A NOVEL CONTAINER-BASED APPROACH FOR INTEGRATING SOLAR FORECAST IN REAL-TIME SIMULATION AND MODEL PREDICTIVE CONTROL

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Abstract

This paper presents an interdisciplinary, novel approach for incorporating day-ahead solar forecast obtained using numeric models into a real-time simulation framework for low-voltage microgrid analysis. The solar forecast data were integrated into the grid simulation at the information, communication, and function levels, utilising the data model and communication structure defined in the international standard IEC 61850. Given the forecast of solar power and a reference trajectory defined by the upper-level grid management system over a sliding predictive time window, a model predictive control scheme has been implemented to compute control setpoints for solar curtailment in a simplified simulation scenario, regardless of the power flow over lines. In the virtualised environment with decentralised intelligent controllers in containers, the control setpoints are communicated between the IEC 61850 client and server and implemented as measures for solar peak-shaving. The test results showed that the model predictive control scheme outperformed trivial linear control methods, suggesting that the container-based virtualisation concept has the potential to be further exploited for practical use cases at the utility and energy market level, and the IEC 61850 standard could be a feasible solution in terms of grid communication and forecast integration.

1 Introduction

In recent years, as the conventional power plants stage out step by step and the share of renewables increases, a part of the system dynamics occasioned by the energy transition is moving from centralised entities to distribution systems, particularly in low-voltage (LV) networks. This change poses new challenges for the operation of distribution systems. Therefore, new concepts and strategies for system stabilisation and optimised flexibility utilisation are currently in demand.

Future electric distribution networks are complex systems containing huge amounts of Distributed Energy Resources (DER), including flexible loads, generating units and energy storage systems. These volatile systems introduce short-term dynamics into the operational process while also giving Distribution System Operators (DSO) more flexibility options. Accurate solar and meteorological forecast data are crucial for operational processes, like reserve capacity management, hybrid system integration, storage utilisation, and participation in energy trading markets. Solar forecasting helps mitigate risks caused by extreme atmospheric events, and improve the utilisation of flexibility provided by DERs to ensure a stable distribution system operation and seamless market integration.

However, the technical integration of solar forecast into operational processes may be complicated due to a variety of standardised and proprietary data storage options, data model structures and communication protocols. As the operation of distribution networks involves the modelling and computation on a larger scale than the centralised operation of transmission networks, innovative approaches combining standardisation and automation aspects must be carried out from a DSO perspective. Furthermore, advanced numerical methods for Optimal Power Flow (OPF) analysis [1] and Model Predictive Control (MPC) [2] need to be implemented with regard to DER and microgrid characteristics in order to compute control setpoints for DER in the sense of solving constrained nonlinear optimisation problems.

This paper proposes the following new concepts: 1) a semi-standardised IEC 61850 data interface for the management and application of meteorological data, including solar forecast; 2) a container-based real-time grid simulation framework to enable microgrid simulation applications with scalable virtualised Intelligent Electronic Devices (vIED). The abbreviation “vIED” was initially introduced by [3] to represent an IED in the cloud. In the context of DER integration, vIED refers to any IED that runs in a virtualised environment, such as a Docker container. To demonstrate the concept of IED virtualisation, a simplified MPC scheme for the peak-shaving on Photovoltaic (PV) systems in a LV microgrid has been implemented and validated within the proposed virtualisation framework.

2 Methodology

Using the IEC 61850 standard as a fundamental element, the proposed simulation framework requires interdisciplinary design and implementation of vital components and interfaces. These concepts are presented extensively in this section.

2.1 Forecasting of Solar Irradiance and PV Feed-in Power

In general, forecasting combines satellite-based Cloud Motion Vectors (CMV) with global Numerical Weather Prediction (NWP) models to derive solar irradiation and other meteorological variables. PV forecast encompasses two modeling aspects: weather modeling and PV system modeling. The primary focus of weather variable forecasting is solar radiation, with secondary attention given to air temperature and other meteorological parameters. Various techniques are employed to forecast solar irradiance, contingent upon the forecast horizon and intended data usage. With meteorological inputs, technical parameters of the PV system, and local site information entering the simulation framework, the PV feed-in power can be calculated using various numerical models. Table 1 compares several commonly deployed solar forecast types in the industry. Each method has advantages and disadvantages considering the forecast timescale and spatial resolution. A more comprehensive overview of solar forecasting and nowcasting is provided by [4] and [5], respectively.

