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Deliverable 4.1, 4.2, 4.3, and 4.4 dated 3 December 2021

DiGriFlex

D4.1 Validation case study and grid operation scenarios,
D4.2 Pre-validation report including results of the power grid simulation tool (Simscape Power Systems and PLECS),
D4.3 Validation report including experimental validation of forecasting algorithms,
D4.4 Validation report including experimental test results in the ReIne laboratory.

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Summary

In this report, we present four deliverables of the project DiGriFlex aiming to "D4.1: Validation case study and grid operation scenarios", "D4.2: Pre-validation report including results of the power grid simulation tool (Simscape Power Systems and PLECS)", "D4.3: Validation report including experimental validation of forecasting algorithms", and "D4.4: Validation report including experimental test results in the ReIne laboratory". WP4 is focused on i) definition of case studies and related grid operation scenarios, ii) pre-validation of optimization using the grid simulation environment, iii) experimental validation of forecasting algorithms developed in WP2, and iv) experimental validation in the ReIne laboratory. This report includes all of the sections from I to iv (equivalent to Tasks 4.1 to 4.4). On a laboratory demonstration platform that mimics a real-world distribution grid, we validate the effectiveness of forecasting and optimization algorithms (outcomes of WP2 and WP3). Despite the uncertainties, the proposed algorithms enable efficient and secure real-time (RT) distribution grid operation, as well as flexibility provision from the LV distribution grid to upstream medium- and high-voltage (HV) grids. Uncertainties arise from the power generation and load power consumption of photovoltaic (PV) systems, as well as the RT deployment of flexibility services. The distribution grid becomes active in providing flexibility services as a result of the proposed algorithms. Bayesian bootstrap quantile regression (BBQR) and distributionally robust chance-constrained (DRCC) programming are used in the forecasting and optimization algorithms, respectively. This report assesses the laboratory demonstration platform's framework as well as the efficacy and validity of developed algorithms.

Contents

1 Introduction

In the context of the energy transition, to accomplish the sustainability goals of energy systems, the penetration of renewable energy sources (RESs) at the distribution grids level must be increased (see [1] for explaining this necessity in the case of Switzerland). This task on the consumption side, however, poses technical and operational challenges for the 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, given the high level of uncertainty in distributed photovoltaic (PV) systems, which are the major source of distributed RESs, power production control and forecasting will be complicated. Third, the stochastic profile of electric vehicle (EV) charging introduces a new source of uncertainty in load 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 load power consumption will improve the distribution grid's observability. For probabilistic forecasting of PV power production, [4] has developed a Bayesian bootstrap quantile regression (BBQR) approach. Furthermore, for load power consumption, [5] has proposed a real-time (RT) forecast based on random forests.

Controllability of distribution grids, on the other hand, will be improved through the development of efficient optimization algorithms. The grid's security will be ensured, and flexibility services will be provided to compensate for the increased uncertainties caused by the stochastic nature of PV system power production and EV load power consumption. A method for controlling the active and reactive power flexibilities of battery energy storage (BES) systems as the major sources for increasing the controllability of distribution grids has been proposed and tested in [6]. A two-stage control framework for dispatching a distribution grid has been developed and experimented upon, utilizing a BES system as a controllable element in [7]. The dispatch plan has been determined at the day-ahead (DA) stage, including the profile that the feeder's connection node must follow during the operation, allowing the BES system to restore an adequate amount of flexibility. A model predictive control algorithm has been presented for the RT stage to compensate for the mismatch between the profile realization of the distribution grid's connection node to the external grid and the DA stage's 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 objective of this paper is to develop and validate efficient forecasting and optimization algorithms for enhancing the observability and controllability of distribution grids. The proposed algorithms, which are based on BBQR forecasting and DRCC optimization, ensure that distribution grids operate safely by taking into consideration operational constraints such as network currents and voltages, as well as the limits of connected components. Furthermore, the proposed algorithms allow us to provide flexibility services from local low-voltage (LV) distribution grids to upstream medium- (MV) and high-voltage (HV) grids, considering operational uncertainties. Using the framework of a laboratory demonstration platform, all forecasting and optimization algorithms are tested and validated on a test case LV distribution grid. In comparison to earlier studies, the key contribution of this paper is that it describes the implementation and validation tests in a reconfigurable distribution grid laboratory environment. The framework and setup of RT data acquisition from the grid, control component interfaces, and software for DA and RT forecasting and optimization algorithms are all provided.

