PANAMA

PRESCRIPTIVE SOLAR ANALYTICS & ADVANCED WORKFORCE MANAGEMENT

D5.2

Field Test Results

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Definition of Acronyms

Abbreviation

DSO	**Distribution System Operator**
DL	**Deep Learning**
LSTM	**Long Short-Term Memory**
K_T	**Clearness index**
MCDA	**Multicriteria Decision Analysis**

Note: Mathematical symbols and terms are explained directly in the corresponding sections.

EXECUTIVE SUMMARY

Deliverable 5.2 titled "Field Test Results" includes information related to the data sharing process and data shared, photos from the field where installations have been done, and lastly some sample results that will be showed at the MWFM tool. Until now, three installations have been done and they will be shown in the coming parts.

1 Data Flow Process

The data flow process is shown in this part, all four stakeholders played an active role in the data sharing part. The process itself and the transferred data can be seen in figure 1. The result maintenance plan will be shown within Inavitas MWFM.

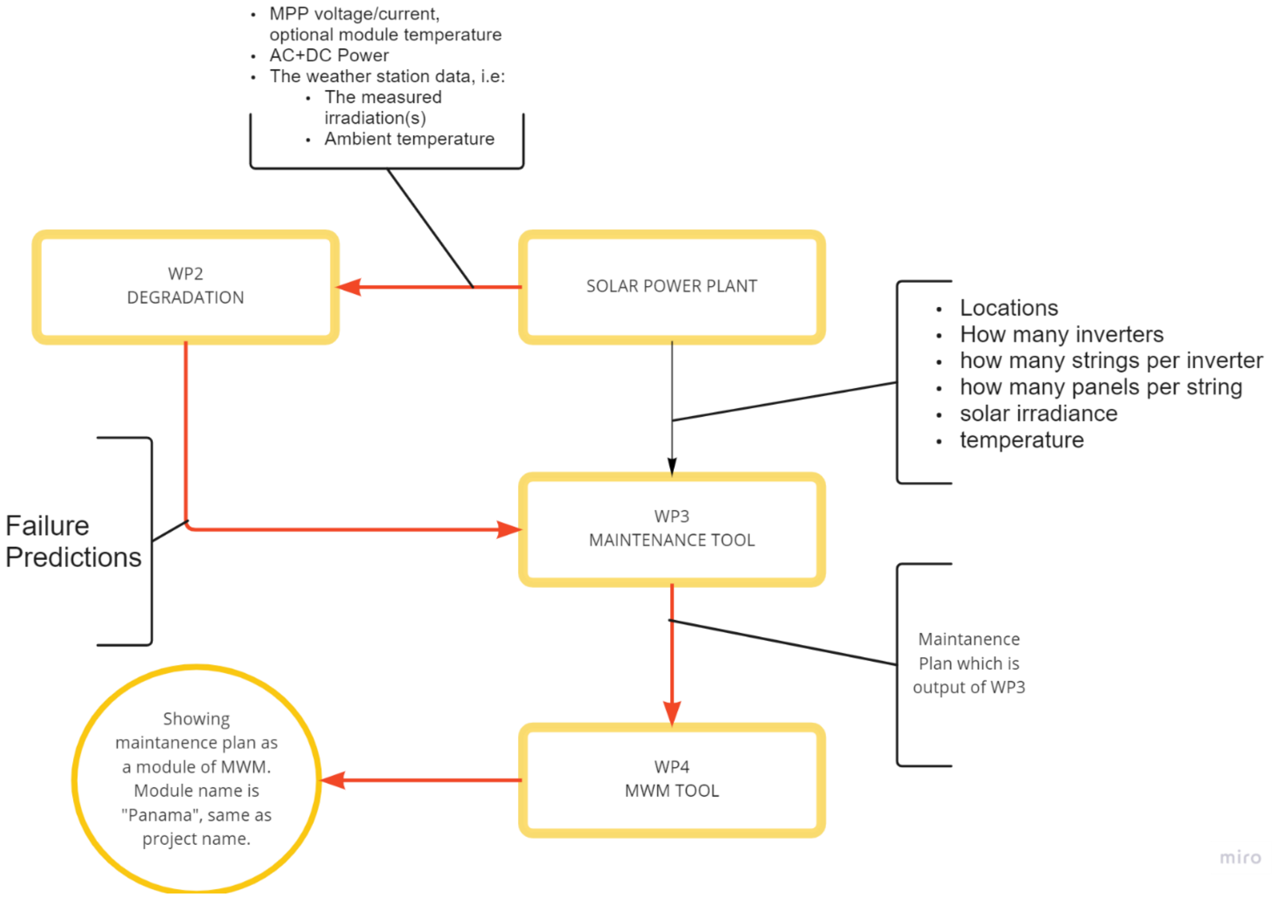

Figure 1: The Data Flow Process of the monitoring data results in the maintenance plan.

