

# A Co-simulation based Optimisation Problem for Smart Converter Reactive Power Control in Distribution Systems

Gioacchino Tricarico  
Dept. of Electrical and Information  
Engineering  
Polytechnic University of Bari  
Bari, Italy  
gioacchino.tricarico@poliba.it

Raju Wagle  
Dept. of Electrical Engineering  
UiT, The Arctic University of Norway  
Narvik, Norway  
raju.wagle@uit.no

Jesus Castro Martinez  
Dept. of Electrical Engineering  
Universidad Carlos III de Madrid  
Leganes, Spain  
jecastro@ing.uc3m.es

Francisco Gonzalez-Longatt  
University of Exeter  
Exeter, United Kingdom  
fglongatt@fglongatt.org

Maria Dicorato and Giuseppe Forte  
Dept. of Electrical and Information  
Engineering (DEI)  
Polytechnic University of Bari  
Bari, Italy  
[maria.dicorato@poliba.it](mailto:maria.dicorato@poliba.it)  
[giuseppe.forte@poliba.it](mailto:giuseppe.forte@poliba.it)

Jose Luis Rueda  
Dept. of Electrical Sustainable Energy  
Delft University of Technology  
Delft, Netherland  
J.L.RuedaTorres@tudelft.nl

**Abstract**—Distribution system networks (DSN) are subject to a drastic evolution in their operation conditions, due to high integration of renewable energy resources (RES) and their ability to regulate the voltage. **This has raised concerns about Hosting Capacity (HC) of the DSN because the results are affected by the reactive power provided by smart inverters or RES.** Moreover, one of the most difficult issues in control and optimization is making effective use of the reactive power capability of smart inverters in reactive power control. Offline optimization of smart inverters may not be enough to address the critical challenges posed by high PV integration. This study investigates the effect of PVs' reactive power support on the DSN to minimise active power losses and control system voltage. An HC analysis is performed on a DSN that lacks any RES to determine the location and capacity of the PV system to be installed. To minimise losses, a co-simulation-based optimization of the reactive power of the PVs' smart inverters is performed downstream the installation. Using co-simulation, detailed mathematical modelling of the DSN in the optimization model can be avoided, allowing the optimization to be completed in less time while maintaining convergence. Faster optimization builds a foundation for using the proposed methodology in real-time optimal reactive power control in a smart distribution network.

**Keywords**—Hosting Capacity, Co-simulation, Reactive Power Control, Differential Evolution, Renewable Energy Resources.

## I. INTRODUCTION

With the rise in integration of variable renewable energy sources in the distribution system networks (DSN), the operation condition of the network has evolved with drastically in terms of operating condition [1]. Moreover, the involvement of the smart inverters in voltage regulation adds more computational burdens for implementing optimal control techniques in the DSN [2]. To incorporate the optimal control technique in such DSN, co-simulation based optimization can be one option to consider [3]. However, detailed description of co-simulation-based optimization problem formulation and solving a optimization problem is still big challenge. Hence, this paper intends to provide detailed description for the co-simulation-based optimization problem formulation and to solve the proposed methodology for obtaining the optimal reactive power control from smart inverter in DSN.

There are various approaches for controlling reactive power in the scientific literature [4]. In the case of a distribution network, OPF created using conventional power-flow techniques like Gauss-Seidel, Newton-Raphson, and fast decoupled load flow may not converge [5]. So, the distribution network is modeled using the LinDistflow equations or sensitivity-based modeling in most works on optimal reactive power control. However, the convergence in such case requires more time depending on the complexity of the network under consideration. Also, due the increased fluctuations in the operating condition of the DSN, optimization problem is required to be completed on short time. Co-simulation based optimization is one of the options to perform faster optimization. Also, the sizing of the RES is also an important aspect to consider before implementing the optimal reactive power control in the network. The capacity of the smart inverter affects the allowable reactive power support from the RES. Also, the nature (inductive or capacitive) of the reactive power support has a huge impact on the total network loss in the network. To operate the network optimally with minimum network loss, optimal reactive power support is to be considered. Optimal reactive power control in power system network is studied in [6]–[9]. However, these papers do not consider the siting and sizing of the renewable energy sources (RES) prior to considering the optimization problem. Hence, in this paper, hosting capacity (HC) analysis is done prior to implementing the optimization problem for the reactive power control.

The focus of this work is to propose a detailed method to perform co-simulation optimal reactive power regulation in DSN to minimise total active power losses. The co-simulation framework has been created between a power system specialised software (PSSS) and a programming language environment. The co-simulation-based optimisation problem has been constructed using the load flow equation of the PSSS and defining a non-explicit objective function in the programming language environment. Specifically, the PSSS and the programming language exploited in this paper are DIGSILENT PowerFactory and Python respectively. This method has been applied to the Kumamoto distribution network. The summary of the contribution made in this paper are listed below.

1. Detailed description of the co-simulation based optimization problem for reactive power control in the distribution networks.

## 2. Hosting capacity computation for obtaining the sizing of the renewable energy sources in the distribution network.

The following sections make up the remainder of the paper. Section II describes the theoretical concepts and formulation of hosting capacity and co-simulation based optimization problem formulation. Section III analyze the hosting capacity of the test system. Similarly, the optimization output analysis is presented in section IV. Finally, the last section highlights the analyses' main contribution and suggests future research directions

### II. PV INSTALLATION AND REACTIVE POWER OPTIMISATION

Hosting capacity (HC) is a powerful method for determining the maximum capacity of new generation that can be installed on each bus without exceeding network constraints. In this paper, an HC analysis is developed to install a photovoltaic (PV) power plant in a distribution network which lacks any renewable energy resource (RES). Following that, an optimization-based method is used to exploit the PV converters to minimise active power losses also while adjusting the voltage within the boundaries via their reactive power control. In the following subsections the two-stage method is described.

