

Towards a Simulation Module for Application in Digital Twins of Photovoltaic Systems

Čedomir Zeljković*, Predrag Mršić*, Petar Matić*, Bojan Erceg*, Branko Blanuša*, Mario Vražić**,
Luka Budin**, Daniel Denkovski***, Živko Kokolanski***

* University of Banja Luka, Faculty of Electrical Engineering, Banja Luka, Bosnia and Herzegovina

** University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia

*** Ss Cyril and Methodius University, Faculty of Electrical Engineering and Information Technologies, Skopje, North Macedonia

Abstract – The digitalization process facilitates the faster integration of renewable energy sources into power systems and enhances their planning and operation. Among contemporary digital technologies, digital twins stand out as virtual replicas of physical system assets, well suited for performance monitoring and optimization. This paper presents initial steps toward the development of a simulation module for digital twins of photovoltaic (PV) systems. The proposed module is implemented in Python and adopts a modular structure composed of astronomical, optical, thermal, and electrical submodels to estimate the AC power output of a PV system. A challenging simulation scenario is considered, in which the output power is calculated using a minimal set of input data, namely global horizontal irradiance, ambient temperature, and wind speed. The simulation results are validated using measurements from a real PV system, demonstrating satisfactory agreement despite limited data availability. The developed simulation module represents a key component of digital twin implementations for PV systems and can be applied to performance monitoring, fault detection, and optimization.

Index Terms – Digital twin, Photovoltaic system, Simulation module

I INTRODUCTION

The ongoing transition of power systems toward decarbonization and sustainability has significantly increased the deployment of renewable energy sources [1]. By reducing greenhouse gas emissions and dependence on fossil fuels, renewable generation plays a key role in achieving long-term environmental and energy policy goals [2]. However, the large-scale integration of renewable energy sources also introduces new technical and operational challenges related to variability, uncertainty, and system stability [3].

Among renewable energy technologies, photovoltaic (PV) systems have experienced particularly rapid growth over the past decade [4]. This trend is driven by continuous cost reductions, technological advancements, and favorable regulatory frameworks. As a result, PV systems are increasingly deployed at both utility-scale and distributed levels, leading to higher penetration levels in modern power systems. While this development contributes to cleaner energy production, it also increases the complexity of system operation and planning.

In this context, digitalization has emerged as an important enabling factor for the efficient integration of renewable energy sources [5]. Advanced sensing, communication, and data processing technologies allow for improved monitoring, control, and coordination of distributed energy resources. Digital tools facilitate real-time system awareness and support data-driven decision-making, thereby enhancing system reliability and operational flexibility.

A particularly promising digitalization concept is the digital twin, which represents a virtual counterpart of a physical system that is continuously updated using operational data. By combining physics-based models with real-time measurements, digital twins enable detailed analysis of system behavior under varying operating conditions. In the case of PV systems, digital twins can support performance assessment, fault detection, predictive maintenance, and operational optimization. Consequently, the digital twin paradigm provides a systematic framework for improving the observability, controllability, and overall efficiency of PV power plants within modern power systems.

With this in mind, the GoToTWIN project leverages the digital twin concept to support faster integration and more efficient operation of renewable energy sources in the Adriatic-Ionian region [6]. By developing interoperable digital twin solutions for renewable assets, the project aims to enhance system observability, flexibility, and data-driven decision-making. The objective of this paper is to present the current progress in the development of the proposed digital twin, with particular emphasis on the simulation module for PV systems, including its modeling approach and initial validation results.

The remainder of the paper is organized as follows. Section II presents the digital twin concept in general, its application in renewable energy systems, and the specific implementation of the digital twin developed within the GoToTWIN project. Section III focuses on the development of a module within the digital twin intended for the simulation of PV systems. Section IV presents the initial results of the simulation module for a test configuration and compares them with real measurements obtained from a specific PV system. Finally, Section V provides concluding remarks along with guidelines for future research on this topic.

II DIGITAL TWIN

A digital twin can be defined as a virtual representation of a physical asset, system, or process that is continuously updated using real-time data from its physical counterpart.

II-1 The Digital Twin Concept

The concept of the digital twin emerged in the early 2000s within the context of product lifecycle management and systems engineering [7]. The basic idea behind the digital twin concept is illustrated in Fig. 1.