2 Field Installations

Five field installation has been planned, of which only three were in operation to obtain monitoring data the within the project's runtime. Therefore, data structure and degradation algorithms were evaluated by using these three systems named as below:

1. Jupiter
2. Merkur
3. Ser

The systems are equipped with ~100kW central inverters.

The data of the systems is collected in 15 minute intervals. The monitored values or each inverter are: Active power, reactive power, DC power, three grid phase voltages, three grid currents. The weather station collects the module plane radiation and the ambient temperature. No values of the DC voltage or current were available. Also, since the systems were recently built, only one year of data was available.

In the following section, photographs are show of one of the systems (Jupiter) as an example.

2.1 Jupiter Field Examples

2.1.1 Weather Station

Figure 2: The weather station monitors the conditions in the module planes.

The most important factor affecting PV system performance is the solar radiation data. However, also other important factors affect performance: the ambient temperature, panel temperature, relative humidity, wind speed, wind direction, atmospheric pressure, and rain. If the total usable incoming radiation in any environmental condition is measured accurately, it will be possible to calculate whether the PV system is producing electricity according to expectations. Data from all these sensors can be used to plan the maintenance of the facility. For example, data on precipitation amount and frequency can help explain low energy yields at high solar radiation due so soiling models.

2.1.2 Energy Analyzer

An **energy analyzer** is a high-tech product that is a control device. When installed into a system, it lets you check the values such as current and power. Moreover, besides those values measured, the device lets you check the power and power factor, plus frequency, harmonic, and voltage as well. So, it is more related to the energy quality of the plant rather than the energy amount.

There is a feature of this device to monitor and analyze possible movements in energy. For this reason, it is considered a helpful and supportive device when it comes to improving the quality of electrical energy. For example, an energy analyzer is required to generate an energy expenditure report for a house or a workplace, or a factory or any production facility. A large number of values of electrical energy are analyzed and saved in report and activity memory by the energy analyzers. Nowadays, many different measures are made within the same device, and some devices also have an external communication feature, e.g. the device seen in figure 3.

Figure 3: Energy Analyzer

2.1.3 RTU and Modem

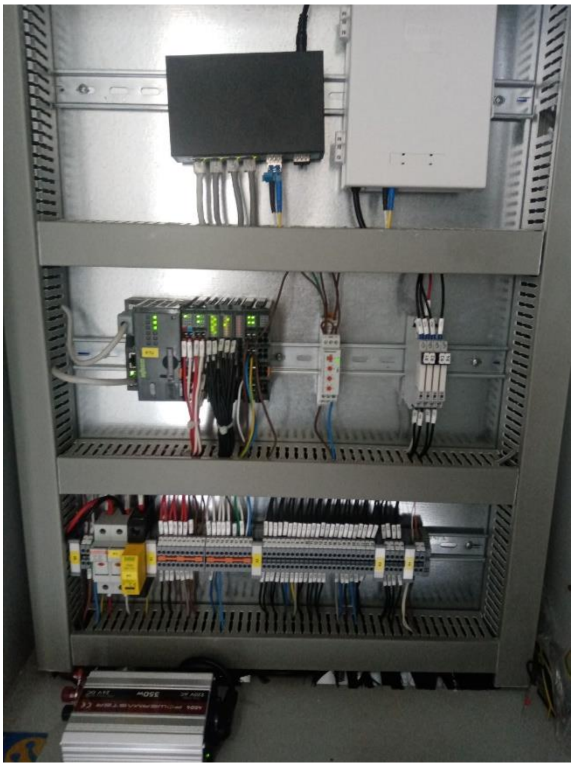

Figure 4: The RTU of the Jupiter system.