#### A. Hosting Capacity

The proposed HC method takes the advantage of one of the power system specialised software (PSSS) toolbox and it is briefly described below; further details on PSSS tools for HC analyses are explained in [10]. Following the network modelling, the candidate buses for installing the PV system must be chosen. Load flow simulations are performed iteratively for each bus, with the PV capacity being properly adjusted according to voltage and thermal limits at each iteration. The convergence is reached when the first constraint limit is reached, providing the maximum capacity that can be installed to the analysed candidate bus. The HC was applied in two extreme operating conditions to obtain a more reliable solution, namely the minimum and maximum load value of the day.

#### B. PV converter reactive power optimisation

The HC simulations have been carried **considering** a unity power factor of the PV system. However, current converter technologies allow to provide reactive power to control the voltage[11]. For this purpose, a co-simulation-based optimisation framework has been developed between a PSSS and an external programming language. The objective function is to minimise the active power losses ( $P_{loss}$ ) and to avoid voltage exceeding the desired boundaries, by means of a penalty function ( $f_V$ ), controlling the reactive power of the PV system converters:

$$\min_{Q^{PV}} F(Q^{PV}) = P_{loss}(Q^{PV}) + f_V(Q^{PV}) \quad (1)$$

in which  $Q^{PV}$  is the vector of the PV converters' reactive power. This is one of the key features of the co-simulation, i.e., it is possible to define non-explicit objective function or constraints deriving from the PSSS, providing a more modelling flexibility. Further details on co-simulation properties are provided in **Error! Reference source not found.**

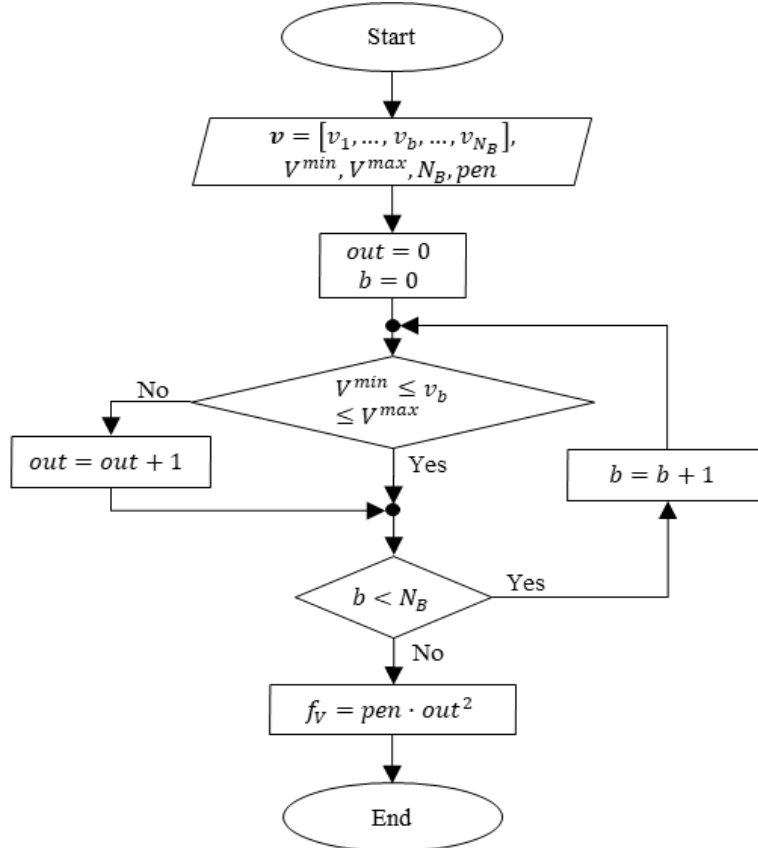


Fig. 1. Voltage penalty rule implemented.

Defining with  $N^{PV}$  the total number of PV system installed in network, the reactive power bounds of each smart converter can be obtained from the following equation:

$$Q_i^{PV} \leq \pm \sqrt{S_i^{PV2} - P_i^{PV2}} \quad \forall i = 1, \dots, N^{PV} \quad (2)$$

where  $S_i^{PV}$  is the rated apparent power of the converter, whereas  $P_i^{PV}$  is supplied active power of the  $i$ -th PV system.

The penalty function of (1) is defined as expression of number of buses exceeding the minimum ( $V^{min}$ ) or the maximum ( $V^{max}$ ) voltage limit. Fig. 1 shows the rule implemented in the programming language environment, where  $\mathbf{v}$  is the vector of the nodal voltages,  $N_B$  is the bus number of the system, in which  $b$  is the index of the generic busbar, whereas  $pen$  is the penalty value.  $f_v$  is function of the square of the outbound index number to force the optimisation to avoid undesired operating conditions. The both the voltages and the losses derive from the PSSS AC load flow simulation, carried on as function of the controlling variable  $Q^{PV}$  set in the programming language environment. Hence, the AC load flow equations represent non-explicit constraints of the optimisation problem. Equation (3) reports the active ( $P_b$ ) and reactive power ( $Q_b$ ) as function of the voltage ( $V_b$ ), the self-admittance ( $Y_{bb}$ ) and the mutual-admittance between two interconnected nodes ( $Y_{cb}$ ).

$$\begin{cases} P_b = Re \left[ V_b^* \left( V_b Y_{bb} + \sum_{\substack{c=1 \\ c \neq b}}^{N_B} V_c Y_{bc} \right) \right] \\ Q_b = Im \left[ V_b^* \left( V_b Y_{bb} + \sum_{\substack{c=1 \\ c \neq b}}^{N_B} V_c Y_{bc} \right) \right] \end{cases} \quad \forall b = 1, \dots, N_b \quad (3)$$

Add a small Figure on co-simulation?