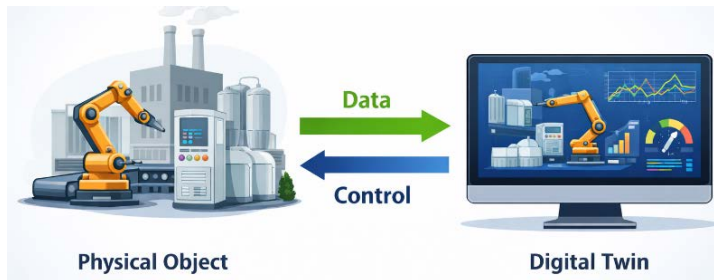


Fig 1. A closed loop digital twin concept

Unlike conventional simulation models, digital twins maintain a persistent and bidirectional connection with the physical system throughout its operational life cycle. This connection enables the digital twin to reflect the current state of the physical asset, as well as to predict its future behavior under different operating conditions. The digital twin paradigm integrates multiple components, including physics-based models, data-driven methods, sensor data, and communication infrastructure. As such, it serves as a unifying framework that bridges modeling, monitoring, control, and optimization. Digital twins are increasingly applied across various domains, including manufacturing, aerospace, healthcare, and energy systems. In the context of energy systems, digital twins enable enhanced situational awareness, predictive maintenance, and performance optimization. Furthermore, they support scenario analysis and decision-making by allowing safe experimentation in a virtual environment. Consequently, digital twins are regarded as a key enabling technology for the digitalization and intelligent operation of modern cyber-physical systems.

II-2 Application of Digital Twins in Power Systems

The digital twin concept can be applied across different segments of power systems, as highlighted in recent review studies [8],[9]. By integrating physics-based models with real-time data, digital twins enhance monitoring, analysis, and optimization of energy infrastructures.

In the generation subsystem, a digital twin may represent an entire power plant or a specific subsystem. In PV power plants, digital twins are used for fault and shading detection, performance assessment, and short-term power forecasting. For hydropower plants, they support optimal operating regime selection, reservoir management, and environmentally compliant water discharge planning.

In the transmission subsystem, digital twins can replicate transmission lines, substations, or network areas, enabling real-time state assessment, thermal rating evaluation, stability analysis, and predictive maintenance.

At the distribution level, digital twins are particularly relevant due to high penetration of distributed energy resources. They can support voltage regulation, loss reduction, congestion management, fault localization, and coordinated control of distributed generation and storage systems.

Overall, digital twins provide a unified framework for improving observability, controllability, and operational efficiency across modern power systems.

II-3 Proposed Digital Twin Architecture

The specific digital twin architecture developed within the GoToTWIN project is illustrated by the block diagram shown in Fig. 2. The digital twin platform is built on the continuous acquisition of data from multiple sources. Physical power plants, such as photovoltaic, wind, or hydropower facilities, provide real-time operational data including power output, equipment status, and efficiency indicators. This information is complemented by local weather sensors delivering key environmental variables, while external data providers supply meteorological forecasts that enable short-term prediction of operating conditions.

All data are collected through an IoT Gateway, which serves as the secure interface between the physical assets and the digital environment. Using standardized data formats and reliable communication protocols, the gateway ensures the timely and consistent transfer of real-time telemetry to the digital twin.

At the core of the system, the Digital Twin Manager maintains a continuously updated virtual representation of the physical assets by integrating real-time measurements with simulated and predicted data. Simulation capabilities are provided through a dedicated toolkit that processes measured and forecast information to evaluate plant behavior under different scenarios, such as changing weather conditions. In parallel, a prediction toolkit applies machine learning models trained on historical data to forecast power production, equipment condition, and potential anomalies, enabling proactive system operation.

Historical data storage supports long-term analysis and model training by archiving telemetry, simulations, and prediction results over time. Finally, the system delivers actionable insights through intuitive 2D dashboards and 3D digital twin visualizations, allowing operators to monitor current performance, compare scenarios, and assess future system behavior.

The developed platform is implemented entirely as an open-source solution to promote cost efficiency, foster community-driven innovation, and align with the European Union Open-X principles. The Digital Twin Manager is realized using Eclipse Ditto, which maintains synchronized virtual representations of physical assets and manages their state through standardized interfaces. Eclipse Hono functions as the IoT gateway, enabling secure and reliable ingestion of telemetry data from field devices. Time-series data storage is supported by InfluxDB, while visualization and user interaction are provided through Grafana dashboards.

