

INTERFLEX – SIMRIS – TECHNICAL MANAGEMENT OF A GRID-CONNECTED MICROGRID THAT CAN RUN IN AN ISLANDED MODE WITH 100% RENEWABLE GENERATION

Milica BOGDANOVIC
RWTH Aachen – Germany

Henning WILMS
RWTH Aachen – Germany

Marco CUPELLI
RWTH Aachen - Germany

Michael HIRST
E.ON – UK

Luis ARTURO HERNANDEZ SALMERON
E.ON – Germany

Antonello MONTI
RWTH Aachen - Germany

ABSTRACT

This paper demonstrates a model predictive control (MPC) approach for microgrids with a significant proportion of renewable energy sources (RES). Forecasts are derived using recurrent neural networks and are included within the MPC. The demonstration is based on E.ON's microgrid site in Simris, Sweden. E.ON plans to deploy a microgrid that can run with 100% renewable generation. Distributed household PV and battery systems are exploited for the required demand flexibility. A central battery system is used as grid forming unit to balance the microgrid. Simulation results show the effectiveness of the proposed approach.

INTRODUCTION

To realize the potential of renewable energy sources as distributed generation we must take a system approach which views generation and associated loads as subsystems or “microgrids” [1]. A microgrid is part of the distribution grid, which comprises generation assets, storage devices, and controllable loads, operating as a single controllable system in **grid connected mode** or isolated from the utility grid in **islanded mode**.

Using residential flexibility for grid services has already been demonstrated in various projects [2]. While being islanded, the microgrid has to cope with relatively high power fluctuations on both the production (wind and PV) and consumption sides. Microgrids should be capable of managing and coordinating their own distributed generation, storages, and loads without a centralized coordination and management from the main grid. Therefore, one of the main ideas behind the microgrid concept is to decentralize the operation of electrical grids [3].

The focus of this paper is on the optimal operation planning of a microgrid. Our aim is to minimize the energy exchange between the microgrid and the main grid while satisfying complex operational constraints, such as the energy balance. Our research proves that the algorithm implemented and the test site used provide meaningful results about the feasibility of the chosen approach. That results support future field-testing at the test site.

DESCRIPTION OF TEST SITE

E.ON has built up and put into operation a microgrid in the South of Sweden in 2017 in Simris. The microgrid consists of a wind turbine as main generation, supported by a ground-mounted PV array and a battery system. Further, a back-up generator is used for test periods in case there is not enough power available from the microgrid's RES when running in islanded mode. The microgrid comprises about 130 E.ON customers of which some have household PV and batteries installed.

The test site includes roughly 5 km of 10 kV cables, which feed eight secondary substations as well as about 11 km of low voltages cables connecting the customers. In island operation, the system is purely fed by devices that are grid-connected by power electronics and without rotating masses.

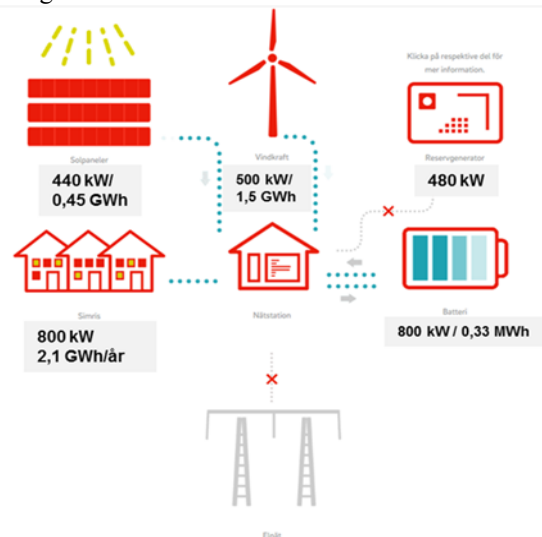


Fig. 1 Schematic of the field test microgrid in Simris

An energy storage system in virtual island mode measures and controls the active and reactive power flows within the microgrid. The central battery system is in charge of the almost instantaneous balancing of the micro grid. In islanded mode voltage and frequency control are provided by the main battery system. The main battery takes on the function of a grid-forming unit during islanded mode. The total on-site renewable generation is about 1MW.

Renewable energy sources in the microgrid (PV plant and wind turbine) are controllable and can be curtailed. Simris' back-up generator is not modelled and used in this test site control, as the aim is to operate our grid using only renewable energy sources. It is assumed that 20 % of the households at the test site have a household PV and battery systems with respective sizes of 4 kW and 6 kWh. Household PVs are non-controllable whereas the household batteries, main battery system and renewable energy sources are controllable assets.

The size of this test site and the number and type of assets installed make this test site ideal for examining benefits that household flexibility can provide for microgrid operation as well as for testing our control algorithms.