A remote terminal unit (RTU) is a multipurpose device used for remote monitoring and control of various devices and systems for automation. It is typically deployed in an industrial environment and serves a similar purpose to programmable logic circuits (PLCs) but to a higher degree. An RTU is considered a self-contained computer as it has all the basic parts that, together, define a computer: a processor, memory, and storage. Because of this, it can be used as an intelligent controller or master controller for other devices that, together, automate a process such as a portion of an assembly line. The remote nature of many telemetry or data collection projects means that they are often cited a distance away from the nearest mains power supply. Off-grid solar or wind-generated power offers a highly cost-effective remote power solution, capable of being deployed in the remotest of locations. Microwatt utilizes modern telemetry, SCADA, RTU and data monitoring equipment that is the most efficient, requiring relatively small amounts of power to record and transmit data from a site.

3 Degradation Algorithm

The degradation of a PV system can be estimated by comparing the actual production to an estimated production. As for individual datapoints large deviations can occur, typically averaging is performed least for full days, to obtain this so called "Performance Ratio" (PR). The better the modelling/twinning of the system, the more stable the PR is, allowing to read lower degradation rates with more certainty.

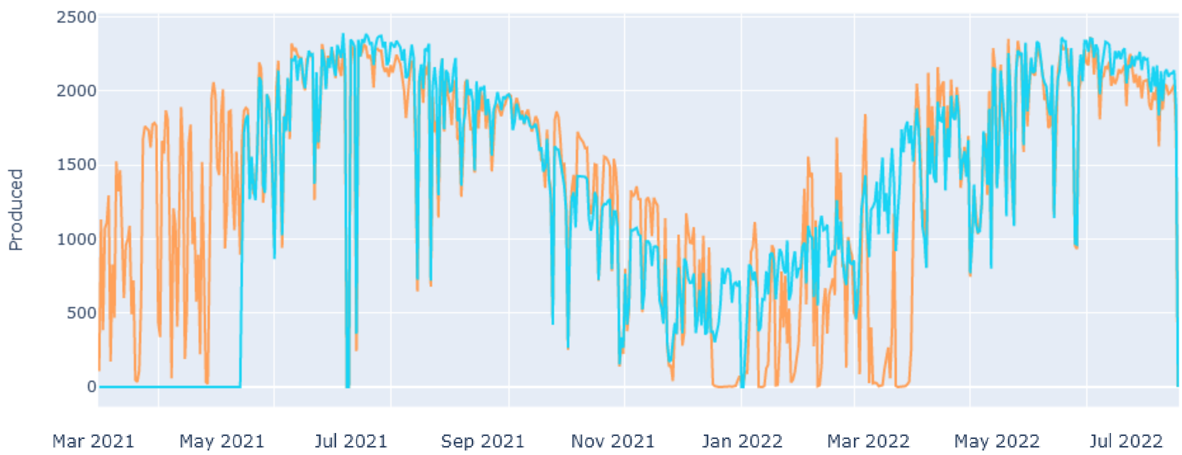

Figure 5: Comparison of prediction (blue) to observed daily production for the MERKUR plant. Strong deviations can be observed in Wintertime, likely due to snow.

As snow is more likely to sustain on PV modules than on the irradiation sensor, often in case of snow, the performance ratio drops radically, as the digital twin would predict production, while in reality there is none.

These events are filtered out by the usage of an algorithm to predict snow likelihood, using the observed temperatures to predict, if snow might be on the modules or not, and if a current underproduction is explainable by that, see Figure 6. Finally, the individual PRs based on the timestamps of the system's monitoring, are averaged and analysed statistically, to obtain the daily PR and its uncertainty, see Figure 7. Since the finest level this method can be performed on are the individual MPP trackers of inverters, the results of this evaluation is outputted as a data table, allowing intercomparison of the parts of the PV systems. By knowledge which parts are how performant, the installation teams can be evaluated even to an individual level, and monetary loss be estimated. To monitor a system in a 5 min interval instead of an hourly interval improves the accuracy of this method by a factor of 3.4. Since not only the degradation is measured, but also the initial PR projected, one can discriminate between initial underperformance and degradation, allowing to pin the origin to initially underperforming material or false handling, causing cell cracks that degrade with time.

