Reliability Evaluation of Cyber–Physical Power Systems Considering Supply- and Demand-Side Uncertainties

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Abstract: To reach effective monitoring and control, a physical power grid couples with a communication network and evolves into cyber–physical power systems (CPPS), but this cyber–physical interdependence may exacerbate failure on the physical/cyber side and may turn into a cascading failure. Furthermore, distributed generators (DGs) and plug-in hybrid electric vehicles (PHEVs) introduced into CPPS add uncertainties to both the supply side and demand side of power energy. In this paper, we detail the model of CPPS and its coupling mechanism in operation and discuss the propagation mechanism of cascading failure within and across a physical power grid and a communication network. For uncertainties of power energy in the supply and demand sides, the generation and load of each day are divided into 24 time segments for modeling. In the case study, the well-being criteria and reliability indexes are employed to analyze the effect of DGs and cyber–physical interdependence on the reliability of CPPS when DGs suffer aging failure and cyber attacks, and the simulations indicate that introducing DGs can effectively enhance the period of healthy and marginal states. Furthermore, cyber attacks can sharply destroy the CPPS compared with aging failure.

Keywords: cyber–physical power systems; cascading failure; distributed generator; plug-in hybrid electric vehicles; uncertainty

1. Introduction

As enormous human-made systems, physical power grids have become the most vital infrastructure in the world. To attain real-time monitoring and control, communication networks are extensively employed coupled with the physical power grid, building cyber–physical power systems (CPPS) [1].

By means of advanced information and communication technology, the operator can remotely access the status of physical power grid for diagnosis. Based on the diagnostic result, the operator generates and distributes control commands to physical devices via cyber devices in a communication network to adjust their parameters. On the other hand, the operation of the communication network is inseparable from a physical power grid. The physical power grid provides the communication network with power energy for operation, and the communication network supplies the physical power grid with control commands for control. This cyber–physical interdependence makes coupled networks efficiently collaborate and support each other to reach autonomy [2].

However, this interdependence also brings out many dangers to CPPS [3]. For instance, when failure occurs in certain cyber devices of communication network, other cyber devices that are disconnected from the giant component (the largest cluster in network) also break down. Correspondingly, the physical devices connected to failure cyber devices malfunction, and other physical devices that violate the constraints of the physical power grid, such as overloading or power-load mismatch, also become faulty and are removed...
from the network. Furthermore, failure physical devices can endanger the coupling cyber devices, which may trigger another series of cascading failure. This cascading failure continues propagating until (i) each device has a support node in a dependent network and (ii) each device meets the constraints of CPPS.

For the attacker, the physical side, due to the high robustness of a physical power grid, is hard to directly implement an attack and the cyber side is the optimal choice to indirectly attack the physical power grid [4]. Thus far, catastrophic blackouts triggered by cyber attack have happened many times in the world, such as the Italy blackout in 2003 [5], the Iran nuclear power plant incident in 2010 [6], the Ukraine blackout in 2015 [7], etc. These incidents manifest that cyber attacks can seriously damage the systems, and cyber–physical interdependence must be considered in the evaluation of CPPS reliability.

Nowadays, both a decrease in fossil fuels and the aggravation of environmental pollution have driven human beings toward developing renewable energy sources, such as hydroenergy, wind energy, solar energy, etc. Thus, a mass of distributed generators (DGs) have been constructed to transform renewable energy sources into power energy for direct usage. However, due to the intermittent nature and uncertainty, the output power of DGs is unstable and varies with ambient weather [8], which augments the uncertainty of power energy on the supply side. Furthermore, abundant plug-in hybrid electric vehicles (PHEVs) connected to a physical power grid increase the consumption of power energy, and the random charging behavior stresses the physical power grid, causing voltage fluctuation on the demand side [9], which augments the uncertainty of power energy on the demand side.