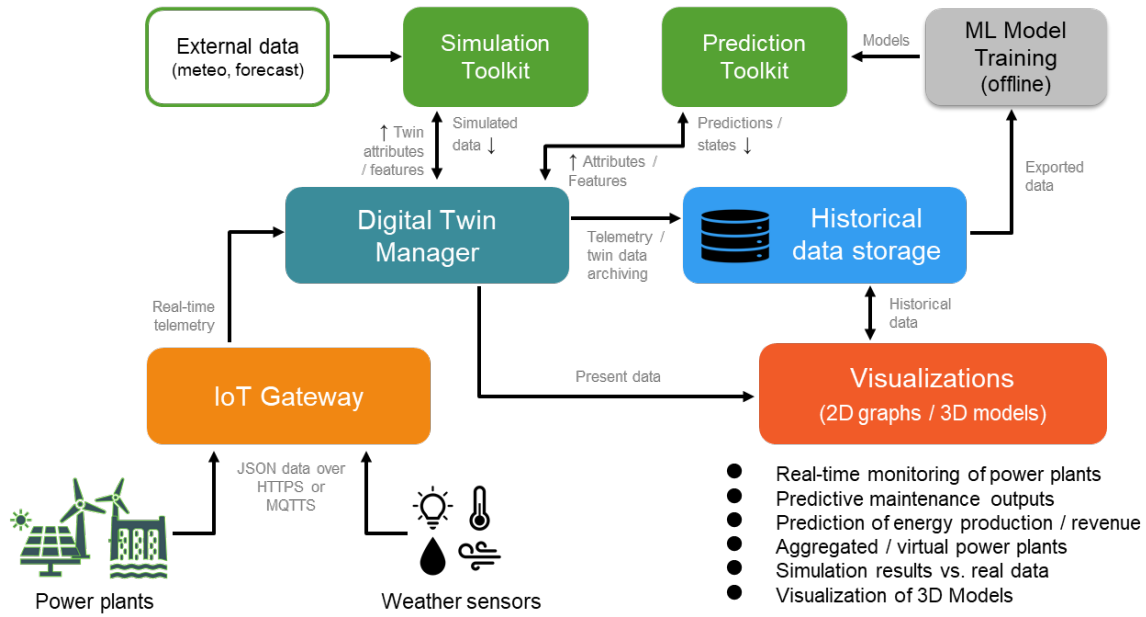


Fig 2. Digital twin architecture

III THE SIMULATION MODULE FOR PV SYSTEMS

In the proposed digital twin architecture, the simulation toolkit represents an important component, since it contains all program routines required for simulation of considered power system entities such as photovoltaic, wind, or hydropower power plants. In this paper, the primary focus is on the development of the module for simulation of PV systems. The purpose of such module is to provide a flexible and computationally efficient environment for reproducing the dynamic behavior of the PV system under varying operating and environmental conditions. By integrating mathematical models of key system components with real or synthetic input data, the simulation module enables performance analysis, what-if studies, and predictive assessments that support monitoring, optimization, and decision-making within the digital twin framework.

III-1 The Simulation Framework

The PV system model is formulated as a framework comprising four submodels: astronomical, optical, thermal, and electrical. The main variables associated with each block, together with their interconnections, are illustrated in Fig. 3. This figure depicts the maximum scope of the simulation module, which determines the expected AC power output of the PV system based on the static parameters of the system and basic meteorological data provided as inputs. When additional measurements are available (such as plane-of-array irradiance, module temperature, string current, and voltage) these values can be directly used to compute the plant's output power, allowing certain blocks to be bypassed. Nevertheless, the corresponding blocks may still be employed for model calibration or for monitoring the behavior of specific PV system components.