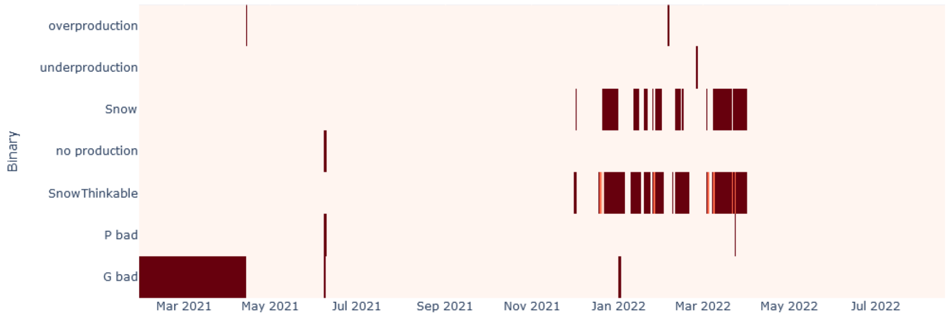

Figure 6: Fuzzy Logic prediction if power outages are likely explainable by snow on the modules.

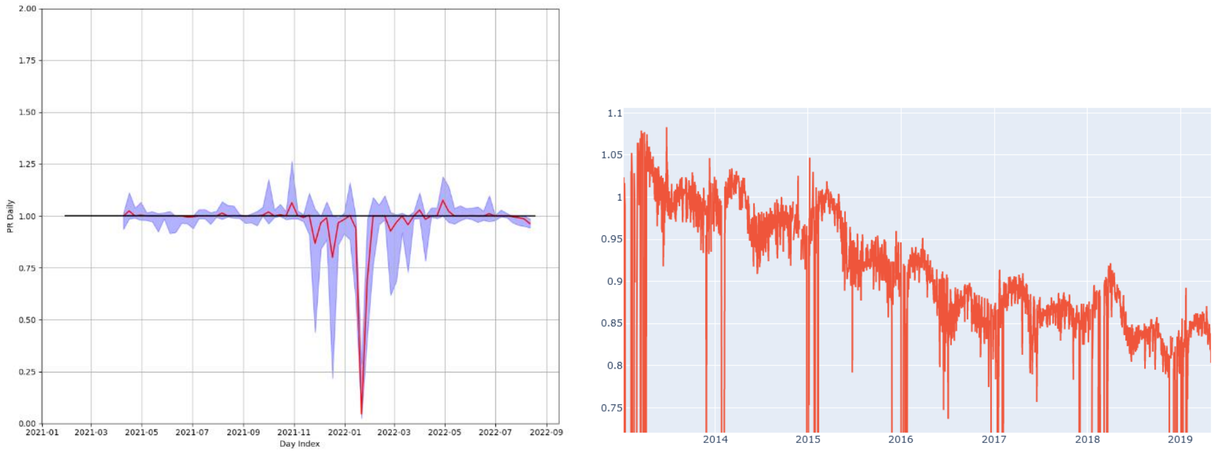

Figure 7: Left: The performance ratio of the SER plant, based on the limited timespan data that was used for the evaluation. The blue bands represent the distribution width of PRs used for the daily averaging, while the black line represents a robust fit obtained by regarding the uncertainty of individual points, as well as the exclusion of snow events. Right: a PR decrease of a known problematic system in Austria, showing a 15% degradation over seven years, calculated without accurate digital twinning.

Plant	Inv	PR degradation per y	PR t0
MERKUR	INV15	-0.78%	99.13%
MERKUR	INV16	-0.98%	101.96%
SER	INV 1	-0.24%	101.07%
SER	INV 2	-0.19%	101.39%
SER	INV 3	-0.08%	99.88%
SER	INV 4	-0.17%	101.90%
SER	INV 5	0.03%	99.85%
SER	INV 6	-0.11%	100.14%
SER	INV 7	-0.29%	101.73%
SER	INV 8	-0.10%	100.12%
SER	INV 9	-0.06%	100.04%
SER	INV 10	-0.04%	100.06%
SER	INV 11	-0.14%	100.22%
SER	INV 12	-0.07%	100.18%
SER	INV 13	-0.12%	100.39%
SER	INV 14	-0.03%	99.99%
SER	INV 15	0.00%	100.98%
SER	INV 16	-0.02%	101.18%

Figure 8: The degradation is evaluated on individual MPP trackers of Inverters, allowing to filter problematic system parts. An expected degradation rate is typically between 0.5 to 1.0 percent/year.