1.1 DiGriFlex project description

The first objective of this research project is to develop effective forecasting and optimal control methods to ensure efficient and secure operation of distribution grids, as well as flexibility and ancillary service provision from local low voltage distribution grids to the upstream medium/high voltage grids, under uncertainties. The source of uncertainties varies from stochastic distributed power generation (e.g., solar and wind power generation) and demand uncertainties to system model uncertainties (e.g., uncertain parameters of overhead lines and cables). Secure operation deals with satisfaction of technical constraints of distribution grids such as nodal voltage limits, power flow limits of lines/cables, and technical constraints of grid connected resources such as distributed generation and battery storage capacity limits. Efficient and optimal operation deals with both of the technical and economic objectives of local distribution operators such as minimization of voltage deviations and line’s losses, maximization of ancillary service provision to upstream medium and high voltage grids, and minimization of real-time imbalances with respect to predefined schedules.

The second objective of the project is to implement the above forecasting and optimal control methods in a test case low voltage distribution grid, and demonstrate the effectiveness of the developed methods for different grid operation scenarios.

1.2 WP4 description

WP3 “Implementation of the proposed methods and algorithms of WP2 and WP3 in a LV distribution grid (ReIne laboratory), and demonstration of their effectiveness under different operational scenarios (test cases)” consists of four tasks:

- Task 4.1: definition of case studies and related grid operation scenarios,
- Task 4.2: pre-validation of optimization using grid simulation environment,
- Task 4.3: experimental validation of forecasting algorithms developed in WP2,
- Task 4.4: experimental validation in the ReIne laboratory.

The next chapter will introduce the detailed contents of each task and its association with the four deliverables planned for this WP.

1.3 Deliverable D4.1 definition

The setup of grid configurations and grid parameters to represent typical LV distribution grids in Switzerland is determined in this deliverable "validation case study and grid operation scenarios" based on the WP1 outcome. Furthermore, grid operation scenarios, including generation/consumption uncertainties and grid component outages, are determined based on the outcomes of WP1, WP2, and WP3.

1.4 Deliverable D4.2 definition

The pre-validation case studies are implemented in a time-domain power grid simulation environment in this deliverable "pre-validation report including results of the power grid simulation tool", according to the above setups of deliverable 4.1. (e.g., Python, Sim-scape Power Systems, or PLECS). The pre-validation success criteria (e.g., level of over/under of nodal voltages as well as over currents of lines or probability of successful deployment of flexibility) are defined.

1.5 Deliverable D4.3 definition

The deliverable "validation report including experimental validation of forecasting algorithms" is the result of three major subtasks. First, the data acquisition, pre-processing, and exploratory data analysis processes are validated. Second, forecasting systems are implemented using algorithms that are run in a statistical programming environment (e.g., MATLAB or R). Third, the outcomes of forecasting algorithms in terms of target variable realizations are validated in terms of appropriate forecasting errors.

1.6 Deliverable D4.4 definition

The "validation report including experimental test results in the ReIne laboratory" is the fourth deliverable of this work package. First and foremost, the link between the forecasting and optimization algorithms is validated. Second, the operation of real-time online optimization with grid constraints and controllable source capabilities is investigated. Finally, the connection between prescheduling and online optimization is validated in terms of grid constraints, communication, and computation requirements.

2 WP planning

2.1 Project plan

Based on the breakdown of activities presented in the previous chapter, the time plan of WP4 shown in Figure 1 has been established.

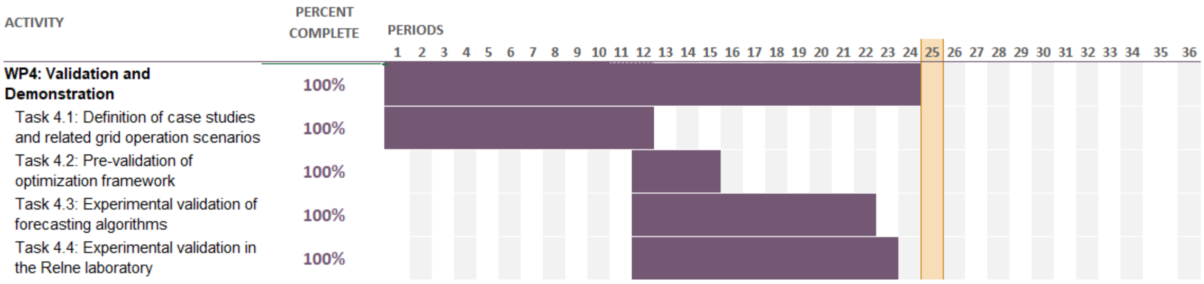

Figure 1: Summary of WP4 time plan

2.2 Tasks description

Figure 1 shows the progress and plan of the proposed tasks in WP4. This report includes the results of tasks 4.1, 4.2, 4.3, and 4.4. In the following, the detailed sub-tasks for these two tasks are listed.