On the forecast provider side, one commonly used way of forecast data provision is stacking the data in formatted text files on a dedicated server. Depending on user configuration, the forecast data can be generated and delivered to the server regularly at different time intervals and with different time steps. Each file contains metadata, timestamps, solar irradiance data, other meteorological data, and if available, the PV feed-in power.

Table 1 Overview of commonly used solar forecast methods

Type	Technique	Use Cases
Nowcasting (0-4 hours ahead)	Sky-cameras (0-1), extrapolation of actual time-series data from measurement devices, or satellite-based CMV models (0-4)	Improve PV power production, PV output ramps management, storage and hybrid systems performance
Intra-day forecasting (up to 24 hours ahead)	NWP models standalone or more often in combination with CMV methods, employing blending methodologies to fit forecasted data to local site or area conditions.	Support short-term energy market, storage, and hybrid systems performance
Day-ahead forecasting	Combination of several NWP models	Improve system balance and anticipate critical events
Multi-day-ahead forecasting	Based on NWP models with a prediction horizon up to 14 days	Support scheduling and maintenance

2.2 Standardised Modelling of Meteorological Parameters

The first step in the semi-standardised forecast integration on the utility side is to map the meteorological parameters onto the IEC 61850 terminology [6], [7]. In the real-time simulation, values of these parameters can be communicated between the vIED and the centralised management system using their unique identifiers, known as Manufacturing Message Specification (MMS) addresses of IEC 61850 Data Attributes (DA). Table 2 shows the MMS addresses of several essential meteorological parameters as an example, while in this work the Global Horizontal Irradiance (GHI) or PV output power is the most relevant. It must be noted that the IEC 61850 DOs for isolation are intended used as solar irradiance for simplicity; in more practical applications, the unit must be specified to avoid unexpected data scale.

2.3 Energy Data Management with IEC 61850

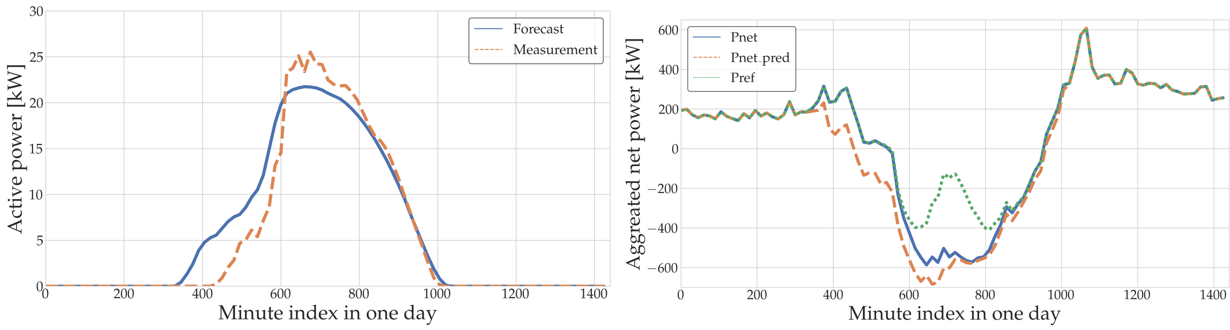
In general, real-time applications require neatly organised data and efficient data interfaces, which can be complicated regarding the selection of communication protocols and data formats. Utilising the hierarchical structure of IEC 61850 data models can help to facilitate energy data management within a utility and eliminate syntax errors in data queries. At the information level, a semi-standardised data interface between vIEDs and a time-series database has been implemented following the IEC 61850 data structure. More specifically, the MMS address of an IEC 61850 DA or sub-DA is split down into column names in the database. Given a unique vIED identification, the combination of column name keywords will point to a distinct data set for data transfer. Such a MMS breakdown for the IEC 61850 DO `METEO/MMET1.HorInsol.mag.f` is presented in Table 3, this data mapping concept has been implemented for the time-series database used in the real-time simulation.

Table 2 Modelling of meteorological parameters with the IEC 61850 standard

Parameter	MMS address
Total horizontal insolation	METEO/MMET1.HorInsol.mag.f
Direct normal insolation	METEO/MMET1.DctInsol.mag.f
Diffuse insolation	METEO/MMET1.DffInsol.mag.f
Vertical wind speed	METEO/MMET1. VerWdSpd.mag.f
Environment temperature	METEO/MMET1. EnvTmp.mag.f
PV output active power	METEO/MMXU1. TotW.mag.f

Table 3 Example of MMS breakdown for the parameter GHI and mapping onto the database structure

IEC 61850 jargon	Column name	Example
Logical Device	LD	METEO
Logical Node	LN	MMET
Data Object	DO	HorInsol
Data Attribute / Sub Data Attribute	DA / SDA	mag.f
Common Data Class	CDC	MV
Functional Constraint	FC	MX



(a) (b)

Fig. 1 (a) Data set for the 30 kW reference PV system after data selection, (b) data set (aggregated values) for a LV microgrid with 100 nodes after data scaling, *Pnet*, *Pnet_pred* and *Pref* represent aggregated net active power by measurements, aggregated net active power by prediction and the reference trajectory.