Fig.2 describes the overall methodology for co-simulation-based optimization problem for reactive power control in distribution network. The network is designed in digsilent power factory. A python program is written to run the power factory through Python API. The optimization is modelled using the Python libraries. The co-simulation is executed for a period of day to compute optimization and the hosting capacity of the network.

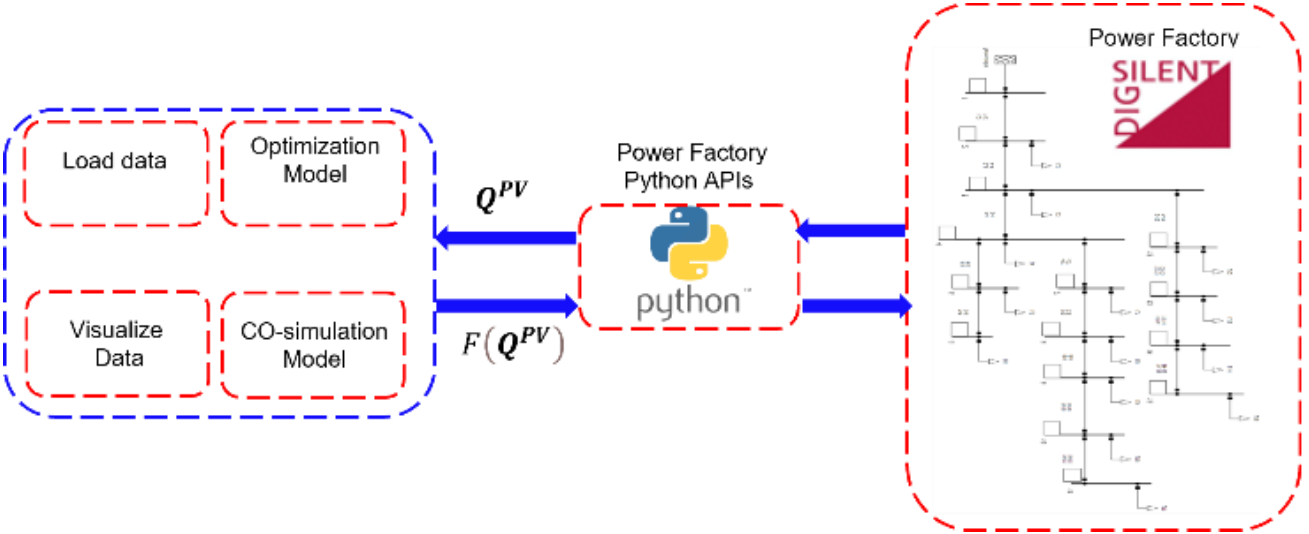


Fig. 2. co-simulation based optimization problem for reactive power control in distribution network.

### III. HC ON KUMAMOTO TEST SYSTEM

The proposed approach has been applied to the Kumamoto distribution system [12], shown in Fig. 2. This network is devoid of thermal rating of the power lines; therefore, a preliminary load flow simulation has been carried on, and the selected rating current are reported in Table I, with the loading percentage.

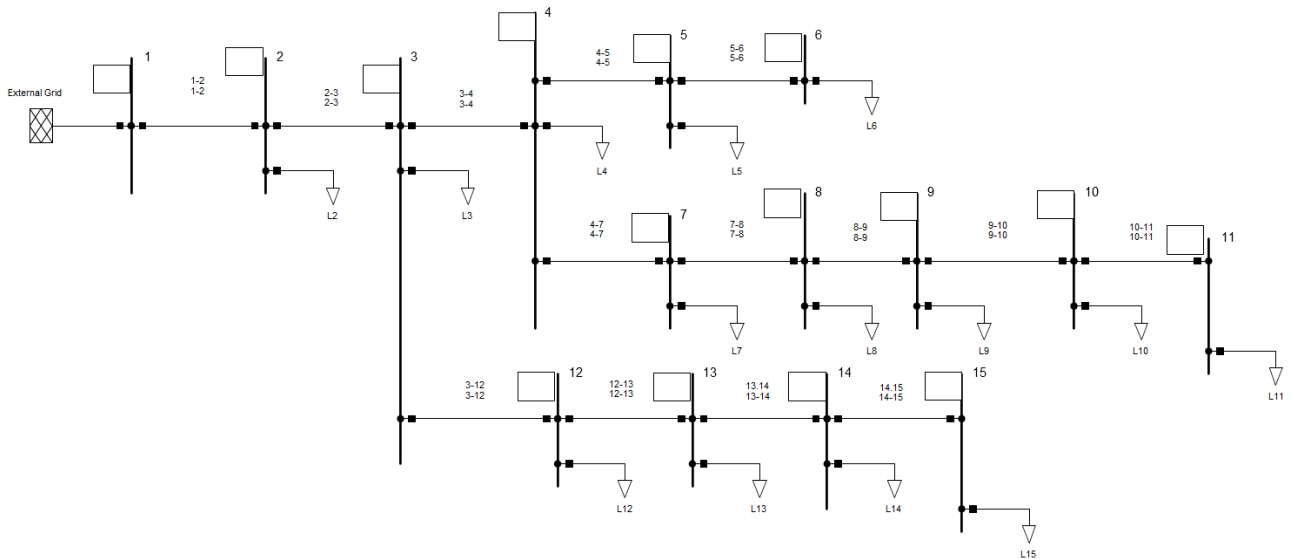


Fig. 3. Kumamoto distribution test system.

