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Real-Time Distribution Grid Control and Flexibility Provision under Uncertainties: Laboratory Demonstration

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***Abstract*—In this paper, we assess the effectiveness of forecasting and optimization algorithms on a laboratory demonstration platform that mimics a domestic distribution grid with a high penetration of photovoltaic (PV) systems. Despite the uncertainties, the considered algorithms ensure efficient and secure real-time (RT) operation of the distribution grid, as well as the provision of flexibility services from the low-voltage (LV) distribution grid to the upstream medium-voltage (MV) grid. Uncertainties arise from the variations in PV systems power production and end-users' power consumption, as well as RT deployment of flexibility services. As a result of the considered algorithms, the distribution grid becomes active in the provision of flexibility services. The forecasting and optimization algorithms are based on Bayesian bootstrap quantile regression (BBQR) and distributionally robust chance-constrained (DRCC) programming, respectively. This paper also evaluates the framework of the laboratory demonstration platform for the deployment of the considered algorithms.**

***Index Terms*—Active distribution grids, flexibility provision, photovoltaic (PV) systems, laboratory demonstration, uncertainties.**

I. Introduction

To accomplish the sustainability goals of energy systems in the context of energy transition, the penetration of renewable energy sources (RESs) in distribution grids must be increased (see [1] for an explanation of this necessity in the case of Switzerland). However, this task on the consumption side poses technical and operational challenges for distribution grids. First, even though the distribution grids are designed for one-way power flow, they must be operated with bidirectional power flow and excessive stress [2]. Second, because of the high level of uncertainty in distributed photovoltaic (PV) systems, which are the primary source of distributed RESs, power production control and forecasting grid operation will be difficult. Third, the stochastic profile of electric vehicle (EV) charging introduces a new source of uncertainty in the end-user's power consumption [3]. The primary solution to all these technical and operational challenges is to improve the distribution grids observability and controllability.

The development of efficient forecasting algorithms for PV power production and end-user's power consumption will improve the distribution grid observability. For probabilistic forecasting of PV power production, [4] has developed a Bayesian bootstrap quantile regression (BBQR) approach. Furthermore, for end-user's power consumption, [5] has proposed a real-time (RT) forecast based on random forests.

The deployment of flexible resources such as battery energy storage (BES) and PV converters, on the other hand, will improve the distribution grid controllability. Furthermore, the development of efficient optimization algorithms will ensure grid security, and flexibility services will be provided to compensate for the increased uncertainties caused by the stochastic nature of PV system power production and EV power consumption. In [6], an algorithm for controlling the active and reactive power flexibilities of BES systems as the major sources for increasing the distribution grid controllability has been proposed and tested. A two-stage control framework for dispatching a distribution grid has been developed and tested, with [7] utilizing a BES system as a controllable element. The dispatch plan has been determined at the day-ahead (DA) stage, including the power profile that the feeder connection node must follow during the operation, allowing the BES system to promise an adequate amount of flexibility. A model

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predictive control algorithm has been presented for the RT stage to compensate for the mismatch between the profile realization of the distribution grid connection node to the external grid and the DA stage decided dispatch plan. Finally, an optimization technique based on distributionally robust chance-constrained (DRCC) programming has been developed in [8] for scheduling the operation of distribution grids for delivering flexibility services to upstream grids.

The main objective of this paper is to deploy and validate efficient forecasting and optimization algorithms for enhancing distribution grids observability and controllability. The considered algorithms, which are based on BBQR forecasting and DRCC optimization, ensure safe operation of distribution grids by taking operational constraints such as network currents and voltages, as well as the limits of connected components, into account. Furthermore, considering operational uncertainties, the considered algorithms enable us to provide flexibility services from a local low-voltage (LV) distribution grid to upstream medium-voltage (MV) grid. Both forecasting and optimization algorithms are tested and validated on a reconfigurable distribution grid laboratory environment using the framework of a demonstration platform. The framework and setup of RT data acquisition from the grid, control component interfaces, and software for execution of DA and RT forecasting and optimization algorithms are all discussed.

