European Research Infrastructure supporting Smart Grid and Smart Energy Systems Research, Technology Development, Validation and Roll Out – Second Edition

Project Acronym: **ERIGrid 2.0**

Project Number: **870620**

Technical Report Lab Access User Project

Artificial Intelligent Digitalized Solutions for Smart Grids (AIDGRIDS)

Access Duration:

24/09/2022 – 08/10/2022 (physical access, J. Lorente, L. Pikolos, G. Makrides), 17/10/2022 – 28/10/2022 (physical access, R. Bharath-Varsh, S. Reisenbauer)

Funding Instrument:	Research and Innovation Action
Call:	H2020-INFRAIA-2019-1
Call Topic:	INFRAIA-01-2018-2019 Integrating Activities for Advanced Communities
Project Start:	1 April 2020
Project Duration:	54 months
User Group Leader:	George Makrides

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 870620.

Report Information

Document Administrative Information	
Project Acronym:	ERIGrid 2.0
Project Number:	870620
Access Project Number:	131
Access Project Acronym:	AIDGRIDS
Access Project Name:	Artificial Intelligent Digitalized Solutions for Smart Grids
User Group Leader:	George Makrides
Document Identifier:	ERIGrid2-Report-Lab-Access-User-Project-Access_AIDGRIDS-01
Report Version:	vn.01
Contractual Date:	14/07/2022
Report Submission Date:	02/01/2023
Lead Author(s):	George Makrides
Co-author(s):	Javier Lopez Lorente, Loucas Pikolos Rao Bharath-Varsh, Sarah Reisenbauer
Keywords:	[smart grids, artificial intelligence], European Union (EU), H2020, Project, ERIGrid 2.0, GA 870620
Status:	Final

Change Log

Date	Version	Author/Editor	Summary of Changes Made
28/12/2022	v1.0	G. Makrides (FOSS)	-

Table of Contents

Executive Summary 7
1 Lab-Access User Project Information 9
1.1 Overview 9
1.2 Research Motivation, Objectives, and Scope 10
1.3 Structure of the Document 10
2 State-of-the-Art/State-of-Technology 12
3 Executed Tests and Experiments 13
3.1 Test Plan, Standards, Procedures, and Methodology 13
3.2 Test Set-up(s) 16
3.3 Data Management and Processing 19
4 Results and Conclusions 21
4.1 Discussion of Results 21
4.2 Conclusions 29
5 Open Issues and Suggestions for Improvements 31
References 32
Appendix A. UCY Microgrid real-time platform 33

List of Figures

Figure 1. UCY-FOSS experimental nanogrid schematic diagram. 13
Figure 2. Infrastructure setup for validation at AIT and demonstration at UCY-FOSS. 16
Figure 3. Typhoon HIL real-time simulation test-bed with AIT HIL controller at AIT. 17
Figure 4. UCY microgrid real-time simulation model including grid fault emulation module. 18
Figure 5. AIT SGC SCADA dashboard for smart inverter interoperability testing. 19
Figure 6. State estimation performance evaluation for average phase voltage at UCY's Administration Building: (a) Plot of actual against estimated voltages, and (b) Histogram of error. 22
Figure 7. Actual and estimated voltage profiles and errors at UCY microgrid PCC. 22
Figure 8. SCADA HIL UCY microgrid dashboard visualising the voltage estimates at the PCC of UCY campus and the variations in voltage when applying different grid faults. 23
Figure 9. Network interconnection diagram of developed net-load forecasting model. 23
Figure 10. Daily nRMSE of the optimal net-load forecasting model applied to UCY microgrid over the test set period. The red dashed line indicates the mean nRMSE. 24
Figure 11. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for setting active and reactive power set-points and (b) Visualising the response at a PQ diagram. 24
Figure 12. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for setting the Volt/Var grid control function and (b) Visualising the response at a Volt/Var characteristic curve and modelled power widgets. 25
Figure 13. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for setting the Volt/Watt grid control function and (b) Visualising the response at a Volt/Watt characteristic curve and modelled power widgets. 25
Figure 14. Voltage estimation performance given by the R^2 and RMSE for the developed linear regression and ANN models for different busbar fractions. 26
Figure 15. Actual and predicted voltage estimates when applying the ANN model trained with historical measurements. 26
Figure 16. Actual and predicted voltage estimates when applying the LR model trained with historical measurements 27
Figure 17. Actual and predicted voltage estimates after reducing bias for (a) ANN model and (b) LR model trained with historical measurements 27
Figure 18. Real-time simulation environment UCY campus microgrid model integrated with voltage state estimator. 28
Figure 19. Project event and presentation delivered by the AIT team to researchers of UCY. 28
Figure 20. UCY microgrid real-time simulation platform dashboard. 33
Figure 21. UCY-FOSS nanogrid dashboard displaying actual measurements of the pilot and simulated conditions (smart inverter set-points and grid faults). 34

List of Tables

Table 1: Test plan of project lab access. 14
Table 2: Evaluation metrics for average phase voltage estimations obtained by the developed state estimation model for the different buildings of UCY microgrid. 21

List of Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
CO	Project Coordinator
CHIL	Control Hardware-in-the-loop
EC	European Commission
DER	Distributed Energy Resource
DSSE	Distribution System State Estimation
EGD	European Green Deal
EU	European Union
LA	Lab Access
LR	Linear Regression
LV	Low Voltage
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Sources
RTS	Real Time Simulation
UG	User Group
UP	User Project
WLS	Weighted Least Squares

Executive Summary

Transitioning to a sustainable energy society and mitigating climate change effects through accelerated energy sector decarbonization is a recognised top priority of the European Union (EU) under the recent European Green Deal (EGD). Artificial intelligence (AI) is a key enabling technology towards an optimally managed renewable-powered energy sector. The aim of the proposed project was to examine the capabilities of next-generation AI-driven grid-supportive tools that facilitate the dynamic and cost-effective management of microgrids at high shares of solar photovoltaics (PV). Specifically, the project focused on the development and accelerated validation of a data-driven voltage state estimator and a grid condition prognostic platform (digital twin) that includes a net-load forecasting model. The activities further entailed the validation of the proposed tools' while coupled to grid supportive controls demonstrated through real-time simulation environments ad control hardware-in-the-loop simulations. To this end, the proposed project is timely pertinent by offering a real-time simulation framework for experimentally validating smart grid analytical tools and demonstrating AI-driven applications (voltage state estimation and net-load forecasting).

The project was performed cooperatively, in two phases:

- A first physical stay of staff members of University of Cyprus was held at AIT Austrian Institute of Technology at the SmartEST Laboratory in Vienna, Austria.
- A second physical stay was performed 2 weeks later by AIT staff members at University of Cyprus in Nicosia at the Low Voltage Experimental Microgrid Lab, Cyprus to implement the developed methods on site.

In the scope of this work, the test system considered for the real-time simulations and the actual site demonstration is the low-voltage (LV) Experimental Nanogrid of UCY-FOSS and the Smart Energy Campus microgrid of UCY. The nanogrid pilot is a flexible and scalable renewable to grid integration infrastructure that includes PV systems, smart inverters, battery storage, smart loads/plugs, smart meters, IoT communication devices and a central energy management system. Along this context, the Smart Energy Campus is a commercial-scale University campus microgrid that comprises of 15 smart buildings and distributed PV systems of capacity 400 kW that are fully monitored and equipped with smart meters as part of the implemented advanced metering infrastructure (AMI) for the acquisition of high-resolution data.

Three test cases were designed for the project:

- Test Case 1 [AIT]: Voltage state estimation tool development and validation for utility-scale microgrids (developed and provided by the applicants) at real-time environments.
- Test Case 2 [AIT]: Short-term net-load forecasting voltage regulation tool development and validation for utility-scale microgrids (developed and provided by the applicants) at real-time environments.
- Test Case 3 [UCY-FOSS]: Grid-condition prognostic digital twin (developed and provided by the applicants) verification for utility-scale microgrids.

As a result of the conducted tests, the performance of the developed voltage state estimator was verified to achieve high accuracies <1% error, when supplied with high-resolution data (high variability solar and demand data) in a software-in-the-loop approach. In addition, the capability of the voltage state estimator to estimate and follow voltage deviations when imputing random grid faults was validated using customised SCADA HIL dashboards. An additional optimisaiton step was carried out in order to further imporve the accuracy of the state estimator. For this purpose, the model was trained using synthetic training data (obtained by performing a power flow analysis of the developed UCY microgrid PowerFactory model) and historic measurements. The evaluation results showed that the devised model, leveraging artificial neural networks (ANNs), exhibited high accuracies and was capable to follow in most cases the actual voltage profiles even at low bus-bur utilisation fractions.

The tests further verified the performance accuracy of the optimally constructed net-load forecasting model that yielded forecasting errors of approximately 4%. Moreover, the provision of grid control functionalities through the real-time simulation model (driven by the implemented tools) was emulated using the AIT SGC with SunSpec inverter protocol support.

Finally, the performed research is expected to enhance the predictive observability and prognostic control of smart grids/microgrids leading to increased grid flexibility for integrating higher shares of PV at the distribution network. Actual-life demonstrations of such intelligent tools are therefore invaluable for grid operators that aim to optimally orchestrate complex distribution system operations at high-RES shares.