2.4 Model Predictive Control for Solar Peak-shaving

In a microgrid simulation, the centralised Microgrid Manager (MGM) performs curtailment on PV systems during peak hours of solar energy generation, to follow the reference trajectory given by an upper-level grid management system. In this context, a simplified MPC scheme has been implemented to compute the optimal control setpoints subject to the active power constraints, while not considering the power flows.

2.5 Simplified Microgrid Simulation with vIEDs

A real-time simulation environment consisting of scalable, containerised vIEDs is applied to replicate the dynamics at the communication level in practice. Following an agent-based approach, the containerised vIEDs represent physical IEDs at different nodes in a LV grid. The data model and MMS protocol defined in IEC 61850 are used as the communication interface between the MGM and vIEDs for standardised data transition. This functionality is provided by the self-developed open-source Python module `pyIEC61850DER` [8], which utilises the Python binding of another open-source module `libIEC61850` [9]. The LV microgrid simulation is simplified by not considering node power injections, node voltages and branch power flows. Since no physical PV inverter is involved in the simulation, a Python function embedded in the vIED implements the data provision and PV curtailment.

3 Implementation

This section focuses on data preparation, vIED configuration, and implementation of the MPC scheme. Technical implementation of fundamental vIED functionalities is out of scope.

3.1 Data Preparation

Data pre-processing is a preliminary step to conduct multiple simulations using an identical setup. Essential data sets and required pre-processing steps are presented in Table 4.

The local DSO collected the measurements via a metering platform from 2015 to 2018, whereas the solar prediction has been available since 2020, resulting in a temporal mismatch between the two data sets. At the time of implementation and testing, data collection and pre-processing of PV measurements from recent years had not been completed. This circumstance required manual generation of plausible data sets as simulation inputs, which would not affect the numerical analysis. The reference PV system, for which solar power prediction is available, has an installed capacity of 30 kW, daily forecast and metering data sets with the lowest root-mean-squared error was considered the best match as shown in Figure 1 (a). This procedure resulted in two data sets representing a clear-sky day for the reference PV system. The solar irradiance is assumed to have been identical in the same region, and the measurements indicate that some PV inverters in the microgrid had not been operating under the registered maximal feed-in power. Therefore, the scaling factor is necessary and it can be denoted by

$$\eta_i = \frac{p_{i,nom}}{30} \times \frac{max\left(p_i^{(1)}, \cdots, p_i^{(1440)}\right)}{max\left(\hat{p}_i^{(1)}, \cdots, \hat{p}_i^{(1440)}\right)} \qquad (1)$$

Table 4 Data sets for the MPC simulation

Data set	Pre-processing step
LV node load profiles	Meter data collected from LV households in 2016, randomly assigned to vIEDs; temporal resolution of 15 minutes, linearly interpolated to 1 minute
Solar generation profile	Meter data collected from small-sized PV systems in 2016, randomly assigned to vIEDs; temporal resolution of 5 minutes, linearly interpolated to 1 minute
Reference day-ahead solar power prediction	Feed-in power prediction in 2023 for a 30 kW PV system, provided by Solargis s.r.o., computed based on numerical models
Scaled day-ahead solar power prediction	Reference prediction multiplied by a scaling factor η
Reference trajectory of net power demand	Artificial permutation on the aggregated net power demand of all households in the LV microgrid

where $i \in \mathbb{N}^+$ stands for the index of a PV system in the microgrid, $p_{i,nom}$ is the nominal active power of i-th PV system, and the two sets $\left(p_i^{(1)}, \cdots, p_i^{(1440)}\right)$ and $\left(\hat{p}_i^{(1)}, \cdots, \hat{p}_i^{(1440)}\right)$ represent measured and predicted values of that PV system the on the same day as the reference PV, with one-minute interval.

It should be mentioned that the computation of active feed-in power depends particularly on the technical setting of the PV panels, such as type, quantity, inclination and orientation. For simplicity, those technical factors were not taken into account when scaling the profiles of solar power prediction.

