# The Impact of Renewable Energy for Occupational Health in the Smart Grid Era

Saki Gerassis, Alberto Abad, Eduardo Giráldez, and Javier Taboada

***Abstract*—The aim of this study is to analyze how the growth of renewable energy in the power market is affecting workers health and what are the cost implications of having a healthier workforce. To tackle this issue, Big Data from occupational health surveillance carried out to over 4,000 workers in Spanish companies is used to unveil hidden patterns and relevant factors affecting workers health. Machine learning is used to create a predictive Bayesian model in order to seek out relevant patterns that allow to design more effective prevention plans. The results obtained shed light on the positive impact that an increasing renewable generation of electricity can produce to workers health in the electric industry. Skin problems are the main pathology identified, where nervous system diseases are found to be reduced for renewable generation workers.**

***Index Terms*—Big data, renewable generation, machine learning, bayesian networks, occupational health.**

## I. Introduction

The Kioto Protocol in 1997 supposed an international commitment to reduce greenhouse emissions due to the scientific evidence that a global warming is occurring because of the excessive proportion of $CO_2$ that is being sent into the atmosphere. From that moment on, many countries signing the Kioto Protocol found in renewable energy the solution to mitigate $CO_2$ emissions. As a consequence, during the following years the growth of renewable energy was relentlessly. By 2003, renewable energy had achieved a 13.3% of the world's total primary energy supply increasing at a 1.8% annual rate [1]. In parallel to this, the different renewable energy technologies experience a leap forwards in energy capture [2], despite still having much room for improvement.

In the 2010s, the change of tendency in the energy sector is already a reality. Sweden with a 53.9% had in 2016 more than half of its gross final consumption of energy from renewable sources [3], something only achievable before by countries like Iceland or Norway where environmental awareness is rooted in the culture [4]. Good results, although not that pronounced, were obtained in northern EU Member States such as, Finland (38.7%), Latvia (37.2%) or Austria (33.5%). However, big differences in the implementation of renewable energy technologies can be appreciated between several countries around the world [5]. With the Paris Agreement in 2016 the aim is now to enhance the implementation of renewable resources, having a fossil fuel divestment that creates finance flows connected to low greenhouse gas emissions and climate-resilient development.

Today, according to the International Energy Agency, renewable energy constitutes two-thirds of the new power added to the world's grids [6]. Solar power is currently the fastest growing renewable source in the world, overtaking the net growth in coal. This increase can be found on the new policies undertaken by several countries, especially in China where coal burning is the responsible of the most air pollution deaths [7]. If this trend continues, there is no indication that renewable energy will not overtake during the coming decades fossil fuel and nuclear energy in the total production of energy. The capacity of renewable energy forecasted globally has been revised upwards several times in the last years, having admitted many authorities an underestimation of the speed at which green energy is growing.

Given such circumstance, it is reasonable to think how the expansion of renewable energies might affect energy industries and their employees. One aspect that has been missed by many, and perhaps underemphasized by others, it is the occupational health resulting from the change in the energy policy. Fossil fuel energy has been largely studied at the workplace due to the difficult conditions that frequently involves for workers. Coal and other energetic minerals are collected from the underground in mines and offshore drill holes. The mining industry is together with construction the most dangerous professional activity showing the worst figures of fatal accidents and occupational diseases [8]. The reason why this happens is due to the manifold risks that fossil fuel workers are exposed during the extraction activities and the hazardous contaminants and radiation that might affect their health in the long turn. Conversely, renewable energy brings about a radical change, notably in the way workers carry out their work in the generation of electricity.

As it is shown in Fig. 1, the introduction of renewable generation in the electrical grid involves a complete change in the way electricity is generated, provoking big changes to those workers exercising their functions in power plants. Transport and distribution are not expected to experience such a big transformations, although it must be taken into consideration the inclusion of new workers in occupations related to e-commerce and energy trading.

Therefore, this study aims to address the implications for occupational health due to the expansion of renewable energies in the generation, transport and distribution of electricity. The paper continues as follows: Section II discusses the wider use of Big Data in the smart grid with the

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goal of improve workers conditions. Section III describes the methodology employed to analyze a big dataset with records from medical examinations carried out to workers in the electric power industry in Spain. Section IV shows the results obtained and their implications in order to have a future healthier workforce that also increase the global performance of the companies in the sector. Finally, Section V outlines the main findings of this study and the future work necessary to reach a seamless integration between workers and companies of the electrical industry in the smart era.