The rest of this paper is structured as follows: Section II explains the considered forecasting and optimization algorithms. Section III describes the framework of the laboratory demonstration platform. Section IV reports the tests results. Finally, Section V concludes the paper.

II. Considered Forecasting and Optimization Algorithms

A two-level rolling framework for forecasting and optimization algorithms is used to determine the optimal and secure operation of a distribution grid under uncertainties. The first level deals with the DA scheduling of controllable resources, whereas the second level deals with the RT scheduling of controllable resources. Fig. 1 depicts the timeline of the two-level rolling framework for forecasting and optimization algorithms.

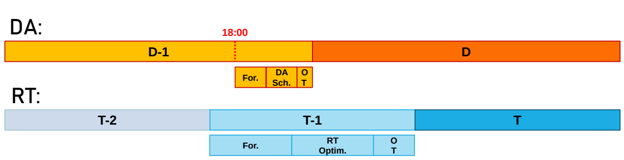

Fig. 1: Two-level rolling framework for forecasting and optimization algorithms.

According to Fig. 1, we forecast profiles of PV power production and end-user's power consumption in DA for the entire day of D using data collected until 18:00 on day D-1. To that end, we must forecast 144 values for each power profile when the resolution is set to 10 minutes. The primary objective of the DA optimization problem is to minimize the relative expected cost of the operation based on forecasted values for the uncertain parameters. This objective function includes the balancing cost minus the total revenues from providing flexibility services to upstream MV grid. As shown in Fig. 1, the optimization problem set-points are decided prior to the start of the day D to consider an operational time (OT).

In RT, we forecast power profiles that occur during T using data collected until interval T-2 as shown in Fig. 1. The objective of the RT optimization problem is to minimize the deviation of controllable resources (i.e., BES and PV systems) from the pre-scheduled set-points obtained from the DA optimization, with respect to the RT realization of the uncertainties. The RT algorithm forecasts PV system power production and end-user's power consumption of the 10-minutes interval T. The set-points are then sent to the controllable resources for activation before the start of time interval T, which also requires some OT.

It is worth mentioning that the technical constraints of the grid, as well as the constraints associated with the capacities of the controllable resources, connect two-level rolling optimization problems in DA and RT (e.g., state of charge of the BES systems). Both considered forecasting and optimization algorithms for the DA and RT are briefly explained below.

A. Forecasting Algorithm

We require two forecasts in DA: PV power production and end-user's power consumption (both active and reactive power). The algorithm used for both DA forecasts is based on an ensemble BBQR approach, which is a combination of individual forecasts from different underlying models. Furthermore, the algorithm has been developed within a probabilistic framework, i.e., the considered algorithm gives predictive quantiles of the target variable for the target forecast horizon.

The forecasting algorithm for PV power production is depicted in Fig. 2. First, a procedure is used to select only the most informative predictors from all of the candidate predictors after evaluating their performance during a validation period. The BBQR method is then used to evaluate the posterior distribution of PV power production by extracting a number of multivariate weight samples from the Dirichlet distribution. Finally, the best sample quantiles are chosen to provide probabilistic forecasting. The details of the PV power production forecast are explained in [4]. The same procedure is also used to forecast the end-user's power consumption (for both active and reactive power).

The considered algorithm for RT forecasting of end-user's power consumption and PV power production is deterministic. As a result, a single spot value is extracted and used as an input to the RT optimization model in the deterministic framework. We used a BBQR-based forecast that predicts only the average value of PV power production and end-user's consumption.