Figure 1 (b) illustrates the aggregated single-day profiles, including the net active power demand of the microgrid under observation, the predicted net power demand, and the artificially generated reference trajectory representing an operation schedule given by an upper-level grid management system.

3.2 Container Configuration and vIED Interfaces

The virtualised simulation environment is constructed using a batch of `pyIEC61850DER` Docker containers, assuming each container is IEC 61850 compliant regarding data modelling and communication. All containers use the same image but are assigned different communication addresses. Figure 2 depicts the overall architecture of the simulation environment. It should be noted that the MGM, the time series database and all containers are located in the same communication network for simplicity, where no network impairment is applied.

In this context, the terminology vIED refers to the Python programme that runs within a Docker container and acts as an IED server. In general, all vIEDs have a similar configuration, which primarily involves defining DA data sources to enable the real-time data interface and selecting input arguments to activate the runtime processing logic. Functionally, the containers only differ in the target data set name for data transfer between the vIED and the time series database. During the real-time simulation, the database interface will be called only once after vIED initialisation, to load daily generation and load profiles as listed in Section 3.1 and store the data locally for runtime processing.

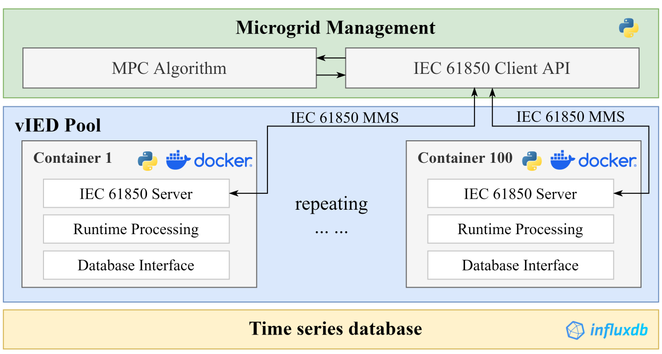


Fig. 2 Schematic representation of the microgrid simulation with vIEDs and a time series database.

Table 5 Relevant parameters for the real-time simulation

Parameter	MMS address
PV active power	PV1/MMXU1.TotW.mag.f
Predicted active power	METEO/MMET1.HorInsol.mag.f *
Load active power	LOAD1/MMXU1.TotW.mag.f
Net active power absorption	PCC/MMXU1.TotW.mag.f
Max active power	PV1/DGEN1.WMaxRtg.setMag.f
Min active power	PV1/DGEN1.WMin.setMag.f **
Control setpoint [0..1]	PV1/DGEN1.OutWSet.setMag.f
Control setpoint [W]	PV1/DGEN1.WMax.setMag.f

* Intended misuse of the DO `HorInsol` as active power prediction
** The DO `WMin` is customised

On the communication side, MGM initialised the IEC 61850 MMS channels using the IEC 61850 client interface provided by `libIEC61850` [9]. The MGM holds these channels open throughout the simulation, and collects data from all vIEDs every 60 seconds, the MMS addresses of associated IEC 61850 DAs are listed in Table 5. In the control direction, only the DO `OutWSet` (float between 0 and 1) is transferred back to the vIEDs, while an internal operation logic of the vIED handles the updating of other associated DOs.

3.3 Implementation of the MPC Scheme

The formulation of the MPC model follows the concept proposed in [10], whilst in this work, the PV inverters are used as flexibility options instead of residential batteries. Assume the LV microgrid contains $I \in \mathbb{N}^+$ households, the simulation period contains $N \in \mathbb{N}^+$ time steps and the MPC scheme considers $K \in \mathbb{N}^+$ predictive time steps (including the current time step n, $n \leq N - K + 1$), then the aggregated net active power demand of the MG at time step n reads as follows:

$$P^{agg}(n) = \sum_{i=1}^{I} p_i(n) = \sum_{i=1}^{I} \left(p_i^l(n) - p_i^g(n)\right) \tag{2}$$

where the superscripts l and g refer to load and generation. The vector that stores the aggregated net active power demand over a sliding prediction time window can be described as $P^{agg} = \left(P^{agg}(n+k)\right)_{k=0,\cdots,K-1} \in \mathbb{R}^K$.

