Reducing the photovoltaic operation and maintenance costs through an autonomous control operation center

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Abstract — **An advanced control operation center to enable corrective, preventive and predictive maintenance, while also ensuring optimal photovoltaic (PV) plant performance was developed in this work. The developed software solution hosts innovative algorithms able to ensure data quality, while also allowing early failure and performance loss diagnosis without disrupting the normal operation of the PV plant. It is primarily based on real-time analysis of measurement data, machine learning and statistical analysis. The solution was validated experimentally against field measurements from an operating PV power plant of 1.8 MW$_p$ installed in Greece. The results showed technical availability and energy yield improvements of the test PV plant by handling intelligently the detected faults through the smart ticketing system. Optimal maintenance planning (e.g., optimum hardware replacement/maintenance, cleaning schedules, etc.) can thus lead to a reduction of operation and maintenance (O&M) costs and hence directly impacting positively the levelised cost of electricity (LCOE).**

Keywords — cleaning optimization, data analysis, diagnosis, fault detection, maintenance planning, monitoring, photovoltaic, ticketing system

I. Introduction

The growing concerns about rising greenhouse gas emissions (GHG) affecting detrimentally the global climate, advocate the need for de-carbonization of the energy sector by reducing the GHG emissions, phasing out fossil fuels and accelerating the shift towards renewable technologies [1]. In fact, the future energy mix is expected to be heavily dependent on renewables, particularly solar photovoltaics (PV), which is set to become the "King of Renewables" [1]. For countries with high solar resource (such as Cyprus, Greece and Spain), PV is expected to play a central part in the future energy mix.

A vital factor that will enable the further growth of the PV technology is the reduction of PV electricity costs by increasing lifetime output, improving the operational efficiency and optimizing system operations [2]. This can be achieved by safeguarding the service lifetime performance through PV monitoring, supervision, maintenance and control of installed systems, hence directly impacting positively the investment cost, levelised cost of electricity (LCOE), and in general PV competitiveness [2].

To tackle the major challenges in increasing PV system performance (as it was recently reported that PV assets continue to underperform by up to 8%, thus highlighting the need for high-fidelity data and greater model transparency [3]) and technological competitiveness, machine learning algorithms and statistical techniques can be developed to enable corrective, preventive and predictive maintenance strategies [4]. The operation and maintenance (O&M) activities consist of two parts: (i) the operations that include remote monitoring, supervision, forecasting, communication and control of the PV power plant and (ii) the maintenance that includes the activities related to the health-state and optimum performance of PV plants. Therefore, ensuring cost-effective and online PV monitoring with automated data-driven operation functionalities is important for improving the LCOE through: (i) increased availability by the on-time triggering of losses/faults (hence increasing the energy yield) and (ii) reduced O&M costs by optimizing hardware replacement/maintenance, thus reducing the reaction and resolution times and hence the manual labor.

In this domain, the key battlegrounds of technical solutions that support high system performance are associated with the capabilities of operation centers that automatically analyze incoming data, provide real-time observability of PV assets, enable failure and health diagnostics, and handle intelligently the detected faults/errors through a smart ticketing system [5]. The scope of this paper is to address the fundamental challenge of automated PV plant operational-state management by developing an autonomous control operation center (i.e., an online software platform, powered by artificial intelligence algorithms and statistical analysis methods). The proposed software solution was validated using historical field data from a large-scale PV power plant installed in Greece. The results showed improvements in the availability and energy yield of the PV plant under study. This was achieved by utilizing the smart ticketing system, that provided the necessary information and steps to fix problems quickly and efficiently.

II. METHODOLOGY

A. Experimental setup - Benchmarking

The developed software platform was benchmarked experimentally using historical field measurements from an operating PV power plant of 1.8 MW_p installed in Larissa, Greece. It comprises of 7824 poly-crystalline-Silicon (poly c-Si) PV modules, each of nominal power of 230 W_p. The PV modules are south oriented, 25° tilted and connected in series to form 326 strings at the inputs of 4 grid-connected inverters (81 or 82 strings connected to the four inverters).