B. Optimization Algorithm

Fig. 3 depicts the overall view of the considered optimization algorithm, which is expressed as two-level rolling optimization. We have a set of decisions that must be made

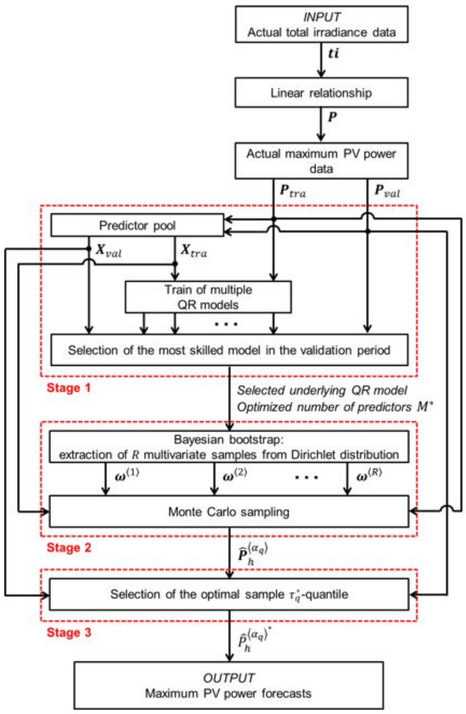

Fig. 2: Forecasting algorithm for PV power systems based on BBQR approach [4].

in the absence of complete information about uncertainties $\vec{\zeta}$ (including magnitudes of PV power production, end-users' power consumption, voltage at slack node, and deployment of flexibility services in RT). The details of DA optimization using DRCC are explained in [8]. Later, complete information on the occurrence of uncertainties is received. Following that, decisions at the second level are made.

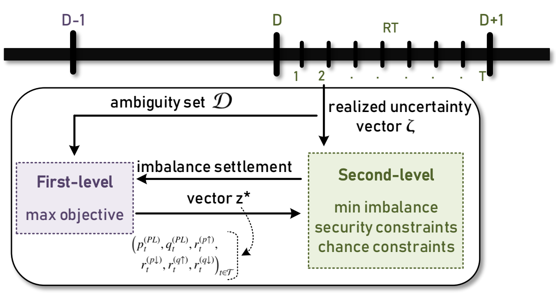

Fig. 3: Two-level formulation of optimization algorithm [8].

At the first level, the objective is to maximize revenue from selling flexibility services to upstream grids while minimizing consumption costs. The distribution grid operator determines the decision variables in the vector $\vec{z}$, which include the planned active and reactive power as well as the flexibilities exchanged with the external grid, at the first level. In the second level, the uncertain parameters in the vector $\vec{\zeta}$ are then realized, and the operator compenstates for the uncertainties using the available distributed resources. As a result, the objective of second level optimization is to minimize imbalances in the power flow at the connection point of the distribution grid while taking into account the distribution grid operating criteria, i.e., the state vector $\vec{x}(\vec{\zeta})$ including set-points of available distributed resources.

A summary of the two-level optimization algorithm under consideration is presented in (1)-(3). Readers can find more information in [8].

$$\text{First level: } \max_{\vec{z}} \, [\text{revenue}(\vec{z}) - \text{cost}(\vec{z})], \tag{1}$$

$$\text{Subject to: } \Pr_{\vec{\zeta}}(\text{Imbalance} \leq \delta) \geq 1 - \epsilon, \tag{2}$$

$$\text{Second level: } \min_{\vec{x}(\vec{\zeta})} \, [\text{Imbalance}(\vec{z}, \vec{x}(\vec{\zeta}))], \tag{3}$$

where δ is the maximum allowable imbalance of the power flow at the connection point, and $1 - \epsilon$ is the confidence level of obeying the maximum allowable imbalance.

III. Framework of Laboratory Demonstration Platform

The ReIne (RÉseaux INtElligents, French acronym for "Smart Grids") laboratory (Fig. 4) has been built at the School of Engineering and Management Vaud (HEIG-VD), Yverdon-les-Bains, Switzerland, to study and plan changes to distribution grids. ReIne is a hardware and software platform, mimicking a wide range of the LV grid topologies at full scale, as well as the MV grid topologies on a per-unit basis. The laboratory allows for the testing of the smart grid algorithms, as well as power electronics equipment, smart meter devices, and so on [9]. The uniqueness of this laboratory, in comparison to other existing structures in Switzerland or around the world [10], [11], is its flexibility, which makes use of both lumped grid elements and actual electrical sources and end-users. It allows for the reconfiguration of the grid topology as well as the connection points of the various sources and end-users.