1 Lab-Access User Project Information

1.1 Overview

USER PROJECT	
User Project Acronym	AIDGRIDS
USER Project Title	Artificial Intelligent Digitalized Solutions for Smart Grids
ERIGrid Reference	131
ERIGRID2.0	4th TA Call
USER GROUP	
Name (Lead)	George Makrides
Organization, Country	University of Cyprus, Cyprus
Names	Makrides, George (1); López Lorente, Javier (1); Pikolos Loucas (1) Bharath-Varsh, Rao (2); Reisenbauer, Sarah (2)
Organizations, Countries	(1): University of Cyprus, Cyprus; (2): Austrian Institute of Technology, Austria
HOST RESEARCH INFRASTRUCTURE	
Name	AIT Austrian Institute of Technology / University of Cyprus
Countries	Austria / Cyprus
Start and End Dates	24 September 2022 – 07 October 2022 (in person), AIT Vienna
(‘In-person’)	17 October 2022 – 28 October 2022 (in person), University of Cyprus, Nicosia
Stay and Access days	In total: Stay Days 15 | Access Days 10 / AIT Vienna George Makrides | Stay Days 08 | Access Days 05 López Lorente, Javier | Stay Days 08 | Access Days 05 Loucas Pikolos | Stay Days 07 | Access Days 06 In total: Stay Days 12 | Access Days 10 / University of Cyprus, Nicosia Bharath-Varsh, Rao | Stay Days 12 | Access Days 05 Sarah Reisenbauer | Stay Days 12 | Access Days 05

1.2 Research Motivation, Objectives, and Scope

Research Motivation

A main challenge in the scope of decarbonising the power sector and aligning with future energy needs, is to ensure seamless renewable energy sources (RES) integration such as solar photovoltaic (PV) in electrical networks, through advanced management and control systems. Along this context, the key technological battlegrounds of renewable-powered grids are associated with the capabilities of intelligent data-driven systems to monitor in real-time and optimally manage the operation of PV systems (control of smart inverters), based on accurate prognostic functionalities. The motivation for carrying out this project has been the current need to mitigate stability challenges of smart grids/micro grids at high shares of solar PV, by enhancing the predictive observability and control functionalities of supervisory systems through artificial intelligence (AI) enabling technologies.

Scopes and Objectives

The scope of the project was to validate and demonstrate next-generation AI-driven grid-supportive tools that facilitate the dynamic and cost-effective management of microgrids at high shares of solar PV. To this end, the project focused on the development and accelerated validation of a data-driven voltage state estimator and a grid condition prognostic platform (digital twin) that includes a net-load forecasting model that is applicable to microgrids. Moreover, the endeavour entailed the validation of the proposed tools' while coupled to grid supportive controls within real-time simulation environments. Specifically, the objectives (O) of the project included the:

[O1] Development and performance evaluation of a data-driven voltage state estimator to estimate voltages at bus-bars of the UCY microgrid at high variability solar and demand data.

[O2] Technical validation of voltage state estimator when limiting the location measurements of the microgrid modelled smart meters and imputing random grid faults to the RTS simulation environment.

[O3] Development and control-hardware-in-the-loop (CHIL) validation of net-load forecasting tool and grid-prognostic platform to provide active and reactive power control (Volt-VAr/Q(U) and Volt-Watt/P(U)) when fed with different simulated net-load profiles.

[O4] Demonstration of voltage state estimator to estimate node voltages of the UCY microgrid by integrating the digital twin model to the actual environment and employing actual smart meter measurements of the microgrid.

[O5] Technical validation and demonstration of time-ahead grid condition prognosis by integrating the digital twin model to the actual environment and demonstrating control signalling for voltage regulation (active and reactive power control, Volt-VAr/Q(U) and Volt-Watt/P(U)).

1.3 Structure of the Document

This document is organised as follows: Section 2 briefly outlines the state-of-the-art/state-of-technology that provides the basis of the realised Lab Access (LA) User Project (UP). Section 0 briefly outlines the performed experiments whereas Section 4 summarises the results and conclusions. Potential open issues and suggestions for improvements are discussed in Section 5. Finally, additional information is provided in the Appendix A. UCY Microgrid real-time simulation platform.

Introductory Note:

This Lab Access project was performed cooperatively, in two phases: A first physical stay of staff members of University of Cyprus was held at AIT Austrian Institute of Technology at the SmartEST Laboratory in Vienna, Austria.

A second physical stay was performed 2 weeks later by AIT staff members at University of Cyprus in Nicosia at the Low Voltage Experimental Microgrid Lab, Cyprus to implement the developed methods on site.

2 State-of-the-Art/State-of-Technology

As the power sector becomes increasingly complex, intelligent tools such as AI are needed to manage systems effectively and derive value from all grid asset generated data [1]. The main driver for smart grid AI technologies is the massive amount of high-dimensional data and the limitations of traditional modelling technologies in information processing. These systems are typically complex and based on big data, creating new challenges and opportunities for testing them. Even more challenging is testing the interactions of such software solutions with actual field devices such as smart inverters and energy management systems for data-driven control applications. Academic institutions and industrial organisations are particularly active in modernising the distribution grid by applying common AI and techniques for generation and consumption forecasting, estimation of operational state, power grid stability assessment and faults detection in the smart grid [2-4].

Generation and demand forecasting are key enabling AI technologies that facilitate the integration of renewables into the smart. Over the past years, many short-term load forecasting (STLF) studies focused on applying modern techniques [5-6] to map the nonlinear relationships between the load and the relevant parameters. Similarly, for PV generation forecasting the most commonly applied supervised learning approaches include deep learning methods [7-8]. In an attempt to reduce system complexity and to further enable efficient energy management, load and RES uncertain variables are combined to form the net-load, which is the variable that describes the difference between aggregated consumption and RES generation. Even though many studies are focusing on day-ahead PV production forecasting and consumption, the lack of a replicable, scalable and standardised method for validating direct net-load forecasting tools coupled to distributed energy resource (DER) control remains yet a landscape for significant improvements. Efforts in this direction are expected to be intensified as renewable-powered microgrids and energy communities increase in both amount and scale.

The recent advent of AI technologies in smart grids has also been the turning point for including distribution level voltage state estimation models. At the transmission system, voltage state estimation based on the weighted least squares (WLS) is widely used and applied with relative high accuracies [9]. Over the past years, the application of distribution system state estimation (DSSE) has gained significant attention, mainly for implementing protection and control techniques envisioned by the smart grid concept. Despite low measurement coverage at the distribution network, pioneer work on DSSE has been conducted by optimising the placement of additional system sensors [10] or deriving pseudo-measurements from existing sensor data using the underlying system model [11]. However, the lack of information about distribution grids, especially at the Low Voltage (LV) level, renders necessary the implementation of accurate state estimation methods that are entirely data-driven. In addition, the extent to which low-observability state estimation techniques are robust to data availability, measurement loss and flexibility to measurement quantities is yet unexplored and can only be examined in an accelerated software-in-the-loop approach. Moreover, the deployment of advanced metering infrastructure in all sections of distribution networks is not cost-effective, hence a model capable to estimate electrical parameters with the highest possible accuracy at a designated point of a distribution network where measurements are not available is of utmost importance.

Finally, the implementation of smart grid/microgrid digital twins towards the effective analysis of the health and operating conditions of the grid is emerging as a powerful tool for improving the safety, reliability and efficiency of smart grids [12-14]. To this end, the proposed work will advance in this field by demonstrating a digital twin for predictive simulations and testing both real-time and AI-driven applications (voltage state estimation and net-load forecasting).

3 Executed Tests and Experiments

3.1 Test Plan, Standards, Procedures, and Methodology

Latest grid codes and interconnection standards in Europe demand for PV and DER to provide advanced grid support features that include voltage and frequency control, response to abnormal situations (LV/HVRT and FRT). Such advanced grid supportive functions are provided in either an autonomous (inverter response to local voltage and frequency conditions) or commanded manner (remote control using communication interoperability protocols).
The test system considered for the real-time simulations and the actual site demonstration is the low-voltage (LV) Experimental Nanogrid of UCY-FOSS, as shown in Figure 1 and the Smart Energy Campus microgrid of UCY. The nanogrid pilot is a flexible and scalable renewable to grid integration infrastructure that includes PV systems, smart inverters, battery storage, smart loads/plugs, smart meters, IoT communication devices and a central energy management system. The electrical network comprises of an incoming underground feeder that is served by a 1 MVA substation.

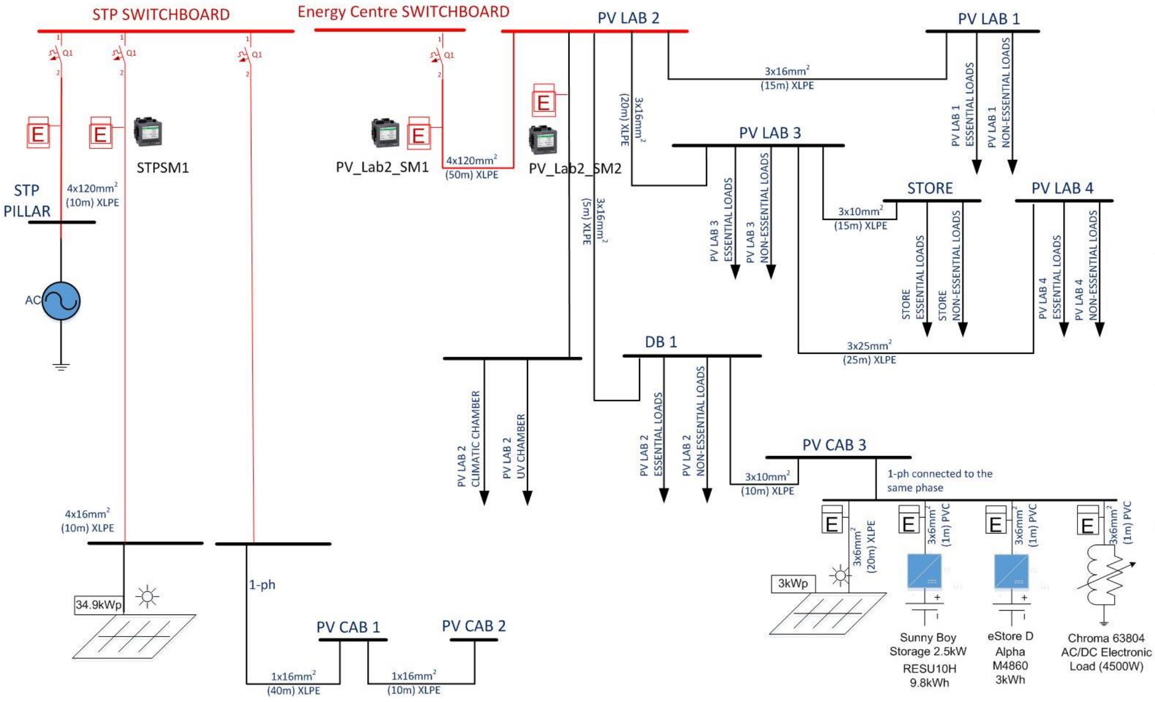


Figure 1. UCY-FOSS experimental nanogrid schematic diagram.