The performance of the PV system and the prevailing meteorological conditions are recorded according to the requirements set by the IEC 61724-1 [6]. The recorded data are stored using a measurement monitoring platform, that comprises of solar irradiance, wind, temperature and electrical operation sensors and stores data at a resolution of 1 second and accumulation steps of 15-minute averages. The meteorological measurements include the in-plane irradiance (G_I) measured with a pyranometer, ambient temperature (T_{amb}), wind speed (W_s) and direction (W_a). The PV system's operational measurements include the module back-surface temperature (T_{mod}), inverter temperature (T_{inv}), string DC current (I_{DC}), array DC current (I_A), voltage (V_A) and power (P_A) and AC output power (P_{out}). Additional yields and performance metrics such as the performance ratio (PR) and the temperature-corrected PR (PR_{TC}) were also calculated [7].

In this work, field data over different time periods were used. Over these time periods, different types of faults (e.g., communication errors, inverter shutdowns, low plant production and PR, equipment malfunctions, etc.) occurred during the operation of the system, which were resolved by technicians. Information about the outage's periods, fault types, O&M events/actions and technicians' feedback were kept in a maintenance log.

B. Autonomous control operation center

The autonomous control operation center integrates monitoring, supervision, maintenance, and fault diagnostic algorithms along with a smart ticketing system. The software platform leverages artificial intelligence algorithms and statistical analysis methods for the quality in operations and decision making. It is based on a modularized architecture to decouple the whole system and allows modules to interoperate autonomously. The architecture consists of four layers/modules as depicted in Fig. 1.

The control operation center continuously analyzes the incoming electrical and weather data for anomalies and outliers (Module 1). The data are initially pre-processed by the data quality assessment (DQA) stage to identify and treat invalid values, thus preparing the data for further performance analysis [7]. Subsequently, the data are aggregated into daily/monthly/yearly blocks. Then, machine learning and statistical algorithms are applied on the cleansed data to diagnose (detect and classify) the failure/performance loss and its type, triggering alarms in case of fault occurrences (Module 2) [8]. Afterwards, the smart ticketing system prioritizes the detected faults (based on the calculated energy and cost impact), derives an optimal maintenance planning, and suggests ways for resolving the detected incidents (Module 3). Finally, the detailed fault description, the criticality of the incidents and the list of suggestions for O&M field actions are visualized through the software platform (Module 4) and forwarded to the technicians.

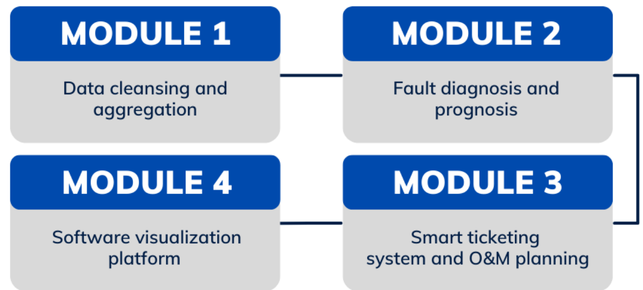


Fig. 1. Module architecture of the control operation center.

C. Data quality assessment

DQA algorithms are initially applied to the available measurements to ensure high-fidelity time series data for further analysis. The DQA stage is used to detect/treat invalid measurements, which may indicate equipment malfunctions, sensors and/or PV faulty operation, thus reducing uncertainty and increasing confidence in energy estimates. The DQA process includes multiple algorithms for data consistency examination, data filtering and imputation/inference, outlier removal, etc. More details are provided by Livera et al. in [7].

The DQA stage also provides information about the technical availability (or uptime), energy-based availability along with insights about possible data errors, technical (performance) issues and fault root causes [9].