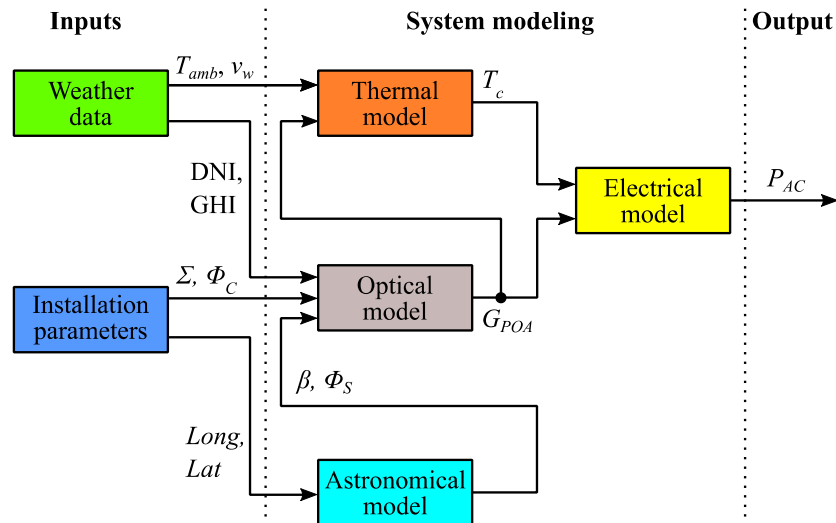


Fig 3. Basic components of the simulation framework

III-2 Astronomical Model

The purpose of the astronomical model is to determine the position of the Sun in the sky for the location of the considered PV system, depending on the day of the year and the time of day. The position of the Sun is defined by two angles: the solar altitude angle β and the solar azimuth angle Φ_s . These angles represent important input variables for calculations within the optical model. Mathematical expressions for determining the solar angles β and Φ_s are derived in many books [10],[11].

III-3 Optical Model

An optical model is necessary to account for the impact of obstacles on the propagation of solar radiation and to determine what percentage of the available solar irradiance will actually reach the PV modules. The crucial output of the optical model is the plane-of-array (POA) irradiance G_{POA} , i.e. the irradiance that is incident on the surface of the PV modules. The orientation of the PV modules is specified by static installation parameters: the azimuth angle (Φ_c) and tilt angle (Σ).

Typical meteorological data often include global horizontal irradiance (GHI), which serves as a universal indicator of the solar potential at a given location. Since the power output of a PV array depends on the POA irradiance, it is necessary to convert the GHI to the plane of the modules. For this purpose, the GHI must first be decomposed into its direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI), after which each component is individually transformed to the plane of the modules. On the other hand, if measuring of POA irradiance is available in the PV system, optical model can be avoided (bypassed).

Several models have been proposed for the decomposition of GHI into DNI and DHI, including the Orgill and Hollands model, the Erbs et al. model, the Boland et al. model, and the DISC and DIRINT models [12]. Decomposition approaches are generally categorized into two types: piecewise empirical models (e.g. Orgill and Hollands, Erbs et al., Boland et al.) and quasi-physical models (e.g. DISC and DIRINT). Piecewise empirical models are purely empirical, relying on correlations between the clearness index ($k_t = \text{GHI} / G_0$) and the diffuse fraction ($k_d = \text{DHI} / \text{GHI}$), where G_0 is the extraterrestrial irradiance. In contrast, quasi-physical models are developed based on physical principles while also incorporating empirical relationships.

The total POA irradiance incident on the module surface is the sum of three components: beam, diffuse, and ground-reflected component. In general, the beam and ground-reflected components are estimated from the DNI using geometric relationships [10], [13]. In contrast, several transposition models have been developed to estimate the diffuse component. These models are typically classified as isotropic (e.g. Liu and Jordan, Koronakis) or anisotropic sky models (e.g. HDKR, Perez et al.) [12]. Isotropic models assume that diffuse sky irradiance is uniformly distributed across the entire sky dome. Under this assumption, the diffuse irradiance received by a tilted surface depends solely on the visible portion of the sky, irrespective of the orientation relative to the Sun. In contrast, anisotropic models account for the non-uniform distribution of diffuse irradiance,

particularly increased intensity near the horizon and in the circumsolar region. In the aforementioned models for calculating irradiance in the POA, the possibility of module shading is not considered.

III-4 Thermal Model

The purpose of the thermal model is to estimate the temperature of PV modules T_c based on meteorological input parameters. On the other hand, if direct measurement of PV module temperature is implemented in the system, the thermal model is not necessary and can be bypassed. Knowing the temperature of PV modules is important, as it significantly affects the efficiency of photovoltaic energy conversion. In commonly used PV technologies, the output power of a PV system typically decreases by more than 3% for every 10°C increase in module temperature.