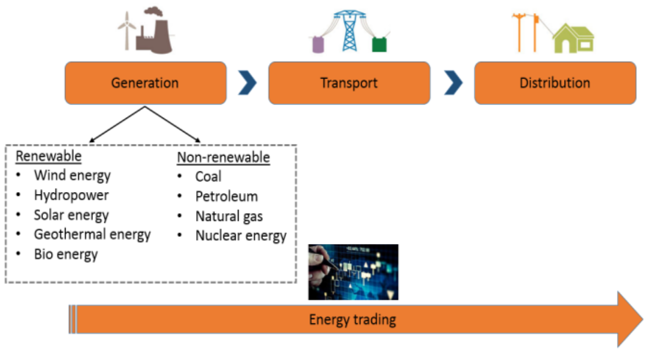


Fig. 1. Layout of the electrical grid where workers exercise their functions.

## II. The Role of Big Data in the Smart Grid

The smart grid is an intelligent electrical grid that makes use of the most recent operational and technological advances to control the generation, transport and distribution of electricity. The consumption of electricity and its real world applications are constantly evolving. As a result, the electrical system is at a final stage of transformation in search for solutions that contribute to create harmony between efficiency, reliability and flexibility.

Big Data and predictive analytics are playing a key role in this transformation. The possibility of introducing Information and Communication Technologies (ICT) to have a real-time control of the electrical networks offers multiple solutions to different problems that not long time ago were complex to solve. In this regard, smart grids improve the quality between producers and consumers at the same time that the new actions implemented guarantee a cost-effective supply of electricity for many people around the world.

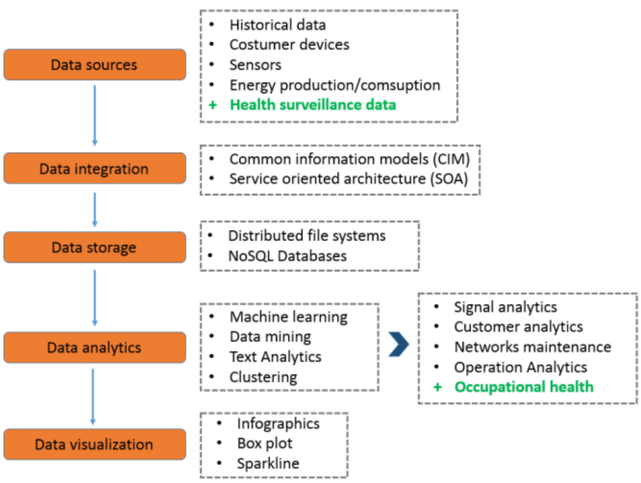


Fig. 2. The life cycle of big data in the smart gird and the future location of occupational health.

Despite these positive advances, the new smart grid architecture will not be completely finished until the industries will improve the work conditions of their employees. The generalization of precarious employment joined to work disorganization it is found to be associated with a deterioration in occupational health and safety [9]. Occupational diseases, injury rates and hazard exposures are a direct cause of losses for companies, which understand now the importance of having a healthy and happy workforce as a means to improve their competitive edge and succeed in the future. The integration of health surveillance data (Fig. 2) in the life cycle of Big Data in the smart grid it is quite straightforward since the smart grid systems have a solid foundation based on modern communication and information structure.

Data analytics will be able to offer relevant insights about the state of health of the workers in the energy industry, just in the same way as important information is obtained from signal or customer analytics nowadays. However, the main obstacle probably will be the corporate commitment to execute these tasks [10]. A fluent transmission and integration of occupational data over the different networks in the smart grid would allow to identify the main drivers for workers' sick leave, allowing to design specific prevention plans to cope with occupational diseases. A satisfactory implementation of occupational health analysis in the smart grid, and in other economic sectors, could improve the quality of public health systems, lengthening workers life free of chronic diseases and reducing costs associated with the frequent duplication of diagnosis tests.