In addition, high-resolution data from the UCY Smart Energy Campus microgrid were utilized for the voltage state-estimation and net-load forecasting evaluations. At present, the Smart Energy Campus is a commercial-scale University campus microgrid that comprises of 15 smart buildings and distributed PV systems of capacity 400 kW that are fully monitored and equipped with smart meters as part of the implemented advanced metering infrastructure (AMI) for the acquisition of high-resolution data, and building management systems (BMS). The data used for this investigation corresponded to the historical observations from 15 smart meters that are installed at all main buildings and include the main electrical variables of active power (*P*), reactive power (*Q*), voltage (*V*) at all phases, currents (*I*) at all phases and frequency (*F*). All measurements were acquired at a resolution of 1 second and recorded as 1-minute averages.

3.1.1 Test Plan

Three test cases were designed for the project:

- Test Case 1 [AIT]: Voltage state estimation tool development and validation for utility-scale microgrids (developed and provided by the applicants) at real-time environments.
- Test Case 2 [AIT]: Short-term net-load forecasting voltage regulation tool development and validation for utility-scale microgrids (developed and provided by the applicants) at real-time environments.
- Test Case 3 [UCY-FOSS]: Grid-condition prognostic digital twin (developed and provided by the applicants) verification for utility-scale microgrids.

The summary and schedule of the test plan followed for the project is outlined in Table 1.

Table 1: Test plan of project lab access.

Dates	Activity
26/9/2022 (in-person)	Kick-off meeting and development of the work plan for the rest of the lab access. Introduction between the user group and the AIT host members. User group skill uptake on the Typhoon HIL platform provided by AIT.
27/9/2022 to 30/9/2022 (in-person)	<u>Test Case 1</u> Development and integration of nanogrid real-time simulation model to AIT Typhoon HIL platform. Development and validation of voltage state-estimator model. Real-time simulations of model carried out for various scenarios by: - Applying high variability solar and demand data. - Limiting the location measurements of the smart meters. - Imputing random grid faults to the microgrid model. Recording of the results for the various scenarios tested.
3/10/2022 (in-person)	User group skill uptake on the AIT Smart Grid Controller (SDC) and SunSpec inverter protocol provided by AIT.
4/10/2022 to 7/10/2022 (in-person)	<u>Test Case 2</u> Development and validation of net-load forecasting model. Software-in-the-loop simulation of net-load forecast data-feeds for active and reactive power control and advanced functions (Volt-VAr/Q(U) and Volt-Watt/P(U)). Validation of SunSpec compliant smart inverter model functionalities.
17/10/2022	User group skill uptake on the UCY microgrid model and

(in-person)	demonstration site provided by UCY-FOSS.
18/10/2022 to 27/10/2022 (in-person)	Test Case 3 Development of PowerFactory model for the creation of machine learning model voltage estimator training datasets. Voltage estimator model improvement and validation against scenario-based simulations. Real-time state-estimator performance verification by employing actual smart meter and PV system data to the digital twin and comparing against the estimated node voltage values.
28/10/2022 (in-person)	Recording of the results and analysis of data obtained for the various scenarios tested.

3.1.2 Methodology

The overall methodology to run the test cases followed a sequentially structured approach for the development and validation of the voltage state estimation and net-load forecasting software tools, and the verification of the integrated grid-condition prognostic digital twin. In particular, the steps involved included the (a) experimental setup and data acquisition, (b) data quality assessment, (c) development of the optimal machine learning voltage estimation and net load forecasting model and (d) performance evaluation.

Experimental setup and data acquisition: Initially, the schematic diagrams of UCY-FOSS nanogrid and UCY campus microgrid (single-line diagram and real-time simulation schematic) were prepared and validated prior to their integration to the real-time simulation platforms. Minor adjustments to the models were made during the first stage in order to integrate to the simulation environment of the AIT Typhoon HIL 604 test-bed and AIT HIL controller.

Data used for the training and testing step of the voltage estimation and net-load forecasting models were exported and checked for data validity and sanity. The historic observations corresponded to 1-minute resolution electric and power quality variables acquired from the installed network of smart meters part of the advanced metering infrastructure (AMI) of the main UCY campus. In particular, data from 15 smart meters across the different buildings of the UCY campus were utilized that included apparent power (S), active power (P), reactive power (Q), voltage (V) at all phases, currents (I) at all phases and frequency (F). All recorded data was merged to form a yearly timeseries of the performance of an actual-life microgrid.

Data quality assessment: Data quality routines were applied to the constructed timeseries in order to ensure high quality data prior to the model development procedure. A sequence of filtering stages, detection methods, data deletion and inference techniques were applied to the given dataset. In case that the invalid data points (i.e., erroneous and missing measurements) account for less than 10% of the entire dataset (i.e., the missing data rate threshold for unbiased analysis), the row deletion technique was applied to remove those values from the dataset. Otherwise, data inference/imputation techniques were used to back-fill the missing measurements. The data cleansing stage resulted to two datasets:

- Dataset 1: Num. of variables - 102, Time resolution - 1-sec and Period - 26/03/2021 until 11/09/2022 (21 months).
- Dataset 2: Num. of variables – 102, Time resolution: 1-min and Period: 26/03/2021 until 24/10/2022 (21 months).

Model development: This step includes an artificial neural network (ANN) development and training for both the voltage estimation and net-load forecasting models. A different model was used to evaluate each building. The input data for each model corresponds to all available data for the same electric variable (e.g., voltage) except that of the building evaluated. The selected architecture for the ANN models was 2 hidden layers with 64 neurons and a single output (i.e., the variable under assessment). The instances to build the training and testing datasets were selected randomly among the whole dataset and the training-testing split was set to 70%-30%.

A PowerFactory simulation model of the University of Cyprus microgrid was used to generate additional training data for the machine learning models. First, the grid model was validated, and plausibility checks were performed. A similar procedure was applied to the generated training dataset by performing an exploratory data analysis step to determine if the magnitudes and distributions of voltages at busbars and active and reactive powers of loads / generators were as to be expected.

Training scenarios were then defined, whereby a scenario was defined as a certain number of observable busbars at defined locations in the grid. The potential observable locations were those with a meter installed. Five random permutations of these locations were generated for a defined number of observable meters. For each of these randomly generated scenarios, ANN and Linear Regression (LR) models were trained and optimised in parameters. Models were benchmarked against each other to compare their performance.

The models, trained purely on artificially generated data, were then exposed to measurements from reality to transfer them from a synthetic environment to a real application situation and monitor their performance. Additionally, both ANN and LR models were tested with measured historical data from the meter sites.

Performance evaluation: Each model addressing the estimation of voltage and forecasting net-load at a different building was evaluated using the commonly employed metrics of the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean bias error (MBE) and coefficient of determination (R^2).

3.2 Test Set-up(s)

The research infrastructure utilized for the lab access tests was the Smart Electricity Systems and Technologies Laboratory (AIT) and the Low Voltage Experimental Microgrid Lab (UCY-FOSS). The overall hierarchy of the infrastructure used is presented in Figure 2.

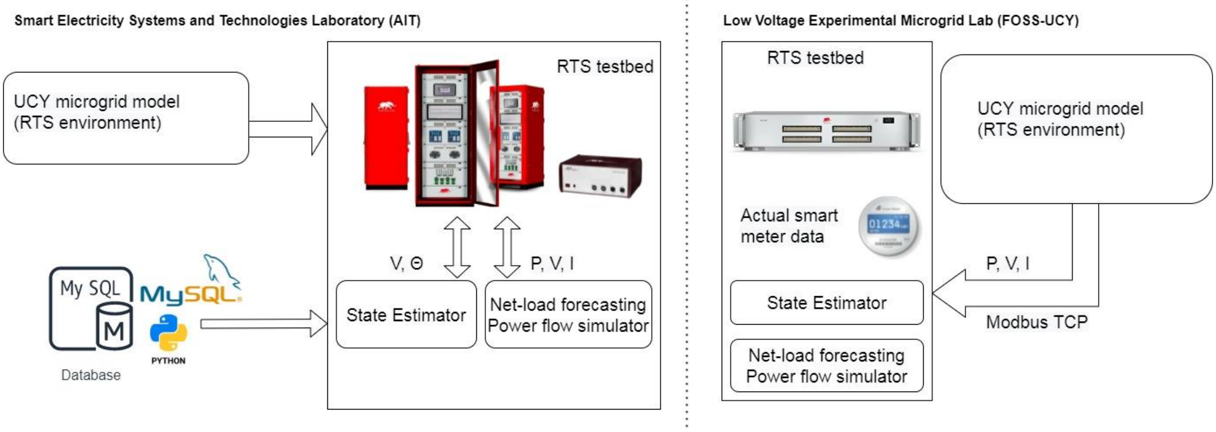


Figure 2. Infrastructure setup for validation at AIT and demonstration at UCY-FOSS.

