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# Applying Climate Big-Data to Analysis of the Correlation between Regional Wind Speed and Wind Energy Generation

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***Abstract*—In an era of growing concern over climate change, several utility companies originally supplied wholesale and retail power mainly made by burning coal, have started to consider and build the clean-energy power systems for resolving global warming problems. Wind power is nowadays regarded as one of the predominant alternative sources of clean energy. In this paper, we discuss our work on utilizing climate big-data associated with wind power, collected from several wind farms over four years, for exploring the correlation between regional wind speed and wind power. Once this huge amount of data are analyzed, it can be used to develop policies for siting wind-power facilities, designing smart charging algorithms, or evaluating the capacity of electrical distribution systems to meet the actual requirement of power load. Our work started with collecting related climate data for building data model to perform analytics work and experiments using Support Vector Regression (SVR) method. Also, we observed the correlations between other factors related to wind speed and wind energy from our empirical model. The preliminary experimental results demonstrate that our developed system framework is workable, allowing for detailed analysis of the important wind-power related factors on specific wind farm regions.**

***Keywords—Wind speed, Wind power, Wind farm, Weather data, Support Vector Regression, Machine Learning***

## I. INTRODUCTION

Over the past years, the global average temperature has increased and continued to rise in the future. Global warming problem is mainly due to greenhouse gas emissions from the burning of fossil fuels. The use of clean energy power source to respond to the global warming pressure regarding fossil fuel dependency poses questions regarding their impacts on the power load forecasting but also on the environment. Wind power is nowadays one of the predominant alternative sources of energy, representing about 10%-15% of the energy consumption in many countries. Among many issues associated with the development of wind power, wind speed is regarded as a key factor of wind power. This is due to the problem that wind power generation is the continuous fluctuations of the wind speed. Such challenges make it difficult to predict the power which will be injected in the distribution network. This often causes difficulties in the energy transportation. Therefore, a solution for analyzing the wind power and provide an appropriate estimation of the produced power is very critical for the management of wind farms. In general, in wind farms, the forecast of produced power is estimated from the prediction of wind speed in the turbines of the farm. In other words, ideally, it is predictable that if a wind farm is located in some area, the area should be of stronger wind speed. The analysis of wind speed situation can be usually performed with the data of measuring devices, or data collected by some open data sources. Data analytics is expected to become more important once considering renewable energy generators with suitable locations to determine which scenario should be employed for the specific geographical location. Big data, by name denotes the data sets that are too "big" to be handled using the existing database tools and methods. The existence of big data has been aware by people since long time ago, but few application systems can access it until recent years. Big data analytics have proved to be useful for many power system applications in a variety of ways such as load forecasting, demand response, wind speed prediction, siting wind turbines based upon spatio-temporal analysis, and so on. A significant number of research efforts have been given to forecasting wind power. The view is taken, therefore in this work we focus the paper on the discussion of the application of the big data analytics approach to a real problem of analyzing wind speed in wind farms. In this work, we took the wind farms in Taiwan as a case study. According to climate data from different areas and the wind energy data collected from various wind farms, we used the support vector regression (SVR) method to analyze the correlation between regional wind speed and wind power by means of big data analytics techniques.

The rest of the paper is organized as follows. In Section II, we provide a brief review of wind power, and SVR. In Section III, we describe the factors and data sources which we chose. Section IV shows our experiment and analysis; Result and conclusion for future work are given in Section V.

## II. RELATED WORK

In recent years, National Renewable Energy Laboratory (NREL) in American developed a series of techniques about wind turbine blades and generator motors[1, 2, 3]. The research work [4, 5, 6] proposed a number of approaches regarding the ways of adding wind turbines to the existing power system, can improve stability in complex systems, reliability assessment and power management.

Kavasseri [7] created a model to forecast wind speeds on the day-ahead and two-day-ahead horizons. According to the forecast of wind speeds and combining power curve of the

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turbine, they get the wind power prediction. Ji et al [8] presented a predictive method by SVR and forecasting error estimation. The result can get the wind speed forecasting accurately in accordance with the estimated forecasting error. The method obviously reduces the mean square error and means absolute percentage error. In same way, Salcedo-Sanz et al [9] predicted wind speed by SVR. They put Evolutionary Programming and Particle Swarm Optimization into predictive system. This method obtained good result in the prediction of Spanish wind farm. In the same place, Torres [10] proposed a prediction method by means of Autoregressive Moving Average process (ARMA) and persistence models. In the longer-term forecasts, they found the ARMA models better than persistence models. Mohandes [11] presented a predictive method by neural networks techniques. They compared neural networks techniques with autoregressive model for evaluation. The result indicates that performance between neural networks technique and autoregressive model analysis for mean speed values is equally matched.