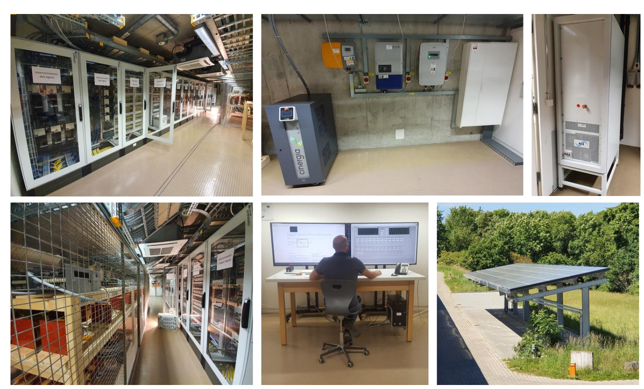

Fig. 4: ReIne laboratory for emulation of distribution grids.

ReIne is made up of a matrix network (switchboard cabinets) in 0-305V that connects production devices, passive and active end-users, and bidirectional power electronics converters. The part of the laboratory that emulates the grid is made up of nine lines with a resistance to inductance ratio of 0.3 up to 3.5, arranged in a matrix. Discrete inductors and resistors are used to emulate all lines.

The considered forecasting and optimization algorithms are tested and validated in the ReIne laboratory. The overall system configuration for this test is depicted in Fig. 5. As shown, the following five key parts were built to close the loop of the control system and validate the performance of the considered algorithms: (1) grid emulation; (2) data acquisition; (3) optimization algorithm execution; (4) forecasting algorithm execution; and (5) control signal activation.

1) Grid emulation: A grid is emulated, including five nodes, six lines, one transformer, one 100kW/63kWh BES system, a PV system with an 8.7kW ABB converter, and a 20kVA/18kW grid simulator, mimicking the end-user at node 3. Fig, 5 depicts the grid configuration and connections between lines and nodes. The magnitude of the HEIG-VD school load is communicated in RT to the grid simulator at node 3, then rescaled by a factor of 1/30. The goal is to control the active and reactive power outputs of the BES system and the PV converter so that flexibility services can be provided at the point of common coupling (PCC).

2) Data acquisition: For handling all measurements and reference/control commands, a supervisory control and data acquisition (SCADA) system based on LabVIEW® has been designed. This allows for the modification of the grid topology by controlling the contactors of the switchboard cabinets, as well as the visualization and recording of measurements. Transducers are used to measure voltages and currents, and three parallel National Instrument CompactRIOs are used to calculate root mean square (RMS) signals, active/reactive power, and harmonics over time scales of 200 milliseconds and 10 minutes. These readings are then grouped on an RT scale and sent to a personal computer (PC) that runs the LabVIEW® code for the SCADA system.

3) Optimization algorithm execution: We have to execute optimization algorithms in DA and RT. Both algorithms are written in Python using GUROBI optimization solvers [12]. The DA one, which is based on DRCC programming, is executed automatically every day at 18:00 after the forecasting algorithm has been executed. On the other hand, the LabVIEW® code calls the RT algorithm every ten minutes, which is based on deterministic linear programming. The RT optimization algorithm takes as inputs both the RT data captured by the SCADA system and the schedule determined by the DA optimization algorithm. Both the DA and RT algorithms are run on the same PC as the SCADA. As a result, a Python node is included in the LabVIEW® to integrate the interface. It is worth mentioning that backup scenarios are included in both Python and LabVIEW® on the occasion that the RT optimization algorithm does not yield a viable solution or an error occurs during the activation process.

4) Forecasting algorithm execution: The BBQR algorithm is being used for DA and RT forecasting. The forecasting algorithms for DA and RT are written in R and are called by Python. To that end, the Python package rpy2 is used for the interface between Python and R. In both DA and RT, the SQL database is used to ingest historical data. The strength of R in developing numerical algorithms is the driving force behind its use in the developed forecasting system.