The following test setups and parameters were utilized to undertake the project activities:

- **Smart Electricity Systems and Technologies Laboratory (AIT)**: The real-time simulation and multi-domain co-simulation test-beds at the AIT were used to validate the performance of the AI-driven tools against different smart grid scenarios. Specifically, the Typhoon HIL 604 real-time simulator test-bed coupled using analogue and digital I/O ports to the AIT HIL control device was used for the model validation tests, see Figure 3.

Figure 3. Typhoon HIL real-time simulation test-bed with AIT HIL controller at AIT.

Tests and sequence:

(1) Real-time state-estimator performance accuracy validation emulating three days by:
   a. Applying high variability solar and demand data.
   b. Limiting the location measurements of the smart meters.
   c. Imputing random grid faults to the microgrid model.

   Special requirements: Equipment - Real-time simulator test-bed (Typhoon HIL technology).

(2) Time-ahead grid condition prognosis for supportive voltage services from PV systems (optimal control for voltage regulation in microgrids) validation using an accelerated software-in-the-loop approach emulating three days by:
   a. Applying net-load forecast data-feeds different net-load forecasted profiles to provide active and reactive power control and advanced functions (Volt-VAr/Q(U) and Volt-Watt/P(U)).
   Special requirements: Equipment - Real-time simulator test-bed with AIT HIL Controller with SunSpec inverter protocol.

- **Low Voltage Experimental Microgrid Lab (UCY-FOSS)**: The infrastructure at UCY-FOSS was used to verify and demonstrate the performance of the AI-driven tools and the digital twin by integrating the actual UCY microgrid measurements (smart meters) to the platform in order to verify the performance accuracy of the models and to demonstrate voltage regulation functionalities from simulated controllable PV systems.
Tests and sequence:

(1) Real-time state-estimator performance verification by:
   a. Employing actual smart meter and PV system data to the digital twin model and comparing against the estimated node voltage values.

(2) Time-ahead grid condition prognosis demonstration by:

a. Employing actual day-ahead net-load forecasts and demonstrating different prognostic reactive and active power control functions for voltage regulation (active and reactive power control, Volt-VAr/Q(U) and Volt-Watt/P(U)).

Special requirements: Equipment – UCY microgrid smart meters, test-bench three kWp PV system with smart inverter and real-time simulator test-bed (Typhoon HIL RTS). Interoperability - Modbus TCP for all smart meters and SunSpec for PV systems.

3.2.1 Task 1.1 – State estimator testing

The state estimator (including the training dataset to train the model) and UCY microgrid network topology (microgrid digitally mapped using OpenDSS and RTS schematic editor), line parameters, smart meter measurements, and net-load profiles were initially prepared and validated for correctness and fidelity.

The state estimator and microgrid model were then integrated to the AIT SMARTEST RTS platform (Typhoon RTS technology) in the scope of performing the test sequences of what-if scenarios (application of high variability solar and demand data, and grid faults). More specifically, the performance of the state-estimator to yield accurate node voltages, given by the RMSE over a daily period, was validated by employing high variability solar and demand data (synthetic and actual) emulating three days in an accelerated software-in-the-loop approach.

Grid faults were further emulated by including a customised grid fault module of several faults (the module emulates a selected grid fault using ideal switches, single and multiple phases to ground and phase to phase faults are supported) within the simulation model, see Figure 4.

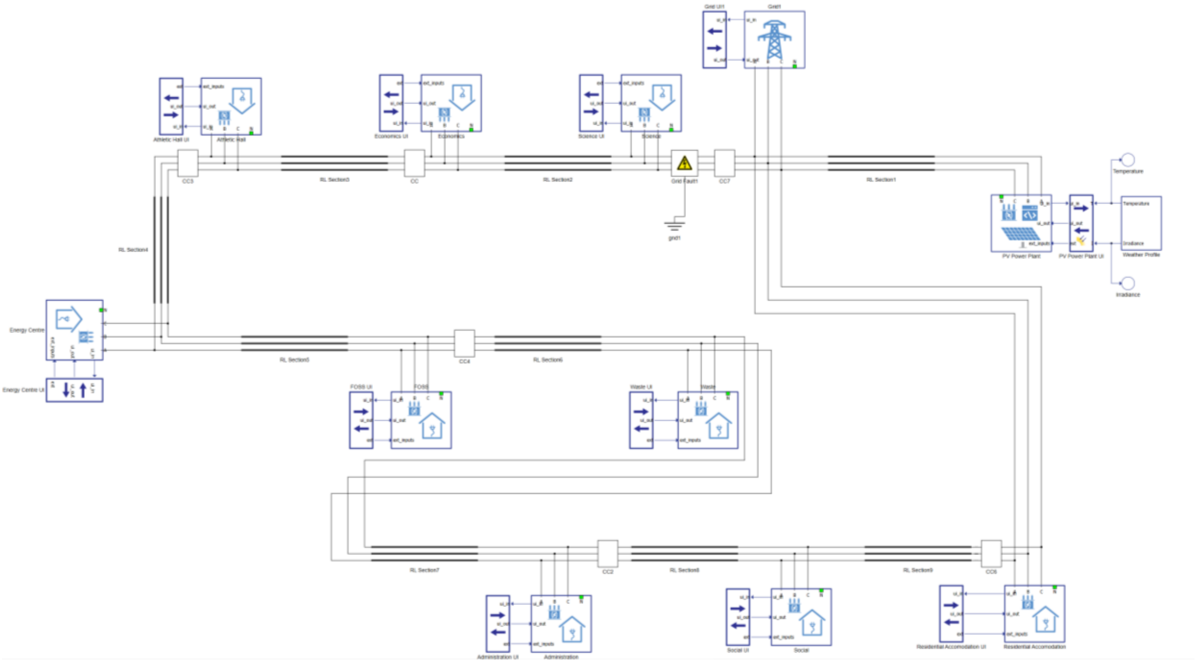


Figure 4. UCY microgrid real-time simulation model including grid fault emulation module.

Furthermore, data-driven tests were developed and applied to assess the robustness of the tool by emulating grid faults, evaluating measurement configurations and reading frequencies in low-observability networks.

Finally, all validation tests provided useful information for further optimising the performance of the developed voltage state estimation tool.

3.2.2 Task 1.2 – Validation of condition forecasting tool

The UCY team developed the short-term net-load forecasting tool using the Keras deep learning interface. The validation tests were performed immediately after the tool was fully integrated into the AIT SMARTEST RTS platform (Typhoon RTS technology), enabling accelerated software-in-the-loop simulations of different voltage regulation functions.

More specifically, the AIT Smart Grid Converter (SGC) Controller with SunSpec inverter protocol support was also utilised to test the capabilities of the tool to provide active and reactive power control (Volt-VAr/Q(U) and Volt-Watt/P(U)) when fed with different net-load profiles (synthetic and actual). The AIT SGC is capable to perform control-hardware-in-the-loop (CHIL) grid integration studies and research within a HIL environment and therefore to overcome the challenges of smart grid and micro grid integration through a flexible and reconfigurable control platform, see Figure 5.

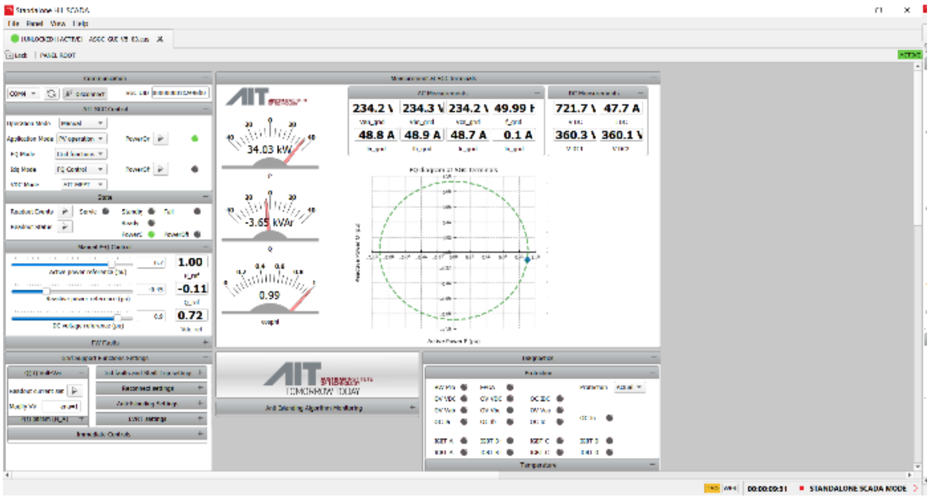


Figure 5. AIT SGC SCADA dashboard for smart inverter interoperability testing.

3.2.3 Task 2.1 – Digital twin verification at UCY microgrid

The state-estimator and net-load forecasting tools were the main building blocks of the AI-driven digital twin of the UCY microgrid (developed using the Typhoon HIL Toolset of microgrid model components). The digital twin was connected using Modbus TCP to all smart meters of the microgrid in order to visualise the actual real-time measurements alongside the foreseen simulation values.

The digital twin was tested at the FOSS-UCY Low Voltage Experimental Microgrid Lab to verify and demonstrate the AI-driven concepts (state-estimation and predictive control) on actual measurements (smart meter and inverter measurements integrated to the digital twin using Modbus TCP).

3.3 Data Management and Processing

The data management and processing strategy applied for the project aimed to manage the data used based on findable, accessible, interoperable and re-usable (FAIR) principles during the implementation of the project, covering Open Science practices and rendering data “as open as possible, as closed as necessary”.

