IJARSCT

ISSN (Online) 2581-9429

IJARSCT
Impact Factor: 6.252

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Volume 2, Issue 2, March 2022

AI Supported Maintenance and Reliability System in Wind Energy Production

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Abstract: *Now a days the technology is advancing at an unbelievable rate. To the point many of us aren't able to efficiently keep up. With the ever- increasing sophistication of Artificial Intelligence [AI]. The environmental impact of the wind power is relatively minor when we compared to that of the fossil fuel power. When Compared to other low carbon sources, wind turbines have one of the lowest global warming potentials per unit of electricity energy generated per power sources. Among the renewable energy arts wind energy plays a significant role and, as forecasted its ratio within the total energy production will rapidly increase. Wind turbines are relatively complex electro-mechanical systems, their smooth functioning is an important economical factor. This is why the monitoring and diagnosis of wind turbines and wind farms gained extreme importance in the past years.*

Keywords: Wind Power

I. Introduction

So, we all know that renewable energies like solar power are the need of the time. But, how does Artificial Intelligence (AI) can help in improving renewable energy supply? Let's see. Global energy demands are growing every year. And, fossil fuels won't be able to fulfil our energy needs in the future. Carbon emissions from fossil fuels have already hit an all-time high in 2018 due to increased energy consumption. On the other hand, renewable energy is emerging out as a reliable alternative to fossil fuels. It is much safer and cleaner than conventional sources. With the advancements in technology, the renewable energy sector has made significant progress in the last decade. However, there are still a few challenges in this sector that can be addressed with the help of emerging technologies. Technologies like AI and Machine Learning can analyse the past, optimize the present, and predict the future. And, AI in the renewable energy sector can resolve most of the challenges**.**

The energy sector worldwide faces growing challenges related to rising demand, efficiency, changing supply and demand patterns, and a lack of analytics needed for optimal management. These challenges are more acute in emerging market nations. Efficiency issues are particularly problematic, as the prevalence of informal connections to the power grid means a large amount of power is neither measured nor billed, resulting in losses as well as greater CO_2 emissions, as consumers have little incentive to rationally use energy, they don't pay for. The power sector in developed nations has already begun to use artificial intelligence and related technologies that allow for communication between smart grids, smart meters, and Internet of Things devices. These technologies can help improve power management, efficiency, and transparency, and increase the use of renewable energy sources. The use of AI in the power sector is now reaching emerging markets, where it may have a critical impact, as clean, cheap, and reliable energy is essential to development. The challenges can be addressed over time by transferring knowledge of the power sector to AI software companies. When designed carefully, AI systems can be particularly useful in the automation of routine and structured tasks, leaving humans to grapple with the power challenges of tomorrow. Access to energy is at the very heart of development. Therefore, a lack of energy access—which is the reality for one billion people, mostly in Sub-Saharan Africa and South Asia—is a fundamental impediment to progress, one that has an impact on health, education, food security, gender equality, livelihoods, and poverty reduction. Universal access to affordable, reliable, and sustainable modern energy is one of the Sustainable Development Goals (SDGs). Yet it will remain just that—a goal—unless innovative solutions and modern technologies can overcome the many energy-related obstacles that plague emerging markets, from a lack of sufficient power generation, to poor transmission and distribution infrastructure, to affordability and climate concerns. In addition, the diversification and decentralization of energy production, along with the advent of new technologies and changing demand patterns, create complex challenges for power generation, transmission, distribution, and consumption in all nations. Artificial intelligence, or AI, has the potential to cut energy waste, lower energy costs, and facilitate and accelerate the use of clean renewable energy sources in power grids worldwide. AI can also improve the planning, operation, and control of power systems. Thus, AI technologies are closely tied to the ability to provide clean and cheap energy that is essential to development. For the purposes of this note, we follow the definitions and descriptions of basic, advanced, and autonomous artificial intelligence that were put forward in EM Compass Note. AI refers to the science and engineering of making machines intelligent, especially intelligent computer programs. AI in this note is a series of approaches, methods, and technologies that display intelligent behaviour by analysing their environments and taking actions—with some degree of autonomy—to achieve specific targets in energy.

