IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

SPECIAL SECTION ON ARTIFICIAL INTELLIGENCE AND COGNITIVE COMPUTING FOR COMMUNICATION AND NETWORK

Received March 12, 2019, accepted March 29, 2019, date of publication April 2, 2019, date of current version April 24, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2908777

A Risk-Based Approach to Automate Preventive Maintenance Tasks Generation by Exploiting Autonomous Robot Inspections in Wind Farms

FABIO LEONARDI[1,2], FABRIZIO MESSINA[1], AND CORRADO SANTORO[1]
[1]Department of Mathematics and Informatics, University of Catania, 95125 Catania, Italy
[2]ENEL Foundation, 00198 Roma, Italy

Corresponding author: Fabio Leonardi (fabio.leonardi@unict.it)

This work was supported by the Universita' degli Studi di Catania through Piano della Ricerca 2016/2018—Linea di intervento 2.

ABSTRACT In this paper, we dealt with some problems of operation and maintenance in wind farms. We focused on the main critical aspects of any maintenance strategy, which must include the identification of the plant elements to inspect as well as the planning of the possible actions aimed at minimizing production losses. At the same time, any maintenance strategy must take into account the possible costs. In fact, those decisions can be made based on risk-based methods. We designed a risk-based maintenance approach to plan inspection tasks to be assigned to service robots in wind power plants. A supervisory control and data acquisition (SCADA) system is employed to collect and manage suitable data (power, wind velocity, and related machine events), and the risk is evaluated on a daily basis over the data collected. The evaluation of the risk is strictly related to the healthiness of the power plant itself. Then, the tasks are created and scheduled based on a certain priority, which is strictly correlated with the evaluated risk. For the analysis of our approach, we used the real data collected on a wind power plant in Greece over 396 days. The power plant is capable to produce an overall power of 7.2 MW, and it is composed of eight wind turbines of 900 KW per each. We observed that, out of 396 days, 50 days presented machine events leading to a related risk evaluation for which our approach will produce 258 inspection tasks. From this analysis, we conclude that the application of the risk-based methodology paired with the exploitation of permanent robots on the field could result in a 225-MWh reduction of the plant's lost production, in other words, an increase of production of 45.6%.

INDEX TERMS Renewable energy, wind plant, risk evaluation.

I. INTRODUCTION

Planning Operation and Maintenance (O&M) of wind turbines is a relevant topic in the field of renewable energy production due to the associated costs. It represents, in average, the 25% of the total cost. Indeed, about 2/3 of the direct O&M costs are due to unplanned maintenance of faulty components [1], since for wind turbines, component failures are relatively common. Failure rates between 1.5 and 4 are reported for onshore wind turbines in one year [1].

Most failures produce relatively short downtime but, on the other hand, they occur with high frequency. Large failures are rare, but they come with a long downtime and expensive repairs. Catastrophic events which cause the total collapse of the turbine are even more rare but they are associated to large economic losses.

Failures are due to deterioration processes of several components, such as fatigue, wear and corrosion, for example in welded connections, blades, bearings and gears. In those cases, online monitoring or manual inspections allows operators to detect the deterioration in order to perform preventive maintenance instead of corrective actions after the possible failure. Moreover, this approach must be supported by a proper condition monitoring system, which must be able to produce information on the health status of the components [2]. In this context, the use of preventive maintenance could potentially reduce the number of failures, then the related costs. Indeed, in case of preventive maintenance,

The associate editor coordinating the review of this manuscript and approving it for publication was Giancarlo Fortino.

repairing operations costs are cheaper than ones related with corrective maintenance, after actual failure is presented, due to shorter down-times. At the same time, maintenance activities usually imply human resources as well as repair costs. As a consequence, maintenance should be planned in order to minimize associated costs.

There are various maintenance strategies aimed at minimizing costs, for instance those which estimates the costs for corrective maintenance by evaluating mean values [3] or performing simulations [4]–[6]. However, for preventive maintenance, many of the methods proposed in the literature do not properly consider real-time information available from condition monitoring systems. Indeed, in most of the approaches, preventive maintenance strategy is based on the statistical analysis of available data where repairing activities and related costs are also available. In fact, as we will show in Section IV, real-time data collected into a CMS (Condition Monitoring System) can be employed in order to obtain prompt insights about the healthiness and the performance of the power plant, as well as the related risk. Condition Monitoring System means a system which enable monitoring of specific equipment's parameters or conditions. Indeed we observed that cumulative daily under-performance, due to technical inefficiencies, in a yea result in greater economic losses compared to the ones related with the main failure events. As a consequence a more profitable approach for preventive maintenance should consider the costs associated with real-time system under performance, rather than statistical ex-post analysis based on registered costs of the repairing interventions.

Last but not least, in the last years robots such as drones and rovers are taking an important role in performing inspections of wind turbines [7]–[12]. The usage of robotic platforms for maintenance is valuable due to the reduced costs w.r.t. humans employment. For such a reason in the near future robots will be permanently employed on each wind power plant dealing with the necessary inspection and surveillance tasks, minimizing the necessity of the human intervention and the related maintenance costs as well as determining a reduced number of expected failures.

In the scenario described above the maintenance processes should be revised in order to add several levels of automation: for instance in any wind park equipped with a reliable CMS, the service robots should be directly engaged on the basis of the power plant CMS data. In particular, the data coming from the distributed sensors are collected at run time from a plant SCADA (Supervisory Control And Data Acquisition), which is capable to provide information about the health status of the wind turbines such as analogical measures and machine events. Risk based algorithms can be employed to associate a risk level to each event, to be used for prompt generation of inspection tasks with a given priority.

Based on the premises above, in this paper we describe a Risk-based maintenance strategy capable to plan inspection tasks to be assigned to service robots in Wind power plants. The Risk is evaluated on a daily basis, in relation with the data collected in the wind power plant, where a SCADA system is employed to collect and manage 10' samples of analogical signals related with wind energy production (Produced Power and Wind Velocity) as well as digital data which are strictly related to the healthiness of the power plant (machine events). These two kind of data provide complementary information which are strictly related. The analogical signals (power and wind velocity) are used to evaluate, on a 10 minutes basis, the amount of lost production against the nominal expected values; this value is obtained by comparing data with the characteristic curve of each wind turbine. Machine events provide additional information about the status of each wind turbine within a defined time interval between a start date and an end date, specifying the specific machine alarm which is cause of the event. Finally, from the risk evaluation point of view, the system will produce proper inspection tasks that will be sent to another system which will be in charge of managing the execution of the received tasks, by controlling the robots (scheduling, allocation of resources and control).