Hansen [12] mentioned that Taiwan is an island of monsoon climate type. The wind speed more than 5 meters per second appears in many areas. The wind speeds of Penghu, Orchid Island and other outlying islands, west coast, Hengchun Peninsula, northeast corner are of great potentials for wind power generation in the area. Louka [13] presented a post-processing method of wind speed prediction by Kalman filtering algorithm. Barbounis [14] employed three types of local recurrent neural networks, including infinite impulse response multilayer perceptron (IIR-MLP), local activation feedback multilayer network (LAF-MLN), and diagonal recurrent neural network (RNN), to develop their long-term wind speed and power forecasting method based on meteorological data. Simulation results shown that the recurrent models outperform the static ones in terms of forecast errors and the improvement gained over the persistent method. Damousis [15] focused on forecasting wind speed and electrical power by Takagi-Sugeno-Kang (TSK) fuzzy model at a wind park. The model was trained using a genetic algorithm-based learning algorithm. The training dataset includes wind speed and direction data, measured at neighboring meteorological stations at a radius up to 30 km.

## III. FACTORS AND DATA SOURCES

Wind is generated by difference in the air pressure. When a difference in air pressure exists, air moves from higher to lower pressure, lead to winds of various speeds.

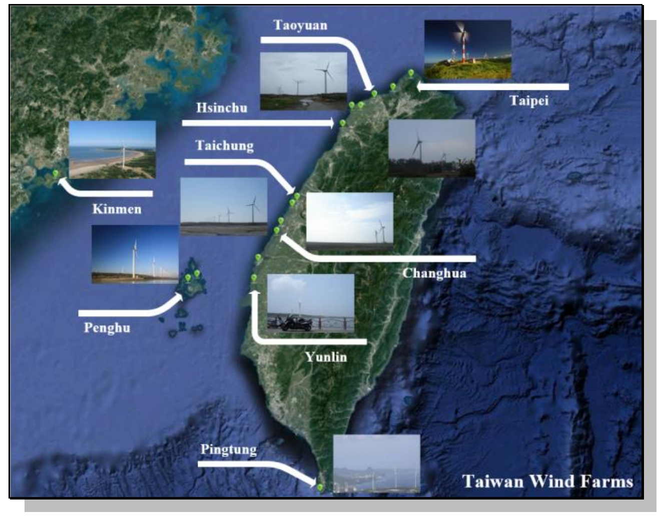


Figure 1. The location of wind farms in Taiwan

When the air velocity is higher, the kinetic energy is greater. The wind turbine converts the kinetic energy of the wind into useful electric power through the transmission shaft. Thus, wind speed is considered as a key factor to wind power. Fig 1. illustrates the wind-farm location in Taiwan.

The system framework is shown in Fig. 2. In this work we particularly investigate the impact of regional wind speed on wind power. We collected the weather data from the weather stations near the wind farm areas in Taiwan, and the wind power data were collected from Taiwan Power Company. Subsequently, we employed the data of wind speed to analyze the correlative between wind speed and wind power. Also, we reserved other climate datasets from the weather stations to further analyze the correlation between other related factors.

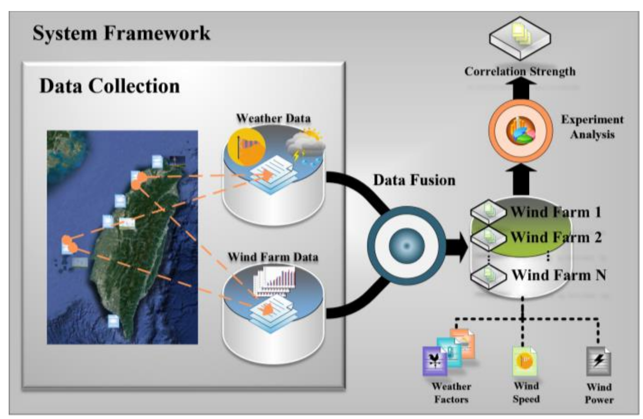


Figure 2. System Framework

## IV. EXPERIMENTS AND ANALYSIS

In this section, we divided the experiment into two parts. In the first part, we analyzed the correlation between wind speed and wind power. In the second part, we analyzed the correlation between other climate factors. Fig. 3 illustrated the data model developed for the experiments.