AI-Business Models in Emerging Markets According to a November 2019 International Energy Agency (IEA) report, some 860 million people around the world lack access to electricity.13 Around three billion people cook and heat their homes using open fires and simple stoves fuelled by kerosene, biomass, or coal.14 Over four million people die prematurely of illnesses associated with household air pollution. For these reasons, the provision of energy goes beyond mere power supply: It is critical to human health and safety.15 Renewables will play an important role in increasing access to electricity, one of the United Nations Sustainable Development Goals (SDGs). According to World Bank data, the global electrification rate stood at 88.9 percent in 2017.16 In terms of sustainability, while the share of energy from renewable sources (including hydroelectric sources) rose from 16.6 percent in 2010 to 17.5 percent in 201617, these sources of power have yet to be widely adopted. This is partly because renewables present a particular challenge to the power grid due to their intermittency and difficulty to plan for in real-time. AI tools' speed, robustness, and relative insensitivity to noisy or missing data can address this by improving the planning, operation, and control of the power system. In doing so, AI can facilitate the integration of renewable energy into power systems to create hybrid low-carbon energy systems.18 Thus the shift to renewables can occur at a much faster rate with the use of AI. India, in particular, has been recognized for its efforts to expand renewable energy production. Currently, India has an installed capacity of 75GW from various renewable energy sources (wind, solar, etc.), and it has a target of 175GW from renewable sources by 2022.20 Despite regulatory efforts aimed at incentivizing clean energy investments, the diffusion and expansion of renewable Energy remains a challenge. AI is being considered as a potential solution to boost renewable energy adoption.

II. Challenges of the Renewable Energy Sector & How AI Can Help

One of the significant challenges of producing renewable energy is the unpredictability of the weather. Solar and wind are the leading sources of renewable energy, and the power generation largely depends on the weather. Although we've efficient technologies in place for weather forecasting, there are going to be sudden changes in the climate that can affect the energy flow. The supply chain of renewable energy is prone to such vulnerabilities. Therefore, it needs to be smoothened enough to cope up with unexpected changes. Secondly, the recent developments in energy storage technology are quite promising. But they are yet to be tested thoroughly. The demand for renewable energy will only increase in the future. And, that's why renewable energy companies should invest in Machine Learning, AI and other emerging technologies to improve productivity and overcome the shortfalls.

Even the large consumers of renewable energy, like supermarkets, factories, offices, and railways can use AI technology to make data-driven decisions. Beyond the investment analysis one can identify that cost is only a factor among further important features listed here and analysed in to compare the effects of different renewable energy sources.

- Price of energy produced
- Greenhouse gas emission during full life cycle of the technology
- Availability of renewable sources
- Efficiency of energy conversion
- Land requirements
- Water consumption
- Social impacts

Taking the same weights for these evaluation aspects wind and hydro energies were found as best solutions. Various aspects are to be found at players of the value chain of wind energy, too:

- Project developers which focus on planning and realization of wind farms
- Electric utility companies on buying and selling the electricity produced, while
- Grid operators on balancing and re-allocation of electricity in the electric net
- Manufacturers concentrate on technological developments

The rate of offshore installations having higher investment cost and risks and the variety of viewpoints when evaluating this branch indicates especial importance of maintenance and reliability of wind farms. Wind turbine generators are data intensive information sources because they incorporate various sensors similar to other branches, e.g., like manufacturing. This allows real condition monitoring and supervision of wind turbines and wind farms also from different locations and supports the preparation of reliability models with statistical information, too. There are also some differences, e.g., wind turbines are operating in continuously changing environmental conditions with sometimes extreme circumstances that is not typical e.g., in the production system because they try to ensure stable and unchanging operation. This variety in environmental effects gives a great difficulty for handling changing conditions but it has also positive side: for statistical and further Artificial Intelligence (AI) analysis and modelling it can ensure a data set collected in various conditions. From the other side the data intensity requires sophisticated data processing techniques and knowledge related to them.