In particular, the data requirements of the project cover two main data categories:

- High-resolution UCY microgrid data acquired over a yearly period from the network of smart meters located within the campus. The data were supplied by UCY-FOSS in order to perform the power flow analysis and real-time simulation model validations.
- Power system and real-time simulation models of UCY-FOSS nanogrid and UCY microgrid. The models and schematics were supplied by UCY-FOSS in order to perform the real-time simulations and validate software module performance against actual measurements.
- Experimental data generated/collected by the project that include instantaneous bus voltage estimates plot directly using the Typhoon HIL SCADA, and the quasi-steady state data such as active powers, and bus voltages that were exported as a csv file to excel, and later plot using graphic tools of R and Python.

4 Results and Conclusions

4.1 Discussion of Results

This section summarises the results obtained for the lab access duration of the AIDGRIDS project. The achieved results for the various scenarios are described in the following sections.

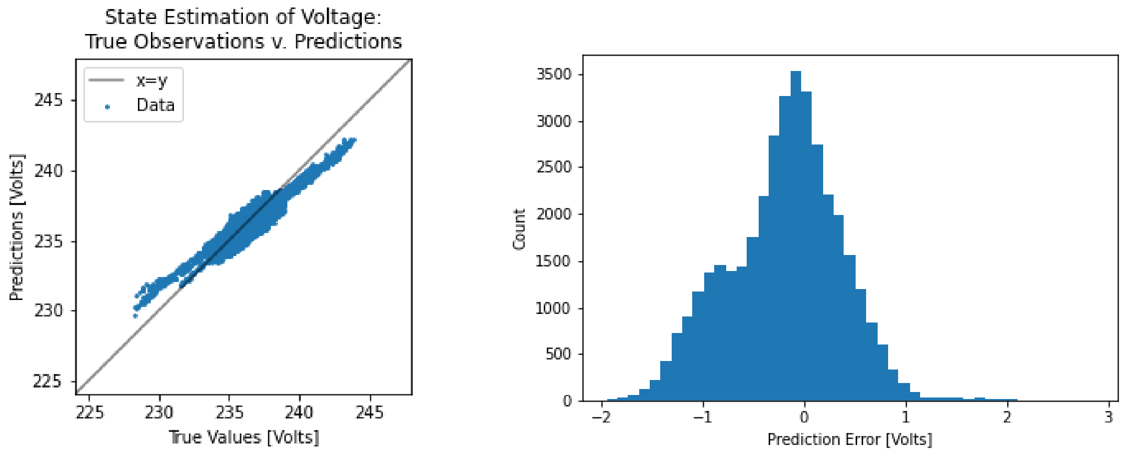
4.1.1 Voltage state estimator development and testing

The performance validation results obtained for the voltage state estimator (model developed using Python programming language) when connected to the UCY microgrid model and operated with 1-minute high-resolution data (high variability solar and demand data) in a software-in-the-loop approach, showed high accuracies <1% error. Specifically, the results for all developed models (all buildings within the microgrid campus) are presented in Table 2. The results exhibited a MAPE in the range of 0.13% to 0.46%, which represents an error of around 0.3 to 1.1 Volts in the estimations of the model. Across all the locations evaluated for the several buildings and smart meters, the model showed a mean error of 0.28% for voltage observations.

Table 2: Evaluation metrics for average phase voltage estimations obtained by the developed state estimation model for the different buildings of UCY microgrid.

Building - Smart Meter (SM)	**MAE (V)**	**MAPE (%)**
Administration Building - SM1	0.454	0.19
Sewage Treatment Plant - SM1	0.361	0.16
Energy Centre - SM1	0.962	0.41
Energy Centre - SM2	0.737	0.31
Energy Centre - SM3	0.805	0.35
Energy Centre - SM4	0.588	0.26
Energy Centre - SM5	0.914	0.39
Athletic Sport Centre – SM1	0.295	0.13
Faculty of Science - SM1	1.072	0.46
Faculty of Science - SM2	0.525	0.23
Student Halls - SM1	0.380	0.16
Social Facility Centre - SM1	0.607	0.26
Faculty of Economics - SM1	0.803	0.34
Mean Metrics in tested buildings	0.654	0.28

An illustration of the predictions of the state estimation model is presented in Figure 6 for the Administration Building. The data presented in the plots corresponds to a MAE of 0.45 V and a MAPE of 0.19%. The development and performance evaluation of the voltage state estimator at different buildings UCY microgrid materialised O1.



(a) (b)

Figure 6. State estimation performance evaluation for average phase voltage at UCY's Administration Building: (a) Plot of actual against estimated voltages, and (b) Histogram of error.

A comparison between the actual and estimated voltage at the point of common coupling (PCC) of the microgrid over an extract of 5 000 observations of the test set period is depicted in Figure 7. The results showed that the model achieved close aggreement to the actual values and was able to follow voltage deviations occuring due to solar irradiance and demand variations, and the occurences of grid faults (emulated line to ground faults).

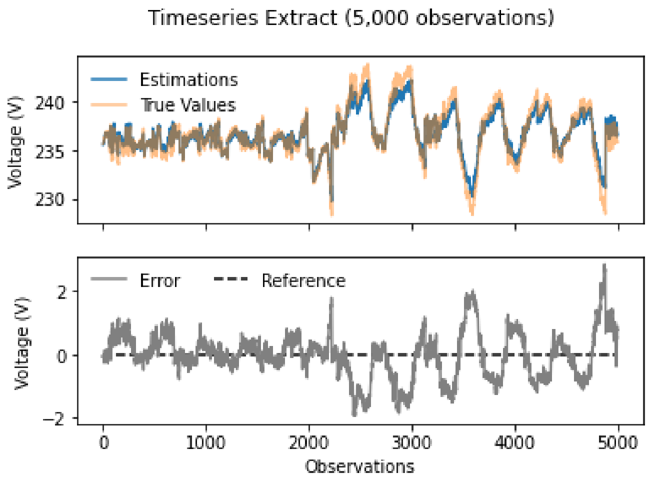


Figure 7. Actual and estimated voltage profiles and errors at UCY microgrid PCC.

The implemented SCADA HIL dashboard presented in Figure 8, demonstrated the capability of the voltage state estimator to estimate and follow voltage deviations when imputing random grid faults. The obtained results of this investigation provided evidence towards the finalisation of O2.

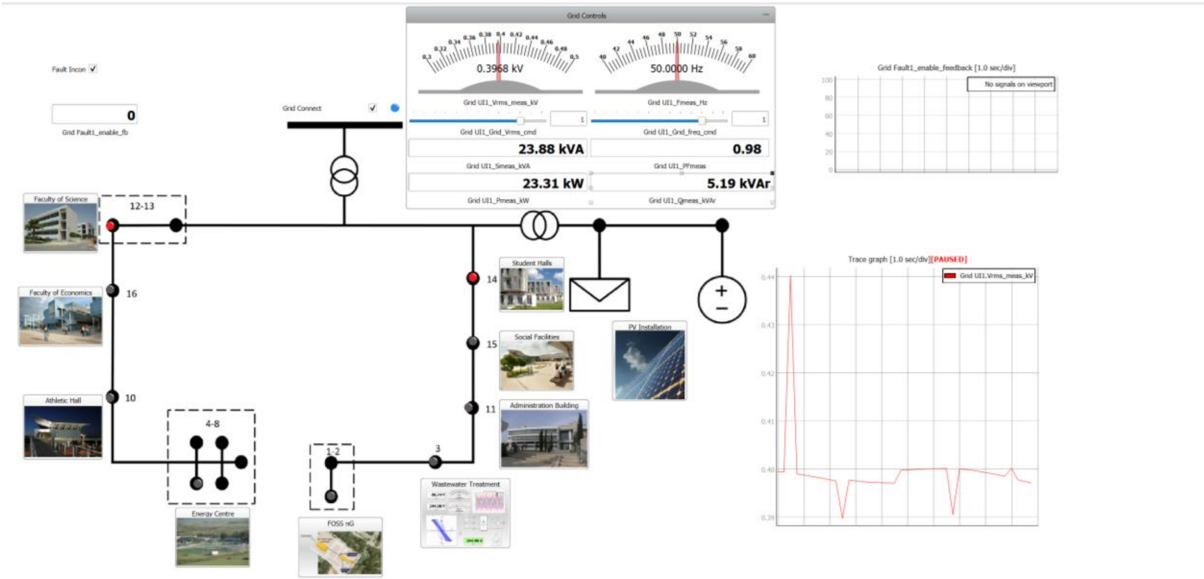


Figure 8. SCADA HIL UCY microgrid dashboard visualising the voltage estimates at the PCC of UCY campus and the variations in voltage when applying different grid faults.

4.1.2 Development and validation of net-load forecasting tool

The supervised training regime (70:30% random data portion train and test set approach) and input feature engineering applied for the development of the optimally performing net-load forecasting model yielded the best-performing ANN model that achieved nRMSE of 3.98%. The network interconnection diagram of the optimal model is depicted in Figure 9, and it comprises of eight input features the historical net-load (HNL), month of the year (M_{year}) day of the week (D_{week}), dew point temperature (DPT), real feel temperature (RF), ambient temperature (T_{amb}), time of the day (T_{day}) and global horizontal irradiance (GHI), 7 hidden nodes and 1 output node (net-load).

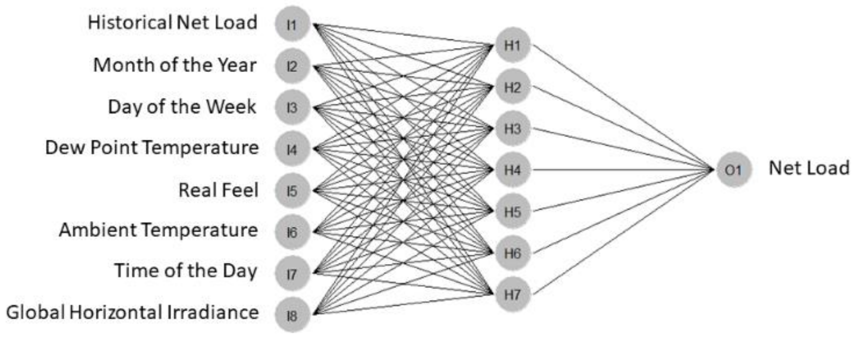


Figure 9. Network interconnection diagram of developed net-load forecasting model.