Thermal models of PV modules are based on heat transfer theory, and numerous modeling approaches can be found in the literature [14]. These models are generally categorized into two main groups: those that use two input variables, and those that rely on three input variables. Two-variable models estimate module temperature based on POA irradiance and ambient temperature (T_{amb}), such as the NOCT and HOMER models. In contrast, three-variable models additionally incorporate wind speed (v_w) as an input variable, such as the Faiman and Sandia models. These models typically provide higher accuracy, particularly in regions characterized by significant and variable wind conditions.

III-5 Electrical Model

The purpose of the electrical model is to describe the electrical behavior of the PV plant. This model determines the expected power output of the PV system based on POA irradiance, PV module temperature, and the system specifications. As illustrated in Fig. 4, the model is divided into two characteristic sections. It should be noted that individual PV arrays and inverters are typically modeled separately, particularly when the PV arrays differ in orientation or configuration.

Several PV module models have been proposed in the literature, ranging from simple approaches that require only a few input parameters to more complex formulations involving detailed PV module characterization [12]. These models can generally be classified into two categories: power-based models and equivalent-circuit models. Power models are based on a single-point efficiency representation of the PV module and estimate the power output at the Maximum Power Point (MPP). Depending on their complexity, they can predict the PV module performance under varying operating conditions with acceptable accuracy. Such models are implemented in software tools such as PVWatts [15] and HOMER [16]. When the full current-voltage (I-V) characteristic of the PV cell is required, models capable of describing its electrical behavior under varying operating conditions must be employed. Various approaches have been proposed to approximate the I-V curve, ranging from empirical models to more physically based formulations. Representative models of this type have been proposed by De Soto et al., Villalva et al., and Walker [12].

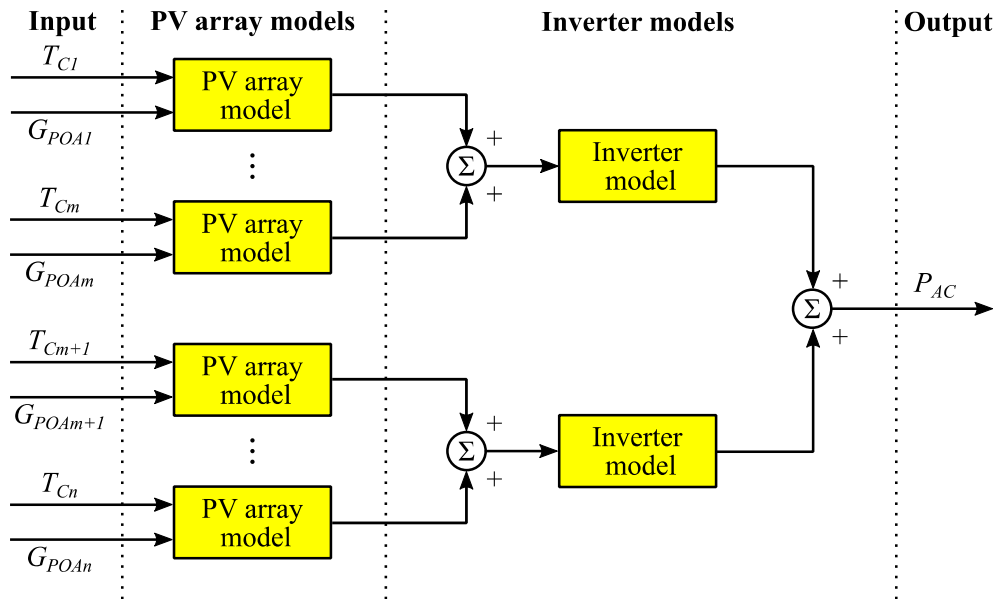


Fig 4. Electrical model layout

One of the most important characteristic of a PV module is its degradation behavior. PV module degradation refers to the gradual decline in their output power over time, which directly affects the total energy yield of the system. Common forms of degradation include light-induced degradation (LID), which occurs within the first days of exposure to sunlight, and potential-induced degradation (PID), which can result from high potential differences between the module and ground. In addition, long-term degradation is driven by exposure to UV radiation, temperature cycling, humidity, and the accumulation of dirt and debris on the module surface. To accurately represent this behavior, degradation is commonly modeled using a piecewise linear curve, which distinguishes between first-year degradation and degradation in subsequent years.