Various condition monitoring and sensing techniques, ordered to different WTG components extended by some fault detection solutions with AI methodologies are enumerated and compared in similar to that explains the relation of condition monitoring to reliability modelling as a tool for handling the changes at the right/wearing outside of a bath curve. Combinations of turbine components and monitoring techniques are highlighted in, hybrid statistical modelling is introduced in for special problem domains however one can find the lack of a comprehensive framework for handling orderings of

- Turbine components
- Failure modes
- Detecting sensors
- Appropriate data processing and monitoring
- Field specific limits
- Failure detection and prognosis tools
- Efficient control modifications
- And appropriate maintenance and repair actions to each- other.

Even the internal structures of these components are not clearly defined up to now.

III. How AI Technology Can Improve the Renewable Energy Sector

The electric grid is one of the complex machines on Earth. However, it is evolving rapidly with the addition of variable renewable energy sources. Due to the inherent variability of wind and solar, the current grid faces many challenges in accommodating the diversity of renewable energy. The utility industry needs smart systems that can help improve the integration of renewables into the existing grid and make renewable energy an equal player in the energy supply. Here's how AI technology can improve the reliability of renewable energy and modernize the overall grid.

3.1 Smart, Centralized Control Centres

The energy grid can be interconnected with devices and sensors to collect a large amount of data. When coupled with AI, this data can give new insights to the grid operators for better control operations. It offers flexibility to the energy suppliers to cleverly adjust the supply with demand. The advanced load control systems can be installed with the equipment, such as industrial furnaces or large AC units, which can automatically switch off when the power supply is low. Intelligent storage units can also be adjusted based on the flow of supply. Additionally, smart machines and advanced sensors can make weather and load predictions that can overall improve the integration and efficiency of renewable energy.

3.2 Improved Integration of Microgrids

AI can help with the integration of microgrids and managing distributed energy. When the community- level renewable energy generation units are added to the primary grid, it becomes hard to balance the energy flow within the grid. The AI-powered control system can play a vital role in solving the quality and congestion issues.

3.3 Improved Safety and Reliability

While the biggest goal of AI in renewable energy is to manage the intermittency, it can also offer improved safety, efficiency, and reliability. It can help you understand the energy consumption patterns, identify the energy leakage and health of the devices. For example, the AI-powered predictive analysis can collect the data from wind turbine sensors to monitor wear and tear. The system will monitor the overall health of the equipment and alert the operator when the maintenance is needed.

3.4 Expand the Market

The integration of AI can help renewable energy suppliers expand the marketplace by introducing new service models and encouraging higher participation. The AI-powered systems will be able to analyse the data related to energy collection and provide insights on energy consumption. This data would help suppliers optimize the existing services and launch new service models. It can also help retail suppliers to target new consumer markets.

3.5 Smart Grid with Intelligent Storage

The integration of artificial intelligence with Intelligent Energy Storage (IES) can provide a sustainable and reliable solution to the renewable energy industry. This smart grid will be able to analyse a vast amount of data collected from several sensors and make timely decisions on energy allocation. This will also help microgrids to efficiently manage the local energy needs while continuing the power exchange with the main grid.

IV. AI-Supported Models in Fragile and Low-Income Countries

New business models built on AI are emerging that target underserved geographical areas where access to electricity remains a daily challenge. For example, Power-Box is a distributed energy system fitted with battery cubes that can store 1.2 kilowatt-hours of solar or wind energy, and a single unit can serve several people. This solution can be scaled to multiple units to power an entire village. Flex Grid is another example that builds an off-grid solution for rural villages. The company secured a grant from Electrify, a European funding body, to establish a testing site in a remote community in Southern Mali where more than 10,000 villages lack access to the electrical grid.

Customers are charged a fixed rate in a tiered pricing structure, which is based on their ability to pay, and payments are made using a text-based system. Currently, Power-Box is being integrated with Internet of Things protocols to integrate remote control of the boxes.