## III. Materials and Methods

### A. Occupational Health Surveillance Data

To carry out this study, a total of 4886 records were collected from medical examinations undertaken to workers in the electric power industry in Spain. These medical tests, which were made during the period 2012-2016, aim to evaluate the employee's medical capability to develop appropriately its work in accordance with the health surveillance program. As it is shown in Table I, the medical records correspond to workers in the different structures of the electric power industry. In a first approach, it can be noticed a slight difference in the mean age. Workers covering the generation process are younger in comparison to transport or distribution. With regard to e-commerce and energy trading workers, they seem to be in between, although this sample counts with significantly less cases.

TABLE I: Database with Health Surveillance Records

| Job Position | Cases | Mean age |
|---|---|---|
| Generation (Renewable) | 899 | 44 |
| Generation (Non-Renewable) | 604 | 45 |
| Transport | 1904 | 46 |
| Distribution | 1438 | 49 |
| E-commerce / Energy Trading | 41 | 46 |
| Total | 4886 | 47 |

The definition of every occupational health surveillance process is related to the medical protocols that try to assess the workplace health risks. Subsequently, these protocols provoke considerable variations in the medical tests depending on the professional activity workers do. To achieve a representative framework of the medical decision making and the workers' health risks, a total of 39 variables have been extracted from the medical records. These variables can be classified in 4 different groups regarding the medical tests undergone: (i) Medical and work history (e.g., age, type of feed); (ii) Physical examination (e.g., blood pressure, hearing exploration); (iii) Specific tests (e.g., spirometry, electrocardiogram); (iv) Blood test (e.g., glucose, cholesterol).

## *B. Machine Learning*

The modeling of occupational health data in this study is performed through the application of machine learning. Within the field of data science, machine learning is a methodology employed to build exploratory and predictive models from the data. Given the complexity and the lack of knowledge about how these 39 medical variables are related, through the application of specific algorithms it is possible to design a predictive model that maximizes the prediction of a target variable. This analytical solution offers multiple possibilities, allowing to make data-driven predictions, at the same time that hidden relationships between the variables are unveiled. Many of the results obtained are frequently unexpected even for experts on the field, leading here to the formulation of new decisions in the field of occupational health supported by trends in the data.

There exist several approaches in computer science to conduct machine learning, such as artificial neural networks, support vector machines or inductive logic programming, among others. However, in this research study Bayesian network modeling represents an attractive option. A Bayesian network is a probabilistic graphical model that reflects the relations of dependency among a set of random variables through a directed acyclic graph (DAG). In other words, if $X=\{X_1, X_2, ..., X_n\}$ constitutes a set of m-dimensional nodes, then a Bayesian network can be mathematically defined as a couplet $X=<Q,P>$, where Q is a directed acyclic graph in which each variable represents one of the nodes $X_n$ and each arc describes a direct dependency relationship between these variables. On the other hand, *P* denotes a set of parameters that quantifies the network, containing the probabilities for each possible value for each variable in the network.

Until not long ago, Bayesian networks were built exclusively manually, where all the probabilistic relationship were stablish by the researcher. However, the introduction of machine learning for building Bayesian networks due to the recent development of Bayesian algorithms that can learn the structure of a network directly from the data opens new opportunities. Given the variables available and their data associated, which constitutes their a priori probability, it is possible to create automatically a predictive model where the only guidance provided is the target node of the machine-learning process. Hence, in terms of machine learning this represents a supervised learning task. For this study, the variable of interest selected is the worker state of health. Understanding how all the variables in the model are related to each other and to the worker state of health would allow to determine important health risks for this sample of workers.

For modeling and computing the Bayesian model, Artificial Intelligence (AI) software BayesiaLab version 7.0.1 [11] was used. This AI package provides a specific environment for machine leaning offering a list of structural learning algorithms based on the Bayesian network paradigm to generate structural models from data. The software orientation has in mind researchers more than computer scientists, something that is reflected in a highly graphical approach which allows to work in a direct way with Bayesian networks using graphs, rather than coding in complex programming languages. This can enable to obtain an easy knowledge acquisition framework of workers health in the electric power industry from occupational health surveillance data.


Fig. 3. Supervised Bayesian network built with ANB algorithm.