Power conditioning equipment, such as inverters, is used to convert DC power into AC power. In many simplified PV system models, inverter efficiency is represented as a constant value. However, in practice, inverter efficiency depends on both the DC voltage and the load fraction at which the inverter operates. Several approaches have been proposed to model the inverter electrical behavior, including the PVWatts model [15], the Sandia model [17], and the formulation by Nottton et al. [18].

IV INITIAL RESULTS

The initial validation of the simulation module was performed by comparing the calculated values with measurements obtained from a real PV system.

IV-1 Test System

The test system used for this purpose was the living lab of the Faculty of Electrical Engineering and Information Technology (FEEIT), Ss. Cyril and Methodius University in Skopje, North Macedonia, commissioned in 2018. The test system consists of 36 PV modules of type Canadian Solar CS6K-280P, each with a nominal power rating of 280 W. The modules are arranged into two strings of 18 modules and connected to an InfiniSolar

inverter with a nominal power of 10 kW. The modules are mounted on a metal rooftop with a tilt angle of 15° and an azimuth orientation of 10° west of south.

Data acquisition is performed using the Stylitis-10 data recorder, a low-power multi-channel logger designed for meteorological and renewable energy applications. It features configurable analogue channels and digital interfaces (MODBUS RTU and SDI-12), enabling direct integration of smart sensors without external signal conditioning. Remote communication is established via Ethernet, and telemetry is transmitted to the digital twin at 15-minute intervals.

IV-2 Scenario under Consideration

In this paper, we consider a scenario in which the output power of a PV system is calculated using a minimal set of input data, consisting of global horizontal irradiance, ambient temperature, and wind speed. The quality of the simulated output power is evaluated through comparison with real measurements obtained from the test system.

It should be noted that this represents the most complex simulation scenario, as it requires the decomposition of irradiance into direct and diffuse components, as well as the estimation of PV module temperature based on irradiance, ambient temperature, and wind speed. Since both of these transformations are based on empirical models, some degree of error is expected to occur in the results. For PV systems where POA irradiance measurements and/or direct module temperature measurements are available, significantly better agreement between simulated and measured output power is expected.

IV-3 Simulator Configuration

The simulation module is implemented in the Python programming language and makes use of the PVLIB library [19].

Determining the position of the Sun in the sky is a well-established deterministic task. The resulting solar position data,

together with the static parameters of the PV system, are subsequently passed to the optical model.

In the considered scenario, the optical model uses GHI as its only dynamic input parameter. This quantity is provided by the corresponding sensor, and its current value is stored within the digital twin manager. In the current version of the code, the DIRINT method is employed to decompose GHI into its direct and diffuse components [20]. Based on these components, the POA irradiance is then determined using an isotropic sky model.

The thermal model is based on the Sandia PV Array Performance Model (SAPM) [17]. The model coefficients are selected for a close-mounted installation configuration, thereby accounting for limited airflow due to the small gap behind the modules. Finally, the estimated values of POA irradiance and PV module temperature are used as inputs to the electrical model. The DC power output of the PV modules is calculated using the single-diode De Soto PV cell model [21]. The AC output power of the system is then derived from the DC power by applying the NREL inverter model [15].

System degradation is also taken into account, with a degradation rate of 2% assumed for the first year of operation and 0.6% for each subsequent year.

IV-4 Results

For testing the developed simulation module in the presented configuration, one week of data from September 2025 (from 2025-09-15 to 2025-09-22) was used. The diagrams of GHI, ambient temperature, and wind speed are shown in Fig. 5.