Considering cyber–physical interdependence in CPPS and uncertainties of power generated on the supply side and the power consumed on the demand side, we implement analytical methods to study the reliability of CPPS both in a connected state and an isolated state when CPPS suffers aging failure and cyber attacks.

1.1. Related Work

Based on research on the 2003 Italy blackout, Buldyrev et al. [3] first proposed ‘one-to-one correspondence’ CPPS model to study the cascading failure mechanism, highlighting the necessity of considering cyber–physical interdependence in designing robust systems. In partially interdependent CPPS model, Zhou et al. [10] found that reducing the coupling strength from 1 (fully coupled) to 0 (no coupling) contributes to an improvement in systems robustness. The authors of [11] raised multiple support CPPS models to improve its robustness and revealed the nonlinear correlation between robustness and controlling cost. On account of a Chinese electrical cyber–physical system, Ji et al. [12] presented the ‘partial one-to-one correspondence’ CPPS model and vulnerability algorithm to assess the vulnerability of Hubei, Sichuan, and central China electrical cyber–physical systems.

For the uncertainties of power generated on the supply side, much work has been conducted to optimize output power of DGs in recent decade. Diesel generators, as the dispatchable DG, are widely employed to balance voltage fluctuation and to reduce uncertainties of power output by other DGs, such as wind turbines, photovoltaic panels, etc. In [13], Milligan et al. evaluated the validity of current assumptions and methodologies on modeling wind power as the penetration level of wind power increases. To accurately model the power curve for forecast of wind power, Zhao et al. [14] proposed a data-driven outlier elimination approach combining quartile method and density-based clustering method that was proven effective and efficient in a case study. In [15], Yang et al. presented a weather-based hybrid method for 1-day ahead hourly forecasting of photovoltaic power output to improve real-time control performance and to reduce possible negative impacts of photovoltaic systems. In order to increase the robustness of systems incorporating solar energy, Liu et al. [16] employed two complementary neural network models, multilayer perceptron network and knowledge-based neural network, to predict future solar energy.

For the uncertainties of power consumed on the demand side, the accurate modeling of randomness to load is the priority. Since the variation of household load is far less than the randomness of DGs and PHEVs, the load of household is assumed to follow the IEEE-RTS
system [17]. Considering the behaviors and interests of vehicle owner, Shafiee et al. [18] proposed a more practical model based on the PHEV fundamental characteristics, battery capacity, state of charge (SOC), and energy consumption in daily trips. In [9], Grahn et al., based on driving patterns due to the type-of-trip and the corresponding charging need, presented a model for PHEV utilization and recharging price sensitivity. This modeling load profiles captured the charging behaviour dependence of the type-of-trip conducted and related the type-of-trip with consumption level, parking location, and charging opportunity. Furthermore, much work on uncertainties of the supply and demand sides have been conducted. In order to minimize the difference between the planned strategies, Yang et al. [19] proposed a bi-layer game-theoretic framework for the interactive energy management of multi-microgrids under the presence of uncertainties imposed by both the supply and demand sides. To deal with the resilience of the distribution system under extreme weather, Zhu et al. [20] presented a new methodological framework integrating mobile emergency generators and prosumer communities to explore the coordination and flexibility of supply-side and demand-side resources. To explore the resilience of microgrids in unforeseen outages, Masrur et al. [21] proposed an airport microgrid tied with the grid using an optimized dispatch of renewable energy technology with energy storage, and Venkataramanan et al. [22] proposed a cyber–physical security assessment metric based on quantitative factors affecting resiliency to measure the cyber–physical security of the system. Based on the introduction of information and communication technology to smart grids, Jimada et al. [23] surveyed the factors affecting reliability, evaluation techniques, case evaluation, and challenges of information and communication technology.

Currently, the research on CPPS has achieved many fruitful results in modeling, but the models merely focus on topological structure, without regard for the uncertainties of generation and load. Moreover, the works on uncertainties of power energy both in supply-and demand-side are abundant, but the coupling uncertainty among DGs receives less attention. Thus, we take an evaluation on reliability of CPPS, considering cyber–physical interdependence and uncertainties of power energy both in the supply and demand sides.