In order to validate the approach described in this work, we performed an analysis on a dataset collected during a period of 396 days (between April 2017 and May 2018) on a Wind Power Plant located in Greece, which has an overall power of 7.2 MW, and which is composed by 8 wind turbines of 900 KW per each. We observed that, out of 396 days, 50 days presented machine events which led to a Risk evaluation and the creation of inspection tasks. The cumulative Lost Production of the 50 days is about 495 MWh. Based on the risk factors computed on the given dataset and associated with each turbine, a total of 258 daily tasks are being created by the designed risk-based maintenance strategy for the entire period. This analysis led to the final consideration that the application of the risk-based methodology, paired with the exploitation of robots on field, could result in a 225 MWh reduction of the plant's lost production, which led to an increase of production of 45.6%.

Summarizing, the contributions provided by this work are the following:

- our analysis confirm that operation and maintenance strategies are needed to planning actions aimed at increasing power plant production and reduce the overall costs, which mainly consist on costs related to plant technical inefficiency and repairing activities;
- we verified that condition monitoring systems can play a key role to detect anomalies in time and exploiting preventive maintenance activities determining a reduction of the corrective maintenance costs;
- our analysis implies that the permanent employment of autonomous robots, operating in the power plant, can maximize the effect of the preventive maintenance based on data and events sent by the power plant itself, leveraging on the speed of the intervention and the reduced activity cost;
- last but not least, risk-based algorithms relying on real-time data can be used in order to dynamically define priority of intervention on a live data-stream, without

the necessity to find correlations with repairing interventions made in the past.

This paper is organized as follows. Section II reports a summary of the main related works. Section III provides an overview of the proposed approach. Section IV thoroughly describes the available Dataset. Section V provides a detailed description of the Risk-based model development, while a numerical example with the experimental results is illustrated in Section VI. Finally, Section VII concludes the paper.

II. RELATED WORK

The problem of scheduling maintenance and inspection operations has been studied for several years in a number of different fields, power plant, wind farms, batch plants, and so on. In this Section we cite some of the researches found in the literature relevant to the approach proposed in our work.

In [13] the authors considers the problem of Power Plant Preventive Maintenance Scheduling (PPPMS) to evaluate which generators should stop their production work in order to allow the operators to perform the necessary periodically checks. The authors designed a model which is the result of the integration of wind power plants or wind farms into a traditional electric generating system which includes thermal, hydroelectric, and nuclear power units, resulting in an optimization problem. They also describe a case study based on a real power system to validate the efficiency of the proposed analysis.

Authors of [14] focuses on the preventive maintenance scheduling as the need to know which generating units should be disconnected for regular inspection for safety pur-posed. As in [13], the problem is considered from the operations research perspective as a question of optimization. The authors used Benders' decomposition technique [15] to solve the resulting model; they also provided an example on which they employed the proposed algorithm in a real power plant setting. The study resulted in the deployment of an efficient organization of preventive maintenance for the considered time-frame.

Another interesting work concerns the production scheduling of multipurpose batch plants in the presence of equipment failure uncertainty [16]. First of all, they integrate uncertainty analysis within the production scheduling stage, such that the probability of performing the resulting schedule is improved and the complete rescheduling of the production plan is reduced. In this manner, the authors could improve the effectiveness of the reactive scheduling strategy each time a deviation from the expected plant status occurred. Then, they minimized the effects of equipment failure on the production schedule by computing the reliability indexes for each plant unit and for each scheduled task. They also considered the relation between the employment of the equipment with low reliability indexes and the production requirements, in order to balance the two factors. Finally, they introduced predictive maintenance strategy to compensate for possible delays produced by the use of the low reliable equipment, providing a complete case study.

A further approach related to wind energy production is presented in [17], which focuses on the optimal operation of wind farms through planning and scheduling of maintenance operations. The authors analyze its impact on the turbine availability as key components of the operational costs. They introduced a formal model of wind farm maintenance, and a technique to solve the optimization problem of maintenance schedules along with an initial set of results and a number of considerations for future research.

Authors of [18] have shown the advantages of a multi-objective optimization approach over the conventional single-objective approach for thermal generating units maintenance scheduling. In particular, they proposed an optimization model on the original multi-objective branch and bound algorithm; they considered power system reliability maximization, fuel costs minimization, and minimization of constraints violations, along with a realistic example of annual maintenance scheduling of 21 thermal generating units.

In [19] the authors discuss the importance of maintenance in the industrial scenario as well as the development of modern maintenance strategies such as the condition-based maintenance (CBM) and the predictive maintenance (PrM). They focused on the importance to assess the impact of these strategies on the maintenance process. In particular, they addressed an example concerning the stochastic crack growth of a generic mechanical component subject to fatigue degradation. They demonstrated that modeling and analysis can provide information useful for setting a maintenance policy.

Authors of [20] focused on the inspection planning in electric power industry. In this case inspection is important to assess the safety and reliability of system components and to be able to identify potential failures in advance. The authors demonstrate the use of a fuzzy relational database model for obtaining an affordable ''ranking'' of components in thermal power systems inspection planning. In particular, they incorporated different aspects concerning safety and reliability, economy, variable operational conditions and environmental impacts. They used fuzzy linguistic terms for criteria definitions, and exploited fuzzy inference mechanisms for the operators' expertise. They also illustrated the behavior of the model, a case study is given using real inspection data.

In [21] a new method for calculating an optimal annual maintenance schedule for the generating facilities of a power system is presented. The authors focused on the minimization of the expected annual production costs. They also selected different objectives, like the optimization of the system reliability. In order to reach their goal, they applied Integer Linear Programming (ILP). They presented the mathematical formulation as well as the results of calculations with the new program; in particular they discussed the accuracy of the results and the computational time needed to get the results.

III. COMPUTATIONAL AND ARCHITECTURAL MODEL

This Section describes the overall risk-based approach in terms of computation steps needed to automate the process.