The accuracy of the optimal net-load forecasting model (constructed from the supervised approach of 70:30% random train and test set) over the test set period for the entire microgrid is shown in Figure 10. In more detail, the direct net-load forecasting model achieved a daily mean nRMSE of 3.98% for the entire microgrid. Figure 10 further shows the nRMSE values variations based on the clearness index (K_t) of the investigated days. A low clearness is exhibited for overcast days whereas high index is provided for clear-sky days. Along this context, the low error provided by the model irrespective of daily clearness index demonstrated its applicability to microgrids with diverse PV shares.

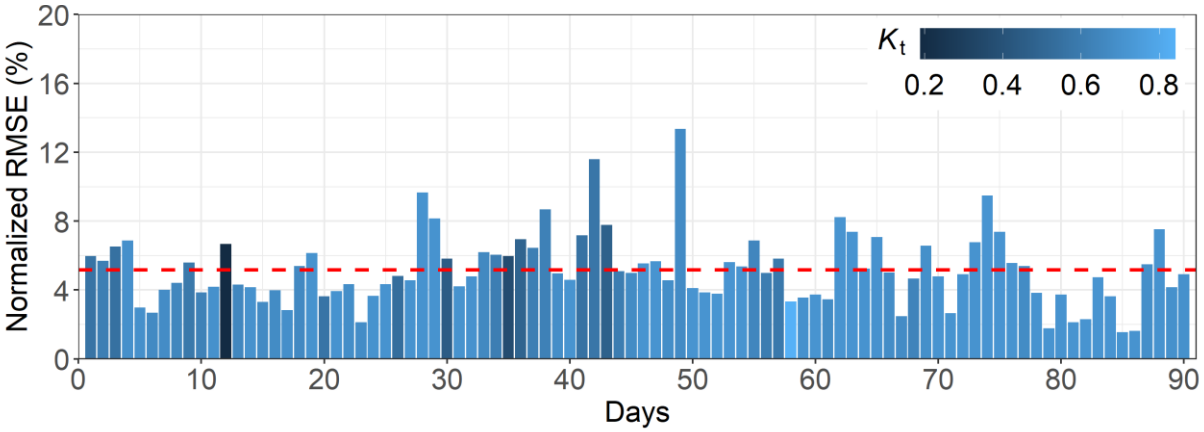
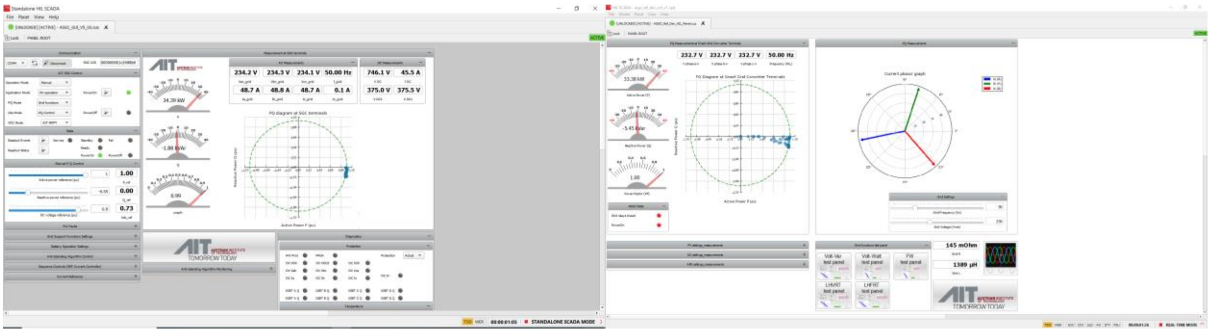


Figure 10. Daily nRMSE of the optimal net-load forecasting model applied to UCY microgrid over the test set period. The red dashed line indicates the mean nRMSE.

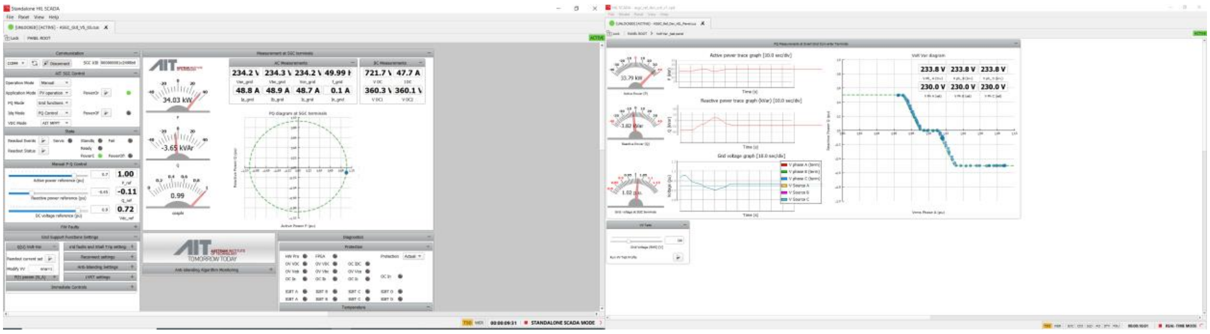
The validation of the model to provide grid control functionalities was emulated using the AIT SGC with SunSpec inverter protocol support. Figure 11 shows the response obtained from the apparatus when setting reactive power set-points. Specifically, Figure 11a shows the application of different power factor set-points and the response is monitored at the PQ diagram of the SCADA HIL interface presented in Figure 11b.



(a) (b)

Figure 11. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for active and reactive power set-points and (b) Visualising the response at a PQ diagram.

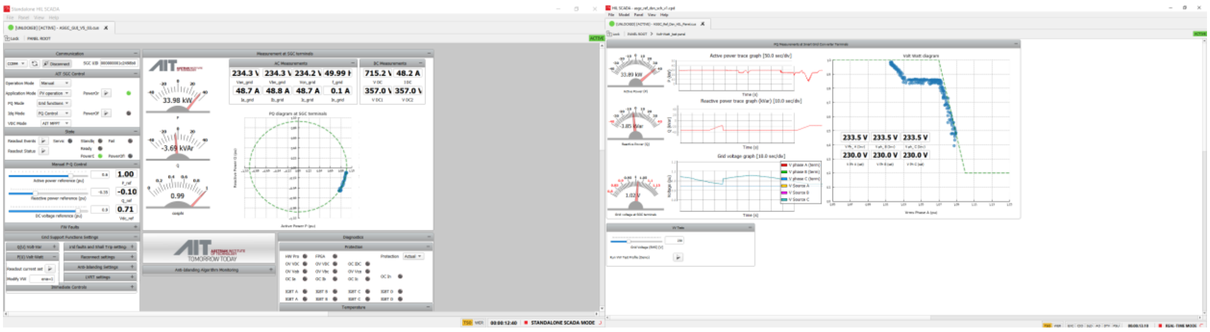
Similarly, the capability to allow advanced grid supportive control functions such as Volt/Var and Volt/Watt was further investigated. Figure 12 shows the results provided when selecting the Volt/VAr grid supportive function. The reactive power points obtained when varying the voltage of the model were in close alignment to the configured Volt/Var curve as presented in Figure 12b.



(a) (b)

Figure 12. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for setting the Volt/Var grid control function and (b) Visualising the response at a Volt/Var characteristic curve and modelled power widgets.

Furthermore, Figure 13 shows the Volt/Watt response of the model at different voltage settings.



(a) (b)

Figure 13. SCADA HIL simulation interface dashboards presenting (a) Front-end interface for setting the Volt/Watt grid control function and (b) Visualising the response at a Volt/Watt characteristic curve and modelled power widgets.

Lastly, the results of the CHIL validation of net-load forecasting tool for active and reactive power control materialized O3.

4.1.3 Digital twin verification at UCY microgrid

To further optimise the performance of the voltage state estimator the machine learning model was trained using synthetic training data (obtained by performing a power flow analysis of the developed UCY microgrid PowerFactory model). Figure 14 shows the comparison graphs for two metrics, the coefficient of determination (R^2) and RMSE over all the trained scenarios derived from the training dataset (application of synthetic data). Five scenarios were performed per number of observed smart meters. This relates to the x-scale in Figure 14, with the value indicating the fraction of all the busbars that were observed in the scenarios. A value of 0.04 corresponds to 11 observed metering points only. Each dot comprises the average value of the metric over all busbar voltages that were predicted. The results showed that the increase of the number of bus-bars utilised for the training of the models, directly improved the estimation accuracy. The highest accuracies were reported for the ANN model (RMSE of approximately 0.00325 p.u.) when 11 metering points were used.

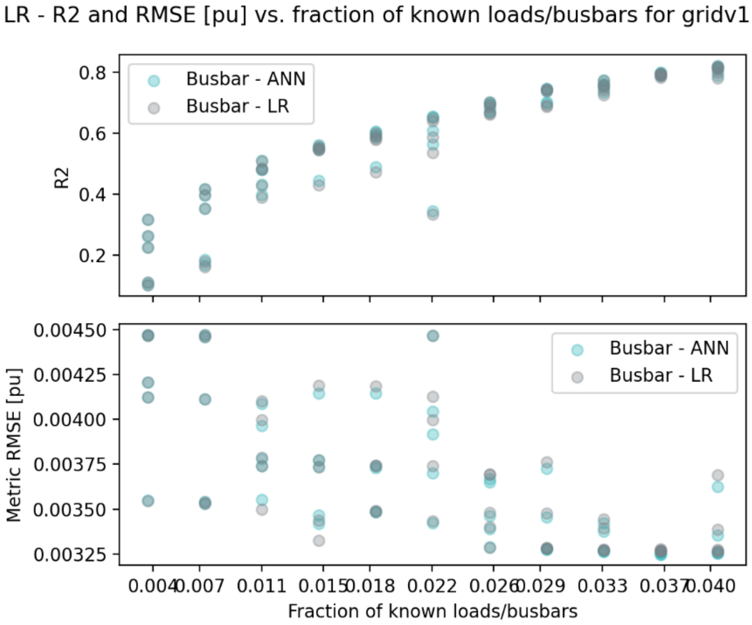


Figure 14. Voltage estimation performance given by the R^2 and RMSE for the developed linear regression and ANN models for different busbar fractions.