MODEL PREDICTIVE CONTROL

One of the possible approaches for microgrid control is a hierarchical control structure. We chose this approach because of the installed test site hardware, its capabilities and their master/slave communication model. This paper will focus on the centralized higher-level controller. Our developed controller uses the concept of model predictive control that has become an interesting approach for energy management purposes in microgrids in recent years. The model predictive control (MPC) provides set points for the batteries charging/discharging power as well as set points for the curtailment of renewables. The state of the system consists of the states of charge (SOC) of the batteries. One time step within our calculations is one hour. The MPC is designed to minimize the exchange of the energy with the main grid, covering demand of the customers and fulfilling the energy balance. This approach can potentially prolong the islanding mode of the microgrid.

A model predictive control is an advanced control technique for multivariable control problems. MPCs use an internal model of a system to generate predictions of the system's future behaviour. The designed MPC finds an optimal plan for running the assets (control set points) for each time step over the prediction horizon starting at the current time step. The optimization is based on predictions of the upcoming demand, production from renewable energy sources and prediction for the state of the system. For the optimization, only the first control input is implemented, and subsequently the time horizon is shifted by one time step. At the next time step, the new state of the system is measured or estimated, and a new minimization is performed whilst considering the new information. This approach is called a rolling horizon control. The control horizon can be chosen to be lower than the prediction horizon within the formulation, to deal with the time lag of the computational intensive calculations. If the control horizon is set to be lower than the prediction horizon as can be seen in Fig. 2, it is assumed that the last calculated control variables remain the same until the end of the prediction horizon [4]. The predictions needed for the application of the MPC are assumed as perfect in the MPC statement and therefore

are not affected by errors.

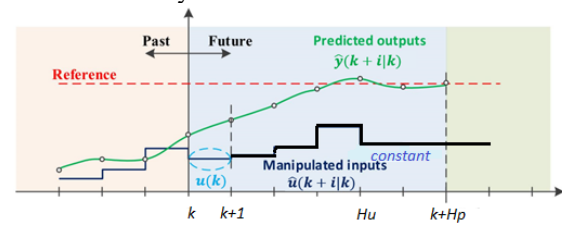


Fig. 2 MPC prediction and control horizon

FORECASTING ALGORITHM

For applying the control strategy as described in the previous section, PV and wind production as well as load need to be forecasted. At the moment, wind and PV production are assumed as perfect forecasts derived directly from measured values due to the current lack of data. These forecasts will be included in future work and will follow the same procedure as described below for load forecasting.

We use a recurrent neural network (RNN) based on long short-term memory cells (LSTM Cells) that possesses cyclic, self-feeding connections [5]. These cycles are capable of capturing time-series dependencies and their dynamic behaviour over a sequence of time steps. Further, the dependency of various independent variables (e.g. weather data) on the dependent variable can be included in this approach in order to deal with the non-stationary and nonlinear characteristics of load time-series [5]. The forecasting algorithm consists of a sequence-to-sequence encoder-decoder structure [6] that enables the forecasting model to capture historic values up to the starting point of the forecast in the encoder. This then provides an ideal starting point to infer the forecasts for the decoder. Fig. 3 depicts this encoder-decoder set up. Both encoder and decoder consist of the same type of RNN cells. These cells take the independent variables (called features here) as well as the previous output as overall input to each time step to infer the output of each time step. As the encoder only encodes historic values, their outputs can be omitted here. The encoder passes the starting point for the decoder in the form of the hidden state of the RNN cells.

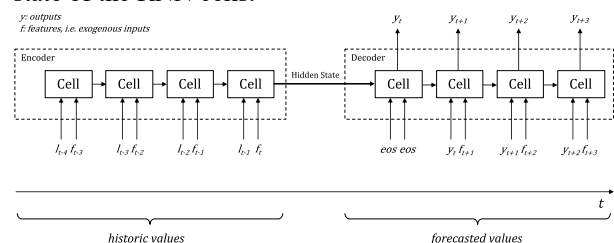


Fig. 3 Forecasting algorithm set up

The advantages of the proposed sequence-to-sequence structure lies (a) in the encoding of historic values and (b) in the t-1 shifted refeeding of its forecasted values. LSTM cells consist of various internal memory vectors (together called hidden state) which are updated continuously as the LSTM cells produce forecasts. Using the encoder for

encoding historic values ensures that all the internal vectors are up to date for the first forecast time steps. Secondly, load time-series show a strong auto-correlation for short time lags. We have found that exploiting this auto-correlation by refeeding the forecasted value of the previous time step to the current time step further improves the forecast accuracy.

