

# Reliability of Electric Vehicle with Wind Turbine Based on Particle Swarm Optimization

Xinyu Feng, Xijing Zhu, Wei Zhao, Xiangmeng Li

School of Mechanical Engineering ,North University of China,Taiyuan 030051, China  
[xinyufeng37192@126.com](mailto:xinyufeng37192@126.com)

This paper aims to study the reliability of electric vehicles with wind turbine, including analysis on its usage and faults possibly occurred, via this approach, the leading causes that induce these faults are identified. On this basis, a Particle Swarm Optimization (PSO) is cited to conduct an in-depth study on the reliability of electric vehicles with wind turbine in an attempt to provide an important evidence for future improvement in terms of its operation safety, etc. This study bears out such fruits that the factors affecting its reliability are the power distribution network containing wind power generator, and the output utility of wind turbine has not been fully utilized. There is lack of analysis on the structural characteristics of power distribution networks. It turns out that the PWO algorithm can help quickly grasp the root that affects the reliability of electric vehicles with wind turbine. This study indeed has a high popularization and application value.

## 1. Introduction

Since the 1940s, the tide of structural reliability study has surged from electronic components. With the dramatic development of social economy, the studies of reliability have borne mature fruits. After 20 ~30 years of development, some studies started to involve the structure reliability which refers to, under given environment and conditions, the capacity that structure itself is subjected to the environment and load in a given use process. The study in this regard has very important significance for improving the capacity of predetermined functions. At the present stage, the application of structural reliability has become rather extensive, including electric vehicles with wind turbine. In the process of practical application, structural reliability involves more fields, such as fatigue fracture, reliability optimization, power, reliability analysis and structural life prediction. As the structural reliability has extended its application, many problems occur and seem more complex than those of electronic components. Throughout the current implementation, available data is not complete enough for structural reliability analysis.

Under an environment where the penetration of electric vehicles with wind turbine is increasing, both the volatility of the wind power output of the electric vehicles and the charging randomness have a direct bearing on the safety and economy of the whole power grid operation. There is a good physical foundation for mutual absorption between electric vehicles and wind power generator. In view of this, the V2G technology introduced hereof can make it more possible to coordinate and optimize the two. On this basis, it is imperative to probe into its reliability.

## 2. Literature review

Since the invention of modern vehicles by German Carle Benz 100 years ago, the automobile industry has been developing rapidly. Now vehicles are closely related to people's daily life. At present, according to statistical analysis, the total volume of global vehicle ownership has exceeded 1.2 billion, and it is still increasing rapidly with tens of millions of vehicles every year. By 2020, the total volume of vehicles in the world is expected to reach more than 1.5 billion.

With the increasing demand for energy and the gradual exhaustion of fossil fuel resources, as well as the increasingly prominent environmental problems, wind power generation, one of the most economic development prospects of renewable energy, has attracted more and more people's favor and attention.

Feijóo and Villanueva divided traditional power system scheduling problem into two kinds: static scheduling and dynamic scheduling. Dynamic scheduling considered the coupling of different time sections. It referred to considering the difference of each unit through the load forecasting results of several time periods in the future, and formulated the output planning of each unit according to a certain scheduling target. It is an optimization problem with double coupling in time and space (Feijóo and Villanueva, 2017). Although the time coupling constraints such as the output power change rate to be considered in dynamic scheduling will lead to the complexity of the problem, the calculation results of dynamic scheduling are more in line with the actual requirements. With the rapid development of the economy, the demand for energy increases significantly, and the environmental problems caused by energy consumption are also gradually emerging. Godoy studied wind power generation and used wind energy as a renewable clean energy instead of conventional energy represented by fossil fuels. It played a prominent role in reducing environmental pollution, adjusting energy structure and reducing the cost of long-term power generation (Godoy, 2018). While wind power brings a lot of benefits, it will also bring a lot of adverse effects, especially when the scale of wind power installed to a certain value may seriously affect the safe and stable operation of the power system, which will seriously restrict the development of wind power. Therefore, it is very important to study the impact of wind power integration on power system. One of the research directions is the dynamic economic dispatch of power system with wind farms. James and others considered the power of wind power as a random variable, and its impact on the system was more reflected in the span of time. It should be more dynamic to study the scheduling problem of power system with wind power (James et al., 2017).