Task 4.1: Definition of case studies and related grid operation scenarios

- Setup of grid configurations and grid parameters to represent typical low voltage distribution grids in Switzerland according to WP1 outcome.
- Setup of grid operation scenarios including generation/consumption uncertainties and grid component outages according to the outcomes of WP1, WP2, and WP3.

Task 4.2: Pre-validation of optimization using grid simulation environment

- Implementation of pre-validation case studies, according to above setups of Task 4.1 in a time-domain power grid simulation environment (e.g., Simscape Power Systems and PLECS).
- Definition of success criteria of pre-validation (e.g., level of over/under of nodal voltages as well as over currents of lines)

Task 4.3: Experimental validation of forecasting algorithms developed in WP2.

- Data acquisition, data pre-processing and exploratory data analysis.
- Implementation of the forecasting systems by means of algorithms run in a statistical programming environment (e.g., MATLAB or R).
- Validation of the outcomes of forecasting algorithms with respect to the realizations of the target variables, in terms of appropriate forecasting errors.

Task 4.4: Experimental validation in the ReIne laboratory

- Implementation of validation case studies in the ReIne laboratory
- Validation of the link between the forecasting algorithms and the optimization algorithms.
- Validation of real-time online optimization regarding grid constraints and controllable source capabilities.
- Validation of link between prescheduling and online optimization regarding grid constraints, communication and computation requirements.

3 Setup of validated 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. Figure 2 depicts the timeline of the proposed two-level rolling framework for forecasting and optimization algorithms.

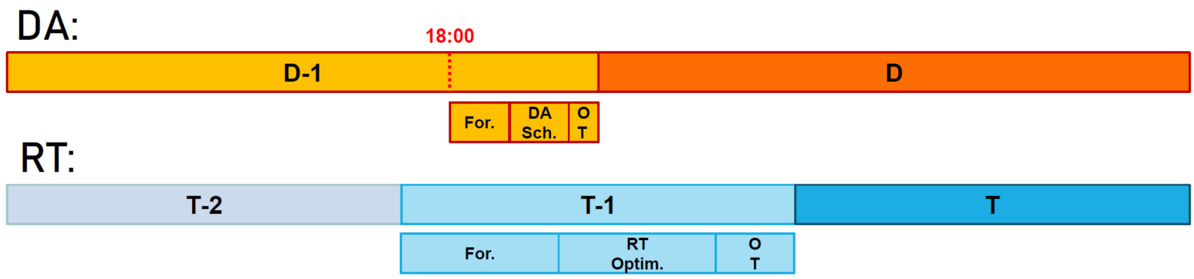

Figure 2: Two-level rolling framework for forecasting and optimization algorithms.

According to figure 2, we forecast profiles of PV power production and load 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 while forecasting the uncertain parameters. This objective function includes the balancing cost minus the total revenues from providing flexibility services to upstream MV and HV grids. As shown in figure 2, the optimization problem's set-points are activated prior to the start of the day D, which includes some operational time (OT).

In RT, we forecast power profiles that occur during T using data collected until interval T-2 as shown in figure 2. 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 load power consumption over the next 10 minutes. 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 forecasting and optimization control algorithms for the DA and RT scales are briefly explained below.

3.1 Forecasting algorithm

In DA, we require two forecasts: for PV energy production and load power consumption (both active and reactive power). The methodology 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 methodology is developed within a probabilistic framework, i.e., the proposed algorithm generates predictive quantiles of the target variable for the target forecast horizon.

The forecasting methodology for PV power systems is depicted in figure 3. 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 WP2. The same procedure was also developed to forecast the load power consumption (for both active and reactive power), as shown in figure 4.