1.2. Contribution

In this paper, we detail the model of CPPS and the coupling relation between a physical power grid and a communication network, i.e., mutual supports in operation and cascading failure in contingency. For uncertainties in CPPS, we divide the year into four seasons and choose a typical day for each season, thus modeling the hourly generation of DGs on the supply side. Additionally, on the demand side, the load of household and PHEVs is modeled relative to human behaviors and habits. In simulation, the CPPS equipped with DGs can effectively improve its reliability, wherein the value of Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE) are reduced, and the period of healthy state and marginal state are enhanced. Introducing cyber–physical interdependence slightly endangers the reliability of CPPS, but this interdependence makes cyber attacks possible. The reliability of CPPS is sharply impaired from cyber attacks, especially when dispatchable diesel generators are attacked.

1.3. Organization

This paper is organized as follows. Section 2 details the CPPS model and cascading failure mechanism. In Section 3, the reliability indexes and well-being criteria are proposed to evaluate CPPS. In Section 4, a case study is conducted to analyze CPPS in a connected state and an isolated state. Section 5 concludes the paper and looks ahead.

2. Model Description

2.1. Systems Model

In CPPS, the physical power grid couples communication network to realize closed-loop control, as in Figure 1. On the one hand, the power energy generated by conventional generators and distributed generators has to meet the demand of load in physical power
grid and is also provided to communication network for consumption. On the other hand, communication network, by means of abundant routers, collects the data on systems status and uploads to server for analysis. Based on data received, the server generates corresponding control commands and then distributes to physical power grid via routers for parameter adjustment.

In this paper, the cyber–physical interdependence of CPPS model employed is the ‘one-to-one correspondence’ proposed by Buldyrev et al. [3]. For each conventional generator, distributed generator, and load terminal in physical power grid, there is particular router deployed connecting them to realize real-time monitor and control. In normal operation, the routers collect the information on load demand and upload to the server for analysis, and then, the server distributes control commands to corresponding generators via routers to adjust the power generated to match the load consumed, reaching the balance between generation and load. In contingency with some generators broken down, the server has to adjust the generators to generate more power energy for consumption. If the summational power energy generated by remaining generators cannot supply all load terminals, certain load terminals should be cut off to maintain the balance between generation and load.

2.2. Model for Cascading Failure

Cyber–physical interdependence indeed brings much convenience to CPPS operation, but it also aggravates the failure in CPPS and may cause catastrophic blackouts. Assuming failure occurs on certain cyber devices, the physical devices, such as photovoltaic panel, wind turbine, etc., cannot receive correct control commands and will quit running, which causes a mismatch between generation and load, resulting in power shortage in certain segments of physical power grid. Meanwhile, the failure physical devices cannot provide
power energy to communication network, invalidating coupling cyber devices. Thus, failure propagates within and across physical power grid and communication network and evolves into more serious cascading failure. The cascading failure in CPPS ends when meeting the following constraints, (1) the devices in the communication network and the physical power grid should satisfy the conditions, i.e., the cyber devices belong to the giant component of the communication network and the physical devices meet the balance between generation and load in the physical power grid; (2) the physical devices and cyber devices have support devices in a dependent network.

The process of cascading failure in CPPS is as follows:

S1: Initial failure: Randomly select and malfunction certain cyber nodes in the communication network to initiate cascading failure;

S2: Cyber failure: With certain cyber nodes broken-down, the remaining cyber nodes that connect to giant component are considered alive, and others are removed from the communication network;

S3: Cyber-physical: According to ‘one-to-one correspondence’ coupling connection, the physical nodes connected to failure cyber nodes are considered faulty and removed from the physical power grid;

S4: Physical failure: Calculate the power generated $P_{\text{gen}}$ and power consumed $P_{\text{con}}$ in the physical power grid. If $P_{\text{gen}} > P_{\text{con}}$, go to S6; otherwise, cut off certain load nodes to balance the generation and load;

S5: Physical-cyber: According to ‘one-to-one correspondence’ coupling connection, the cyber nodes connected to failure physical nodes are considered faulty and are removed from communication network. Return to S2;

S6: Failure termination: The cyber nodes and physical nodes meet the constraints of the communication network and the physical power grid, and all have support nodes in a dependent network.