In case of unexpected system behaviour, alerts are created based on the discrepancy between digital twin and real production.

4 Optimization tool

4.1 Forecasting models

During the project, three different forecasting models have been implemented. Each one deals with a different forecasting horizons, i.e., 15-min ahead, 1-h ahead, and day ahead. The models' development is based on DL and specifically LSTM. LSTM is a type of Recurrent Neural Network. It is particularly useful for handling time series data and its advantage lies in its ability to identify dependencies between various features, such as the time series data of PV power and solar irradiation. Additionally, the LSTM can retain important information from previous time steps, thus effectively capturing the temporal correlation in data.

At each forecasting horizon, different inputs have been used to examine the forecasting accuracy. Table 3 includes the description of the inputs that result in the lowest forecasting error.

Table 1. Description of inputs utilized at each forecasting horizon.

Forecasting Horizon	Description of inputs
15-min ahead	PV power, solar irradiation, and panel temperature are utilized to formulate the samples. The ward method is applied to the train samples and divided into three clusters and estimate the centroids. Accordingly, each cluster is used to train different forecasting models. Finally, we find the centroid of the cluster with the minimum Euclidian distance from each test sample, and the prediction is obtained from the model which was trained with the samples of the specific cluster.
1-hour ahead	The model's inputs consist of the two previous time steps of the PV power generation, the solar irradiation, and the module's temperature, and provide the prediction of the first time step (15min-ahead). Afterward, the PV power prediction of the first time step is used as input in order to predict the second time step. The procedure is executed

	iteratively until the prediction of the next hour is achieved (Figure 5). In this case, we assume that weather predictions about solar irradiation, and temperature are available. The ward method is applied to the train samples and divided them into three clusters. Accordingly, each cluster is used to train different forecasting model. Finally, we find the centroid of the cluster with the minimum Euclidian distance from each test sample and the prediction is obtained from the model which was trained with the samples of the specific cluster.
day-ahead	To predict the PV generation of the next day the model takes as inputs the PV power, the solar irradiation and the panels' temperature. The selection of the time steps depends on the forecasting time, as presented in Figure 6. Additionally, the PV power profiles have been utilized as inputs, as derived by the K_T. Specifically, according to K_T, the power data of the training set are separated into three categories: a) mostly cloudy, b) partly cloudy, and c) clear. Afterwards, three PV power profiles were derived for each category, by calculating the mean value of the PV power generation. It should be noted that every time we have information about the actual PV power of the day we predicted, the day is added to the respective category, according to the K_T, and the PV power profile is recalculated.

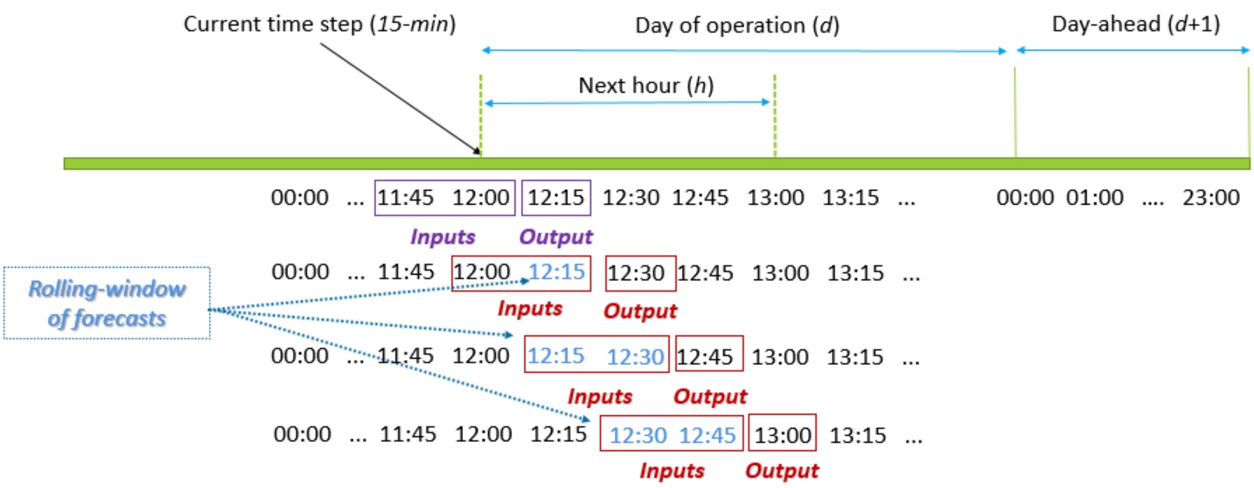

Figure 9 Hour-ahead forecasting process.