V. How Can AI Support Large Integration of Renewable Energy?

Excess solar or wind power is stored during low-demand times and used when energy demand is high. As a result, AI can improve reliability of solar and wind power by analysing enormous amounts of meteorological data and using this information to make predictions and decisions about when to gather, store, and distribute wind or solar power. On the other hand, AI is also used in smart grids to help balance the grid. AI analyses the grid before and after intermittent units are absorbed and learns from this to help reduce congestion and renewable energy curtailment. AI is also gaining ground in Latin

America. Argentina has embarked on a modernization effort of its power grid infrastructure by investing in automation of power distribution, remote reading of energy meters across several cities, and the implementation of renewable energy generators. In Baja California, IFC is helping CENACE (Centro Nacional de Control de Energy) model the effect of cloud coverage on solar generation to help balance the grid with batteries. The AI algorithms developed help the ISO react in seconds to provide primary regulation to stabilize the grid. In much of Sub-Saharan Africa, access to home electricity remains a challenge. Africans spend as much as $17 billion a year on firewood and fuels such as kerosene to power primitive generators.24 There are glimmers of hope, however. Azuri Technologies developed a pay-as- you- go smart-solar solution used in East Africa and Nigeria. Azuri's Home Smart solution is built on AI. It learns home energy needs and adjusts power output accordingly—by automatically dimming lights, battery charging, and slowing fans, for example—to match the customer's typical daily requirements. The company recently secured $26 million in private equity investment to expand its solutions across Africa.

VI. Wind Energy Production – Status and Challenges

Wind energy is one of the most promising branches today. Global installed wind-generation capacity onshore and offshore has increased by a factor of almost 75 in past two decades ,jumping from 7.5 gigawatts(GW)in 1997 to some 564GW by 2018,according to IRENA'S latest data .This economic trend involve dramatic technical developments, and as result, today, the electricity produced by the wind turbine is 180 times compared to that of 20 years ago, at less than half the cost per kWh and it decreases with 10% every time the total capacity is doubled. Here 80% of the total costs is to fix and arise then establishing the wind turbine generator (WTG). One of the most important challenges in comparison of cost at various producers and operators is the lack of universally agreed set of cost categories.

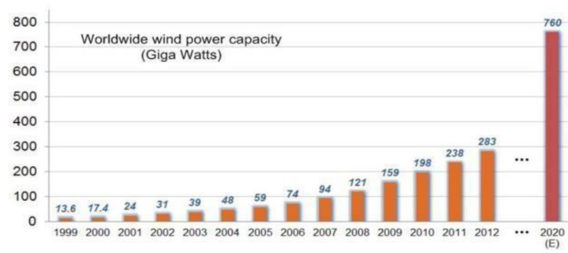

Figure: World-wide wind power capacity (Giga Watts) from 1999-2020

The growth in the number of wind farms in energy production as well as the increasing market shares in energy production, the growing rate of offshore installations having higher investment cost and risks and the variety of viewpoints when evaluating this branch indicates especial importance of maintenance and reliability of wind farms. Wind turbine generators are data intensive information sources because they incorporate various sensors similar to other branches. This allows real condition monitoring and supervision of wind turbines and wind farms also from different locations and supports the preparation of reliability models with statistical information. There are also some differences, e.g., wind turbines are operating in continuously changing environmental conditions with sometimes extreme circumstances that is not typical. This variety in environmental effects gives a great difficulty for handling changing conditions but it has also positive side: for statistical and further Artificial Intelligence (AI) analysis and modelling it can ensure a data set collected in various conditions. From the other side the data intensity requires sophisticated data processing techniques and knowledge related to them.

6.1 Logical Architecture of an Advanced WTG Health Monitoring System

WP3 is targeting to develop the Logical Architecture of an Advanced Wind Turbine Generator (WTG) Health Monitoring System (AWTGHMS). It is not only an architecture design but active also in the field of idea approval. The Fig. 1 shows the architecture of the AWTGHMS. The different AI supported maintenance and reliability systems in wind energy production components of the system are developed in consecutive tasks comprehend by the Task 3.0 for guaranteeing the overall consistency of the monitoring architecture. Logical architecture definition of required hierarchical system breakdown guarantees a common WTG & Wind farm level integration from a diagnosis, prognosis & health monitoring point of view.