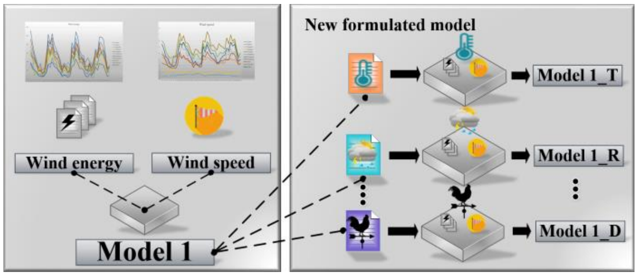

Figure 3. Model Formulation

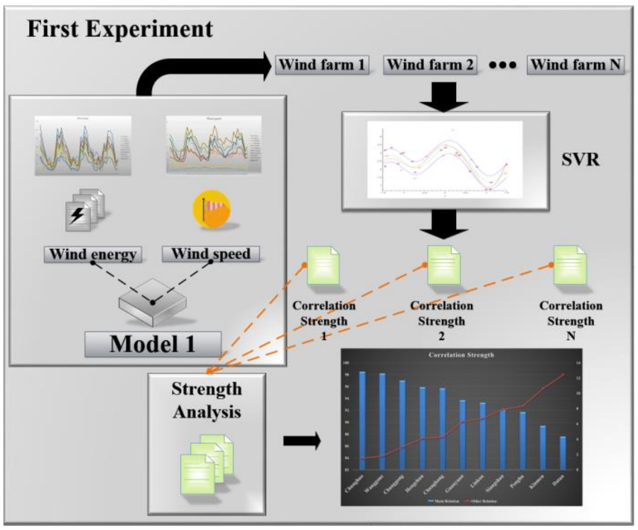

Figure 4. Experimentation (I)

First, we used the squared correlation coefficient of SVR to compute the correlation strength of wind speed and wind energy in different wind farms. The first experimentation is illustrated in Fig. 4.

After that, by comparing the strength of correlation we obtained experimental result of analyzed regional difference. Furthermore, we explored the influence of climate factors on wind power. As a result, in the second experiment, we randomly selected four wind farms from previous test for experimentation to validate our framework model. Experimenting with various climate factors including temperature, humidity, rainfall, and wind direction, we performed second experiment to discover possible climate impacts on wind power.

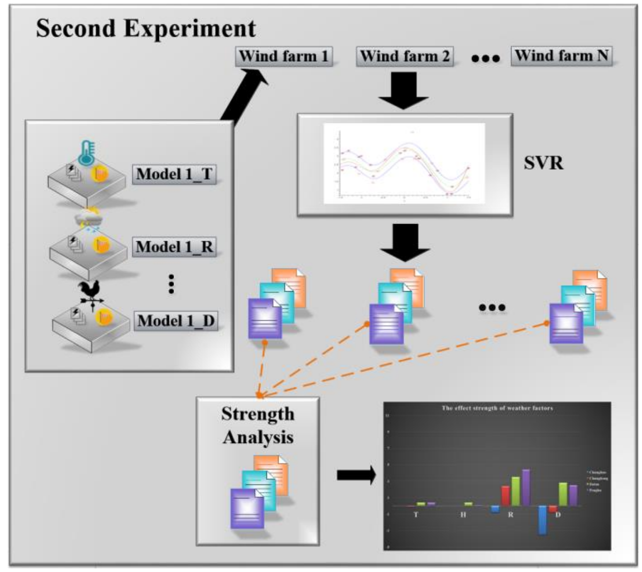

Figure 5. Experimentation (II)

## V. Results and Conclusion

### A. *Results of experiments*

In the first experiment, we used the collected data of wind energy and wind speed to create a data model (i.e. model 1). We took data collected from selected wind farms to perform Support Vector Regression (SVR) experiments. Based on the experimental result, we carried out analytics work for obtaining correlation strength of wind speed and wind energy factors among selected wind farms. The experimental results are significantly different, as shown in Table I. Table I indicated the degree of correlation between regional wind speed and the level of energy among selected wind farms. The result is illustrated in Fig. 6.