The application of historical data to the trained models demonstrated that the model could be trained with purely synthetic data and exhibit high performance accuracies with the historical data (from the artificial world to reality). More specifically, 200 measured values from the historic dataset were randomly selected and measured against predicted values. The results were compared for a scenario with a single unobserved smart meter, which was a smart meter for a building located at the centre of the feeder. For this investigation, the models trained on purely synthetic data were exposed to real measurement values for the first time. The results depicted in Figure 15 showed that the ANN model exhibited high accuracies and was capable to follow in most cases the actual voltage profiles. The model provided MAE of 0.0036 and MBE of 0.0017 when applied to the entire microgrid.

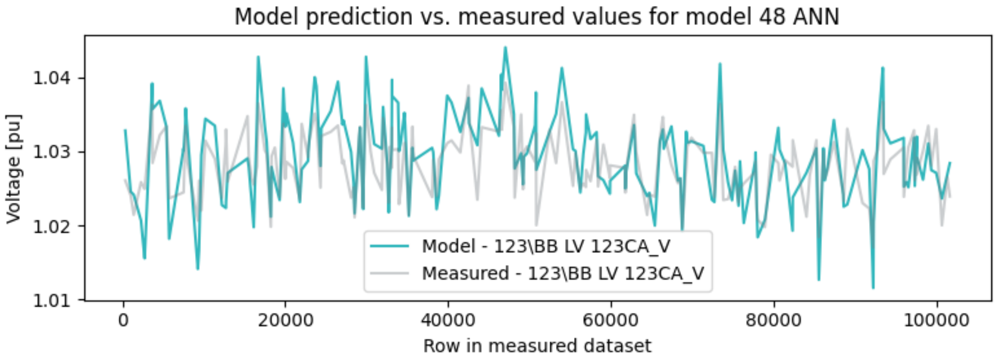


Figure 15. Actual and predicted voltage estimates when applying the ANN model trained with historical measurements.

Moreover, the application of historical data to the trained LR model showed a low magnitude bias (offset) but otherwise followed the measured value as presented in Figure 16. The low magnitude bias was encountered in some scenarios which warranted further inspection of the grid model and the effects of the model on the training dataset. The model provided MAE and MBE of 0.0014 when applied to the entire microgrid.

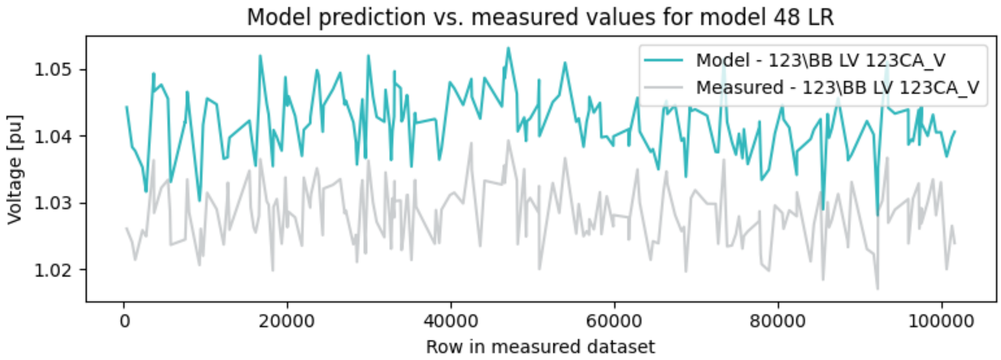
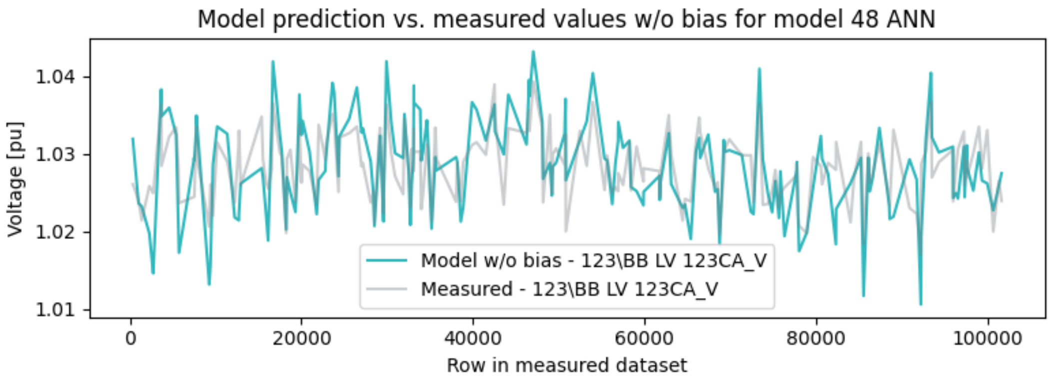
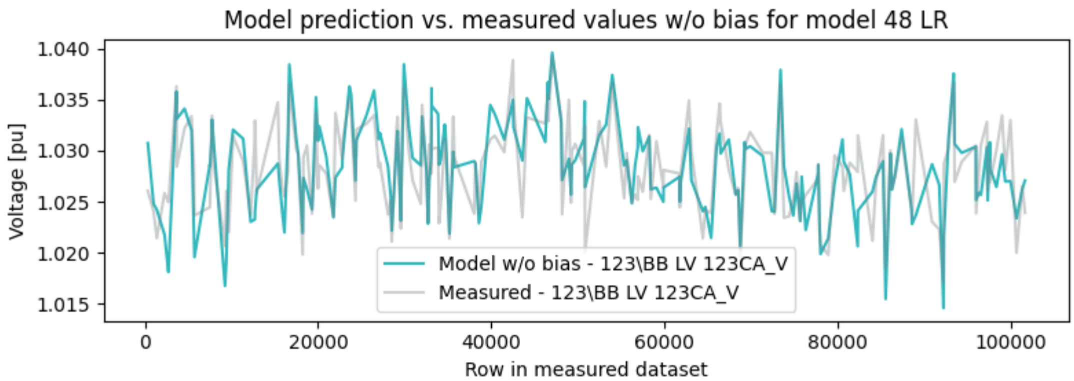


Figure 16. Actual and predicted voltage estimates when applying the LR model trained with historical measurements.

A final optimisation step was applied to the constructed models in order to reduce the exhibited bias. The ANN has less bias error but higher absolute error and standard deviation error. Almost all the error in the linear regression is a bias of 0.014 p.u. in voltage. Figure 17 shows the plots for both the ANN and LR model after subtracting the bias from the predictions and re-plotting.



(a)



(b)

Figure 17. Actual and predicted voltage estimates after reducing bias for (a) ANN model and (b) LR model evaluated with historical measurements.

The demonstration of the state estimator to estimate node voltages of the UCY microgrid by integrating the digital twin model to the actual environment and employing actual smart meter measurements of the microgrid (trained with synthetic data) finalised O4.

Finally, the successful transfer of the optimised data-driven models to the real-time simulation grid model poses a proof of concept for the developed method and the materialisation of O5.

Figure 18 shows that the voltage state estimator was able to estimate the voltage at the PCC of the UCY campus microgrid demonstrating high accuracies when compared to the actual real-time measurements.

Figure 18. Real-time simulation environment UCY campus microgrid model integrated with voltage state estimator.

Finally, to support the dissemination of the project an event was organised by UCY-FOSS, whereby the project results were presented by the AIT team to researchers of UCY.

Figure 19. Project event and presentation delivered by the AIT team to researchers of UCY.

4.2 Conclusions

The AIDGRIDS project focused to validate and demonstrate next-generation AI-driven grid-supportive tools that facilitate the dynamic and cost-effective management of microgrids at high shares of solar PV. In this context, the lab access activities entailed the accelerated validation of an operational voltage state estimator, a net-load forecasting tool and a grid condition prognostic platform (digital twin) applicable to microgrids. Moreover, the endeavour included also the demonstration of the capabilities of software AI-driven tools' while coupled to grid supportive controls within real-time simulation environments

The validation results for the developed voltage state estimator that was connected to the UCY microgrid model and operated with 1-minute high-resolution data (high variability solar and demand data) in a software-in-the-loop approach, showed high accuracies <1% error. In addition, the capability of the voltage state estimator to estimate and follow voltage deviations when imputing random grid faults was presented using customised SCADA HIL dashboards.

Moreover, an optimally performing net-load forecasting model yielded the best-performing ANN model that achieved a nRMSE of 3.98% was developed and validated by applying a supervised training regime (70:30% random data portion train and test set approach) and input feature engineering. To this end, the validation of the model to provide grid control functionalities was emulated using the AIT SGC with SunSpec inverter protocol support.

To further optimise the performance of the voltage state estimator the machine learning model was trained using synthetic training data (obtained by performing a power flow analysis of the developed UCY microgrid PowerFactory model). The results showed that the ANN model exhibited high accuracies and was capable to follow in most cases the actual voltage profiles even at low bus-bur utilisation fractions.