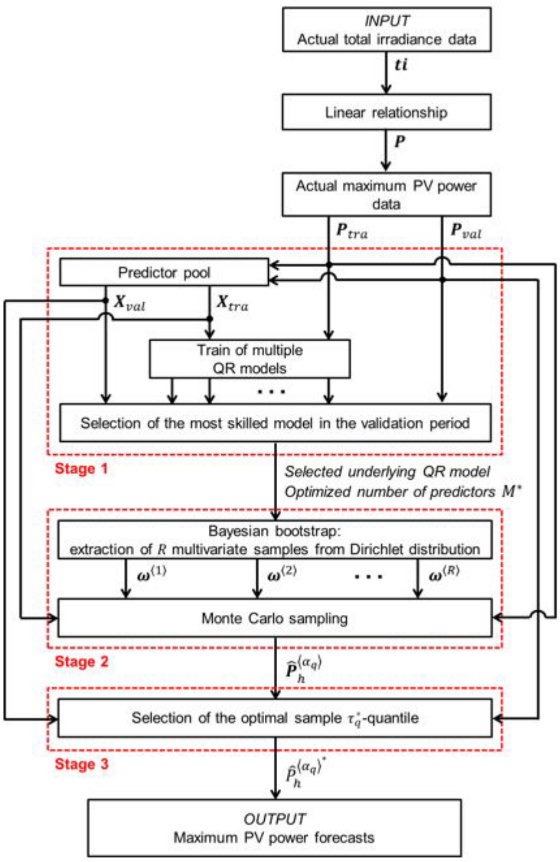

Figure 3: Forecasting methodology for PV power systems based on BBQR approach.

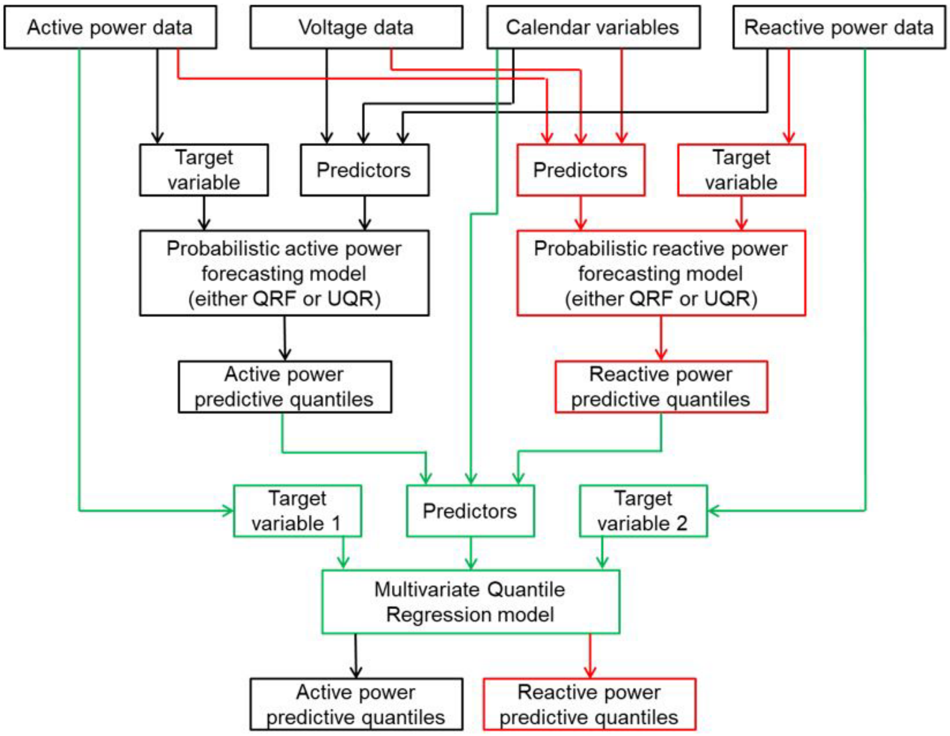

Figure 4: Forecasting methodology for load power consumption based on BBQR approach.

The developed methodology for RT forecasting of load 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. WP2 presents the derivative-persistence (DP) model for RT forecasting of PV power production.

3.2 Optimization Algorithm

Figure 5 depicts the overall view of the proposed optimization algorithm, which is expressed as two-level rolling optimization. We have a set of decisions to make that must be made in the absence of complete information about random events. These are known as first level decisions, and they are made using DRCC programming (the details of DA optimization using DRCC are explained in WP3). Later, complete information on the occurrence of random events is received. Following that, decisions at the second level are made.