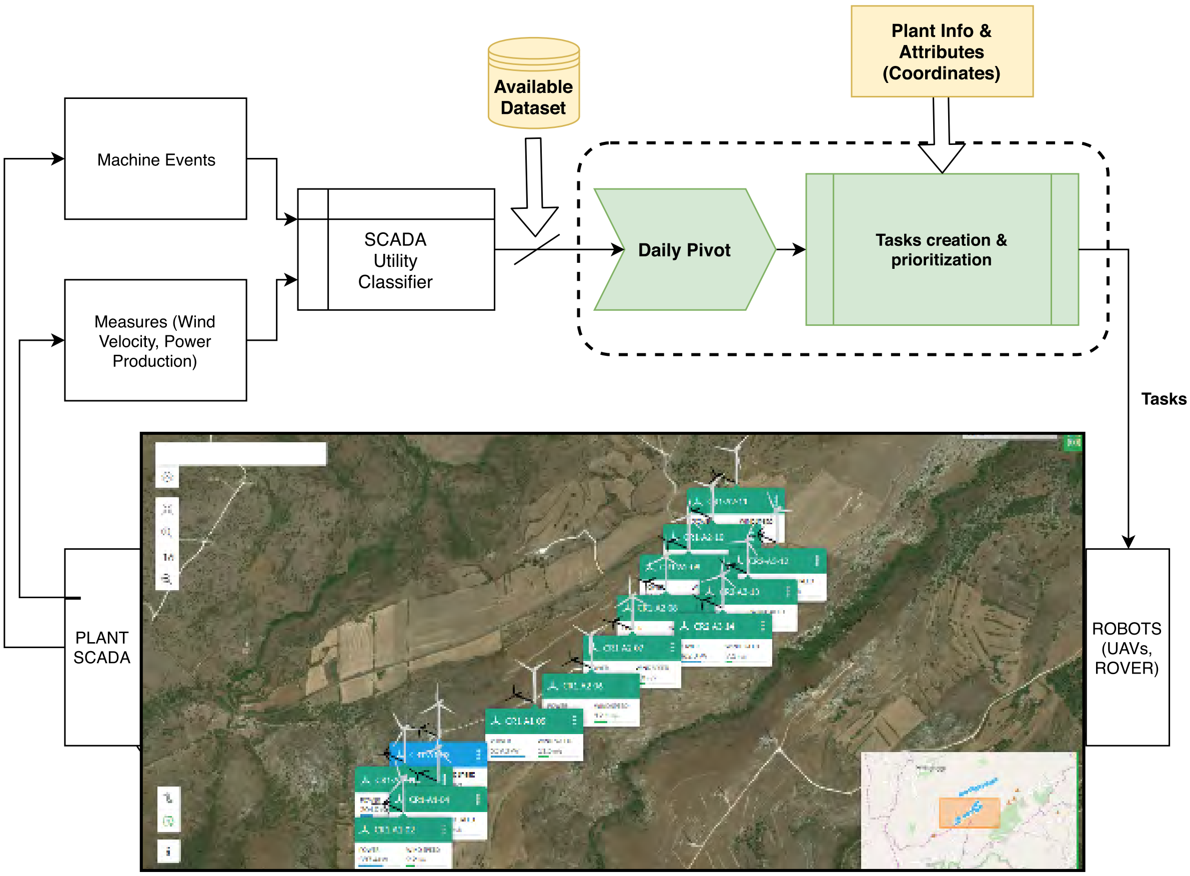

FIGURE 1. Logical approach schema.

Figure 1 illustrates the several steps, from the data acquisition for the power plant up to the daily inspection tasks planning:

1) The Plant SCADA collects and stores all the operational data produced by the sensors of the wind turbines. In particular, for each turbine, measures, such as wind velocity and power production, as well as the related machine events such as grid curtailments, turbines stops events and so on are collected on a 10 minute basis. Events and related classification will be deeply described in Section IV-A. Measure data provide complementary information about the events in the field. Indeed, these measures are used to evaluate (on a 10 minutes basis) the amount of lost production against the nominal expected values, in relation with the characteristic curve of each wind turbine. Machine events provide run-time additional information about the status mode of each wind turbine within a defined time interval between a start date and an end date, specifying the machine alarm which is cause of the event.
2) Data is then analyzed and classified by the Utility Classifier, as discussed in Section IV-B.
3) The next phase represents the core of the approach, which is articulated into the two green-colored computational steps illustrated in figure 1:
   - In the first phase, the Daily Pivot is used to compute, on a daily basis, the number of occurrences and the probability of each classified event against the others, as well as the lost production associated to each event. This phase is described in Section V-A.
   - The second phase is represented by the task creation, it is described in details in Section V-B. In order to focus on predictive maintenance actions, in this phase, events related to occurred faults and maintenance events are filtered out. Then, on the remaining events which could hide unexpected behaviors, a task is created and Risk function is computed in order to define a priority of intervention.
4) Each task, which is specific for wind turbine, is fed with the related coordinates, latitude and longitude, so that the task is ready to be assigned to a Service Robot on field for the execution, as illustrated in Fig. 2.

IV. DATASET

Historical Data were collected from a Wind Power Plant located in Greece, with an overall nominal capacity

FIGURE 2. Robot Inspector executing an inspection task on field.

of 7.2 MW, and composed of 8 wind turbines of 900 KW of nominal capacity each. Measurements were recorded covering the period of April 01, 2017 - April 31, 2018, with 396 days of observations. Dataset includes a number of time series related to each wind turbine, where each row represents an event, already classified with a specific cause, and a related value of Measured Production and Lost Production. We remark that a new event appears in the Dataset only once it is concluded, presenting a final date and time, with related cumulative values of measured production and lost production during the event itself. This aspect will be taken into account in section V-A.

We report in Table 1 a sample of the collected dataset: each event includes the reference to the specific wind turbine (1st column), Start and End date (2nd and 3rd columns), Event duration (4th column), Event description and cause (5th and 6th columns), Cause classification (7th column), Measured Production and Lost Production (8th and 9th columns).

A. DATASET ANALYSIS

A preliminary analysis of the 1-year Dataset highlighted the events classification, which was useful to extract the event causes for the hole power plant, as follows:

- Cause class 100, "Automatic action" refers to quick turbine restart because of local automation rules deployed into the Plant SCADA.
- Cause class: 200, "Corrective unplanned maintenance" refers to manual intervention from field operators, in case of unexpected occurred failures.
- Cause class: 300, "Fault" refers to failures of wind turbines which result in Turbine stops.
- Cause class: 400, "Grid Fault" refers to failure of the Grid to which the Wind Plant is connected. This imply that it's not possible for the power plant to deliver energy in the grid.
- Cause class: 500, "Preventive maintenance" refers to manual intervention from field operators, in case of planned and recurrent activities.
- Cause class: 600, "Technical inefficiency" refers to under-performance of the wind turbines for the given period.
- Cause class: 700, "To be reclassified" refers to events for which the default event classification could be wrong.
- Cause class: 800, "Unknown" refers to events for which a better investigation is needed.

The 1-year Dataset analysis allows us to make the following considerations (see Table 2):

- The event causes for which an inspection activity can help to identify anomalies aiming at prevent incoming failures are Cause class from 600 to 800.
- The most of the under performances, in terms of lost production, are related to technical inefficiencies.