TABLE I. RATED CURRENTS OF THE KUMAMOTO NETWORK

Line	Rated current [kA]	Loading [%]
Line 1-2	1.00	99.9
Line 10-11	0.50	69.3
Line 12-13	0.26	20.1
Line 13-14	0.26	18.3
Line 14-15	0.26	8.5
Line 2-3	1.00	96.6
Line 3-12	0.26	28.1
Line 3-4	1.00	81.6
Line 4-5	0.26	33.9
Line 4-7	1.00	57.8
Line 5-6	0.26	6.9
Line 7-8	1.00	47.7
Line 8-9	0.50	85.1
Line 9-10	0.50	78.3

DIgSILENT PowerFactory is the chosen PSSS for HC analysis, and the user manual contains additional information on this methodology [13]. A daily profile has been assigned to the 14 installed loads, keeping the original load power factors. Fig. 3 shows the quarter-hour load profile, with a peak value of 16.88MW and a minimum value of 1.98 MW, that are the conditions in which the HC has been analysed.

Table II presents the HC results with voltage limits of  $[0.95 \div 1.05]$  pu and maximum line loading of 100%. Only Bus 1, the interconnection point with the external grid, was left out of the HC analysis. The external grid is configured as a slack bus with a target voltage of 1.02 pu. The maximum loading ( $L_{\cdot}$ ) is the limiting bound in both cases. Specifically, during peak load, the minimum and maximum PV capacity at Bus 6 and Bus 2 are respectively 5.36 MW and 36.38 MW. Furthermore, the installation of PV results in a slight increase in voltage on the examined buses, with the maximum occurring at Bus 11 with 1.036 pu. During the minimum load, the HC result has a lower PV capacity while the voltages are higher than the previous case. Indeed. On Bus 14 and Bus 15 the reach bound is maximum voltage. The minimum and maximum capacity RES occur on Bus 15 and Bus 2, with capacities of 3.18 MW and 21.50 MW, respectively. In relation to the HC results, the PV systems have been connected on the Bus 2 ( $PV_2$ ) with a capacity of 20 MVA, and on Bus 11 ( $PV_{11}$ ) with 10 MVA. The first is the bus with the highest generation that can be installed, whereas the second is the bus on which is connected the greatest load. The PV capacity choice criterion is based on obtaining central hours of the day with a production greater than the required load.

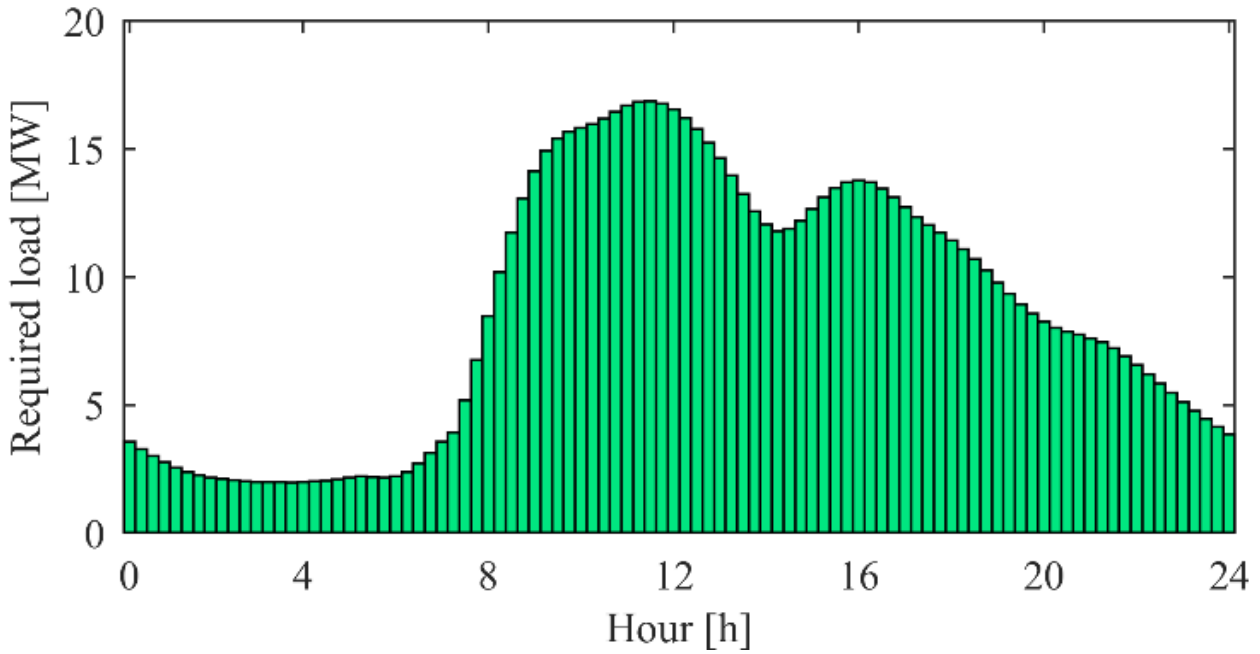


Fig. 4. Quarter-hour daily load profile of Kumamoto network.

TABLE II. MINIMUM AND PEAK LOAD HC RESULTS.