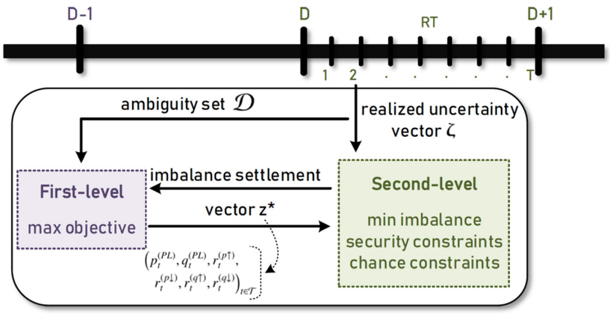

Figure 5: Two-level formulation of the optimization algorithm.

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 planned flexibilities, at the first level. The uncertain parameters in the vector $\vec{\zeta}$ are then realized in the second level, and the operator uses available distributed resources to compensate for the uncertainties. As a result, the objective of second level optimization is to minimize imbalances while taking into account the distribution grid's operating criteria, planned active/reactive power, and requested flexibilities.

4 Experimental Validation in ReIne

The ReIne (RÉseaux INtElligents, French acronym for ``Smart Grids") laboratory (figures 6 and 7) 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 for mimicking a wide range of the LV grid's topologies at full scale, as well as the MV grid's topologies on a per-unit basis. The laboratory allows for the testing of the smart grid's control methods, 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's elements and actual electrical sources and load. It allows for the reconfiguration of the grid's topology as well as the connection points of the various sources and load.

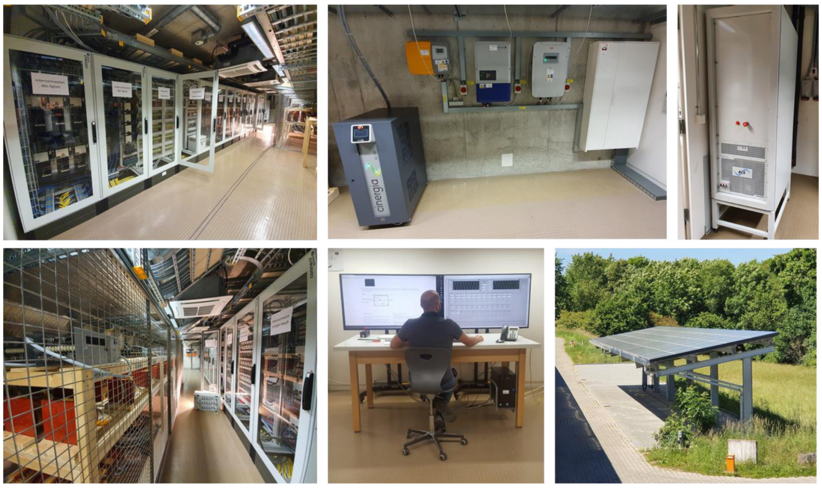

Figure 6: ReIne laboratory for emulation of distribution grids.

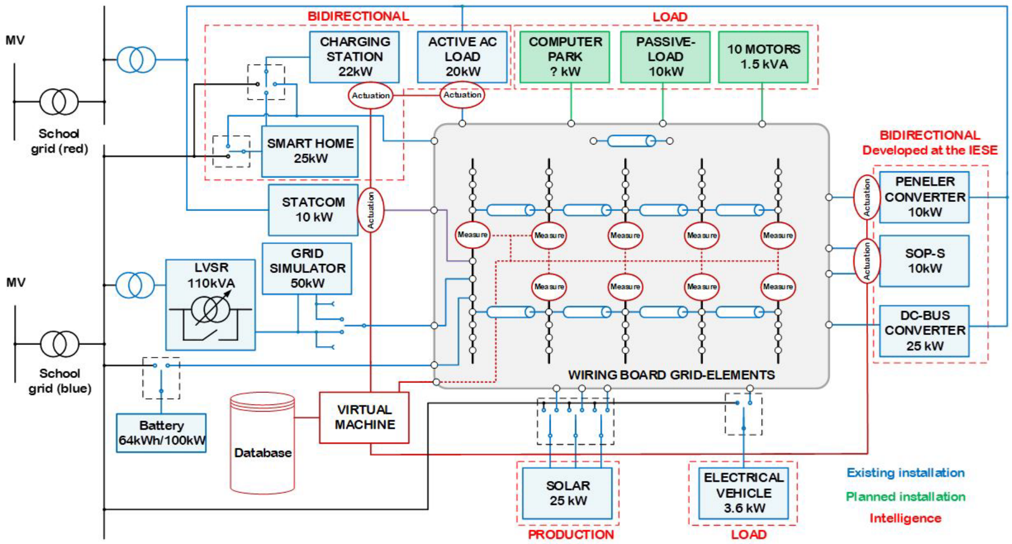

Figure 7: Configuration of ReIne laboratory and connected elements.