At present, billions are being invested in making energy systems more intelligent with smart devices and software-based data-driven solutions, and this transformation is only at the beginning. In this domain, the project's expected impacts are categorised as scientific, technological/economic and societal:

- **Impacts – Scientific**
  Enhance scientific knowledge for testing AI-driven software solutions in smart grids.
  Target groups: Academic community relevant to AI technologies in smart grids.
  Scale and significance: The scientific expertise gained in validating and optimising the AI-driven state estimator and forecast-based control tool enables the academic community to develop new smart grid test procedures for emerging software tools.
- **Impacts - Technological/Economic**
  Advances in the field of integrating digital twin solutions for smart grids/microgrids.
  Target groups: Energy and AI industry and utility/microgrid operators.
  Scale and significance: The development of integration procedures for digital twin solutions enables the energy and AI R&I industry to become competitive, tackling challenges for seamlessly integrating predictive tools and facilitating renewable-powered microgrid developments.
- Increase PV competitiveness and shift to green electricity for sustainable economies.
  Target groups: Electricity consumers.
  Scale and significance: Facilitating the seamless integration of high PV shares through trust assessment of novel AI-driven control solutions enables reduced green electricity costs for consumers, leading to a flexible and reliable electricity system. Especially in the case of Cyprus (islanded grid system), it is expected that integrating solar PV shares of 30% at the grid (EU target by 2030) can reduce electricity cost to €0.02/kWh, according to

the IEA World Energy Outlook (2020). At present, the whole-sale electricity in Cyprus is €0.12/kWh.

- **Impacts – Societal**
  Enhance pathways for renewable-powered microgrids and a clean environment.
  Target groups: General public.
  Scale and significance: The set framework for testing and accelerating the acceptance of AI-driven smart grid solutions facilitates the development of renewable-powered microgrids, leading to CO_2 reduction and increasing welfare.

Finally, the performed research is expected to enhance the predictive observability and prognostic control of smart grids/microgrids leading to increased grid flexibility for integrating higher shares of PV at the distribution network. Moreover, the optimally data-driven grid-supportive services and testing framework created new knowledge to advance in the field of REs integration and unlock the potential of data-driven tools. Therefore, intelligent tools are invaluable for grid operators and electricity market actors to optimally orchestrate complex distribution system operations at high-RES shares.

5 Open Issues and Suggestions for Improvements

The project involved the use of real-time simulation units (Typhoon HIL 604 and 606 devices), peripheral connected controllers and high-resolution data acquired from a network of smart meters installed within UCY microgrid to validate in an accelerated software-in-the-loop approach the performance of AI-driven software tools for smart grids.

To this end, all planned tests to verify and demonstrate the capabilities of the developed tools were completed without significant challenges.

Lastly, the following potential improvements are recommended in order to facilitate the seamless integration and transfer of real-time simulation models amongst different real-time simulation test-beds:

- Use of standardised naming conventions for model input parameters to avoid re-naming and mapping.
- Use of latest version (updated versions) of Python libraries/packages to avoid software compatibility issues when Python scripts are integrated to real-time simulation models.
- Use of core couplings at different segments of large real-time simulation schematics to avoid simulation errors and incompatibilities when transfer to previous software releases and devices.

References

[1] International Renewable Energy Agency, Innovation landscape for a renewable-powered future, International Renewable Energy Agency, 2019.

[2] Bose, B.K. Artificial intelligence techniques in smart grid and renewable energy systems—Some ex-ample applications. Proc. IEEE 2017, 105, 2262–2273.

[3] Ali, S.S.; Choi, B.J. State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Re-view. Electronics 2020, 9, 1030.

[4] Lytras, M.D.; Chui, K.T. The Recent Development of Artificial Intelligence for Smart and Sustainable Energy Systems and Applications. Energies 2019, 12(16), 3108.

[5] Z. Yun, Z. Quan, S. Caixin, L. Shaolan, L. Yuming and S. Yang, "RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment", IEEE Trans. Power Syst., vol. 23, no. 3, pp. 853-858, Aug. 2008.

[6] Chin Wang LOU and Ming Chui DONG, "Modeling data uncertainty on electric load forecasting based on Type-2 fuzzy logic set theory", Engineering Applications of Artificial Intelligence, vol. 25, no. 8, pp. 1567-1576, 2012.

[7] Preda, S.; Oprea, S.; Bâra, A.; Belciu, A. PV forecasting using support vector machine learning in a big data analytics context. Symmetry 2018, 10, 748.

[8] Benali, L.; Notton, G.; Fouilloy, A.; Voyant, C.; Dizene, R. Solar radiation forecasting using artificial neu-ral network and random forest methods: Application to normal beam, horizontal diffuse and global components. Renew. Energy 2019, 132, 871–884.

[9] A. Abur and A. Gmez Expsito, Power system state estimation: theory and implementation, New York, NY: Marcel Dekker, 2004.

[10] S. Bhela, V. Kekatos and S. Veeramachaneni, "Enhancing observability in distribution grids using smart meter data", IEEE Trans. Smart Grid, vol. 9, no. 6, pp. 5953-5961, Nov. 2018.

[11] E. Manitsas, R. Singh, B. C. Pal and G. Strbac, "Distribution system state estimation using an artificial neural network approach for pseudo measurement modeling", IEEE Trans. Power Syst., vol. 27, no. 4, pp. 1888-1896, Nov. 2012.

[12] Brosinsky C, Westermann D, Krebs R: Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. In 2018 IEEE International Energy Conference (ENERGYCON). 2018; 1–6.

[13] Jain P, Poon J, Singh JP, et al.: A Digital Twin Approach for Fault Diagnosis in Distributed Photovoltaic Systems. IEEE Trans Power Electron. 2020; 35(1): 940–956.

[14] H. Pan, Z. Dou, Y. Cai, W. Li, X. Lei and D. Han, "Digital Twin and Its Application in Power System," 2020 5th International Conference on Power and Renewable Energy (ICPRE), 2020, pp. 21-26.

Appendix A. UCY Microgrid real-time platform

The UCY microgrid real-time simulation platform is a digital twin model of the Smart Energy Campus of UCY, implemented using real-time simulation models (Typhoon HIL technology) and integrating smart meter measurements in order to create an integrated real-time grid observability solution, which monitors the existing smart meters (installed at each University building) and all PV and storage systems into a singular central platform, see Figure 20. The front-end dashboard of the platform displays the real-time measurements acquired using Modbus TCP from all installed smart meters and weather stations.

Figure 20. UCY microgrid real-time simulation platform dashboard.

As depicted in Figure 21, the platform is further configured with widgets and masks that include set-points for smart inverters and imputation of grid faults (Line-to-line, neutral and earth faults). The right-hand side of the dashboard visualises the actual measurements acquired from the installed smart meters and the influence of the changes and grid faults to the simulated parameters. The platform is simulated using the Typhoon HIL 604 real-time simulation test-bed of UCY-FOSS.

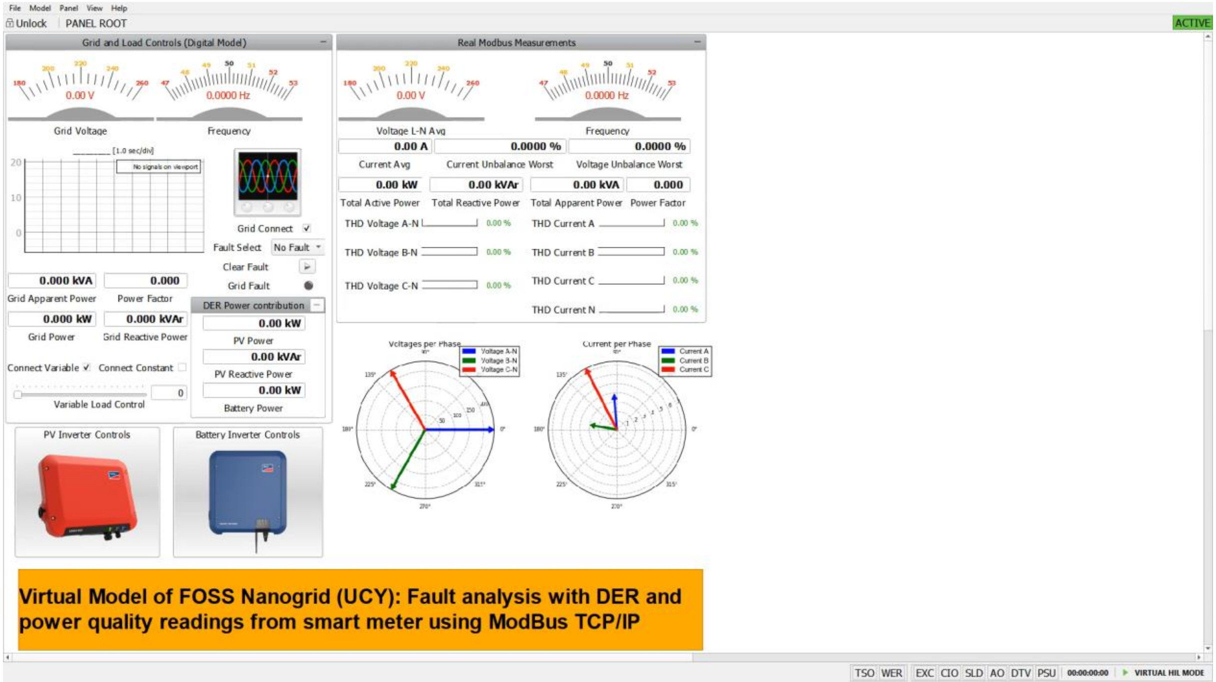


Figure 21. UCY-FOSS nanogrid dashboard displaying actual measurements of the pilot and simulated conditions (smart inverter set-points and grid faults).

Disclaimer

Copyright Notice

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 870620.