5) Control signal activation: The BES and PV converter set-points in RT are determined by a code written in Python running on the PC. These set-points are managed by LabVIEW® in RT and transmitted via the Modbus interfaces of BES and PV converter systems. It is worth mentioning that the ABB converter requires an interface relay module in order to receive Modbus commands. To accomplish this, an additional expansion board and a programmable logic controller (PLC) are added to the converter to transfer Modbus control signals to it.

IV. Test Results

The considered forecasting and optimization algorithms, as well as the described laboratory demonstration platform, were tested for one month (September 2021). Because of the demonstration purpose, the operational time-step is set to 2.5 minutes rather than 10 minutes. Furthermore, both forecasting and optimization algorithms in RT can be run for the given example grid in less than 2.5 minutes, ensuring that the set-points are ready for activation.

Fig. 6 depicts the outcome of forecast algorithms for an end-user's consumption (both active and reactive power) on September 24^{th}, 2021 (as an example day). The shaded area around the DA forecast in Fig. 6 represents the error prediction based on the confidence level of 90%. Because the DA algorithm employs probabilistic forecasting, we can estimate the forecast error with any arbitrary confidence level.

We anticipate that the RT forecast will be closer to the actual end-user's power consumption than the DA forecast. This expectation is correct for active power because the mean absolute error (MAE) of DA forecasting is 0.35kW and that of RT forecasting is 0.22kW during the test month. On the other hand, the MAE of DA and RT forecasting of reactive power are 0.23kVar and 0.22kVar, respectively. As a result, there is not much of improvement in the RT forecast of reactive power.

A good selection of input predictors based on the type of end-user is a determining factor of forecast algorithms performance. The school load here is heavily influenced by working hours and holidays. As a result, adding a feature that represents such data significantly improves the results.

The forecast results for PV power production on September 24^{th} and 25^{th}, 2021 are depicted in Fig. 7. The shaded area in Fig. 7 represents the maximum error of DA forecasting at a 90% confidence level. This area can be determined since we employed a probabilistic forecasting algorithm. As can be seen, 24^{th} and 25^{th} of September were sunny and partly cloudy days, respectively. As a result, the performance of the DA forecast for September 24^{th} was more acceptable. The effectiveness of the RT forecast is clear on both days because the available power follows the RT forecast. It is worth noting that the deployed power is also shown in Fig. 7, as PV system power can be curtailed based on the optimization solution.