Table 1 summarizes the main characteristics of the laboratory. ReIne is made up of a matrix network (switchboard cabinets) that connects production devices, passive and active load, and bidirectional power electronics converters. The part of the laboratory that emulates the grid is made up of nine lines arranged in a matrix. Discrete inductors and resistors are used to emulate all lines.

Table 1: Main characteristics of ReIne.

Voltage range:	0-305V
Nominal power:	100kVA
Earthing system:	TN-S without residual-current devices
Wiring type:	Line with R/X from 0.3 up to 3.5
Nominal Power:	100kVA
Controls mode:	(1) Centralized SCADA; (2) Distributed GridEye
Purpose:	Research, industrial, and education

The proposed forecasting and optimization algorithms are tested and validated in the ReIne laboratory. The overall system configuration for this test is depicted in figure 8. As shown, the following five key parts were built to close the system loop and validate the performance of the proposed solution: (1) grid emulation; (2) data acquisition; (3) optimization codes; (4) forecasting codes; and (5) control signal activation.

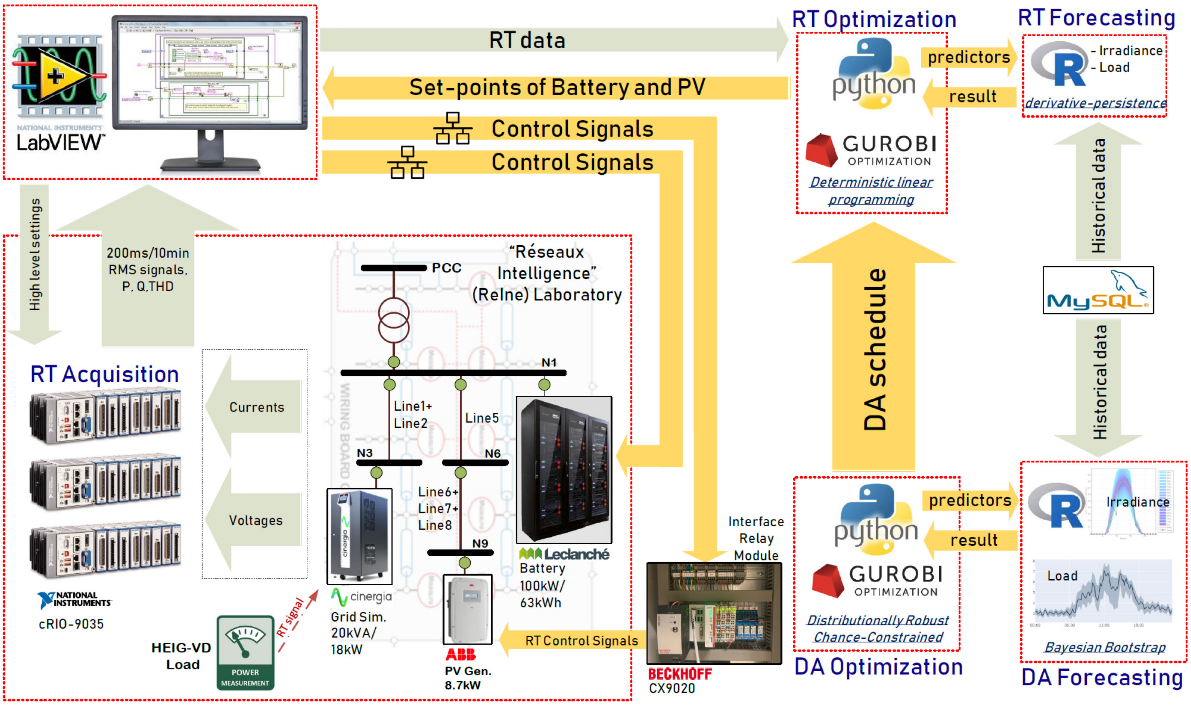

Figure 8: Overall system configuration for a laboratory demonstration platform.

4.1 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 load at node 3. The grid configuration and connections between lines and nodes are depicted in figure 8 in the block of ReIne. 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).

4.2 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's 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.