D. Fault diagnostics and alarms

Data-driven fault diagnostic algorithms (e.g., outlier detection, machine learning and comparative techniques) and open-source libraries (e.g., RdTools [10]) are applied to detect underperformance incidents (e.g., failures and performance losses), that cause power losses [4], [11]. Faults that can be detected by the fault diagnostic engine include inverter malfunctions, string disconnections, partial shading, soiling, performance degradation, etc. [4], [12]. Apart from the detection part, the diagnostic algorithms are also capable of categorizing the detected fault incidents into different root causes [8], providing also the energy loss breakdown list [4]. In case of underperformance incidents, alarms are generated by the fault diagnostic engine. These alarms are used along with the alarm signals generated by the inverter to determine the fault root cause [4]. The results of the fault diagnostic algorithms and the generated alarms are then forwarded to the ticketing system.

In this work, emphasis is given on the diagnosis of soiling, which was recently characterized as a multibillion-dollar issue in operating PV power plants [13]. Soiling losses caused at least a 3% to 4% loss to global annual PV energy production in 2018, accounting for €3-5 billion lost revenue [13]. And this is expected to further increase in the upcoming years due to the expanding number of deployed PV systems in regions highly prone to soiling.

E. Smart ticketing system

The smart ticketing system uses as inputs the detected data quality issues, underperformance incidents and the alarm signals to generate recommendations for field maintenance actions (to be performed by the technicians). The detected faults and errors are prioritized (i.e., incidents of low criticality indicated by green color, incidents of medium criticality indicated by yellow color and incidents of high criticality indicated by red color), based on the calculated energy and cost impact [4], deriving an optimal maintenance schedule in an attempt to optimize the O&M activities and reduce the associated costs.

The smart ticketing system finally alerts the technicians about the fault/loss root cause, while also providing a list of recommendations for field actions (accessible through the software platform) to resolve the problem [4], [5].

F. Visualization of autonomous operation center results through the software platform

ACTIS ERP is the user interface of the autonomous control operation center [14]. The ACTIS ERP is a comprehensive asset management solution, that integrates centralized real-time monitoring with alerting and ticketing, O&M activities, asset and project management in a single software platform. The software platform can be accessed remotely from any device, anytime and anywhere via internet.

It displays current and historical performance data, key performance indicators (KPIs) of PV assets and portfolios, financial and operational indications, alarms, detected incidents, breakdown list of energy losses, O&M events, and a list of recommendations for field actions. The health-state of PV components and the generated tickets are also displayed.

G. Economic impact of proposed O&M actions

To evaluate the economic impact of O&M actions, economic models based on metrics such as the LCOE and the Net Present Value (NPV) were used. The LCOE reflects the project's economic feasibility, while NPV evaluates the profitability of an investment (i.e., compares the revenues and costs over the project lifetime) [15], [16].

These economic metrics also allow the identification of the best time to conduct an artificial cleaning in a PV system (i.e., when the financial loss due to soiling surpasses the cleaning cost), thus optimizing the cleaning schedules by considering factors like the cleaning cost, the soiling rate, and the PV plant size [15].

The impact of the soiling on the LCOE and on the O&M costs was recently analyzed in [17]. Soiling and snow-related losses were found to be the second most severe fault category, accounting for approximately 25% of total lost energy. The study also showed that additional cleanings could reduce losses by up to 11%, but the economic viability depended on the cleaning costs and electricity prices.

Another recent study [18] demonstrated that actual PV cleaning can lead to an increase in the energy yield, having a positive impact on LCOE and NPV. Comparing the actual cleaning date with the optimal cleaning date, it was found that the actual cleaning was performed with a 7-day delay, resulting in lower improvement in NPV and LCOE.

III. RESULTS

A. Data quality assessment

DQA algorithms were initially applied to field measurements of the test PV plant. The data cleansing algorithms were used to restrict measurements within predefined physical limits [7] and to identify/treat invalid measurements. Over the period from January to December 2022, the DQA detected 5.28% invalid data points (e.g., erroneous and missing values). The application of DQA algorithms for inspecting and treating missing and erroneous data improved the PV plant availability.

