage magnitudes are affected by the load. The MAS load indicates a weaker seasonal dependency because of the higher share of agricultural loads.

EXAMINATION B: ANALYSIS OF THE LOSS-REDUCING OPERATION

The above described control algorithm aims at preventing limit violations of voltages and currents, as well as optimizing losses. Therefore, an important performance indicator is the loss reduction compared to the uncontrolled base case operation. In Table 3 a simulation result summary is given. Compared to the year 2016, the 2035 simulations show a higher loss reduction potential. This can be explained by the overall generation increase in both scenarios. Also the ST scenario offers more potential due to its explicitly higher share of the wind generation and thus higher loss changes. Only few voltage violations, caused due to forecast errors and eliminated by an additional reconfiguration, appear. The overall switching actions number decrease in 2035, which indicates an improvement of the loss reduction efficiency.

Table 3: Summary of the simulation results

year	scenario	losses reduction	switching actions	violations
2016	ST	13.9 %	4838	6
	MAS	5.2 %	1798	0
2035	ST	23.7 %	3282	33
	MAS	10.2 %	300	4

Daily base case network losses and corresponding reduced loss energy are depicted in Figure 6. In fact, the total annual losses in MAS scenario are only marginally lower (approx. 2.6 %) than in ST scenario. Despite that, major loss savings of the ST scenario happen in the winter period, especially corresponding to the wind generation peaks. In contrast, the MAS scenario reveals weaker seasonal dependency.

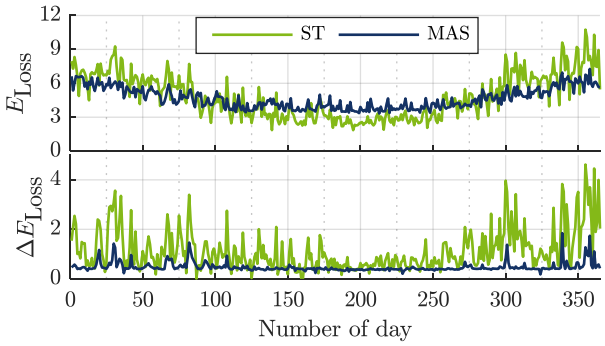

Figure 6: Daily base case losses and loss reduction (2035)

CONCLUSION & OUTLOOK

The paper highlights the impact of different input data sets used for the simulation of grid control algorithms. Time series based on scaled measurements from the test network and a multi-agent based approach were used for nodal active power models. MAS showed that individually modelled consumers result in a different peak load and alternative seasonal behaviour compared to the ST approach. As to the distributed generation, the impact of the input data characteristics (e.g. wind velocity measurement) is visible at the active power model output. Network reconfiguration, based on the residual load forecast, could be successfully tested with different data and for future scenarios. With growing share of the distributed generation the effect of loss saving by grid control becomes more noticeable. Although both input data modelling approaches lead to differing control quality, none of them can be defined as a reference. This points out that the question of the load and generation structure definition is of great importance. In order to adopt a control strategy for a particular network, different time series parameter should be applied and tested.

In future, the MAS could be extended by enhanced stochastic load models and explicitly modelled industrial loads. Moreover the simulation results point out DSO's necessity to establish a sophisticated data basis of their grids and grid participants. Thereby individual unit characteristics could be reproduced in the MAS.

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