Bus	Peak Load				Minimum load			
	P [MW]	L. [%]	V [pu]	Limiting element	P [MW]	L. [%]	V [pu]	Limiting element
2	36.38	99.8	1.020	1-2	21.50	99.9	1.034	1-2
3	35.78	99.9	1.020	2-3	21.38	99.9	1.034	2-3
4	33.26	99.8	1.024	3-4	21.22	99.8	1.035	3-4
5	6.68	99.8	1.020	4-5	5.44	99.9	1.041	4-5
6	5.36	99.9	1.020	5-6	5.18	99.9	1.043	5-6
7	29.70	99.9	1.029	4-7	20.70	100.0	1.037	4-7
8	28.38	99.9	1.031	7-8	20.50	100.0	1.037	7-8
9	17.65	100.0	1.034	8-9	10.51	99.9	1.046	8-9
10	17.02	99.9	1.034	9-10	10.48	99.9	1.047	9-10
11	16.19	99.9	1.035	10-11	10.32	99.9	1.048	10-11
12	6.16	99.9	1.020	3-12	5.30	99.9	1.041	3-12
13	5.91	99.8	1.023	12-13	5.27	99.9	1.046	12-13
14	5.85	99.9	1.028	13-14	4.64	87.7	1.050	Bus 14
15	5.38	99.9	1.029	14-15	3.81	72.2	1.050	Bus 15

The PV systems daily production is set exploiting a winter day profile provided in [12], and their quarter-hour production is depicted in Fig. 4. The PV systems supply power to the network within 8:15 to 17:45. The peak production occurs at 13:00 with roughly 18.6 MW, and a total energy of approximately 113 MWh. Furthermore, from 12:30 to 14:45 the PV systems production exceed the required load, exporting the difference to the external network (red bars). Finally, Fig. 5 depicts the maximum and average loading of the lines with and without the PV penetration. The PV penetration has a positive impact on the line loading, the higher is the penetration, the greater is the loading reduction. During the daylight hours the maximum loading has a mean reduction of 19.1%, where the maximum loading moved from 88.6 % to 69.1 %. Analogously, the mean loading is subject to a mean reduction of 14.5 %.

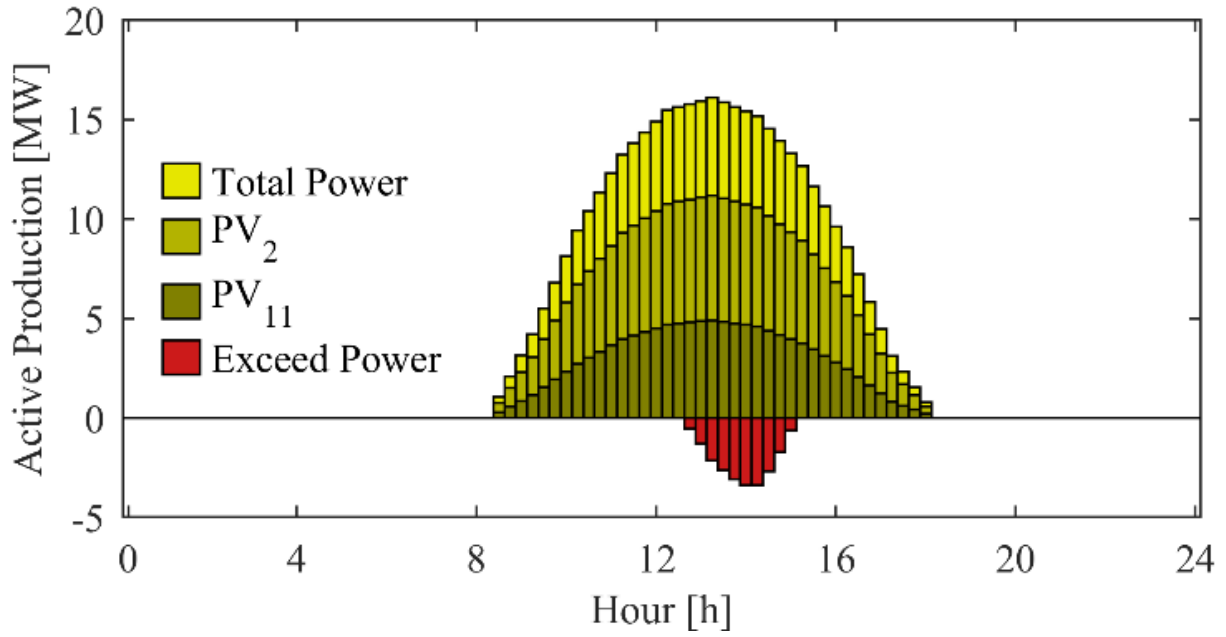


Fig. 5. Installed PV system active power production.

