



## Estimation of renewable energy and built environment-related variables using neural networks – A review



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### ABSTRACT

This paper presents a review on the application of neural networks for the estimation, forecasting, monitoring, and classification of exogenous environmental variables that affect the performance, salubrity, and security of cities, buildings, and infrastructures. The forecast of these variables allows to explore renewable energy and water resources, to prevent potentially hazardous construction locations, and to find the healthiest places, thus promoting a more sustainable future. Five research themes are covered—solar, atmospheric, hydrologic, geologic, and climate change. The solar section comprises solar radiation, direct and diffuse radiation, infrared and ultraviolet radiation, clearness index, and sky luminance and luminous efficacy. The atmospheric section reviews wind, temperature, humidity, cloud classification, and storm prediction. The hydrologic section focuses on precipitation, rainfall-runoff, hail, snow, drought, flood, tides, water levels, and other variables. The geologic section covers works on landslides, earthquakes, liquefaction, erosion, soil classification, soil mechanics, and other properties. Finally, climate change forecasting and downscaling of climate models are reviewed. This work demonstrates the wide range of applications of these methods in different research fields. Some research gaps and interdisciplinary research opportunities are identified for future development of comprehensive forecast and evaluation approaches regarding the estimation of renewable energy and built environment-related variables.

### 1. Introduction

This paper presents a review on the application of neural networks for the estimation, forecasting, monitoring, and classification of renewable energy and other environment-related variables that affect the built environment. Contrarily to other reviews on these methods, the purpose of this work was not to complete an in-depth literature review of a particular application topic (e.g. HVAC systems, building energy consumption, or solar radiation) but rather to carry out a transversal review on their application in different fields that are relevant to a sustainable built environment. The main purpose of this approach is to interrelate topics that are naturally connected, such as solar and atmospheric, or hydrologic and geologic, but that are typically addressed in literature as isolated subjects.

Besides the estimation of energy-related variables allowing to plan and explore renewable energy resources—i.e., by predicting the solar potential of a region, prevailing winds and speed, stream flows, reservoir levels, tide levels, biomass distribution on land, and geothermal potential—and the forecast of water-related variables that allow to manage the water resources—i.e., by estimating future precipitation,

reservoir levels, groundwater levels, snow depth and land cover, and droughts—, a sustainable built environment is dependent, among other factors, on guaranteeing the safety and quality of the natural resources and land use. Therefore, other environment-related variables were also covered, such as the occurrence of storms and their severity, flash floods, seashore water levels, water quality (sediments concentration and salinity levels), stability of soils (landslide susceptibility, liquefaction of soils, subsurface cavities, soil mechanics), soil erosion process estimation, soil classification, and determination of organic matter.

Some variables have an impact on the sustainability of the built environment and should not be analyzed autonomously. For instance, estimating the solar radiation on buildings surfaces and simultaneously predicting cloud cover and classification allows an accurate dimensioning of renewable solar devices (i.e., photovoltaics and thermal collectors) and the development of smart energy management systems. Whenever wind speed and direction profiles are added to the estimation process, hybrid systems can be considered as well. The accurate prediction of sky clearness and luminance allows the satisfaction of indoor visual comfort in buildings, thus reducing the consumption of electric energy by artificial lighting. Other atmospheric variables, such as

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ambient temperature and relative humidity, have impact on the thermal comfort in buildings, thus their accurate forecast may help in designing more energy efficient buildings and managing renewable energy according to the occurrence of heat waves or other extreme weather events. Additionally, the prediction of future climate change scenarios allows the design of more robust buildings and cities. Therefore, the objectives of this study were: to analyze and review the most important works that cover a wide range of environment-related variables that are exogenous to the built-environment but affect the performance, safety, and salubrity of cities, buildings, energy systems and infrastructures; to identify future opportunities and gaps for interdisciplinary research for the development of comprehensive forecast and evaluation approaches that take into account the various inter-related elements of the environment.

As expected, the number of articles published is vast. For this reason, a document selection methodology was used. The first step entailed the exhaustive collection of papers published in international journals and/or conference proceedings. From these, a total of 1658 documents (including review papers) were selected and classified into distinct groups according to the learning algorithm output variables. For each document, the number of citations was determined and in each group the documents were ranked by citations. The articles with the highest number of citations published after 1999 were selected.

After this introductory section, the Section 2 section provides the reader with the basic information on the modeling, terminology, and estimation accuracy indicators of the models. In the Section 3 section, five main themes are analyzed. The first four themes are related to solar (covers 14% of total documents), atmospheric (14%), hydrologic (53%), and geologic (17%) problems. The fifth is related to the forecast of climate changes (2%). Each theme is divided into groups according to the estimated variables. The number of documents and percentage per group are listed in Table 1. Evidently, some groups emerge as the main research topic within each theme, such as solar radiation, wind speed, precipitation and runoff, and soil mechanics for solar, atmospheric, hydrologic, and geologic-related themes, respectively. Even though the topic division may seem clearly delineated, assigning some of the groups within each theme was not as easy, as their boundaries are not clearly defined (e.g. should precipitation prediction be included in the hydrologic or the atmospheric subsection?). Ultimately, the documents were assigned according to the estimated phenomena. Lastly, a discussion on the articles analyzed is presented, followed by the conclusions.