Through studying the power system in addition to conventional energy resources such as thermal power and hydroelectric power, Lund increasingly accepted the integration of new energy sources such as wind power (Lund, 2017). As a renewable clean energy, wind energy does not require any fuel cost except the necessary investment and maintenance costs. Compared with thermal power, it can bring more long-term environmental and economic benefits to the dynamic economic dispatch of the power system. However, Masaud and so on pointed out that, different from traditional generation mode, the wind power output depended on the size of the wind speed. Although the wind speed prediction technology was developing, it was far less than the prediction precision of the load (Masaud et al., 2017). As a kind of green energy, wind power can save fuel cost and benefit environmental protection by replacing some of the capacity of thermal power units. Compared with the thermal power and hydropower output in the traditional power system, the randomness and volatility of wind speed will result in the unpredictable and uncontrollable characteristics of the wind power output. Poudel and others stated that these problems would not have a great impact on the power system. But with the large increase of wind power grid size, this energy randomness would bring serious security risks to the operation of the system (Poudel et al., 2017). Therefore, it is urgent to study the impact of wind farm integration on power system dispatching, and establish an optimal scheduling model according to the characteristics of wind power. In the traditional automobile field, the development level of automobile technology in China is relatively backward than that in developed countries such as Europe and the United States. But as far as electric vehicles are concerned, the gap between China's automobile technology level and industrialization level is relatively small. In recent years, there are some accumulation of related research and development of electric vehicles in China. Radha Krishna and Biswal pointed out that, on the one hand, seizing the opportunity and actively promoting the development of electric vehicles make China catch up with Europe and the United States and other automobile powers in electric vehicles. On the one hand, it could also improve the scientific research and innovation ability of China's vehicle industry and enhance international status and international competitiveness (Radha Krishna and Biswal, 2016).

With the continuous development of the traditional automobile industry, its dependence on energy and pollution to the environment has become a prominent social problem. Because of its prominent advantages of energy saving and environmental protection, electric vehicles have become the focus of research in the automotive field, representing the development trend of automobiles in the future. The control system is the core part of the electric vehicle drive motor, and its performance determines the dynamic performance of the electric vehicle. Safdar and others selected the permanent magnet brushless DC motor as the driving motor of the electric vehicle, and established the mathematical model of the brushless DC motor system and the dynamic model of the electric vehicle (Safdar et al., 2017). The double closed loop control method was used to analyze the causes of torque ripple of Brushless DC motor, and the hysteresis loop method was adopted to solve the problem. The signal detection method of two kinds of Brushless DC motor with position sensor and sensorless sensor was given. In combination with the characteristics of electric vehicle, the signal detection method with position sensor was selected.

To sum up, in the above research work, the electric vehicle is mainly studied. The concept of particle algorithm is used to carry on the omni-directional analysis of the wind power vehicle, and further research through the DC motor system, the related mathematical model, and the related concepts of dynamics. Therefore, based on the above situation, the reliability research of the wind power electric vehicle is focused on based on

particle swarm optimization (PSO), which does not have a great impact on the power system when the scale of the wind loading machine occupies a relatively small proportion of the total installed capacity. However, with the large increase in the scale of the wind power grid, the energy randomness will bring serious security risks to the dispatching operation of the system. Therefore, it is urgent to study the impact of wind farm integration on power system dispatching, and establish an optimal scheduling model according to the characteristics of wind power.

### 3. Method

Combined with the National Natural Science Foundation of China, this paper analyzes structural probability, non-probability, hybrid reliability and optimization design with the PSO algorithm. It outlines as follows: in Chapter 3, in virtue of advantages that the Support Vector Machines (SVM) deal with small sample learning and prediction, SVM regression is used as a reconstruction tool for structural implicit limit state equations. Combined with the interval analysis in the first-order second-moment method and the non-probabilistic set theory, the structural probability and non-probabilistic reliability analysis based on the SVM are proposed. Integrated with the Intelligent Single Particle Optimizer (ISPO) and the hybrid reliability model, a hybrid reliability optimization comes out based on the ISPO. See Figure 1 for a column diagram of the augmented and cumulated newly installed in 2008-2013. In 2015, the National Development and Reform Commission (NDRC) issued the "China Wind Power Development Roadmap 2050" and led to the future direction and goals for wind power generation: it is projected that the capacity of total wind turbines installed will reach 20, 40, and 1 billion kw by 2020, 2030, and 2050, respectively.

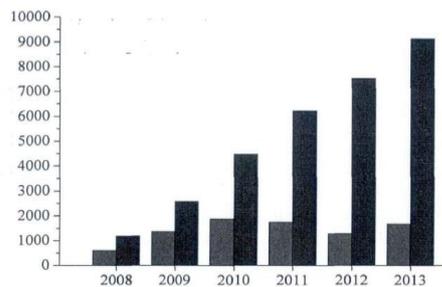


Figure 1: New and accumulated installed capacity of China's wind power from 2008 to 2013

## 4. Results and analysis

### 4.1 PSO algorithm

In the PSO algorithm, each particle represents a solution in the D-dimensional space, then the state of the particle  $i$ ,  $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ ; the velocity vector of each particle is  $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ . Each particle has experienced an optimal state  $P_{best} = (P_{i1}, p_{i1}, a, p_{i1})$ , the group experiences the optimal state  $P_{best} = (p_{g1}, p_{g1}, \dots, p_{gD})$ . The whole particle swarm updates its velocity and position by tracking individual extremum and population extremum, and seeks the optimal solution in the solution space. The basic PSO algorithm reflects a topology known as an asteroid domain, where each particle can communicate with other particles surrounding it to form a seamlessly connected network, as shown in Figure 2.