4.3 Optimization codes

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

4.4 Forecasting codes

The BBQR and DP methods are being used for DA and RT forecasting, respectively. Both the forecasting codes for DA and RT are written in R and are called by the main Python code. 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 the development of numerical algorithms was the driving force behind its use in the forecast.

4.5 Control signal activation

The BES and PV converter set-points in RT are determined by Python code running on the PC. These set-points are managed by LabVIEW code 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.

5 Test Results

The proposed forecasting and optimization algorithms, as well as the described demonstration platform, were tested for one month (during September 2021). During a meeting on September 28, 2021, the online demonstration was also presented to SFOE representatives (Dr. Michael Moser and Dr. Denis Peytregnet) and other project partners from Depsys and EPFL. Because of the demonstration purpose, the operational time-step in this test is set to 2.5 minutes rather than 10 minutes. Furthermore, both the 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 and that there is no practical challenge.

Figure 9 depicts the outcome of forecasts for load power consumption (both active and reactive power) on September 24, 2021 (as an example day). The shaded area around the DA forecast in figure 9 represents the error prediction based on a 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 load 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 0.22kW for RT forecasting during the test month. On the other hand, the MAE of DA and RT forecasting of reactive power, on the other hand, are 0.23kVar and 0.22kVar, respectively. As a result, there is not much of an improvement in RT forecast of reactive power.

A good selection of input predictors based on the type of load is a determining factor of forecast 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.

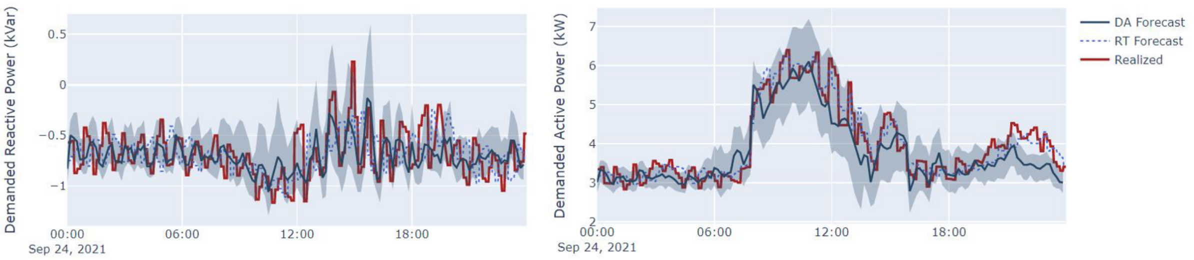

Figure 9: Forecast output for load power consumption on September 24, 2021.

The forecast results for PV power production on September 24 and 25, 2021 are depicted in figure 10. The shaded area in figure 10 represents the maximum error of DA forecasting at 90% confidence level. This area can be determined since we employed a probabilistic forecasting algorithm. As can be seen, 24 and 25 of September were sunny and partly cloudy days, respectively. As a result, the performance of the DA forecast for September 24 was more acceptable. The effectiveness of the RT forecast, on the other hand, is clear in both types of days because the available power follows the RT forecast. It is worth noting that the deployed power is also shown in figure 10, as PV system power can be curtailed based on the optimization algorithm solution.

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 the weather data for the PV system location. The forecasting will be significantly more accurate if such data inputs are added to the predictors of the forecasting algorithm.

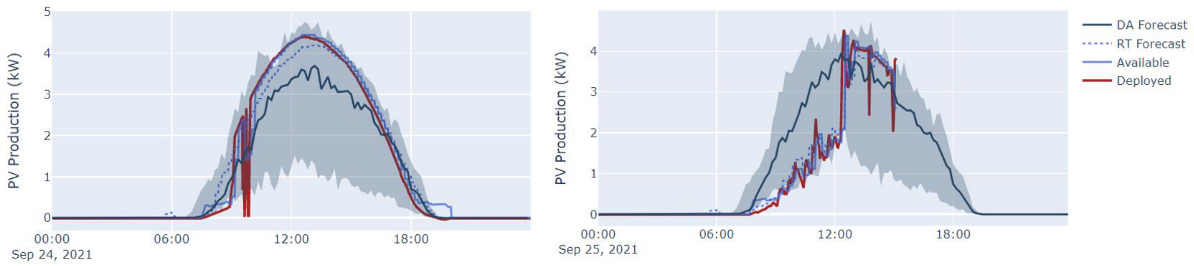

Figure 10: Forecast output for PV power production on September 24 and 25, 2021.