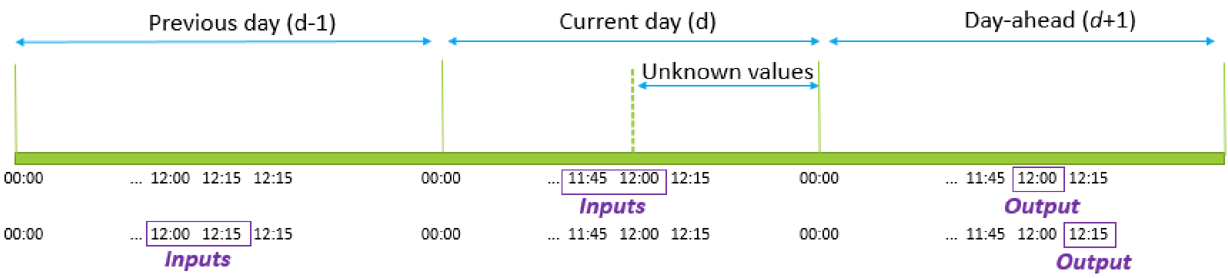

Figure 10 Day-ahead forecasting process.

4.2 MCDA model

MCDA is a decision-making tool, which is widely used for decision-making processes. It can explicitly evaluate multiple conflict criteria that may refer to economic and technical constraints, risk factors, and others. The main concept of MCDA analysis is not to provide the optimal solution of a problem. Instead, it evaluates the alternatives, i.e., all feasible solutions, by providing a ranking number for each one. In this way, the experts can think about the results of each decision and reject or accept the solution. Several MCDA techniques have been proposed in the literature. However, the TOPSIS method is selected for the implementation of the MCDA model, due to its simplicity and flexibility.

TOPSIS method is implemented into seven main steps as follows:

Step#1. Create the decision matrix X with m alternative solutions and n criteria, with the intersection of each criterion and alternative given as x_{ij} :

$$X = \begin{array}{cccccc} & z_1 & z_2 & \cdots & z_n \\ A_1 & x_{11} & x_{12} & \cdots & x_{1n} \\ A_2 & x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ A_m & x_{m1} & x_{m2} & \cdots & x_{mn} \end{array} \quad (1)$$

Step#2. Construct the $R = \left(r_{i,j}\right)_{m\times n}$ matrix, which is the normalized X . Each $r_{i,j}$ element is denoted as:

$$r_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{k=1}^{m} x_{k,j}^2}},\ i = 1,2,...,m,\ j = 1,2,...,n \quad (2)$$

Step#3. Construct the weighted normalized decision matrix V as:

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \quad (3)$$

where each element $v_{i,j}$ is denoted as:

$$v_{i,j} = w_{i,j} r_{i,j} \quad (4)$$

where, $w_{i,j}$ is the weight assigned to the connection of solution i (A_i) with criterion j (z_j). The weights are defined by the decision maker and influence the results of the decision process. This is the main characteristic of the TOPSIS method since with this approach the user can change the weights in order to satisfy his/her needs.

Step#4. Calculate the ideal (S^+) and the inti-ideal (S^-) alternative as:

$$S^+ = \left\{ \left\langle \max v_{i,j} \mid j \in J \right\rangle, \left\langle \min v_{i,j} \mid j \in J' \right\rangle \right\} \quad (5)$$

$$S^- = \{\langle \min v_{i,j} \mid j \in J \rangle, \langle \max v_{i,j} \mid j \in J' \rangle\} \quad (6)$$

where $J = \{1, 2, ..., n\}$ are the criteria having a positive impact on the solution and $J' = \{1, 2, ..., n\}$ are the criteria having a negative impact on the solution. Considering this, the ideal solution is the maximum value of the positive impact and the minimum of the negative impact, while the anti-ideal solution is the minimum value of positive and the maximum value of negative impacts.