B. UTILITY CLASSIFIER AND LOST PRODUCTION

As shown in Fig.1, the Dataset is produced by the Utility Event Classifier, where an algorithm works on both 10' samples measurements of Wind velocity and Power production signals and Machine events produced by the Plant SCADA. Those signals are both referred to each wind turbine. The Classifier, leveraging on the measurements, computes the power curve of the specific wind turbine model, that is the characteristic curve of the wind turbine, taking as input the Wind speed and as output the power.

Since each wind turbine power curve is characterized by a certain statistical distribution (mean ν and variance σ), we are able to define a confidence interval where a parameter k defines the acceptance interval. Then, in order to classify every registered values (V_j, P_j), where V represents the wind level and P the registered power in the turbine registered every 10 minutes, an efficiency analysis is carried out using the following procedure. For each pair (V_j, P_j), and considered the wind bin values (i.e. wind power and velocity) that approximates V_j, two alternatives are possible, as follows:

- if $(\nu - k\sigma) - P_j \leq 0$, then the record is classified as *normal behavior* of the operating WTG, since the bin falls inside the acceptance interval.
- if $(\nu - k\sigma) - P_j > 0$ the record is classified as *abnormal behavior* of operating WTG (stop or under-performance), since it falls outside the acceptance interval.

For each abnormal record, a value of "Power Loss" (PL) is calculated w.r.t. the possible references, as P_j: $PL = \nu_j - P_j$, i.e. as the difference between the historical mean ν_j and the power produced. The system then associates all the power losses computed in a certain period of time to the resulting event coming from the "machine events" data flow, which is classified according to the desired utility classification in relation with the nature of the event (i.e. the cause classes defined in section IV-A).

V. MODEL

As discussed in Section III, the aim of this approach is to automate the creation of daily inspection tasks (based on the information given by the SCADA system) to be assigned to service robots permanently hosted in a power plant.

TABLE 1. Dataset sample. M.P. = measured production. L.P. = lost production.

WTG	StartDate	EndDate	Dur.	Desc.	Class	CC	M.P.	L. P.
1	2017/04/01 11:20:00	2017/04/01 14:20:00	03:00:00	Not downtime	Unknown	800	0.12	0.00
1	2017/04/01 14:20:00	2017/04/01 16:00:00	01:40:00	Inefficiency	Technical Inefficiency	600	0.10	0.13
1	2017/04/01 16:00:00	2017/04/04 01:20:00	2.09:20:00	Not downtime	Unknown	800	2.76	0.00
1	2017/04/04 01:20:00	2017/04/04 08:30:00	07:10:00	Inefficiency	Technical Inefficiency	600	0.48	1.21
1	2017/04/04 08:30:00	2017/04/06 09:27:24	2.00:57:24	Not downtime	Unknown	800	5.89	0.00
1	2017/04/06 09:27:24	2017/04/06 09:45:52	00:18:28	Cable twistedRight 23 turns	Automatic action	100	0.00	0.00
1	2017/04/06 09:45:52	2017/04/07 23:10:00	1.13:24:08	Not downtime	Unknown	800	5.42	0.00
1	2017/04/07 23:10:00	2017/04/08 02:00:00	02:50:00	Missing info	To be reclassified	700		0.00
1	2017/04/08 02:00:00	2017/04/08 04:50:00	02:50:00	Not downtime	Unknown	800	0.64	0.00
1	2017/04/08 04:50:00	2017/04/08 05:00:00	00:10:00	Inefficiency	Technical Inefficiency	600	0.02	0.02
1	2017/04/08 05:00:00	2017/04/08 05:10:00	00:10:00	Not downtime	Unknown	800	0.03	0.00
1	2017/04/08 05:10:00	2017/04/08 05:40:00	00:30:00	Inefficiency	Technical Inefficiency	600	0.04	0.07
1	2017/04/08 05:40:00	2017/04/08 07:00:00	01:20:00	Not downtime	Unknown	800	0.17	0.00
1	2017/04/08 07:00:00	2017/04/08 08:40:00	01:40:00	Inefficiency	Technical Inefficiency	600	0.12	0.78
1	2017/04/08 08:40:00	2017/04/08 08:50:00	00:10:00	Not downtime	Unknown	800	0.03	0.00
1	2017/04/08 08:50:00	2017/04/08 09:00:00	00:10:00	Inefficiency	Technical Inefficiency	600	0.01	0.02
1	2017/04/08 09:00:00	2017/04/08 16:20:00	07:20:00	Not downtime	Unknown	800	0.24	0.00
1	2017/04/08 16:20:00	2017/04/08 19:10:00	02:50:00	Missing info	To be reclassified	700		0.00
1	2017/04/08 19:10:00	2017/04/08 23:30:00	04:20:00	Not downtime	Unknown	800	2.35	0.00
1	2017/04/08 23:30:00	2017/04/09 00:10:00	00:40:00	Inefficiency	Technical Inefficiency	600	0.17	0.25

TABLE 2. Analysis of events and lost production. Ev. = events (number), Ev.% = events (percentage), and L.p. = lost production.

Event cause	Ev.	L.p. (MWh)	Ev. (%)	L.p. (%)
Automatic action	23	0.0000	2%	0%
Corrective unplanned maintenance	7	0.7835	1%	0%
Fault	46	26.4028	4%	5%
Grid fault	2	0.0000	0%	0%
Preventive maintenance	8	0.0131	1%	0%
Technical Inefficiency	507	498.5400	49%	95%
To be reclassified	91	0	9%	0%
Unknown	359	0	34%	0%
Total	1043	525,7393		

Risks evaluation is mainly implemented into the Daily Pivot component (see section V-A), which is used for calculating, on a daily basis, the number of occurrences and the probability of each classified event as well as the lost production associated to each event (as detailed in Section V-B).

In particular, we consider those events for which an inspection would be useful to prevent incoming failures, in other words already occurred faults and corrective maintenance events are filtered out.

The Risk function is defined as in formula 1

$$R = P \cdot C = P \cdot LP \tag{1}$$

Here P is the Probability of event occurrence and C the consequence of that event. The consequence of considered events are both technical and economical. In particular technical consequences are related with bad performance in terms of lower energy production against the expected one. That imply also an economical loss, equal to the lost energy production (MWh) multiplied by the unitary cost of energy (euro/MWh).

Probability P lies between 0 and 1, while the Lost Production LP is a greater than zero, and the value is proportional to the duration of the related event.