The DA schedule and realized power at the PCC of the LV grid in RT are shown in figure 11. The shaded area of figure 11 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 services deployment is also simulated. The asked power is represented by a dotted blue line based on the simulated behavior (which is always between the determined flexibility boundaries). As can be seen, the realized active and reactive power in RT complies with the requested power.

Three reasons contribute to the difference in realized active power in RT versus asked power: First, the forecast error in RT cannot 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 load power consumption are reflected in output power. Third, the BES system converter's 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 the converter of this BES system.

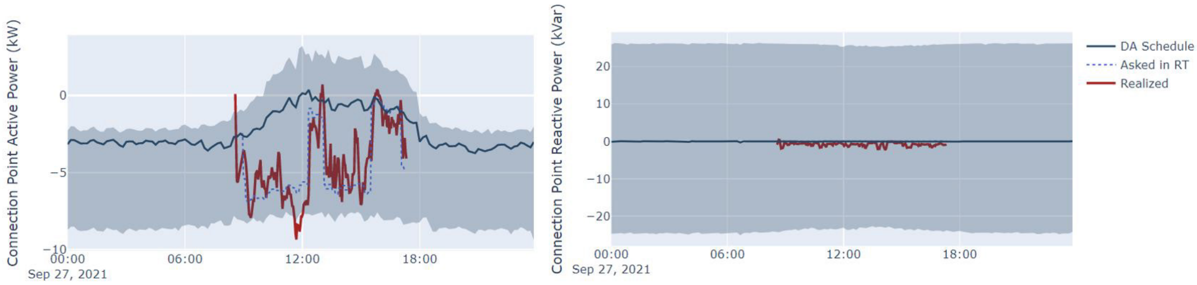

Figure 11: Optimization output at the grid's connection point on September 27, 2021.

6 Conclusion and Next Steps

In this report, the laboratory demonstration platform for the DiGriFlex project (real-time distribution grid control and flexibility provision under uncertainties) is presented. The platform is created in the ReIne laboratory, which mimics and emulates various distribution grid configurations. For the experiment, a 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 grid operation. The following major lessons were learned from the test results and the demonstration platform that can be applied to related industrial products:

- The accuracy of the BES systems converter in activating set-points in various operating ranges must be considered.
- The proposed solution's scalability in terms of the number of nodes and components must be taken into account.
- The access to historical data and communicating predictors as forecast inputs were the bottlenecks of the proposed algorithms.
- Forecasting and optimization algorithms can be decomposed and parallelized to run on multiple processing units at the same time.

In future work to address the above lessons, a comparative evaluation of stream processing frameworks is needed for the implementation of RT control engines in distribution grids.

7 Appendix A: Description of Optimization Codes

The optimization algorithm proposed in WP3 is written in Python and implemented with the optimization package Gurobi. This code requires the following packages: "gurobi", "rpy2", "sql-connector", "sklearn", "scipy", and "statsmodel". Because the LabVIEW interface only works with 32 bit versions of Python, the version 3.6.8 32 bit of Python must be used to run this code.

To run the DA optimization code, open the file "DiGriFlex DA.py." The bat file "DA code.bat" is also created, which executes this code automatically. You can also run the RT optimization code by running the file "DiGriFlex Sim.py." The bat file RT code is also created, which automatically executes this code. The results are saved in the "/Results/" folder. The results can also be plotted using the jupyter file "/Figures/plotting.ipynb." The code is written with git version control, and code documentation is available.

8 Appendix B: Description of Forecasting Codes

The forecasting code can be found in the folder "/Functions R." For DA and RT forecasting, the following codes are used:

- Function_DayAhead_Bayesboot_irra.R: This code is used for PV power production DA forecasting.
- Function_DayAhead_Bayesboot_P.R: This code is used for DA forecasting of loads' active power consumption.
- Function_DayAhead_Bayesboot_Q.R: This code is used for DA forecasting of reactive load power consumption.
- Function_LQR_Bayesboot_irra.R: This code is used for PV power production RT forecasting.
- Function_LQR_Bayesboot_P_v2.R: This code is used to forecast the active power consumption of loads in RT.
- Function_LQR_Bayesboot_Q_v2.R: This code is used to forecast the reactive power consumption of loads in RT.

The training datasets used in the forecasting codes are located in the folder "/Data" and are labelled "DATA_tra", "DATA_tra_Irr", "DATAP_tra", and "DATAQ_tra".

9 Bibliography

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