Step#5. Calculate the distances between each alternative i and: a) the ideal-solution and b) the anti-deal solution.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - A^+\right)^2}, \; i = 1, 2, ..., m \quad (7)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{i,j} - A^i\right)^2}, \; i = 1, 2, ..., m \quad (8)$$

Step#6. Calculate the relative closeness of each alterative i to the positive ideal solution.

$$P_i = \frac{d^-}{d^- + d^+} \quad (9)$$

Step#7. Sort the alternatives i according to the values of P_i.

In our case, the MCDA model is developed to address the problem of O&M scheduling. The main advantage of the deployment of the MCDA model is its ability to take as inputs not only qualitative but also qualitative criteria for the estimation of the alternatives. The selected criteria and the type of each criterion, i.e., qualitative, and quantitative, are presented in Table 2. It should be noted that the day ahead forecasts are utilized as input, i.e., criterion z12. In this way, the ranking number is assessed considering the expected PV power production as well.

Table 2. MCDA criteria.

Code	MCDA criteria	Quantitative	Qualitative
z1	Distance between the locations	✓	
z2	Time needed to travel between the locations	✓	
z3	Type of route to the PV site		✓
z4	History of fault occurrences on the PV site		✓
z5	System complexity		✓
z6	Level of personnel expertise		✓
z7	Urgency		✓
z8	Unavailability of personnel	✓	
z9	Working hours	✓	
z10	End of maintenance activities	✓	
z11	Transportation time of spare parts	✓	
z12	Forecasted PV power		✓

z13	Severity of fault	✓
z14	Severity of weather conditions	✓

5 Sample Test Results

Sample test result for Jupiter field can be seen the below table. The first column shows the number of iterations while other columns emphasized the parameters related to general cost while the alternative column shows the work order solution. In this part, “d” means day, “p” means team, and “c” means location.

	Atlternatives	S+	S-	Pi	Fuel_Cost	osses_Cos	alary_Cos	Total_Cost	Rank
604	[['d0', 'p0', 'c0', 'c1', 'c2', 'c0'], ['d0', 'p1', 'c0', 'c4', 'c5', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
629	[['d0', 'p0', 'c0', 'c1', 'c5', 'c0'], ['d0', 'p1', 'c0', 'c4', 'c2', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
605	[['d0', 'p0', 'c0', 'c1', 'c2', 'c0'], ['d0', 'p1', 'c0', 'c5', 'c4', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
749	[['d0', 'p0', 'c0', 'c5', 'c4', 'c0'], ['d0', 'p1', 'c0', 'c1', 'c2', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
726	[['d0', 'p0', 'c0', 'c4', 'c2', 'c0'], ['d0', 'p1', 'c0', 'c5', 'c1', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
714	[['d0', 'p0', 'c0', 'c5', 'c1', 'c0'], ['d0', 'p1', 'c0', 'c4', 'c2', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
725	[['d0', 'p0', 'c0', 'c4', 'c2', 'c0'], ['d0', 'p1', 'c0', 'c1', 'c5', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
664	[['d0', 'p0', 'c0', 'c4', 'c5', 'c0'], ['d0', 'p1', 'c0', 'c1', 'c2', 'c0']]	0.002318	0.005178	0.690769	65.364	0	149.28	214.644	1
58	[['d0', 'p1', 'c0', 'c4', 'c5', 'c0'], ['d1', 'p1', 'c0', 'c1', 'c2', 'c0']]	0.002396	0.005106	0.68063	65.364	39.60579	149.28	254.2498	9
75	[['d0', 'p1', 'c0', 'c5', 'c4', 'c0'], ['d1', 'p1', 'c0', 'c1', 'c2', 'c0']]	0.002396	0.005106	0.68063	65.364	39.60579	149.28	254.2498	9
71	[['d0', 'p1', 'c0', 'c4', 'c2', 'c0'], ['d1', 'p1', 'c0', 'c1', 'c5', 'c0']]	0.002419	0.005095	0.678096	65.364	55.44811	149.28	270.0921	11
72	[['d0', 'p1', 'c0', 'c4', 'c2', 'c0'], ['d1', 'p1', 'c0', 'c5', 'c1', 'c0']]	0.002419	0.005095	0.678096	65.364	55.44811	149.28	270.0921	11

Figure 11 Work Order Solution Forecast