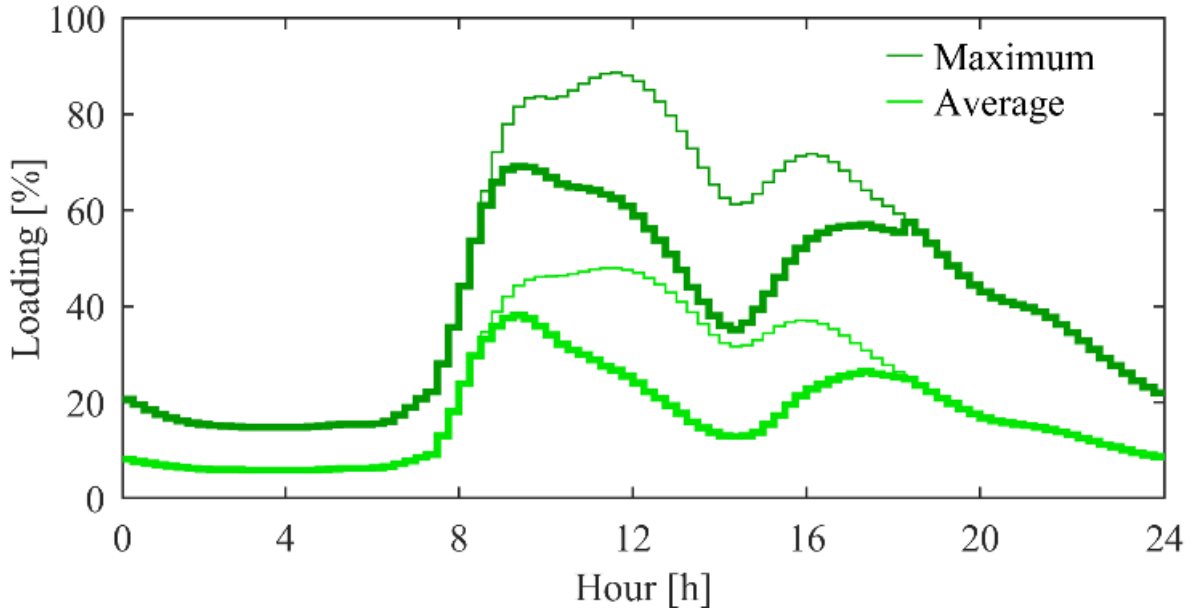


Fig. 6. Maximum and average line loading with (thicker) and without (thinner) PV production.

#### IV. REACTIVE POWER OPTIMISATION

The co-simulation framework was modelled using PowerFactory as the PSSS and Python as the programming language environment. Hourly load flow simulation has been configured in PowerFactory to exploit active and reactive power balance equations as non-explicit constraints, as well as the losses and the voltage penalty function of (1) in the optimisation problem. In Python, the SciPy library [14] was used to model the optimisation problem using the Differential Evolution solver [15]. Considering the HC results from Table II, the voltage boundaries for all buses have been set to  $[0.99 \div 1.035]$  pu, to force the optimisation to redispatch the reactive power, whereas the penalty constant ( $pen$ ) is 1000. The simulations have been performed on a laptop with an 8 core i7-10870H processor running at 2.20 GHz and a RAM of 32 GB.

Fig. 6 depicts the base case losses as well as the losses after the optimisation problem has been solved. During the day, the base case losses range from 4.7 kW to 132.6 kW, for a total energy loss of 862.5 kWh. On the contrary, the optimal solution has lower volatility, varying from 3.0 kW to 130.9 kW, with a total energy loss of 843.0 kWh; therefore, a reduction of the daytime losses of 19.5 kWh has been achieved. Fig. 7 depicts the statistic values of the voltages before and after the optimisation. On the one hand, prior to optimization, the average nodal voltage is close to the upper bound of 1.035 pu until 07:00, owing to the low loading of the lines and for the low required load. Following that, the increase in load as well as the energy supply by PV systems cause a sudden drop in average voltage, reaching a low of 1.016 pu at 09:00. Throughout the day, the average voltage follows an increasing and decreasing trend with lower slopes. The optimal solution, on the other hand, meets the voltage constraints throughout each hour. Specifically, until 07:00, the average voltage is close to the slack bus's target voltage. Then it fluctuates

between a maximum of 1.030 pu and a minimum of 1.020 pu. Fig. 8 shows the optimal reactive power provided by PV systems to the network. As can be seen, the voltage trend closely follows the dispatched reactive power of the PVs: when they produce inductive reactive power (negative sign), the optimal average voltage is lower than the base case ones; whereas, when they withdraw inductive reactive power (positive sign), the optimal average voltage is higher than the base case ones.