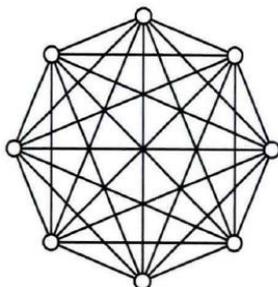


Figure 2: Star domain topology

#### 4.2. Reliability analysis method

To perform structural reliability analysis, first we determine the random variables that affect the structural reliability on several fronts such as geometric composition, material properties, service environment, and load conditions of structure, and define statistical properties of each random variable according to physical truth of the structure, such as mean and standard deviation, as well as relevant distribution types, etc. The failure modes of the structure depend on its failure types. The relationship between each random variable and the structural system response is defined by the finite element method, motion simulation, etc. Then the structural reliability modeling is performed by means of probabilistic analysis, and the statistical properties of each random variable are transferred to the structural system response, thus obtaining the structure reliability or reliability index. Structure reliability analysis can be divided into two types, i.e. the direct analysis methods, which also includes the approximate analysis and digital simulation, and indirect analysis method. As shown in Table 1, the reliability analysis of each structural system in an electric vehicle with wind turbine is given.

Table 1: Reliability analysis of structural systems

| The subsystem    | i     | 1    | 2    | 3    | 4   | 5    |
|------------------|-------|------|------|------|-----|------|
| Unit reliability | $P_1$ | 0.96 | 0.93 | 0.85 | 0.8 | 0.75 |
| The unit price   | $C_1$ | 3    | 12   | 8    | 5   | 10   |

The above PSO algorithm can solve the problem with relevant parameters as follows: experiment environment: PC,PIV1.7GH: CPU,256MRAM,WindowsXP, the simulation software is Madab6.5; parameter settings: the population size is 20, the max evolution algebra is set to 100, and the acceleration is constant. An adaptive PSO algorithm is adopted herein, and the weight  $w$  linearly decreases from 0.9 to 0.4. The algorithm runs randomly for 50 times and the actual optimal solution found is (2,2,2,3,2). At this time, the system reliability is 0.90317, and the total cost is RBM 81.

#### 4.3 Reliability optimization method

At present, the structural reliability optimization is usually solved by Lagrang multiplier method, penalty function method, complex shape method, best vector type method, gradient projection type algorithm, and the like. Among them, the best vector type method is a heuristic optimization algorithm, which uses a gradient step and the best vector step along the negative gradient direction of the objective function to approximate to optimal solution, especially for the constraint optimization problem of the linear objective function, it has a higher convergence precision and computational efficiency. Here describes how to solve the problem of minimizing the structural mass under the constraint of structural reliability using the best vector type method. Refer to Figure 3, set the initial design point at 4), move the design point to the constraint boundary along the negative gradient of the objective function, then to 4 along the optimal vector direction (direction D in Figure 3), and to the constraint boundary in the direction of the negative gradient of the objective function, repeat the above procedures to approximate to the optimal solution.

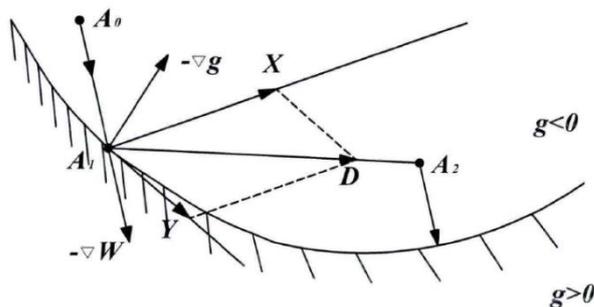


Figure 3: Optimal vector direction

Table 2 is the results that the PSO algorithm and other algorithms run randomly for 50 times. As shown in Table, in the process of random operations for 50 times, the reliability optimization algorithm proposed herein based on particle swarm can find the optimal solution every time, that is, the probability of finding the optimal solution is 100%; while other algorithms find the optimal solution 8 times, 12 times, 22 times, namely, the probability of finding the optimal solution is only 16%, 24%, 44%, respectively. The search efficiency of PSO algorithm is far higher than that of other algorithms, which fully demonstrates the availability of the algorithm.