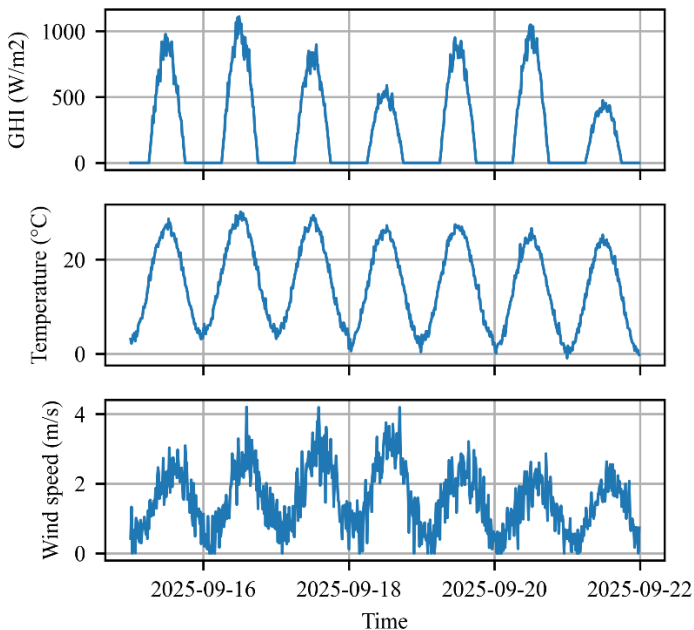


Fig 5. Sample input data

The results for two illustrative days, presented as a comparison between the measured and simulated AC output power, are shown in Fig. 6. Based on the presented diagrams, it can be observed that larger errors occur during the mostly sunny days (example day: 2025-09-16). The agreement between measured and simulated values is very good during the morning and afternoon hours, while deviations occur around solar noon.

During partly cloudy days (example day: 2025-09-18), the overall agreement is improved, with simulated and measured values matching reasonably well throughout the day.

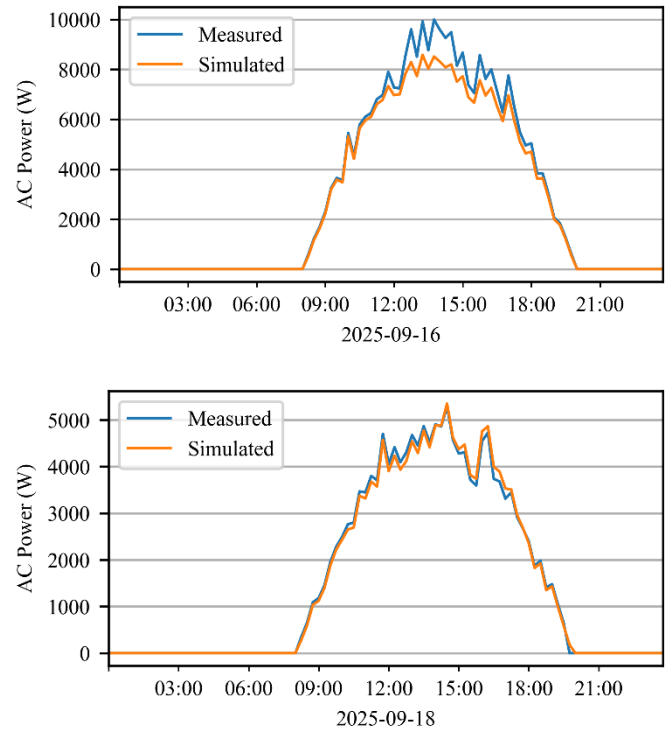


Fig 6. Comparison between measured and simulated power output of the FEEIT PV system during a mostly sunny day (2025-09-16) and a partly cloudy day (2025-09-18)

The performance metrics, including the normalized root mean square error (nRMSE) and the normalized mean absolute error (nMAE), are summarized in Table 1. The values are presented separately for the illustrative mostly sunny day, the illustrative partly cloudy day, and for the entire week. During the calculation of these indices, nighttime hours were excluded, since due to zero irradiance the measured and simulated values coincide without error.

Table 1. Error metrics (with night hours excluded)

Period	nRMSE	nMAE
2025-09-16	6.25%	4.65%
2025-09-18	1.19%	1.04%
Whole week	3.48%	2.27%

IV-5 Further Work

Although the presented simulator configuration yields satisfactory results, further improvements are considered possible. Future work will include the evaluation of alternative models for irradiance decomposition and PV module temperature estimation. In addition, parameters that are not known with complete certainty (such as the degradation rate of PV modules or the thermal model coefficients, which depend on the mounting configuration) may be identified and fitted using optimization-based approaches.