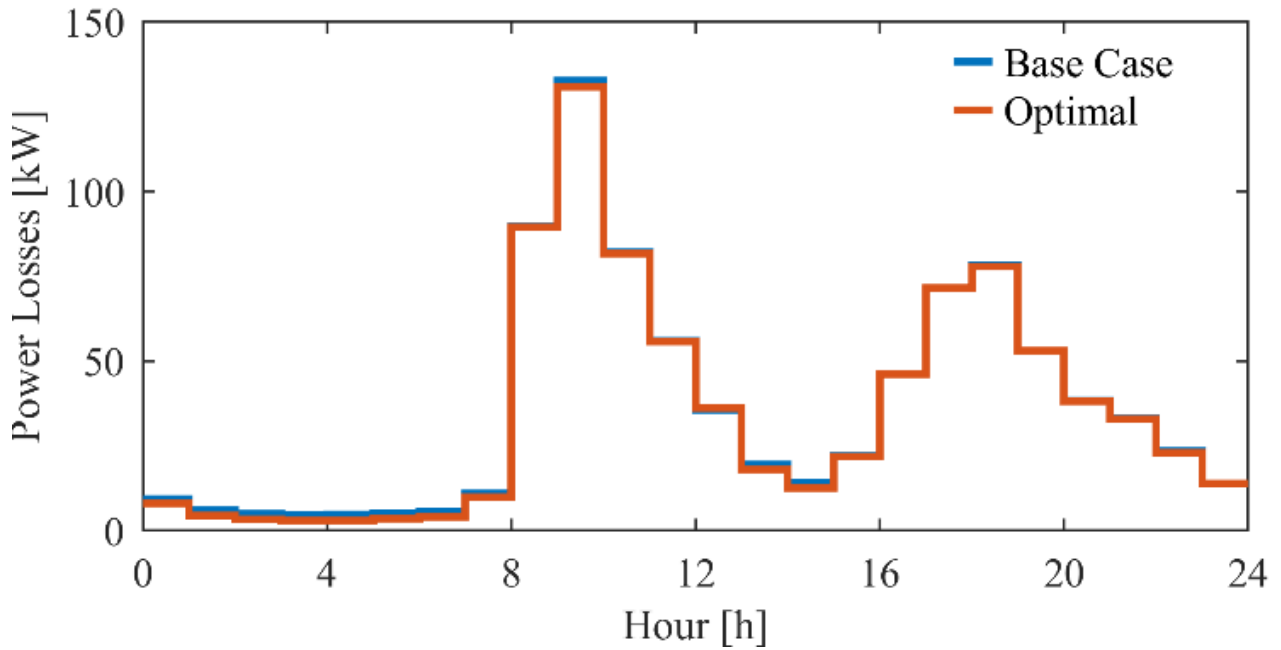


Fig. 7. Base case (blue) and optimal (red) system losses.

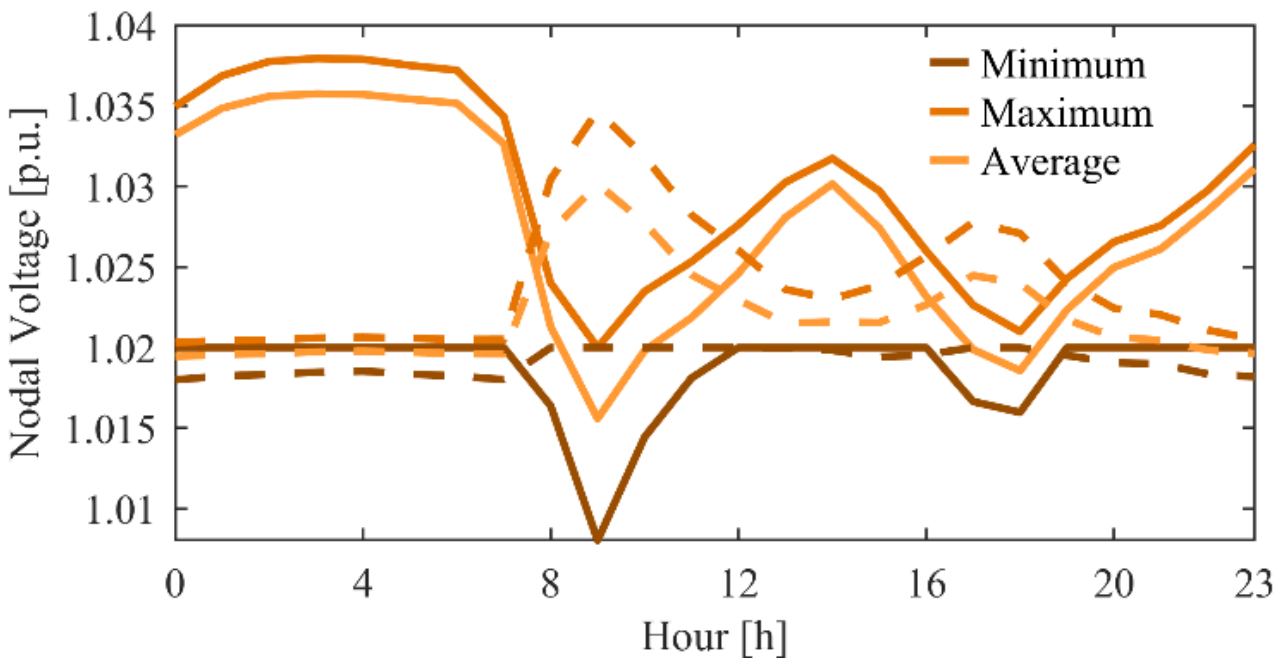


Fig. 8. Base case (line) and optimal (dashed) minimum, maximum and average hourly nodal voltage.