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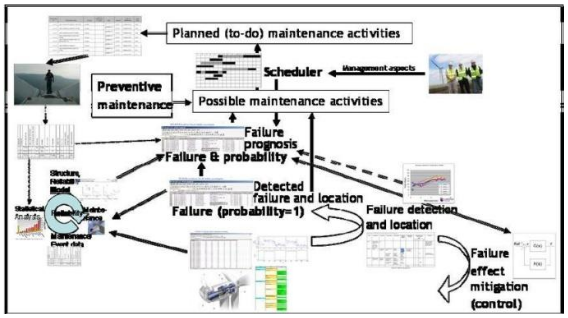


Figure: The architecture of an Advanced WindTurbine Generator (WTG) Health Monitoring System (AWHMS)

Improvements in the cost-effectiveness of wind turbines will drive designers towards more 'intelligent' control algorithms inside the task which play an important part in actively improving the reliability of components and sub-systems. Advanced controllers which receive multiple inputs and make use of this information for regulation of structural loads and vibrations as well as for maximization of energy output are already under development, test and, in some cases in commercial operation. The objective of the work to be conducted in this task is to investigate the extent to which such advanced control algorithms might be extended to address reliability issues. Changes to both closed loop and supervisory control will be considered. The former will include, for example, the active control of structural loads and vibrations by means of pitch activity in response to measured loading and vibrational motion whereas the latter might include supervisory control action, for example, to de-rate the torque transmitted through the gearbox in response to abnormal behaviour detected by appropriate sensors.

The purpose of the Task 3.2 is to develop agents for the detection of specific incipient failure modes in the whole turbine. The algorithms are developed from the analysis of indications extracted from different monitoring signals on each important turbine system including blades, nacelle, yaw system, drive train, turbine control system and electrical control system. The mission of these algorithms is to determine and identify which turbine system has progressed from a nominal to a malfunction condition.

The purpose of the Task 3.3 is to develop agents for the location of specific incipient failure modes identified before, integrated with the knowledge developed in failure effect mitigation and failure detection. The algorithms are developed from analysis of monitored variables on the turbine system. The mission of these algorithms is to locate which turbine system has progressed from a nominal to a malfunction condition. This includes design and development for the integration of detection and location agents with other global SCADA systems operating on the wind turbine and wind farm.

The aim of Task 3.4 is to develop algorithms which can provide a prognosis for the incipient failure modes detected and located before. In this way the algorithms attempt to predict the residual life and reliability of the components for which the incipient faults have been detected. This will form the basis for the repair and maintenance strategies of the next two tasks.

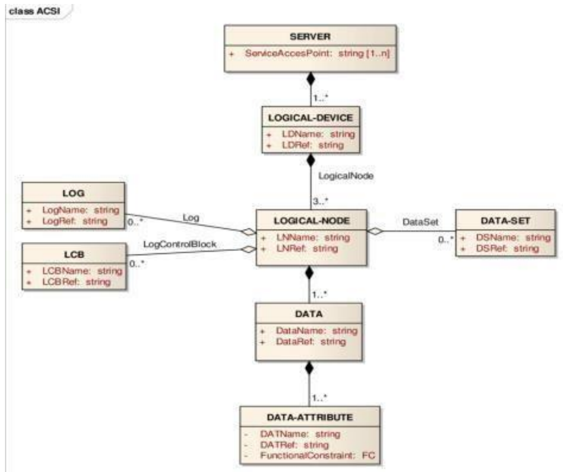
The purpose of the Task 3.5 is to generate maintenance activities based on the repair prognosis for the faults detected and located to effect improvements to the availability of the wind turbine. Having a list of maintenance assignments is to plan maintenance activities based on the repair prognosis for the faults detected and located from and the maintenance activities generated. This Task 3.6 gives maintenance operators the work plan of maintenance activities.