2.3. Model for Supply-Side Uncertainty

The DGs in this paper include wind turbines, photovoltaic panels, and a diesel generator. Due to the uncertainty of the wind speed and solar irradiance, the hourly data of generation are modeled for analysis. In this model, the year is divided into four seasons and a typical day is chosen for each season. This typical day is further divided into 24 time segments, and each corresponds to the hourly interval. Thus, there are 96 time segments for the year. In the following, the hourly output power of wind turbine and photovoltaic panel is modeled.

2.3.1. Output Power of Wind Turbine

The output power of wind turbine directly relates to wind speed; thus, the modeling of wind speed is basic.

The wind speed is modeled using the Weibull probability density function [24], and the distribution probability of wind speed $v$ is as follows:

$$f(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right]$$

$$k = \left(\frac{\sigma}{v_m}\right)^{-1.086}$$

$$c = \frac{v_m}{\Gamma(1 + 1/k)}$$

where $v_m$ is the mean wind speed and $\sigma$ is the standard deviation.
The output power of wind turbine [8] is

\[
P_{WT} = \begin{cases} 
0, & 0 \leq v \leq v_{ci} \\
\frac{v_{ci}}{v_r - v_{ci}} \cdot \frac{v_r}{v_r - v_{ci}} \cdot \frac{v_r - v}{v - v_{ci}} \cdot P_{rated}, & v_{ci} \leq v \leq v_r \\
P_{rated}, & v_r \leq v \leq v_{co} \\
0, & v \geq v_{co} 
\end{cases}
\] (4)

where \( v_{ci}, v_r, \) and \( v_{co} \) are the cut-in speed, rated speed, and cut-off speed of the wind turbine and \( P_{rated} \) is the rated output power of wind turbine.

2.3.2. Output Power of Photovoltaic Panel

Different from wind speed, the output power of photovoltaic panel is closely relative to the time segment of day. Obviously, the value of solar irradiance is zero at night, and the low ambient temperature cannot start the photovoltaic panel. The output power of photovoltaic panel [25] is modeled as follows:

\[
T_c = T_A + I_\beta \cdot \frac{N_{OT} - 20}{0.8} 
\] (5)

\[
I = I_\beta [I_{sc} + K_i (T_c - 25)] 
\] (6)

\[
V = V_{oc} - K_v \cdot T_c 
\] (7)

\[
FF = \frac{V_{MPP} \cdot I_{MPP}}{V_{oc} \cdot I_{sc}} 
\] (8)

\[
P_{PV} = N \cdot FF \cdot V \cdot I 
\] (9)

where \( T_c \) is the cell temperature in °C, \( T_A \) is the ambient temperature in °C, \( I_\beta \) is the solar irradiance on a horizontal plane in MW/m², \( N_{OT} \) is the nominal operating temperature in °C, \( I_{sc} \) is the short circuit current in A, \( K_i \) is the current temperature coefficient in A/°C, \( V_{oc} \) is the open circuit voltage in V, \( K_v \) is the voltage temperature coefficient in V/°C, \( FF \) is the fill factor, \( V_{MPP} \) is the voltage at maximum power point in V, and \( I_{MPP} \) is the current at maximum power point in A.

2.3.3. Output Power of Diesel Generator

Diesel generator as the dispatchable DG can stably provide power energy to systems in case of power shortage. In [26], Hamzeh et al. pointed out that the output power of diesel generator units is controllable without any associated uncertainty and the DG has a firm generation capacity. Thus, in this paper, the rated power of diesel generators employed for the case study is set as 1.5 MW.