Employing this algorithm, we were able to produce reasonably accurate results for 24h forecasts on synthetic load data from Simris. These forecasts we utilized in our MPC. Adding ambient temperature readings as exogenous inputs, we obtained a normalized percentage root mean square error of 0.867% and a R^2 coefficient of determination of 0.9496.

We have found that the employed forecasting architecture outperforms similar RNN based forecasting techniques. A standard RNN as presented in [5] resulted in a R^2 of 0.9168.

SIMULATION RESULTS

The Simris MPC energy management approach is simulated and tested for one month in 2016. The simulated period starts on 26.5.2016 at 20h and ends on 26.6.2017 at 19h. As a forecast input the MPC uses the forecasted load for the specified period as well as on site measured PV and wind production. The battery's charging and discharging efficiency is 0.9. The maximum household battery power for charging and discharging is 3 kW. The prediction of the household PV production is included from the PVWatts calculator [7]. The chosen prediction and control horizon for the MPC is 24 steps (24 hours). At the beginning of the simulation, it is assumed that all household batteries and the main battery system are charged to 50% of their capacity.

Results show that the microgrid is capable of staying in islanded mode for 617 hours of the 744 simulated hours, totaling 83% of the time. We assume that the microgrid is capable of being in islanded mode if there is no energy exchange with the main grid in an hour. One reason for such a good result is that the simulated time span from end of May until end of June exhibits an extensive PV production. The following Fig. 4 shows the grid exchange with the main grid for the first 7 days of the simulated period. In the problem statement, importing energy from the main grid results in a negative value of power exchange with the main grid and vice versa. Fig. 4 shows that the microgrid is not in islanded mode because it is importing energy from the main grid. For the time steps during which the microgrid is not in islanded mode, the production of renewables does not suffice to cover the entire consumption and the batteries are empty, so we need to extract energy from the main grid (load peak in the afternoon hours). Without the MPC implementation and the same set-up of the microgrid, the islanded mode would have expanded to only 215 hours. The grid exchange for the same first 7 days is shown in Fig. 5. Comparing Fig. 4 with Fig. 5 also shows that the global peak of exchanged power is lower with the implemented

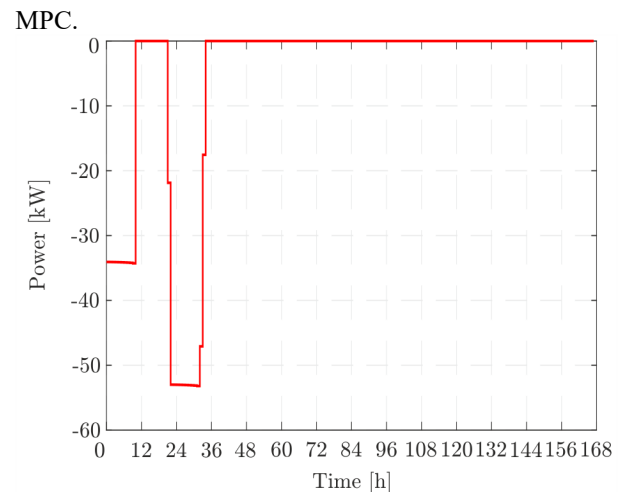


Fig. 4 Grid exchange with the main grid for the first 7 days simulated

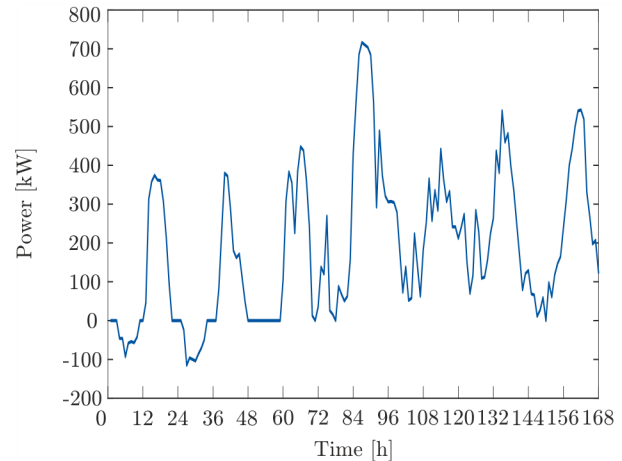


Fig. 5 Grid exchange without MPC algorithm for the first 7 days simulated

The SOC (state of the charge) of the main battery system and the forecasted residuals between production and consumption is simulated and shown for the first 7 days in Fig. 6.