The technical availability of the plant was then calculated (see Fig. 2). Over the yearly evaluation period, the uptime was higher than 98.30%. The whole plant (or part of it) was down for approximately 250 hours due to communication loss with the PV plant/inverters, grid problems and/or grid outage.

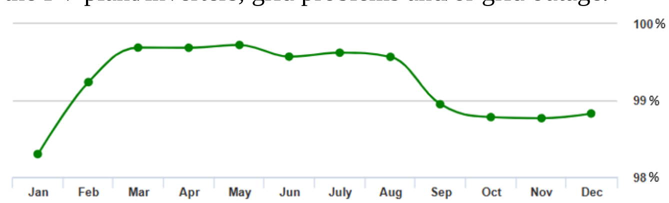


Fig. 2. PV plant availability over the period from January to December 2022.

B. Fault diagnostics and alarms

Over a 1-year period (January - December 2022), the test PV system produced 2,659 MWh. The fault diagnostic algorithms detected several fault incidents (e.g., plant was down, inverter shutdown failures, string problems, soiling, etc.), accounting for 24.38 MWh (0.92%) of lost energy. For the detected fault incidents, alarms were triggered by the engine and by the inverter itself (i.e., failed and warnings that appeared in the supervisory control and data acquisition system). The alarms were used to determine the fault root cause (e.g., inverter failures, string disconnections, soiling, shading, vegetation, etc.).

The classification of failures resulted to increased PV plant availability and optimized hardware replacement/maintenance.

The classification of the detected O&M incidents, 23 associated with corrective maintenance (i.e., faulty material, loose connections, malfunction of equipment, extreme weather conditions, defective PV modules, soiling, correction and maintenance works, grid problems/failure, grid undervoltage, inverter fault, ground fault, etc.) and 6 associated with preventative maintenance (e.g., vegetation), is shown in Fig. 3. Most of the detected incidents were due to PV plant related failures (41.38%). Other root causes included vegetation, monitoring system errors, power plant uninterruptible power supply (UPS) system problems, soiling, communication and electrical errors.

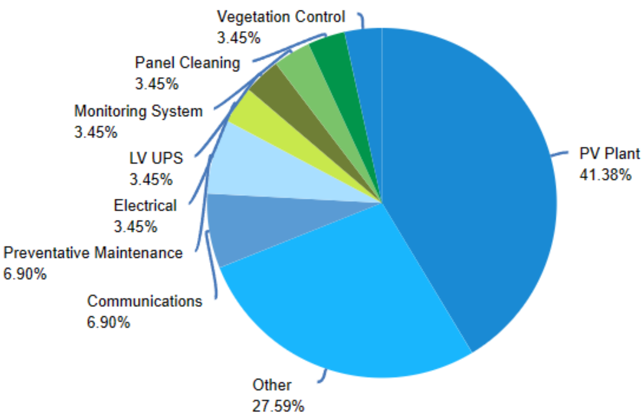


Fig. 3. Classification of detected O&M incidents for the test PV plant over the period from January to December 2022.

The RdTools python library [10] was then used to evaluate the PV production and to calculate rates of performance degradation and soiling loss. The Year-on-Year (YoY) method was used to estimate the performance loss rate (PLR), while the Stochastic Rate and Recovery (SRR) [19] method was used to identify soiling losses and cleaning events. The cleaning events were detected by observing positive shifts in the DC performance profile and using linear regression analysis to fit dry periods of at least 14 days. The SRR model generated potential soiling profiles through Monte Carlo simulation, and the median value of each day was extracted as the soiling profile per inverter.

Snow losses were also detected by analyzing PV performance parameters along with weather data.

For a reliable short-term performance evaluation, at least a 5-year time series data should be available to yield credible results [20]. To this end, field measurements over the period from February 2013 to January 2019 were used.