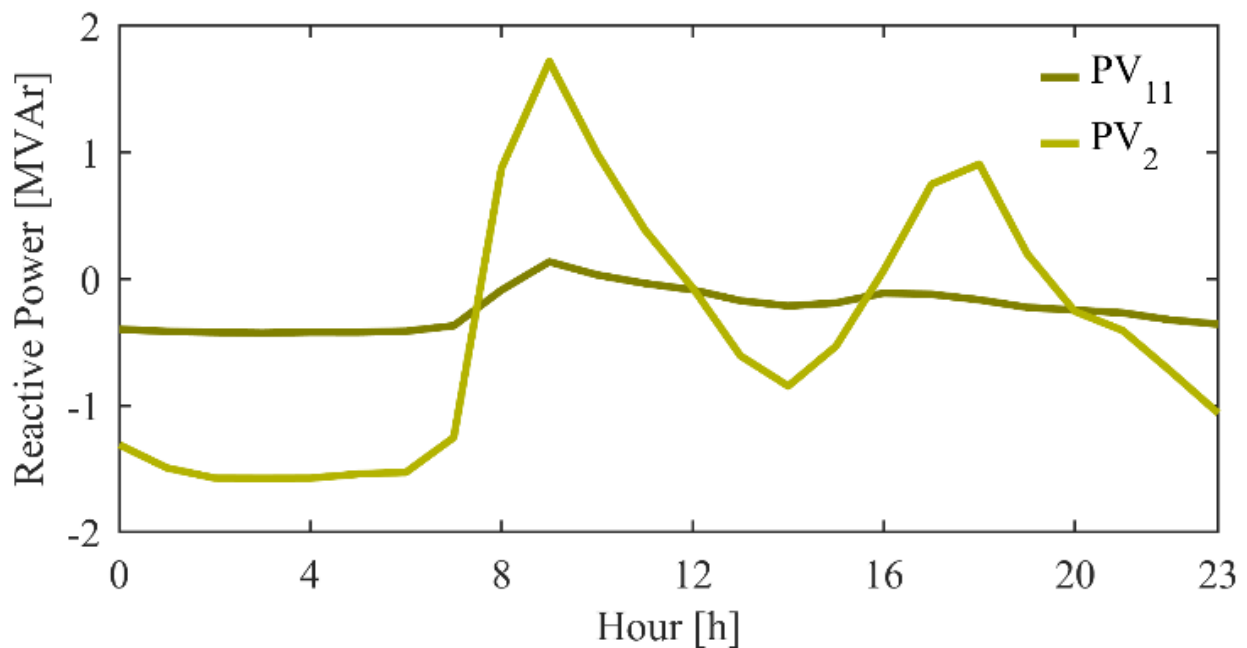


Fig. 9. Hourly optimal reactive power provided by the PV converters.

## V. CONCLUSIONS

The current paper proposes a methodology for installing PV systems into a distribution network devoid of any RES power plant using HC analysis and controlling the reactive power of the installed PV systems using an optimisation problem to minimise the system's active power losses. The HC was performed in two extreme scenarios: the daily minimum and maximum system load of the winter peak day, properly assigned. The buses were chosen based on the highest generation that could be installed and the maximum installed load. The installed PV system was then given a suitable daily power production profile. The results show that, in addition to the suitability of the installed location, the lines' power flow during daylight hours is subject to lower loading than the initial network without RES. As a result, the power supplied by PV systems is a first step toward reducing system losses.

Following that, the DE algorithm was used to dispatch the reactive power of the PV converters in a co-simulation-based optimisation problem, with the goal of minimising losses and limiting nodal voltages. Throughout the day, there has been a further reduction in losses. Furthermore, the optimization improves the nodal voltage trend by reducing extreme values and variation over two consecutive time steps. The results can be improved further by installing PV systems in more buses with lower rated power to control the local voltage, reducing the losses, rather than installing two larger PV systems.

Further work can address the definition of reactive power costs to remunerate the service provided by the owner of the PV system, as well as the costs of active power in order to evaluate the benefits even from an economical perspective.

## REFERENCES

- [1] M. H. J. Bollen *et al.*, "Power Quality Concerns in Implementing Smart Distribution-Grid Applications," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 391–399, 2017.
- [2] D. Sampath Kumar, O. Gandhi, C. D. Rodríguez-Gallegos, and D. Srinivasan, "Review of power system impacts at high PV penetration Part II: Potential solutions and the way forward," *Sol. Energy*, vol. 210, pp. 202–221, 2020.
- [3] D. Pettersen, E. Melfald, A. Chowdhury, M. N. Acosta, F. Gonzalez-Longatt, and D. Topic, "TSO-DSO Performance Considering Volt-Var Control at Smart-Inverters: Case of Vestfold and Telemark in Norway," in *2020 International Conference on Smart Systems and Technologies (SST)*, 2020, pp. 147–152.
- [4] M. Jalali, V. Kekatos, N. Gatsis, and D. Deka, "Designing Reactive Power Control Rules for Smart Inverters Using Support Vector Machines," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1759–1770, 2020.
- [5] T. Ochi, D. Yamashita, K. Koyanagi, and R. Yokoyama, "The development and the application of fast decoupled load flow method for distribution systems with high R/X ratios lines," in *2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, 2013, pp. 1–6.
- [6] H. J. Liu, W. Shi, and H. Zhu, "Distributed Voltage Control in Distribution Networks: Online and Robust Implementations," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6106–6117, 2018.
- [7] A. Safavizadeh *et al.*, "Impacts of voltage control methods on distribution circuit's photovoltaic (PV) integration limits," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 84–94, Mar. 2019.
- [8] M. Jafari, T. O. Olowu, and A. I. Sarwat, "Optimal Smart Inverters Volt-VAR Curve Selection with a Multi-Objective Volt-VAR Optimization using Evolutionary Algorithm Approach," *2018 North Am. Power Symp. NAPS 2018*, 2019.
- [9] M. N. Acosta, F. Gonzalez-Longatt, M. A. Andrade, and J. R. Torres, "Optimal Reactive Power Control of Smart Inverters: Vestfold and Telemark



Regional Network,” in *2021 IEEE Madrid PowerTech*, 2021, pp. 1–6.

- [10] M. Z. Ul Abideen, O. Ellabban, and L. Al-Fagih, “A review of the tools and methods for distribution networks’ hosting capacity calculation,” *Energies*, vol. 13, no. 11, pp. 1–25, 2020.
- [11] G. Tricarico, R. Wagle, M. Dicorato, G. Forte, F. Gonzalez-Longatt, and J. L. Reuda, “Zonal Day-Ahead Energy Market: A Modified Version of the IEEE 39-bus Test System,” in *2022 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, 2022.
- [12] S. Li, K. Tomsovic, and T. Hiyama, “Load following functions using distributed energy resources,” in *2000 Power Engineering Society Summer Meeting (Cat. No. 00CH37134)*, 2000, vol. 3, pp. 1756–1761.
- [13] DigSilent PowerFactory version 2022, “User Manual,” 2022.
- [14] P. Virtanen *et al.*, “SciPy 1.0: fundamental algorithms for scientific computing in Python,” *Nat. Methods*, vol. 17, no. 3, pp. 261–272, 2020.
- [15] R. Storn and K. Price, “Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces,” *J. Glob. Optim.*, vol. 11, no. 4, pp. 341–359, 1997.