Then, since economic loss is computed from the performance loss, we take into account only the independent

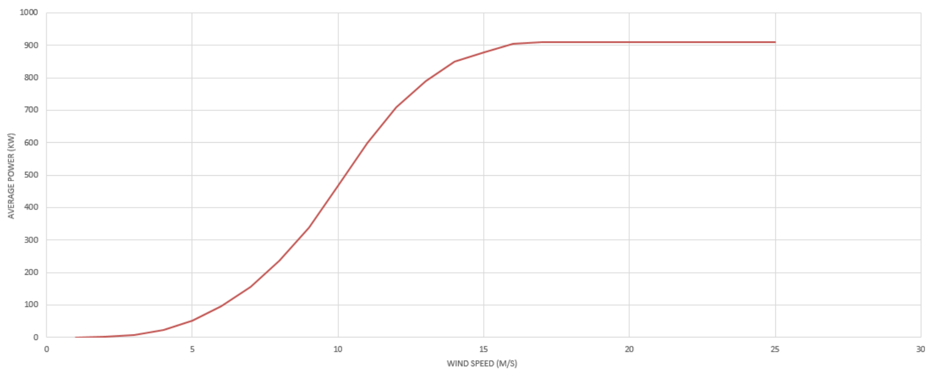

FIGURE 3. Wind turbine - power curve.

TABLE 3. Average duration of events.

Event Cause	Ev.	Avg. no. days
Automatic action	23	0.0122
Corrective unplanned maintenance	7	0,0320
Fault	46	0.0695
Grid fault	2	0.0003
Preventive maintenance	8	0.0046
Technical Inefficiency	507	0.0972
To be reclassified	91	0.0946
Unknown	359	0.5305
Total	1043	0.2417

variable performance loss, obtaining the last expression of formula 1, where *LP* represents the value of Lost Production (LP).

In a subsequent phase tasks are created. Tasks are specific for wind turbine and are fed with the related coordinates, latitude and longitude, so that each task is ready to be assigned to a Service Robot on field. As detailed into section V-B, task priorities will be based on the cumulative Risk value.

A. DAILY PIVOT

As already shown in Table 1, the Dataset consists of a sequence of events with a Start Date and an End Date, with a period which may vary from hours to few days. The goal of creating daily tasks with a given priority – based on the risk value associated to each event – is accomplished into two steps performed per each wind turbine, as shown in Fig. 3.

Since each event appears in the Dataset only when it is concluded, values of measured production and lost production cannot be produced before its end. Then the event is simply labeled with the day of the end date, as if it occurred entirely in the day of the final date, as illustrated in in Figure 4. This particular approach leads to an approximation which does not impact on the event distribution along the days. Indeed, it can be verified that the average duration of events is much less than a day (see Table 3), as a consequence the daily event allocation does not introduce relevant offsets w.r.t. the original events distribution.

Algorithm 1 Dataset Processing

Data: D: dataset of events, T: vector of type of events
Result: R: The risk vector for all kind of events
forall the *e in D* **do**
  et $\longleftarrow$ event_type(e);
  $N[et] \longleftarrow N[et] + 1$;
  $LP[et] \longleftarrow LP[et] + 1$;
end
tot_events $\longleftarrow$ 0;
forall the *et in T* **do**
  tot_events $\longleftarrow$ tot_events + $N[et]$;
end
forall the *et in T* **do**
  P[et] $\longleftarrow N[et]/tot\_events$;
  R[et] $\longleftarrow P[et] * LP[et]$;
end

More than one event of different classes can appear in the same day on each wind turbine. In order to take this aspect into account, we computed, for each single day, the probability of occurrence of every specific class of events against the others, the correspondent cumulative values of Lost production and, finally, the resulting risk values by formula 1. At this regard, Algorithm 1 illustrates the simple computations needed to calculate the risk for each class of event.

The output of this computation is represented by a "Risk Matrix" for each wind turbine as a Time Series, where a Risk values has been computed for each event cause class. A sample of the output, which refers to a single turbine (WTG1), is shown in Table 4.

B. TASK CREATION

In the second step, we consider only those events which could lead to incoming failures. Then, in order to enable preventive maintenance activities, events related to already occurred faults and maintenance events on field are filtered out, and a cumulative value of Risk is computed per each wind

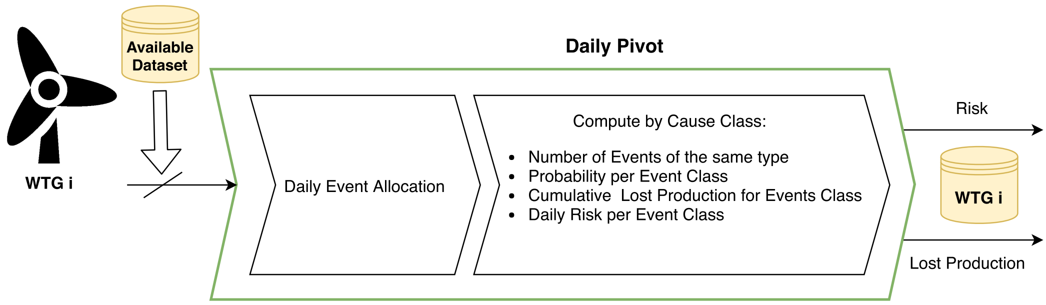

FIGURE 4. Daily pivot sub-steps.

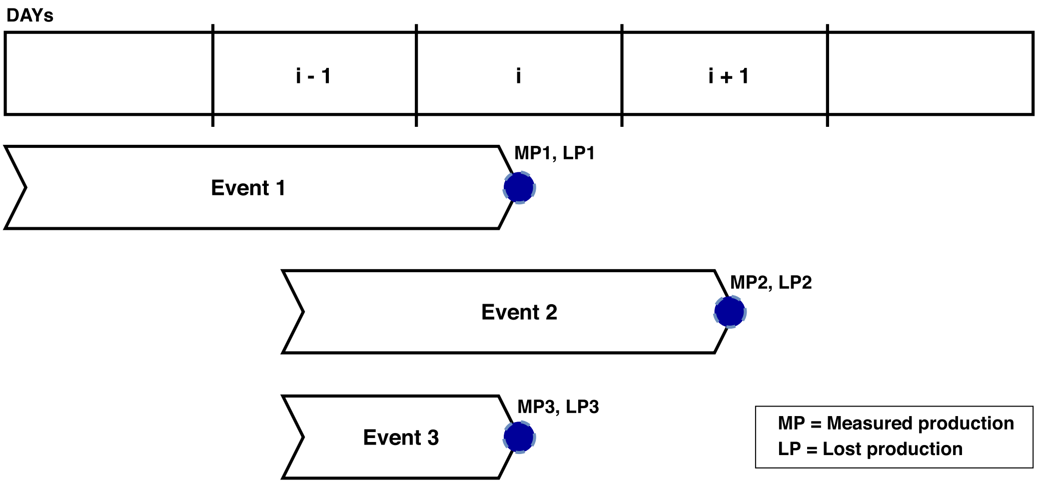

FIGURE 5. Daily event allocation.