The feedback of operators and also the reliability model developed in the previous Work Package for design for reliability and understanding failures and their mechanisms are also included among the inputs of the ARMS realizing a closed loop for high system availability.

Due to technological changes, wind energy has become an important commercial option for large scale power production. However, wind energy resources are highly variable, and the resulting swing in the generation capacity can cause instability in the power grid. Today there is a growing zeal about using the power of the wind to generate environmentally friendly renewable energy and reduce our dependence on fossil fuel resources. In a report published by the United Nations, it is recommended that the maximum emission of CO_2 should not exceed 44 gigatons by 2020, falling to 40 gigatons by 2025 and further to 22 gigatons by 2050. With the current rapid development and growth in wind generation, there is a need for serious research on different areas of wind energy conversion systems (WECs) and energy management, in particular, wind speed prediction and power forecasting. As the wind speed and nonlinear fluctuations represent the main components in the prediction of the energy output of wind turbines, investigating wind energy production from wind turbine machines at a given location requires an intensive study of wind distribution in terms of its availability, direction, hourly distribution,

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 2, Issue 2, March 2022
Impact Factor: 6.252

diurnal variation, and frequency. In contrast to conventional power plants, the electricity generated from wind turbines depends mostly on meteorological conditions, in particular, the magnitude of the wind speed, the atmospheric turbulence, and the control of the wind turbine characteristics.



Conceptual-class-model of the ACCIAI for the Prediction of Wind Speed, in Saudi Arabia

VII. Tracking Data Collection and Analysis

7.1 Data Structures, Content and Cleaning

In order to prepare the ground a data cleaning is implemented to provide high quality data for the forthcoming data analysis. The field data currently available for the analysis came from two sources:

- Work orders (some thousand records)
- SCADA data from central databases

The work orders store the repair works performed on the wind turbines. The SCADA data is available in 3 delimited text files. The data are available for the same wind turbines that were referenced in the
Work Orders file. The three files contain the following information

- Alarm information (some ten thousand records)
- Wind information (some million records)
- Energy information (some million records)

The alarm information contains the trigger events of the different sensors in the wind turbine. The wind information stores averages of the wind speed measured at the different wind turbines. The energy information stores also average the energy produced on the different wind turbines. Because of the volume of the records and for having structural, consistent data structure the data was loaded into an Oracle database. This database could be queried during the data processing and analysis.

The work orders are edited by hand; therefore, it is highly possible that small syntax errors might occur during the editing phase. Since the failure modes are an important piece of information in the later processing, it is very important that two different spellings of one failure mode are not considered as two failure modes.

The automatic filtering is realized by applying AI techniques based on Porter's stemming and a clustering algorithm. The algorithm works as follows:

- Divide every expression into words
- Drop the stop words (small words that does not influence the meaning)
- Find the stem of every word
- Add the word to the dictionary (in this case a list of words used at least once in an expression)
- Calculate the word vector of every expression. The word vector is a sparse vector that contains 1 only at positions where the dictionary stores the contained words.
- Cluster the identical vectors

The algorithm is applied to the corpus of all failure modes, sub-systems, assemblies, sub-assemblies, and part expressions. The clustering algorithm found some tens of clusters that have more than one member. Examples of clusters are displayed in Table 1 below. The identical expressions are filled in the database as identical records having the same index numbers.

Group No	Expression 1	Expression 2	Expression 3
6	Blade Repair	Blade Repairing	Blades Repairing
7	Elevator Repair	Elevator Repairing	
8	Vibrations Sensor	Vibrations Sensors	
9	Yaw Sensor	Yaw Sensors	
….	….	….	….

Table 1: Example of identical expressions

In order to visualize the dependencies first the work orders are clustered into dependency groups. Dependency groups mean a set of work orders that have some connections between them. The dependency groups are determined in this analysis based on the date stamp. Two work orders are considered dependent if they occurred on the same turbine and the difference of the two date stamps is less than some days. In other words, if two failure modes occur close together, they most probably influence each other, e.g., they are dependent.