Table 2: Comparison of algorithms

| algorithm                     | The results of    |                       |                      |               | Best solution number |
|-------------------------------|-------------------|-----------------------|----------------------|---------------|----------------------|
|                               | Mean value (yuan) | Worst solution (yuan) | Best solution (yuan) | Best solution |                      |
| Simulated annealing algorithm | 87.6              | 109                   | 81                   | 8             | 8                    |
| Genetic algorithm (ga)        | 87.3              | 102                   | 81                   | 12            | 12                   |
| Ant colony algorithm          | 86.2              | 98                    | 81                   | 22            | 22                   |
| Particle swarm optimization   | 81                | 81                    | 81                   | 50            | 50                   |

#### 4.4 Impact of reliability indicators for wind turbines

In order to verify how different number of wind turbines affect the system reliability indicators, at node 15, node 20, and node 25: (1) no wind turbine unit is accessed, (2) one wind turbine unit is accessed, respectively; (3) 2 wind turbines are accessed, respectively; (4) 3 wind turbines are accessed, respectively. The curve of system reliability indicator is shown in Figure 4. From the trends of each fold line in Figure 4, it is deduced that SAIDI, CAIDI, ASAI, and ENS indicators of the system have been improved after accessing the wind turbine. The SAI remains unchanged because it operates independent of whether the system accesses the wind turbine. With the increase in the number of wind turbines, the scope of island will widen, and the loss of power loads will gradually decrease, which will further boost the reliability of the system. However, when there is more wind turbines, the system reliability indicator goes down until it achieves saturation. Therefore, various factors must be given to determine the number of wind turbines to be put into operation.

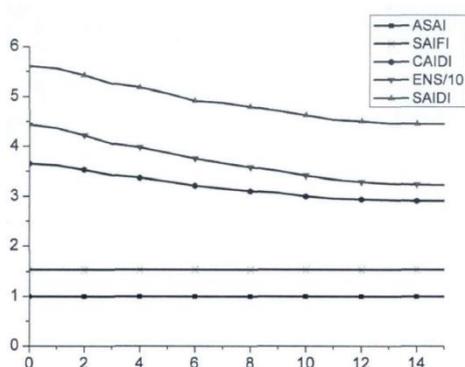


Figure 4: Reliability index line graph of wind turbine platform different from time system

#### 4.5 Impact of electric vehicle access on reliability

Assume that the impact of electric vehicle access on reliability is simulated in the unordered charging and ordered charge-discharge scheduling modes of the charging station, and the reliability indicators are shown in Table 3.

Table 3: The system reliability indicator different from that of the model

| Reliability index | Not connected to the EVs | Unordered patterns | It's ordered |
|-------------------|--------------------------|--------------------|--------------|
| SAIFL (Time/door) | 1.536                    | 1.536              | 1.536        |
| SAIDI/(h/door)    | 5.612                    | 5.612              | 5.507        |
| CAIDL(h/door)     | 3.65                     | 3.653              | 3.584        |
| CAIDL(h/door)     | 99.9359                  | 99.9359            | 99.9371      |
| ENS(MW.h/years)   | 44.43                    | 51.91              | 50.53        |

## 5. Conclusion

The wind turbine is modeled for reliability, given the derating and fault operation. It is therefore more practical; the next, it includes the analysis of failure modes for the power distribution network containing the wind turbine. Search method of the switch region block can quickly mark out a regional block model for a complex distribution network. Pre-stored region attributes can greatly reduce the number of components in the fault

impact analysis with clear hierarchies; in the end, this study ends up a reliability evaluation algorithm designed for distribution networks containing wind turbines. The simulation results show that the wind turbine accessed to the system can improve the reliability indicator of partial loads and improve the reliability of the system; for the wind turbine, there is an optimal number of accesses, so that it is required to integrate various factors to determine its inputs; wind power generator unit improves system reliability but far less than the non-intermittent power supply; when the access position of the wind turbine is different, due to the standalone partition strategy, it improve the system reliability indicator at different degrees.

The reliability evaluation and coordination optimization of electric vehicles with wind turbine are explored herein, but further investigation is also required for the following reasons: (1) when the assessment of its distribution network reliability doesn't involve the distribution power flow distribution. In some cases, the distribution of the line power flow may overrun; (2) the electric vehicles studied herein refer to private cars. The well-established coordinated scheduling strategy and model are not applicable to buses and taxis. Therefore, further study is required for motorcycle types, thus making the scheduling of electric vehicles broader; (3) during the establishment of a wind turbine-electric vehicle-thermal power coordination optimization model, the constraint of wind power integration online and offline is not considered, and the start-stop constraints of the thermal power unit is not involved in the objective function. These constraints will be given in the next study.

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