Over the investigated period (February 2013 to January 2019), an annual PLR of -0.90%/year was obtained. In parallel, the SRR model detected 34 cleaning events with the inverters experiencing low/limited soiling losses, with average(s) soiling rates of -0.26%/day to -0.0009%/day for the investigated period (see Fig. 4).

According to the maintenance log records, it was found that the O&M company regularly cleaned the PV modules twice a year. This practice can account for the significantly lower level of soiling losses observed, in contrast to the higher values commonly reported in the literature, which indicated soiling rate values up to -3%/day [21].

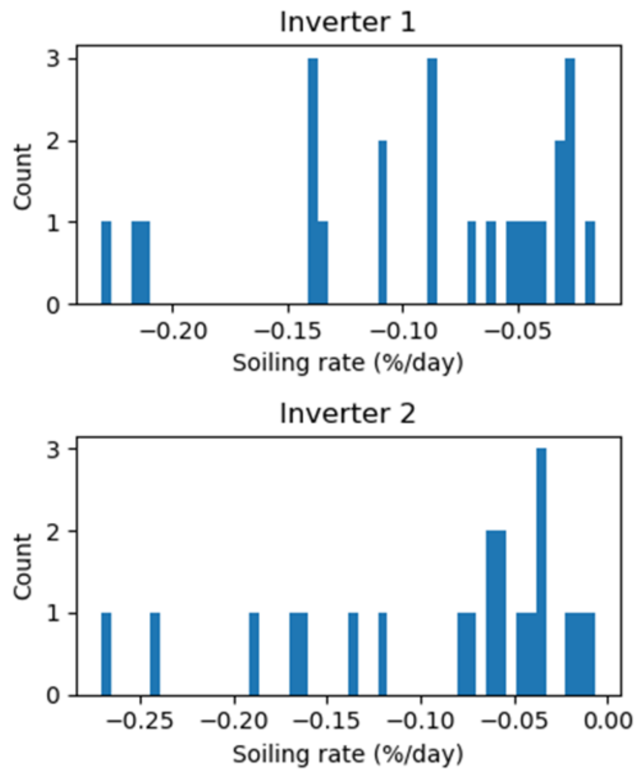
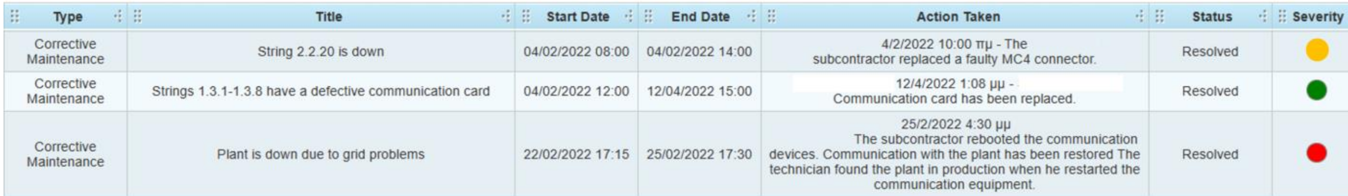


Fig. 4. Soiling losses experienced by inverters 1 and 2 of the test PV plant over the period from February 2013 to 2019.

C. Smart ticketing system and software visualization platform

The smart ticketing system processed the detected fault incidents and alarm signals to: (i) recommend specific field operations (e.g., corrective actions) to be performed by the technicians and (ii) provide insights and information regarding the fault root cause to the technicians to resolve the problem. It is worth noting here that the list of O&M recommendations is automatically generated. The field actions were also prioritized and scheduled based on the incident's severity (i.e., impact of the incidents on energy and cost) and finally forwarded to the responsible technicians. Eventually, the technicians executed the recommended field actions to improve operations (i.e., saving time, reducing O&M costs, and improving PV output production). The technicians were obliged to reach the PV plant within 4 daytime hours and 24 hours from the time of detecting the problem for medium and high criticality incidents, respectively.