TABLE 4. Sample of Risk values computed for WTG1.

Time			Cause Class							
Day	Month	Year	100	200	300	400	500	600	700	800
1	4	2017	0	0	0	0	0	0.0631	0	0
4	4	2017	0	0	0	0	0	0.6061	0	0
6	4	2017	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
10	1	2018	0	0	1.8664	0	0	0	0	0

turbine by selecting the event cause class from 600 to 800:

$$CR(j) = \sum_{cc \in \{600,700,800\}} R_{cc}(j)$$

where CR(j) is the cumulative risk value for the wind turbine j, and $R_{cc}(j)$ is the risk related to the cause class cc for the turbine j.

A sample of the computed cumulative risk –based on the previous sample reported in Table 4 – is reported in Table 5.

At this point each turbine is associated to a set of values of cumulative Risks for different days. A further step is represented by the construction of a matrix where each column represents the cumulative risk of a given turbine, and each row represents a single day. This step is represented in Figure 6 and labeled "*merge*", and Table 6 represents a sample of the computed cumulative risks for all the turbines: we can observe that there are days with no risk, as well as days with risks for several different wind turbines.

TABLE 5. Sample of cumulative risk values computed for WTG1.

Time			
Day	Month	Year	Cum. Risk
1	4	2017	0.0631
4	4	2017	0.6061
6	4	2017	0
...	...	...	...
10	1	2018	1.8664

At this point a number of tasks is created, where each task is related to a cell of the risk matrix having a value different than zero. In a next step, a priority is defined for each created task; in order to assign priorities to the tasks, the daily cumulative risks are properly sorted and a task object is created per each

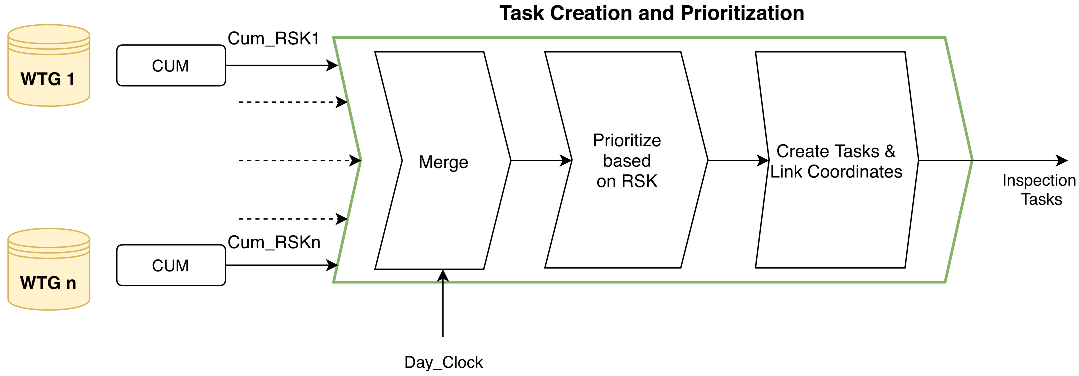

FIGURE 6. Task management.

TABLE 6. Matrix of cumulative risks for WTG1–WTG8.

YEAR	MONTH	DAY	WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8
2017	8	1	2.2759	2.4150	0.8877	1.1816	0.4599	1.9196	0.9395	1.4899
2017	8	2	1.5370	1.7438	1.3188	1.7493	1.6697	1.5257	1.6140	0.8180
2017	8	3								
2017	8	4		0.0086		0.0152		0.0062		0.1312
2017	8	5	1.6061	1.9729	1.9078	2.4265	2.5180	2.3938	2.5163	2.6090
2017	8	6				0.0086			0.0304	0.0799
2017	8	7				0.0086				0.0180
2017	8	8								
2017	8	9				0.0060				0.0782
2017	8	10								0.0931
2017	8	11		0.0217					0.0169	
2017	8	12		0.0966	0.0243	0.0785	0.1368	0.1329	0.1503	0.0365
2017	8	13	0.0067	0.0104						
2017	8	14		0.1100	0.0106	0.0288	0.0068			0.0725
2017	8	15	1.6734	2.2022	1.9185	2.2958	2.4121	2.2801	1.9936	2.0091
2017	8	16	0.7552	1.1868	0.8109	0.8579	0.8620	0.7983	0.9021	0.7926
2017	8	17	0.1591	0.3496	0.1560	0.1735	0.1834	0.1333	0.2280	0.1366
2017	8	18		0.0230		0.0316	0.0053		0.0096	0.1048
2017	8	19				0.0096				
2017	8	20								
2017	8	21								
2017	8	22								
2017	8	23								
2017	8	24	1.1853	1.3209	1.1595	1.4342	1.3260	1.4271	1.2437	1.0929
2017	8	25	2.9392	3.0015	2.9288	3.0360	2.8504	3.0144	2.8145	2.8901
2017	8	26	1.1177	1.2526	0.5952	1.0418	0.8708	0.2121	0.3189	0.1440
2017	8	27	0.1013	0.1365		0.0804	0.1714		0.0602	0.0135
2017	8	28								
2017	8	29		0.0128		0.0115				
2017	8	30								
2017	8	31					0.0400			
2017	9	1								

wind turbine that presents a Risk, feeding it with the related coordinates, latitude and longitude, as well as Priority and Risk Value, so that the task is ready to be assigned to a Service agent (e.g. a Robot) for the inspection on field. Table 7 shows an example of the computed priority, where columns 4th-11th represents the turbine numbers. Figure 7 represents a schema of the information included in a task.

VI. DISCUSSION AND RESULTS

Here we briefly discuss the results obtained by applying the approach detailed in Section V on the dataset described in Section IV. Out of 396 days – which is the period of the available dataset – our approach selected 50 days having events for which prompt inspections could bring results in terms of evidences to be gathered from the service robot on field, and a total of 258 tasks to be assigned for the hole Wind Power plant (see table 8).

Those numbers does not take into account the effects of the inspections and the related maintenance activity. Indeed, if a robot detects an anomaly and a preventive maintenance activity takes successfully place, the anomaly which generated the event and the related task should not re-appear for a certain time, reducing so the number of next tasks.

TABLE 7. Computed priority.