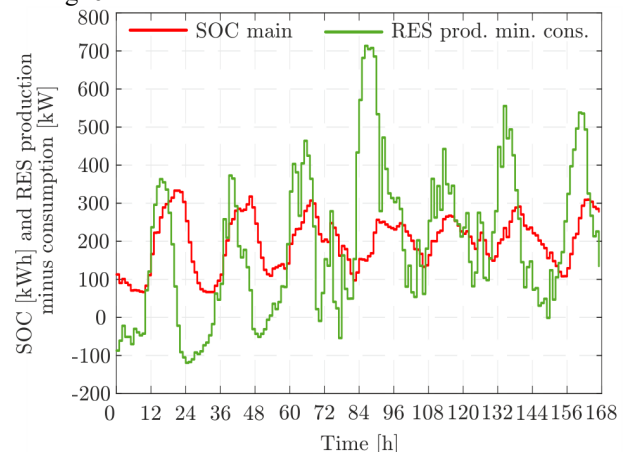


Fig. 6 SOC of the main battery and difference between production and consumption for the first 7 days simulated

The rolling horizon control bases its optimization on future scenarios. This approach showed good results in dealing with renewable peak production. It discharges batteries while building up towards the peak and uses the

energy to meet load demand. During the production peak (84h-96h in Fig. 6), the MPC does not charge the main battery to its full capacity because of a high renewable production forecast that exceeds the forecasted demand in the future time steps (during entire prediction horizon). Instead, the MPC starts charging the battery whilst curtailing renewables at the same time. The MPC tries to optimize usage of batteries together with curtailing renewables, since the algorithm in its current implementation does not penalize curtailing of renewables.

As the MPC aims at minimizing the energy exchange between the microgrid and the main grid, it curtails renewables to prevent feed in to the main grid. This is depicted in the following Fig. 7. The figure shows a regularity in curtailing PV in off-peak load hours in combination with the highest PV production during the day as well as high state of charge of the batteries.

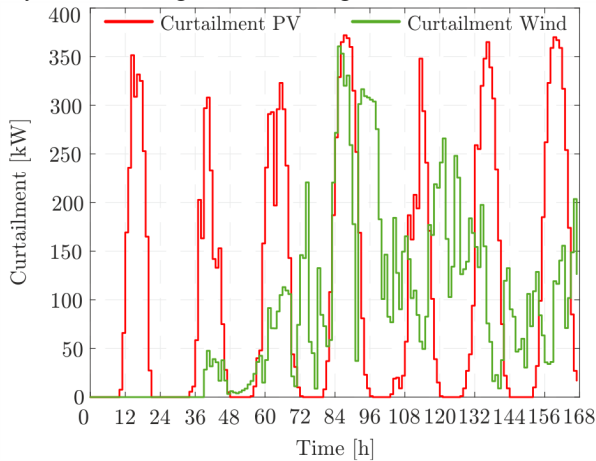


Fig. 7 Curtailment of renewables for the first 7 days simulated
Increasing the percentage of customers with installed household battery and PV systems can support the system to stay in islanded mode for longer periods. Assuming double the number of the customers having household battery and PV systems installed, shows an increase in the capability of islanding to 632 h. In a second scenario with double the main battery system capacity, increases the capability of islanding to 658 h.

Taking the actual measured data for load, wind and PV as a forecast and simulating the MPC over the entire year 2016, shows that the overall time during which Simris is capable of islanding is 4500 hours, equalling 51.23 % of the time.

For comparison, an instantaneous minimization of the energy exchange between the microgrid and the main grid is performed. This instantaneous minimization optimizes each time step without looking into future and uses only the data available in each time step, i.e. current measurements. This optimization results in a possible islanded time of 4062 hours. Hence, the MPC showed a better performance in comparison to the non-rolling optimization. Table 1. shows the different results for the MPC (rolling optimization) and the instantaneous minimization. The results also show that the instantaneous minimization curtails renewable

production more than the MPC. The renewable curtailment of the instantaneous minimization is 797.93 MWh, whereas the MPC curtails 715.57 MWh. Therefore, the MPC outperformed the instantaneous optimization in this field as well. The main reason for this is that the MPC is capable of utilizing the batteries more effectively.

Table 1. Potential islanding time of Simris microgrid with optimization and MPC algorithm

Percentage of customers with PV and battery	Instantaneous minimization- Percentage/Potential number of hours in islanded mode	MPC- Percentage/Potential number of hours in islanded mode
20 %	46 %; 4062h	51%; 4500h
40 %	48%; 4233h	55%; 4797h

CONCLUSION AND FUTURE WORK

In this paper, we proposed and proved the effectiveness of centralized MPC approach to address the problem of minimizing the energy exchange between a microgrid and a main grid utilizing battery flexibility. We further demonstrate the viability of this approach for the Simris test site. Our results show that the MPC approach outperforms a static minimization in the key aspects of maximizing the use of RES as well as the minimization of energy exchange with the main grid.

In future work, we will evaluate alternative optimization goals and enhance the forecasting techniques by a more sophisticated data pre-processing using auto-encoders.

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