2.4. Model for Demand-Side Uncertainty

The power consumed in this paper consists of usage of household, charging of PHEVs, and power loss, wherein power loss accounts for 5% of total consumed by household and PHEVs [27]. In [28], Yang et al. studied on-line demand-side management in Microgrid considering the uncertainties of the demand side including end-user (general energy consumer) and multiple PHEVs and further proposed a two-stage real-time demand side management method including different time scales.

2.4.1. Usage of Household

Due to the variations of household load being less than the other uncertainties such as wind speed and solar irradiance, the load of household is considered invariant in each hourly time segment. The load profile of household without considering PHEVs is assumed to follow the IEEE-RTS system [17].
2.4.2. Charging of PHEVs

The charging time of PHEVs is relative to the traveling distance and traveling time, and the charging schedule is relative to the departure time and arrival time. The SOC in any time segment for PHEVs is the crucial factor affecting the decision to charge or not, and the SOC \([9]\) is updated as

\[
SOC^{t+1,j} = \begin{cases} 
SOC^{t,j} + \frac{P_{ch}}{\eta_{ch}} \Delta t, & \text{Charging} \\
SOC^{t,j} - C_{co}(v^i, c^j) \Delta t, & \text{Consuming} \\
SOC^{t,j}, & \text{Disconnected}
\end{cases}
\]

where \(P_{ch}\) is the charging load, \(\eta_{ch}\) is the charging efficiency, \(\Delta t\) is the time step, and \(C_{co}(v, c)\) is the electric power consumption as a function of the velocity and the electricity consumption level.

Furthermore, the charging demand load of PHEVs drawn from physical power grid is modeled as

\[
E_{t+1,j} = \begin{cases} 
E_{t,j} + \frac{P_{ch}}{\eta_{ch}} \Delta t, & \text{Charging} \\
E_{t,j}, & \text{Else}
\end{cases}
\]

In this paper, the load consumed by PHEVs in a workday and weekend is considered the same for simplification, and the charging load demand is relative to the SOC of PHEVs, arrival time, and departure time.

3. Reliability Evaluation

To assess the reliability of CPPS under multiple uncertainties covering the supply and demand sides, the well-being criteria and reliability indexes are employed in this paper.

The well-being criteria includes three states: healthy state, marginal state, and at-risk state, corresponding to the difference value between available reserve capacity and load.

\[
\Delta G^t = P_{gen}^t - P_{con}^t - P_{loss}^t
\]

where \(P_{gen}\) is the power generated including output power of wind turbine, photovoltaic panel, and diesel generator; \(P_{con}\) is the power consumed including usage of household and charging of PHEVs; and \(P_{loss}\) is the power loss.

\[
\begin{cases} 
\text{healthy}, & \Delta G^t \geq C_{pti} \\
\text{marginal}, & 0 \leq \Delta G^t < C_{pti} \\
\text{at-risk}, & \Delta G^t < 0
\end{cases}
\]

where \(C_{pti}\) is the fixed percentage of the total installed capacity in MW.

The reliability indexes employed are Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE). The LOLE is the expected number of hours per year that the power system cannot meet its demand, and the LOEE is the expected amount of power energy per year not being served to consumers during the period considered due to system capacity shortages or unexpected severe power outages.

\[
LOLE = 8760 \sum_{\Delta G^t < 0} p_{\Delta G^t}
\]

\[
LOEE = 8760 \sum_{\Delta G^t < 0} |\Delta G^t| \cdot p_{\Delta G^t}
\]

where \(p_{\Delta G^t}\) is the probability that \(\Delta G^t < 0\).

The flowchart of proposed well-being assessment and reliability evaluation is shown in Figure 2. As can be seen, the process of assessment is as follows. First, initialize CPPS, including the topology of physical power grid and communication network, along with
their coupling connection. Then, set fault to trigger cascading failure. When the cascading failure ends, check the well-being state $\Delta G'$ according to the power generated, consumed, and loss at time $t$ and conduct a well-being assessment and reliability evaluation.