Let the control variable $u_i(n)$ denote the change of curtailment (`OutWSet`) at time step $n \in \mathbb{N}^+$, which will cause changes in the constraints at the following time step $n+1$ in terms of flexibility provision. For instance, let the values of the reference trajectory be stacked in the vector $\zeta \in \mathbb{R}^K$. Then the vector $u_i = \left(u_i(n), \cdots, u_i(n+K-1)\right), i \in \{1, \cdots, I\}$ contains the predictive control setpoints for PV system i over the discrete prediction time window $[n : n+K-1]$. Accordingly, all control values at one MPC step can be described as $u = (u_1, \cdots, u_I) \in \mathbb{R}^{2IK}$. With this system setup, the optimisation problem is defined as:

$$\begin{aligned} \min_{u} \quad & \|P^{agg} - \zeta\|_2^2 \\ \text{s.t.} \quad & p_i^{g,min} \leq p_i^{g,curt} \leq p_i^{g,max}, \;\; i \in \{1, \cdots, I\} \end{aligned} \tag{3}$$

Algorithm 1 MPC(I, K, N) for solar peak-shaving

1: Initialisation: set $n := 1$
2: **while** $n \leq N - K + 1$ **do**:
3: Collect measurements: $p_i^g(n)$ and $p_i^l(n)$
4: Collect forecast $\hat{p}_i^g(n)$ and $\hat{p}_i^l(n)$
5: Compute forecast deviation $\hat{p}_{i,dev}^g(n)$
6: Collection predictions for future time steps
7: **for** $k \in \{1, \cdots, K-1\}$ **do**
8: Collect $\hat{p}_i^g(n+k)$ and $\hat{p}_i^l(n+k)$
9: Correct forecast using $\hat{p}_{i,dev}^g(n)$
10: **end for**
11: Collect ζ, compute P^{agg}, update constraint matrices
12: Solve problem (3), compute u
13: Modify $u_i(n)$ in case of curtailment relaxation
14: Communicate $u_i(n)$ with vIEDs to perform control
15: Update $u_i(n+k)$ for $k \in \{1, \cdots, K-1\}$
16: $n \rightarrow n + 1$
17: **end while**

The main workflow of the MPC scheme is presented in Algorithm 1, the for-loop for i is omitted. At each time step, the nonlinear problem (3) on line 12 is solved using the Python method `scipy.optimise.minimise` [11]. Whereas the benchmark is a linear method that calculates the deviation from the reference value at each time step and implements control setpoints for all PV systems in proportion to the nominal active power (`BM_max`) or available flexibility (`BM_flex`). For instance, a curtailment relaxation mechanism based on a time-counter has been added to the benchmark method.

4 Test and Results

4.1 Simulation without vIEDs

Before applying the MPC scheme to the virtualised simulation environment, a test without real-time communication to vIEDs was conducted to investigate the performance of the MPC solvers. In other words, all data were stored locally and loaded at each time step when required, representing the MGM operation on daylight hours, which has a time step index $n \in [480, 1020]$, or 8:00 to 17:00 Central European Summer Time (CEST, UTC+2). Multiple local tests were carried out using two solvers for constrained optimisation: Sequential Least Squares Programming (`SLSQP`) and trust-region interior point method (`trust-constr`) [11], as well as different sizes for the prediction time windows.

Figure 3 compares the test results using different setups by assessing absolute deviations from the reference trajectory. In general, the MPC solvers outperformed the two benchmark methods, particularly when relaxing the PV curtailments, as the MPC scheme has better knowledge about the prospective changes in net power absorption. Notably, a larger prediction time window had a detrimental influence on the MPC tests. One possible cause is the cumulative inaccuracy in the solar prediction. In [12], examples are provided to demonstrate that shorter

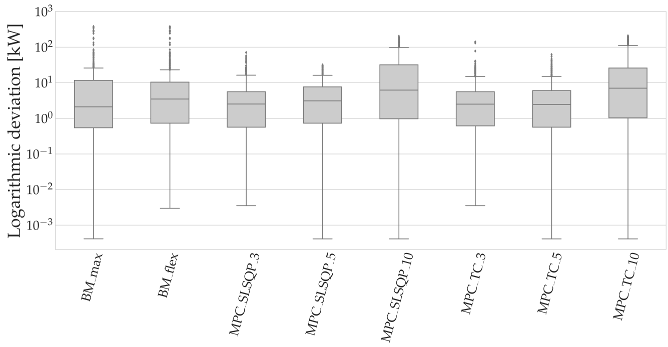


Fig. 3 Comparison of the deviations using different setups. The last digit in the tick labels denotes the MPC time window size.

horizons may improve the accuracy of an MPC scheme in terms of weather-dependent optimisation problems. The MGM ran on a Windows Server 2012 machine with an 8-core processor. The computation time is not critical for the test with $K = 3$ (converged in 2 seconds); as the window size increases, the required computation time for each nonlinear optimisation step grows drastically due to the computation incorporating large sparse matrices.