YEAR	MONTH	DAY	Lowest Priority							Highest Priority
2017	8	1	5	3	7	4	8	6	1	2
2017	8	2	8	3	6	1	7	5	2	4
2017	8	3	0	0	0	0	0	0	0	0
2017	8	4	0	0	0	0	6	2	4	8
2017	8	5	1	3	2	6	4	7	5	8
2017	8	6	0	0	0	0	0	4	7	8
...	...	...	...	...	...	...	...	...	...	...
2017	8	31	0	0	0	0	0	0	0	5
2017	9	1	0	0	0	0	0	0	0	0

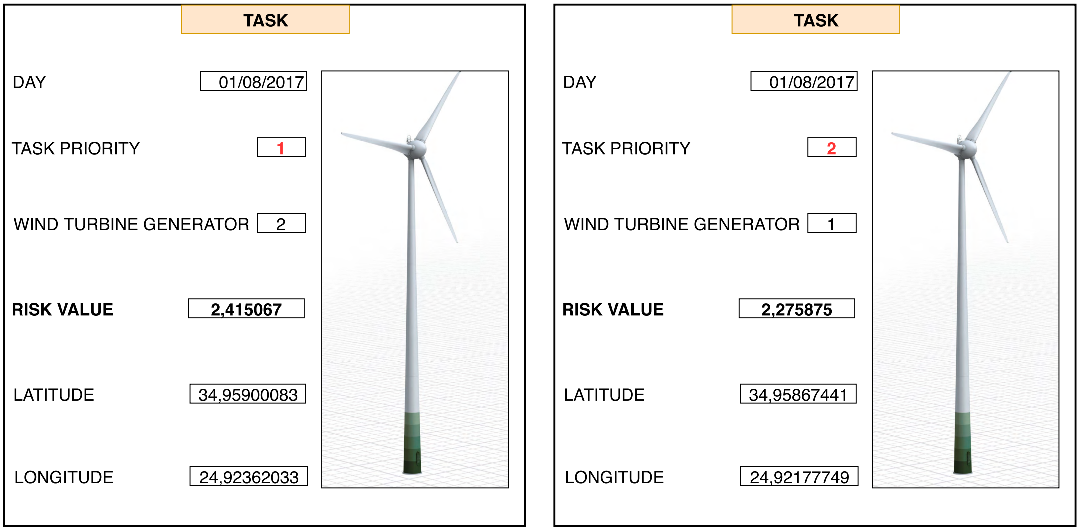

FIGURE 7. Sample of two first task objects on WTG 1 & 2, on 01/08/2017.

TABLE 8. Tasks generated.

Turbine	WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8	Total
No. of generated tasks	29	35	28	38	31	26	34	37	258

TABLE 9. Avoided low performance.

	WTG1	WTG2	WTG3	WTG4	WTG5	WTG6	WTG7	WTG8
Avoided LP	27,1	35	26	32	26,2	23,5	28	27,8
Total LP	58,5	71	54	67	63,3	58	59,8	62,7
Avoided LP%	46,30%	49,30%	48,10%	47,80%	41,40%	40,50%	46,80%	44,30%

In order to highlight this important aspects, let us assume that, for each wind turbine, after 10 own related tasks of inspection being performed by the robot inspector due to detected anomalies, the anomaly which was cause of the under-performance has been detected and resolved.

Indeed, there's not assurance about the success of a single inspection, in terms of visual detection of a mechanical problem which could be the cause of the future failure, leveraging on robot's equipment such as thermal imaging camera. In case the problem is going to be persistent, it will generates frequent alerts and related inspection tasks. The higher number of inspections, in such cases, determine an higher probability to successfully detect the cause of the problem and determine its resolution through a related maintenance activity.

It is reasonable also to assume that, once the problem has been detected and resolved, it will not appear for the rest of the year.

Then, it is possible to determine the percentage of avoided Lost Production thanks to the assigned inspection tasks, as shown in Table 9.

VII. CONCLUSIONS

Exploitation of permanent service robots hosted within wind power plants, whose daily engagement for inspections is driven by a specific data driven strategy based on risk analysis over Plant SCADA Data, could lead to an important reduction of the plants lost production.

Risk-based algorithms relying on real-time data can be used in order to dynamically define priority of intervention on a live data-stream, without the necessity to find correlations with repairing interventions made in the past.

Dataset analysis clearly reports that cumulative daily plant under-performance due to technical inefficiencies in a year result in greater economic losses compared to the ones related with the main failure events. So an efficient Risk-based strategy aimed at creating inspection tasks for preventing incoming failures should be based mostly on prioritization of intervention in relation with Technical inefficiency events, managing priorities of intervention on the basis of the risk values daily computed over all the WTGs belonging to the plant. The proposed approach, validated over a 396 days dataset collected by the SCADA of a Wind Power Plant located in Greece, which has an overall nominal power of 7.2 MW and which is composed by 8 Wind Turbines of 900 KW per each, could lead to an increase of production of 45.6%.

Future works could include the extension of this approach also to a solar power plants. The main differences to be taken into account is the fact that the solar power plant components are distributed over a wide area, so inspection tasks should be not related to a specific coordinates as for the wind turbines. In that case a different logic shall be defined in order to define portions of area to be inspected, mostly composed by solar panels.

Future works could be also focused on the execution of the inspection tasks once assigned to the execution management system (EMS) in charge of manage the robots hosted in the power plants. Indeed, tasks execution shall deal with other daily optimization problems, such as providing robots with the best dynamic paths to be followed for reaching the assigned targets. This objective could include, but is not limited to obstacles avoidance, collision detection, robots battery consumption, robots cooperation (in case of many robots) and so on.

Let's assume to provide plants with more than one service robot, and a certain number of base-station to be located around the plant in order to both, gather data collected by the robots and allow robots to recharge their batteries. Base stations could act also as edge computing node, and receive the tasks previously generated and prioritized from the cloud.

Each task is going to produce a list of operative jobs for the robot, in order to perform the expected work, for instance: - Send Confirmation Message: robot to confirm the mission has been received; - Go-To-Point: robot to execute the required actions to reach the target point and perform the inspection of the related area; - Evaluate State of Charge: robot to evaluate its remaining energy to eventually perform other tasks/missions and share the info to the execution management system (EMS); - Return to Home: to allow the robot to return to the base station, according to its state of charge; - Update Status: robot to communicate to the EMS that it is available again for a new task execution.

A robot selection algorithm should be also implemented to define the robot to which assign the task, once it is received through a base station. The algorithm should verify the status of each robot and the related availability, and proceed with the evaluation of the task execution by minimizing a cost function based on the distance between the robot and the task inspection target point.

REFERENCES

[1] W. Engels, T. Obdam, and F. Savenije, "Current developments in wind-2009," Energy Res. Center of The Netherlands, Sint Maartensvlotbrug, The Netherlands, Tech. Rep. ECNE-09-96, 2009.