## IV. Results and Discussion

### A. Network Structure

The supervised Bayesian model obtained is shown in Fig. 3. This model was built using the algorithm Augmented Na ïve Bayes (ANB). The execution of ANB algorithm involves a double architecture constituted by a Na ïve structure (grey arcs Fig. 3) enriched with the relations between those variables that increase the prediction of the target node (black arcs Fig. 3). The result is a Bayesian model easy to understand with a good balance between prediction accuracy and computing time.

### B. Network Structure

From the model structure it is possible to obtain knowledge about the variables interaction. Those variables in the model linked with black arcs in Fig. 3 have a strong relation of dependence. The ANB algorithm draw those arcs with the highest influence regarding the network complexity. This means that there exist more relations, although those represented are the ones offering more knowledge with regard to the prediction of the target variable (state of health). Therefore, when it comes to stress the relations that might have a greater importance for the state of health of workers in the electric power industry, the following ones should be taken into consideration:

- HDL Cholesterol → {Tryglicerides} and {LDL Cholesterol, Job position}
- Type of feed → Job position {Skin exploration, Neurological Examination}
- Gender → {Weight, BMI} and {Hemoglobin → {Uric acid, Total cholesterol, Glucose}}
- Medicines use → Age {Sleep time, Alcohol use}
- Tobacco use → {Geographic location, Spirometry}
- Systolic blood pressure → Diastolic blood pressure
- Sleep quality → {Sleep ease, Sleep perception}

### C. Bayesian Inference

Some of the patterns obtained show the big differences that can exist in certain health habits depending on trivial variables such as the job position or the age. In this case, the job position has a great influence on the result of skin exploration and neurological examination, which in turn is influenced by the type of feed. Moreover, the HDL and LDL Cholesterol are also related to the job position. In conclusion, for electric power industry workers in Spain the job position plays a key role having a direct influence on the result on possible skin or neurological pathologies. The relation between job position and skin exploration can be easily understood in this work domain, knowing that workers are on a regular basis in touch with wires and cables through which electricity circulates. However, neurological problems are more difficult to discuss here, although the type of feed has always undoubtedly influence. In the next subsection, Bayesian inference is carrying out to shed on this and other issues.

Regarding the distribution sector, this is the most different having a plateau with a similar proportion of workers whose age range from 36 to 65 years old. Surprisingly, this sector is almost immune to the reduction of workers with increasing age. The reasons behind this are difficult to figure out, however, in terms of occupational health can be found interesting remarks.

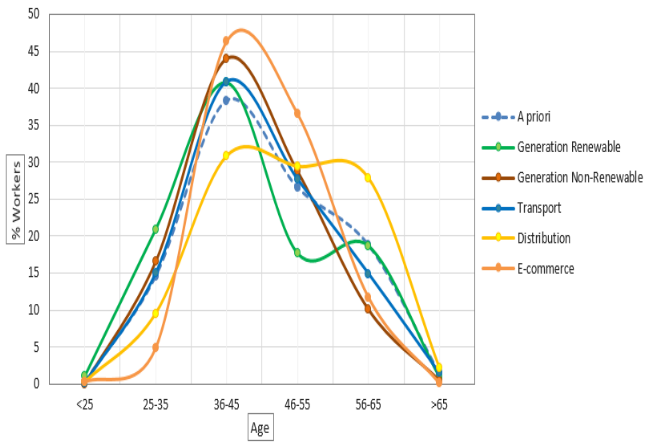


Fig. 4. Probability age profile of workers in the different sectors of the electricity power industry.