4.2 Simulation with vIEDs and IEC 61850 Communication

In the next step, the setup with MPC solver `SLSQP` and the prediction time window with length $K = 3$ were applied to the virtualised simulation environment explained in Section 3.2. At each time step n, an IEC 61850 data update was performed by communicating with all vIEDs in a loop. For simplicity, the predicted values for load and generation over the time window $[n, n+2]$ were assumed to be known for the MGM.

The test with vIEDs has been performed multiple times on a Network Attached Storage (NAS) with a 3400 MHz processor and six cores. Most tests could produce expected results, as shown in Figures 4 and 5, in which the actual aggregated net power demand is not significantly deviated from the local test. While in one test, large deviations could be observed starting from time step 950. Considering that the NAS ran into an out-of-service state at the same time due to critical CPU and memory usage, these deviations could have been caused by delayed processing and control execution within the vIEDs.

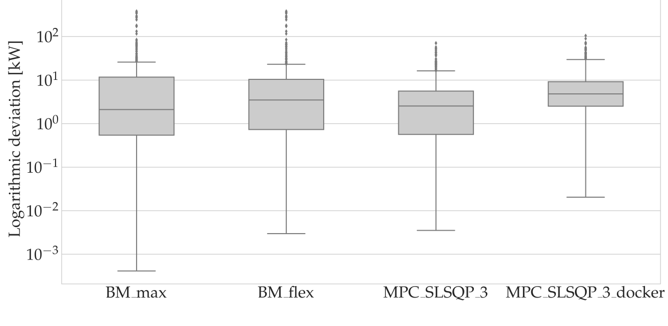


Fig. 4 Comparison of local MPC tests and one test in the virtualised environment with vIEDs.

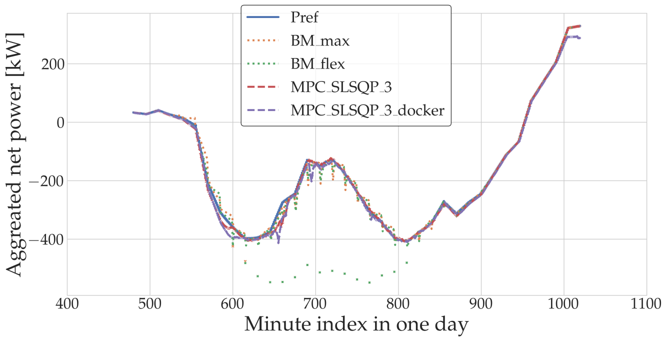


Fig. 5 Direct comparison of net active power absorption using different solvers and the reference trajectory in the same test as in Figure 4, outliers are plotted as scatters.

Several other tests showed different scales of non-critical deviations compared to the results collected in the local test, which could be caused by inconsistent time synchronisation in vIEDs or restricted computation capacity of the NAS.

5 Conclusion and Outlook

The work presented in this paper has demonstrated an interdisciplinary, novel approach for integrating solar forecast into the microgrid simulation, combining virtualisation and standardisation aspects. Implementing data interfaces based on the IEC 61850 data structure could improve efficiency on the data management side. With regard to new flexibility provision options, a simplified MPC scheme has been developed for MGM to enable PV peak-shaving utilising solar power forecast. In a virtualised real-time simulation framework consisting of IEC 61850 compliant vIEDs, the MPC showed a stable performance despite the limited computation capacity of the host system for containers. As container technology for virtualisation has gained popularity in many industrial domains, more practical container applications for distribution power network simulation could be promising and effective.

Further research is needed in various directions to enhance the technological feasibility of the proposed microgrid simulation approach. In terms of standardised data modelling, more DER types should be considered, and arrays can be used to store forecast data instead of single data points. Regarding the simulation framework and its components, DER emulators should be implemented as alternatives to internal data processing logic, artificial communication network impairments can be applied to imitate real-world disturbances; and instead of artificially generated data sets, the simulation should be tested on data sets that do not have temporal mismatch. To tackle the restrictions of computation capacity, the virtualised simulation should be performed on a high performance computing system. From a numerical standpoint, advanced prediction-correction mechanisms can be used to minimise the impact of forecast inaccuracies on the MPC scheme; for instance, complex non-linear problems that consider network stability constraints, such as OPF, need to be intensively investigated.

6 Acknowledgements

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