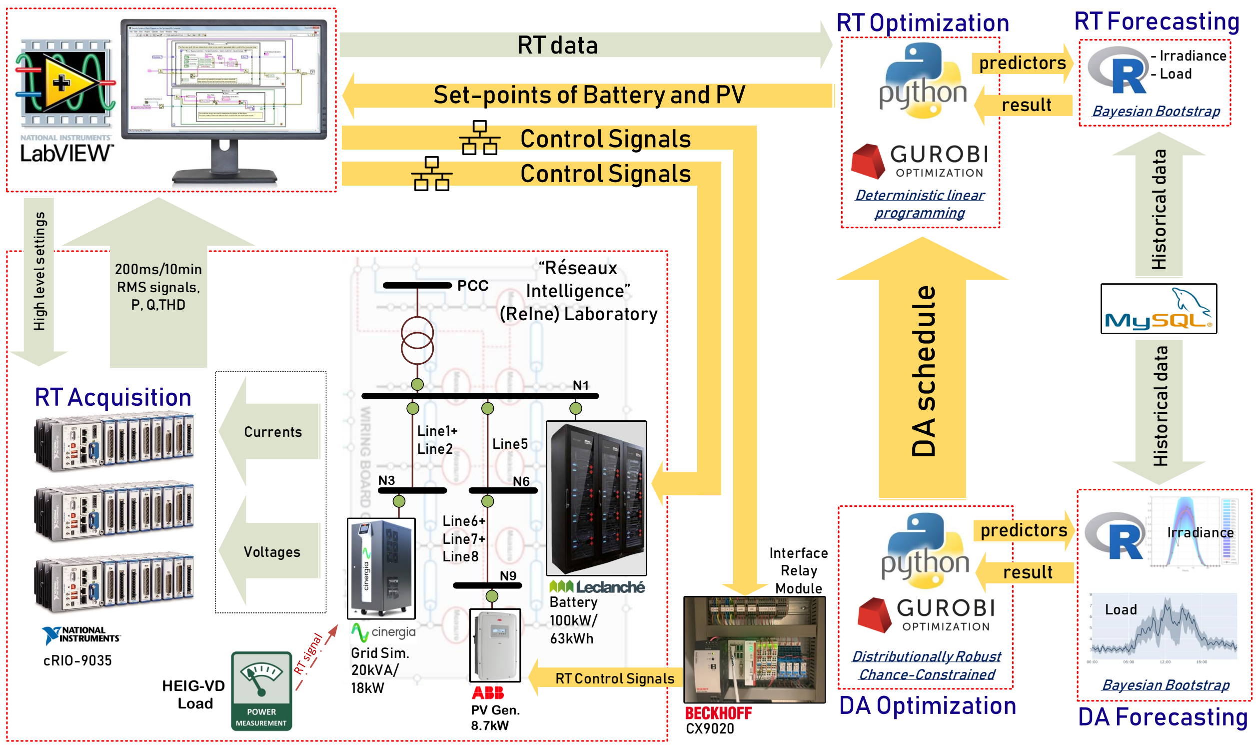

Fig. 5: Overall system configuration for a laboratory demonstration platform.

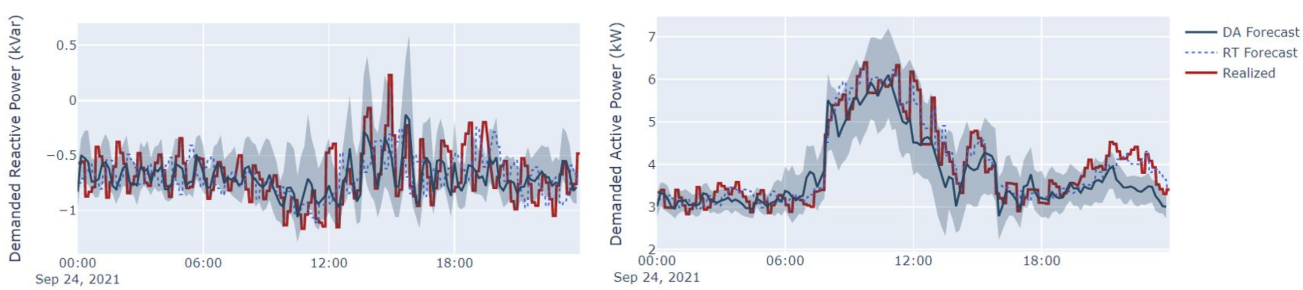

Fig. 6: Outcome of forecast algorithms for end-user's power consumption on September 24th, 2021.

The MAE of PV power production forecasting in DA is 0.28kW (on average, 12%). The MAE is reduced to 0.14kW (an average of 6%) using the RT forecast. It is worth mentioning that these forecasts do not incorporate external weather data for the PV system location. The forecasts will be significantly more accurate if such data inputs are added to the predictors of the forecasting algorithm.

The DA schedule and realized power at the PCC of the LV grid in RT are shown in Fig. 8. The shaded area of Fig. 8 also depicts the active and reactive power flexibilities surrounding the scheduled power (in both upward and downward directions). The behavior of the upstream grid operator in terms of flexibility service deployment is also simulated. The requested power is represented by a dotted blue line based on the simulated behavior (which is always between the determined flexibility boundaries). The realized active and reactive power in RT complies with the requested power with average accuracy of 15%.

The difference in realized power in RT versus requested power is caused by three factors: First, the forecast error in RT can not be zero. Second, the BES and PV systems set-points are changed every 2.5 minutes, so short-term variations in PV power production and end-user's power consumption are reflected in the output power. Third, the BES system converter accuracy is not perfect across all set-point ranges. Here, we used a 100kW battery in this test for the set-points less than 10kW. This is the worst power range for that converter.