V CONCLUSION

This paper highlights the importance of digitalization of the power system as a key enabler for increasing the penetration of renewable energy sources. Particular emphasis is placed on the digital twin concept, which offers significant potential for improving monitoring, planning, and optimization processes. The work focuses on the initial steps in the development of a simulation module for a digital twin of a PV system within the GoToTWIN project.

The results demonstrate that it is possible to develop simulation routines capable of estimating the output power of a PV system using a limited set of input data, consisting of global horizontal irradiance, ambient temperature, and wind speed. Such a simulation module can be employed for PV system performance monitoring, fault detection, and optimization. As further reductions in output power estimation error are considered achievable, future work will investigate alternative optical, thermal, and electrical models, as well as parameter fitting techniques based on measurements obtained from the monitored PV system.

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AUTHORS

Čedomir Zeljković – University of Banja Luka, Faculty of Electrical Engineering, cedimir.zeljkovic@etf.unibl.org, ORCID [0000-0002-1467-0035](https://orcid.org/0000-0002-1467-0035)

Predrag Mršić – University of Banja Luka, Faculty of Electrical Engineering, predrag.mrsic@etf.unibl.org, ORCID [0000-0002-8717-7292](https://orcid.org/0000-0002-8717-7292)

Petar Matić – University of Banja Luka, Faculty of Electrical Engineering, petar.matic@etf.unibl.org, ORCID [0000-0001-9954-374X](https://orcid.org/0000-0001-9954-374X)

Bojan Erceg – University of Banja Luka, Faculty of Electrical Engineering, bojan.erceg@etf.unibl.org, ORCID [0000-0002-4813-0467](https://orcid.org/0000-0002-4813-0467)

Branko Blanuša – University of Banja Luka, Faculty of Electrical Engineering, branko.blanusa@etf.unibl.org, ORCID [0000-0003-1005-3985](https://orcid.org/0000-0003-1005-3985)

Mario Vražić – University of Zagreb, Faculty of Electrical Engineering and Computing, mario.vrazic@fer.hr, ORCID [0000-0001-9065-7134](https://orcid.org/0000-0001-9065-7134)

Luka Budin – University of Zagreb, Faculty of Electrical Engineering and Computing, luka.budin@fer.hr, ORCID [0000-0001-6334-9638](https://orcid.org/0000-0001-6334-9638)

Daniel Denkovski – Ss Cyril and Methodius University, Faculty of Electrical Engineering and Information Technologies, daniel.d@feit.ukim.edu.mk, ORCID [0000-0001-6010-4387](https://orcid.org/0000-0001-6010-4387)

Živko Kokolanski – Ss Cyril and Methodius University, Faculty of Electrical Engineering and Information Technologies, kokolanski@feit.ukim.edu.mk, ORCID [0000-0003-4372-1273](https://orcid.org/0000-0003-4372-1273)

Razvoj simulacionog modula za primjenu u okviru digitalnih blizanaca fotonaponskih elektrana

Rezime – Proces digitalizacije omogućava bržu integraciju obnovljivih izvora energije u elektroenergetski sistem i unapređuje planiranje i upravljanje njihovim radom. Među savremenim digitalnim tehnologijama posebno se izdvajaju digitalni blizanci, kao virtuelne replike fizičkih elemenata sistema, pogodne za praćenje performansi i optimizaciju. U ovom radu predstavljeni su prvi koraci u razvoju simulacionog modula za digitalne blizance fotonaponskih (PV) sistema. Predloženi modul implementiran je u programskom jeziku Python i zasnovan je na modularnoj strukturi koju čine astronomski, optički, termički i električni podmodeli za procjenu AC izlazne snage PV sistema. Razmatra se zahtjevan simulacioni scenario u kojem se izlazna snaga sistema izračunava na osnovu minimalnog seta ulaznih podataka, koji obuhvata globalnu horizontalnu iradijansu, ambijentalnu temperaturu i brzinu vjetra. Simulacioni rezultati validirani su poređenjem sa mjerenjima sa realnog PV sistema, pri čemu je pokazano zadovoljavajuće slaganje uprkos ograničenoj dostupnosti ulaznih podataka. Razvijeni simulacioni modul predstavlja veoma važnu komponentu implementacije digitalnih blizanaca PV sistema i može se koristiti za praćenje performansi, detekciju kvarova i optimizaciju.

Ključne reči – digitalni blizanac, fotonaponski sistem, simulacioni modul