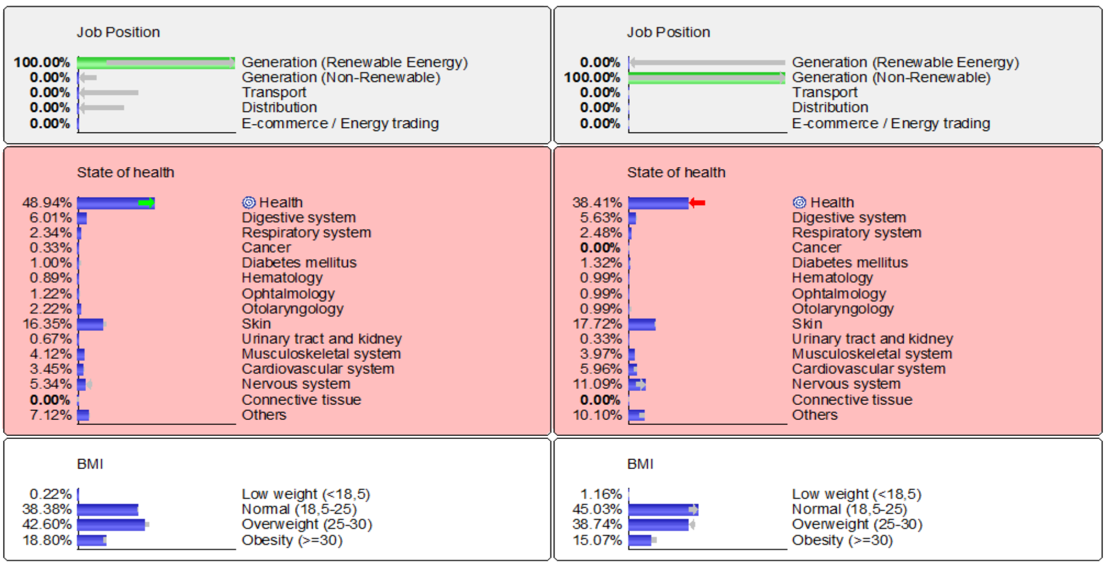


Fig. 5. Inference results for state of health and BMI depending on the workers' job position in the generation sector.

When setting evidence to analyze the workers state of health in the generation sector (Fig. 5), renewable generation has a higher proportion of healthy workers (48.94%) in contrast with non-renewable generation (38.41%). This finding may reflect that renewable generation is also more desirable in terms of occupational health than non-renewable generation. By now, it is still soon to identify which of these diseases have an occupational origin produced by the environmental effects of work tasks. However, these results joined to the fact that renewable generation is free of the harmful effects of coal or radioactivity to the health makes stronger the argument that the introduction of renewable energy could bring a positive change for workers health.

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Another interesting result is the proportion of workers with problems in the nervous systems. Nervous system diseases are with 11.09% the second pathology for workers in the non-renewable generation sector, against the 5.34% of workers in the renewable sector. This is in line with the results obtained by other researchers [12], [13] or Greenpeace [14] who found a correlation between nervous system diseases and coal pollution (non-renewable generation). In common, both share skin problems as the main pathology among their workers. This seems reasonable for workers in the electric power industry.

Lastly, it is necessary to stress the multiple possibilities of analysis that Bayesian modeling offers through machine learning. In Fig. 5, the inference for job position was made with the variables state of health and BMI. The BMI presents similar results either for renewable or non-renewable generation, although should be noticed that more than 50% of workers in these sector have overweight or, even worse, obesity. Apart from this result, the reader can see here the almost countless analytical combinations that this tool offers. It can be easy to get overwhelmed by the alternatives that big data and predictive analytics provide. For this reason, it is necessary to define a strategy and overlook the hype, cutting to what is going to add value.

## V. Conclusion

This study tackles the future occupational health change that smart grid workers are suffering and are expected to suffer in the next years due to the increase of renewable energy production. To analyze this situation, a total of 4886 records were collected from medical examinations undertaken to workers from companies in the electric power industry in Spain. These data were used to build a Bayesian predictive model by using machine learning, so that all the variables analyzed in the medical tests could offer meaningful insights about which are the main factors affecting workers health. As a result, it was found the implication of renewable generation in a higher proportion of healthy workers, in contrast with non-renewable generation. Skin problems are the main pathology among these workers, having nervous system diseases a high incidence on non-renewable generation workers. All this has led to the conclusion that renewable energies can have a positive incidence on workers health, since these new technologies do not generate the contaminants that traditional sources of energy use to do.

Further research is needed to evaluate other factors that are influencing workers state of health and how are they related to different sectors in the electric power industry. It was found a different age profile between the sectors of the electric industry. The knowledge of the health conditions of workers may have a great economic repercussions in the future, since specific and more effective prevention programs could be designed attending to the findings encountered. Finally, it is important to highlight the importance of incorporating occupational health analytics in the life cycle of Big Data in the smart grid. Only a happy and healthy workforce can take clean energy to the next level.

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