V. Conclusion and Future Work

In this paper, the laboratory demonstration platform for the DiGriFlex project (real-time distribution grid control and flexibility provision under uncertainties) is presented. The

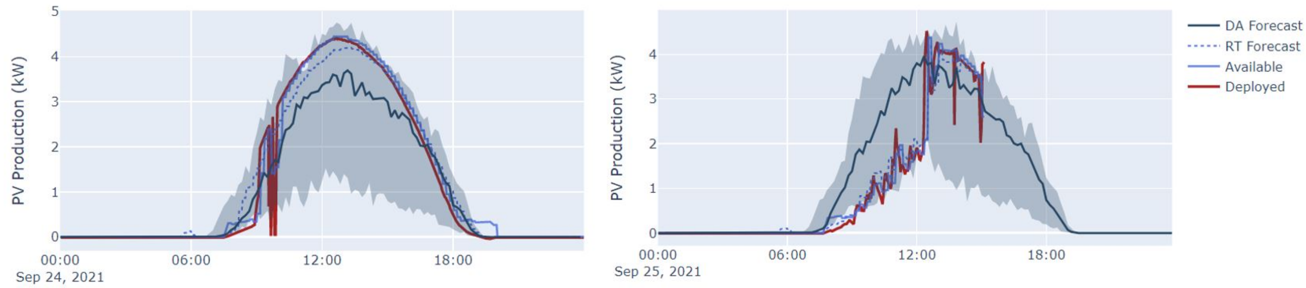

Fig. 7: Outcome of forecast algorithms for PV power production on September 24th and 25th, 2021.

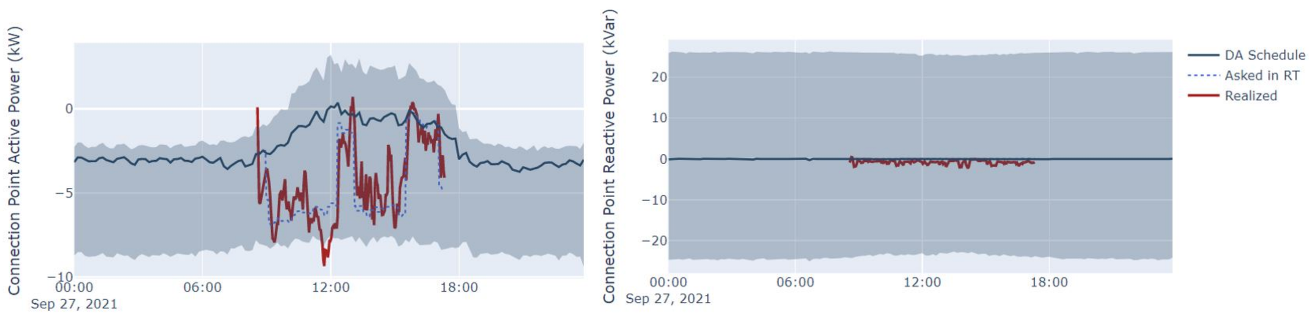

Fig. 8: Optimization output at the grid connection point on September 27th, 2021.

platform is created in the ReIne laboratory, which emulates various distribution grid configurations. For the experiment, a control loop of data acquisition, data storage, forecasting uncertainties, optimization, and control activation is implemented. The control loop operates automatically on the DA and RT scales, taking into account the uncertainties in the grid operation. The following major lessons have been learned from the test results and the laboratory demonstration platform that can be applied to the related industrial products:

- The accuracy of the BES systems converter in activating set-points in various operating ranges must be considered.
- The scalability of optimization and forecasting algorithms in terms of variables must be taken into account.
- Access to historical data and communicate predictors for forecasting are the bottlenecks of considered algorithms.
- Forecasting and optimization algorithms can be decomposed and parallelized to run on multiple processing units at the same time.

In future work, different processing frameworks to be used in RT control of distribution grids can be compared to address the above lessons, particularly the scalability issue.

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