Table I.
The Correlation Strength AMONG Wind Farms.

| Wind Farm | Correlation Strength (%) | 1 - Correlation Strength (%) |
|---|---|---|
| **Chunghuo** | 98.5 | 1.5 |
| **Wanggone** | 98.2 | 1.8 |
| **Changgong** | 97.0 | 3.0 |
| **Hengchun** | 95.9 | 4.1 |
| **Chungkong** | 95.7 | 4.3 |
| **Guanyuan** | 93.7 | 6.3 |
| **Linkou** | 93.3 | 6.7 |
| **Siangshan** | 92.1 | 7.9 |
| **Penghu** | 91.7 | 8.3 |
| **Kinmen** | 89.4 | 10.6 |
| **Datan** | 87.6 | 12.4 |

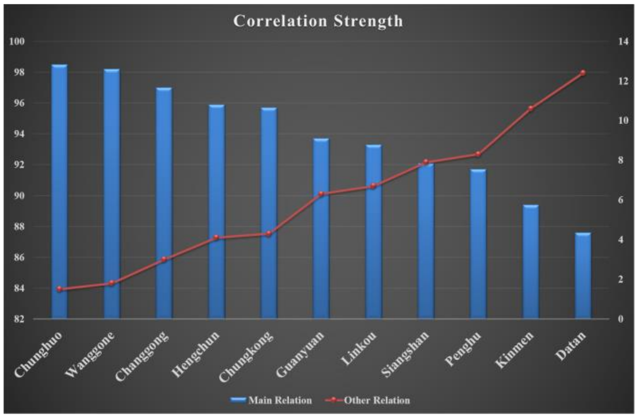


Figure 6. Experimental Result (I)

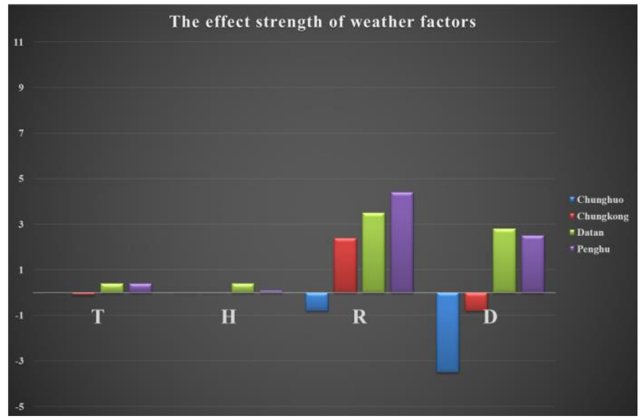


Figure 7. Experimental Result (II)

In the second experiment, we used the same model in first experiment and further experimented with dataset of four wind farms randomly selected from the first experimental wind farms. We separated the selected climatic factors, and combine alone with the data model from first experiment. We carried out our analytics work for obtaining correlation strength using same technique employed in the first experiment. The experimental result is shown in Table II, where Model 1 is the model used in the first experiment. Model 1_T represents the original Model 1 with a joint variable **temperature**, Model 1_H represents the original Model 1 with a joint variable **humidity**, Model 1_R represents the original Model 1 with a joint variable **rainfall**, and Model 1_D represents the original Model 1 with a joint variable **wind direction**.

Table II.
CORRELATION STRENGTH OF WEATHER FACTORS AMONG WIND FARMS.

| Wind Farm | Correlation Strength (%) | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 1_T | Model 1_H | Model 1_R | Model 1_D |
| **Chunghuo** | 98.5 | 98.5 | 98.5 | 97.7 | 95.0 |
| **Chungkong** | 95.7 | 95.6 | 95.7 | 98.1 | 94.9 |
| **Datan** | 87.6 | 88.0 | 88.0 | 91.1 | 90.4 |
| **Penghu** | 91.7 | 92.1 | 91.8 | 96.1 | 94.2 |

Table III indicates the difference among the factors. Additionally, the regional difference among wind farms can be found in Fig. 5

Table III.
DIFFERENCE OF CORRELATION STRENGTH AMONG CLIMATIC FACTORS.

| Wind Farm | Difference of Correlation Strength (%) | | | |
|---|---|---|---|---|
| | Model 1_T | Model 1_H | Model 1_R | Model 1_D |
| **Chunghuo** | 0 | 0 | -0.8 | -3.5 |
| **Chungkong** | -0.1 | 0 | 2.4 | -0.8 |
| **Datan** | 0.4 | 0.4 | 3.5 | 2.8 |
| **Penghu** | 0.4 | 0.1 | 4.4 | 2.5 |

## B. *Conclusion*

In this paper, we analyzed the correlation between regional wind speed and wind power by experimenting with Support Vector Regression technique. Our work started with collecting related climate data for building data model to perform analytics work and experiments using Support Vector Regression (SVR) method. Also, we observed the correlations between other factors related to wind speed and wind energy from our empirical model. The preliminary experimental results demonstrate that our developed system framework is workable, allowing for detailed analysis of the important wind-power related factors on specific wind farm regions.

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