All work order pairs – or failure mode pairs – in a dependency group represent an edge in a dependency graph. As the graph is defined, every edge receives a weight, which is equal to the cardinality of the occurrences. If the weight of the edge is 2, then it means that the given pair of failure modes appear exactly twice on the same turbine within the time window prescribed.

To visualize the dependencies a minimum edge weight is defined to filter out the edges from the graph whose weight is less than the specified minimum. The reason behind this filtering is quite simple, the lower weight of the edges, the less probable the real dependency. In Fig. 4 a dependency graph is displayed with minimum edge weights equal to 3. Edges having bigger weight are drawn with thicker lines. This simple dependency graph does not necessarily reveal direct, real dependencies between the failure modes, but it definitely helps to build a better quilter.

7.2 Data analysis

As the preliminary task a clustering of the work orders was carried out. This analysis is a very simple way to find out dependencies between failures. Since every work order corresponds to a failure mode, therefore the work order clustering is equivalent to the failure modes clustering. The idea behind the analysis is the following: let us assume that failure modes that regularly occur together have dependencies between each other. Visualizing these dependencies might immediately reveal some real –which means here accepted by experts– dependencies between the different failure modes. In order to visualize the dependencies first the work orders are clustered into dependency groups. Dependency groups mean a set of work orders that have some connections between them. The dependency groups are determined in this analysis based on the date stamp. Two work orders are considered dependent if they occurred on the same turbine and the difference of the two date stamps is less than some days. In other words, if two failure modes occur close together, they most probably influence each other, e.g., they are dependent. All work order pairs – or failure mode pairs – in a dependency group represent an edge in a dependency graph. As the graph is defined, every edge receives a weight, which is equal to the cardinality of the occurrences. If the weight of the edge is 2, then it means that the given pair of failure modes appear exactly twice on the same turbine within the time window prescribed. To visualize the dependencies a minimum edge weight is defined to filter out the edges from the graph whose weight is less than the specified minimum. The reason behind this filtering is quite simple, the lower weight of the edges, the less probable the real dependency. In the Figure below a dependency graph is displayed with minimum edge weights equal to 3. Edges having bigger weight are drawn with thicker lines. This simple dependency graph does not necessarily reveal direct, real dependencies between the failure modes, but it definitely helps to build a better qualitative understanding of the provided information, consequently engineering check is needed using this result.

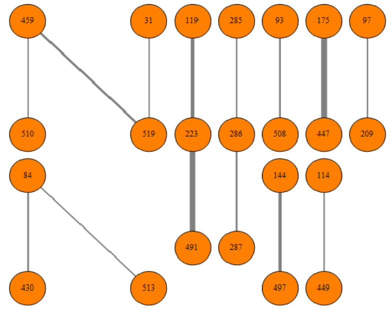


Figure: Dependency-graph-with-minimum-edge-weight-3

VIII. Conclusion

The environmental effects of wind power are relatively minor, compared to those of more traditional energy sources. Among the renewable energy, wind energy plays a significant role and, as forecasted its ratio within the total energy production will rapidly increase. Wind turbines are relatively complex electro-mechanical systems, their smooth functioning is an important economical factor. This is why monitoring and diagnosis of wind turbines and wind farms gained extreme importance in the past years. Concentrating on monitoring, diagnosis and maintenance issues the novel logical architecture of an advanced wind turbine health monitoring system harmonized with the recent standard series on communications for monitoring and control of wind power plants was introduced. Wind turbines have several built-in sensors measuring various physical characteristics during the operation and SCADA systems serve with huge amounts of data. This allows applying artificial intelligence techniques for analysing the dependencies among data. Similar to other branches, to manufacturing, exploration of this new knowledge the necessary models for condition monitoring can be set up ensuring a part of the content for the introduced advanced wind turbine health monitoring system.

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IJARSCT

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