## 2. Neural network

Since the 1950s, when Turing [1] idealized that machines could learn, learning algorithms have been developed and applied in several problems. One of those is the artificial neural network, which consists of interconnected units called neurons, nodes, or perceptrons [2]. The perceptrons were formulated by Rosenblatt [3] as being capable of containing information in the *connections* and, therefore, possess the capability to memorize and recognize patterns. In a network, the neuron has as input the output values of the preceding neurons. The incoming weighted values are summed and an activation function is applied to the total—logistic sigmoid, hyperbolic tangent, tan-sigmoid, wavelet, Gaussian, softmax, threshold, and identity functions, just to mention a few—to limit the amplitude of the neuron output.

There are several types of neural networks [4]. For instance, the simplest one is the linear network (LN), which comprises just two layers for input and output variables, or more complex and popular multi-layer perceptron network (MLP), which may have one or more hidden layers with different number of neurons. The selection of the activation function depends on the kind of modeling data and scale of values.

However, for the neural network to work properly, the network weights must be optimized. This process is called calibration or training. Two of the most common training algorithms are the standard

**Table 1**  
Number of documents per group.

|                                         | n   | %      |
|-----------------------------------------|-----|--------|
| <b>Solar-related</b>                    | 218 | 13.81% |
| Solar radiation                         | 173 | 79.36% |
| Solar radiation on tilted surface       | 11  | 5.05%  |
| Direct and diffuse radiation            | 18  | 8.26%  |
| Infrared and ultraviolet radiation      | 8   | 3.67%  |
| Clearness index                         | 6   | 2.75%  |
| Sky luminance                           | 2   | 0.92%  |
| Luminous efficacy                       | 1   | 0.46%  |
| <b>Atmospheric-related</b>              | 223 | 14.12% |
| Wind speed                              | 122 | 54.71% |
| Wind speed profile                      | 3   | 1.35%  |
| Wind direction                          | 7   | 3.14%  |
| Dry bulb temperature                    | 33  | 14.80% |
| Wet-bulb temperature                    | 3   | 1.35%  |
| Dew point temperature                   | 4   | 1.79%  |
| Relative humidity                       | 3   | 1.35%  |
| Water vapor and cloud liquid water path | 1   | 0.45%  |
| Cloud classification                    | 30  | 13.45% |
| Fog prediction                          | 7   | 3.14%  |
| Thunderstorm prediction                 | 10  | 4.48%  |
| <b>Hydrologic-related</b>               | 830 | 52.56% |
| Precipitation                           | 191 | 23.01% |
| Rainfall-runoff                         | 148 | 17.83% |
| Hail                                    | 3   | 0.36%  |
| Snowfall                                | 7   | 0.84%  |
| Snow cover                              | 11  | 1.33%  |
| Snow depth and snow water equivalent    | 13  | 1.57%  |
| Evapotranspiration                      | 79  | 9.52%  |
| Drought severity index                  | 25  | 3.01%  |
| River flow                              | 82  | 9.88%  |
| Flood                                   | 59  | 7.11%  |
| Wave height                             | 7   | 0.84%  |
| Tide level                              | 27  | 3.25%  |
| Groundwater level                       | 64  | 7.71%  |
| Lake level                              | 16  | 1.93%  |
| Reservoir inflow                        | 36  | 4.34%  |
| Sediments concentration                 | 54  | 6.51%  |
| Salinity                                | 4   | 0.48%  |
| Water temperature                       | 4   | 0.48%  |
| <b>Geologic-related</b>                 | 272 | 17.23% |
| Landslide susceptibility                | 35  | 12.87% |
| Earthquake classification               | 58  | 21.32% |
| Liquefaction prediction                 | 31  | 11.40% |
| Erosion estimation                      | 3   | 1.10%  |
| Soil classification                     | 4   | 1.47%  |
| Subsurface cavities                     | 9   | 3.31%  |
| Soil mechanics                          | 74  | 27.21% |
| Soil organic matter                     | 4   | 1.47%  |
| Soil organic carbon                     | 2   | 0.74%  |
| Ground temperature                      | 5   | 1.84%  |
| Thermal resistivity                     | 2   | 0.74%  |
| Thermal conductivity                    | 1   | 0.37%  |
| Electric resistivity                    | 7   | 2.57%  |
| Hydraulic properties                    | 37  | 13.60% |
| <b>Climate change</b>                   | 36  | 2.28%  |

n – number of documents; % – group percentage

back-propagation [5] and the Levenberg-Marquardt [6], which change the network weights in the direction of minimizing the differences between the model's predicted values and the aimed values. Recently, population-based evolutionary algorithms have also been used, such as genetic algorithms (GA), differential evolution, and particle swarm optimization (PSO) techniques. After the training phase, the models must be validated and tested against unseen data—usually a part of the original dataset. To assess their accuracy, statistical performance indicators are used. However, different analysis is required depending on the type of model, whether it is a regression—it fits a set of estimated values with observed ones—or if it is a classification

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