An example of detected incidents and taken O&M actions is provided in Fig. 5 along with additional details (i.e., fault



Type	Title	Start Date	End Date	Action Taken	Status	Severity
Corrective Maintenance	String 2.2.20 is down	04/02/2022 08:00	04/02/2022 14:00	4/2/2022 10:00 πμ - The subcontractor replaced a faulty MC4 connector.	Resolved	
Corrective Maintenance	Strings 1.3.1-1.3.8 have a defective communication card	04/02/2022 12:00	12/04/2022 15:00	12/4/2022 1:08 μμ - Communication card has been replaced.	Resolved	
Corrective Maintenance	Plant is down due to grid problems	22/02/2022 17:15	25/02/2022 17:30	25/2/2022 4:30 μμ The subcontractor rebooted the communication devices. Communication with the plant has been restored The technician found the plant in production when he restarted the communication equipment.	Resolved	

Fig. 5. Screenshot depicting some of the detected O&M incidents for the test PV plant, their status, severity and action taken to resolve the incident.

description, severity of incident, date of occurrence, details of the dispatching technician to the field and action taken).

The results showed improvements in the availability and energy yield of the test PV plant by handling intelligently the detected faults through the smart ticketing system. Due to the smart management of incidents and optimal maintenance planning, only 0.92% (instead of 12.4% as simulated by Python Photovoltaic Reliability Performance Model [22]) of the produced energy was lost over the yearly period for the test PV system, while the plant's downtimes were minimized.

It is worth noting here that for longer evaluation periods (i.e., more than 1 year), the benefits would be greater (e.g., increased energy yield by ~6%, less downtime and reduced O&M costs by up to 10%) [5], [23].

D. Impact of cleaning optimization on economic metrics

In lack of information on the maximum extent of soiling (i.e., the losses in conditions of no mitigation), a cleaning optimization methodology was conducted on the available time series data to evaluate the impact of cleanings using two economic metrics (i.e., LCOE and NPV).

The results showed that after the first two cleanings, the inverters experienced low/limited soiling losses, with averages of 0.9% to 1.4% for the period between February 2013 to January 2019. This means that, for the given site, each cleaning can cost in between 0.6 and 1.3 €/kW, making regular soiling mitigation not profitable for this plant [5].

The actual cleaning activities could not only increase the energy output but also had a positive effect on LCOE and NPV, thereby reducing the cost of energy production from the PV system and increasing profits [18].

When considering LCOE, the optimization of cleaning is heavily influenced by the installation, and O&M costs. On the other hand, while the installation and O&M costs do impact profits, the NPV is not affected by them. Instead, the NPV is influenced by factors such as the cleaning cost, electricity prices, energy generation, degradation rates, and the recovery of losses through cleaning.

IV. Summary Of The Work

A software platform was designed to optimise the O&M strategies and automate operations of PV systems. The proposed solution is predominantly progressing further the field of PV operational data quality, online fault diagnosis and automatic field operations. This is achieved through the development of an autonomous control operation center, that analyses the measurements collected from the constant monitoring of PV plants. The control operation center integrates monitoring, supervision, maintenance, and online fault diagnostic algorithms along with a smart ticketing system. The incorporated algorithms allow the early identification and classification of failures (through the fault detection engine) and ensure quality in operations and decision making (through the smart ticketing system). The smart ticketing system considers the alarms and the severity of the incident for maintenance planning and provides the necessary information and steps to fix problems quickly and efficiently. As such, improvements in the PV plant availability, energy yield, O&M costs and hence, LCOE are achieved.

To conclude, the development and operation of an autonomous control operation center helps to improve the PV plant availability, the intervention, response and resolution times. Therefore, O&M actions are taken effectively and timely by the corresponding asset owners or operators/contractors, thus safeguarding the PV performance and minimizing the investment risks, the associated costs and hence the LCOE.

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