[2] B. Lu, Y. Li, X. Wu, and Z. Yang, "A review of recent advances in wind turbine condition monitoring and fault diagnosis," in *Proc. IEEE Power Electron. Mach. Wind Appl.*, Jun. 2009, pp. 1–7.

[3] L. W. Rademakers, H. Braam, M. B. Zaaijer, G. J. Van Bussel, "Assessment and optimisation of operation and maintenance of offshore wind turbines," presented at the EWEC, 203.

[4] L. W. Rademakers, H. Braam, T. S. Obdam, P. Frohböse, and N. Kruse, "Tools for estimating operation and maintenance costs of offshore wind farms: State of the art," presented at the EWEC, 2008.

[5] J. Philips, C. Morgan, and J. Jacquemin, "Evaluating O&M strategies for offshore wind farms through simulation-the impact of wave climatology," in *Proc. OWEMES*, 2006, pp. 20–22.

[6] P. Stratford, "Assessing the financial viability of offshore wind farms," presented at the EWEC, 2007.

[7] F. Messina, G. Pappalardo, and C. Santoro, "Integrating cloud services in behaviour programming for autonomous robots," in *Proc. Int. Conf. Algorithms Architectures Parallel Process.* Cham, Switzerland: Springer, Dec. 2013, pp. 295–302.

[8] F. Messina, G. Pappalardo, and C. Santoro, "Designing autonomous robots using golem," in *Proc. 15th Workshop Dagli Oggetti Agli Agenti*, vol. 1260, 2014.

[9] F. Messina, G. Pappalardo, and C. Santoro, "A goal-centric framework for behaviour programming in autonomous robotic systems," in *Proc. IEEE/ASME 10th Int. Conf. Mechtron. Embedded Syst. Appl. (MESA)*, Sep. 2014, pp. 1–6.

[10] M. De Benedetti, F. D'Urso, F. Messina, G. Pappalardo, and C. Santoro, "Uav-based aerial monitoring: A performance evaluation of a self-organising flocking algorithm," in *Proc. 10th Int. Conf. P2P, Parallel, Grid, Cloud Internet Comput. (3PGCIC)*, Nov. 2015, pp. 248–255.

[11] M. De Benedetti, F. D'Urso, F. Messina, G. Pappalardo, and C. Santoro, "3D simulation of unmanned aerial vehicles," in *Proc. WOA*, 2017, pp. 7–12.

[12] M. De Benedetti, F. D'Urso, G. Fortino, F. Messina, G. Pappalardo, and C. Santoro, "A fault-tolerant self-organizing flocking approach for UAV aerial survey," *J. Netw. Comput. Appl.*, vol. 96, pp. 14–30, Oct. 2017.

[13] S. Perez-Canto and J. C. Rubio-Romero, "A model for the preventive maintenance scheduling of power plants including wind farms," *Rel. Eng. Syst. Saf.*, vol. 119, pp. 67–75, Nov. 2013.

[14] S. P. Canto, "Application of benders' decomposition to power plant preventive maintenance scheduling," *Eur. J. Oper. Res.*, vol. 184, no. 2, pp. 759–777, Jan. 2008.

[15] A. M. Geoffrion, "Generalized benders decomposition," *J. Optim. Theory Appl.*, vol. 10, no. 4, pp. 237–260, Oct. 1972.

[16] E. Sanmartí, A. Espuña, and L. Puigjaner, "Batch production and preventive maintenance scheduling under equipment failure uncertainty," *Comput. Chem. Eng.*, vol. 21, no. 10, pp. 1157–1168, Jul. 1997.

[17] A. Kovács, G. Erdös, L. Monostori, and Z. J. Viharos, "Scheduling the maintenance of wind farms for minimizing production loss," in *Proc. 18th IFAC World Congr.*, Italy, Jan. 2011, pp. 14802–14807.

[18] B. Kralj and N. Rajaković, "Multiobjective programming in power system optimization: New approach to generator maintenance scheduling," *Int. J. Electr. Power Energy Syst.*, vol. 16, no. 4, pp. 211–220, Aug. 1994.

[19] E. Zio and M. Compare, "Evaluating maintenance policies by quantitative modeling and analysis," *Rel. Eng. Syst. Saf.*, vol. 109, pp. 53–65, Jan. 2013.

[20] A. Sergaki and K. Kalaitzakis, "A fuzzy knowledge based method for maintenance planning in a power system," *Rel. Eng. Syst. Saf.*, vol. 77, no. 1, pp. 19–30, Jul. 2002.

[21] K. W. Edwin and F. Curtius, "New maintenance-scheduling method with production cost minimization via integer linear programming," *Int. J. Elect. Power Energy Syst.*, vol. 12, no. 3, pp. 165–170, Jul. 1990.

FABIO LEONARDI received the master's degree in electronic engineering, with a specialization in automation and control of complex systems. He is currently pursuing the Ph.D. degree in computer science with the University of Catania, dealing with machine learning techniques and predictive maintenance algorithms supported by a big data infrastructure. He started his career at the Research Sector, National Institute for Nuclear Physics (INFN), where he was involved in the development of control boards and software systems for data acquisition and real-time monitoring of signals acquired from hundreds of underwater optical and acoustic sensors. Hired by E-Distribuzione, the Italian distribution system operator (DSO), in 2010, he entered the Energy Distribution Sector, managing the development projects of the MV/LV electrical grid, analyzing and supervising the energy flow utilizing data remotely acquired and ingested into a control and monitoring systems, and supporting the implementation of distributed innovative sensors for smart grid projects. Since 2014, he has been with the Renewable Energy Sector, Enel Green Power, as a member of the Global Control and Monitoring Systems Unit, managing projects on SCADA systems, control and monitoring rooms' development at worldwide level, and the design and implementation of big data analytic infrastructure. Since 2016, he has been selected as a Research Fellow of Enel Foundation, leading research projects in the technology sector, with a focus on big data, robotics, and artificial intelligence.

FABRIZIO MESSINA received the Ph.D. degree in computer science from the Department of Mathematics and Informatics, University of Catania, Italy, in 2009, where he is currently an Assistant Professor. His research interests include distributed systems, complex systems, simulation systems, and trust and recommender systems.

CORRADO SANTORO received the Laurea degree in computer engineering from the University of Catania, in 1997, and the Ph.D. degree in computer engineering from the University of Palermo, in 2001. He is currently a Researcher with the Department of Mathematics and Informatics, University of Catania. His research interests include large-scale distributed systems, intelligent autonomous systems, and robotics.