![Flowchart](image)

**Figure 2.** The flowchart of the well-being assessment and reliability evaluation.

### 4. Case Study

In this section, simulations were performed to analyze the impact of multiple uncertainties on CPPS in MATLAB R2015b, employing Monte Carlo simulation technique and complex network theory package. Based on the uncertainties on the supply and demand sides in Section 2, we figure out the load generated by wind turbine, photovoltaic panel, and diesel generator and consumed by household and PHEVs and analyze the impact of uncertainties on the well-being assessment and reliability evaluation of CPPS through cyber–physical interdependence.

#### 4.1. Simulation Systems

The distribution grid employed in this paper is a 20 kV feeder in Sirjan City of Iran [29], as in Figure 3. Based on the segmentation concept, this distribution grid is divided into three segments by means of location of circuit breaker, and the peak loads of each segment without PHEVs are 1.847 MW, 1.3 MW, and 2.94 MW. The substation in distribution grid is supplied with four 2 MW transformers, and the distribution of distributed generators is as Table 1. The distribution of cyber devices in communication network including either routers and one server follows a double-star structure [30].

| Notation | Notion          |
|----------|-----------------|
| DG1      | Diesel generator|
| DG2      | Photovoltaic panel|
| DG3      | Diesel generator|
| DG4      | Wind turbine    |
| DG5      | Wind turbine    |
For any cyber and physical device in CPPS, there are two states: up and down. To investigate the impact of device state on systems reliability, the hourly state of devices must be determined. The up and down states of devices can be generated by simulating their failures and repairs based on historical data [31],

\[
up-time = -MTTF \cdot \ln(u_1) \tag{16}
\]

\[
down-time = -MTTR \cdot \ln(u_2) \tag{17}
\]

where \(MTTF\) and \(MTTR\), respectively, are mean time to failure, which is the inverse of failure rate, and mean time to repair, which is the unavailability duration of device, and \(u_1\) and \(u_2\) are uniformly distributed samples on \([0, 1]\).
Thus, the hourly state of device $j$ at time $t$ can be determined as

$$D(j,t) = \begin{cases} 1, & t \in \text{up-time} \\ 0, & t \in \text{down-time} \end{cases}$$ (18)

### 4.2. DGs Suffering Aging Failure

#### 4.2.1. Systems in Connected State

The circuit breakers along with routers connected to them are failure free, while other devices follow $MTTF$ and $MTTR$.

- Case 1: The physical power grid equips without DGs.
- Case 2: The physical power grid equips with DGs.
- Case 3: The physical power grid equipped with DGs couples with communication network.

As in Table 2, comparing case 2 with case 1, the reliability indexes, and values of LOLE and LOEE are declining. This indicates the probability that the load loss decreased and that the reliability of CPPS improved. The well-being state, a period of the healthy state, grew, and period of marginal and at-risk states shortened. Obviously, multiple DGs including wind turbines, photovoltaic panels, and a diesel generator, working as the complementary power source, periodically provide power energy to systems, effectively improving the reliability of CPPS. Due to uncertainties of the demand side in CPPS, the load consumed by household and PHEVs obviously influences the well-being criteria and reliability indexes and increases the period of marginal state and at-risk states, especially in case 1 when a lacking load is generated by DGs. In most cases, the charging of PHEVs always occurs at home after work, and the demand for power is urgent due to long travel distances. Meanwhile, the power demand in households is suddenly increased due to the usage of electric appliances. Compared with the power consumed by household, the power consumed by PHEVs is more. Furthermore, the uncertainties of PHEVs can easily destroy the reliability of systems through massive number of PHEVs connected to power system, seriously weakening both the well-being criteria and reliability indexes.

| Table 2. Reliability evaluation. |
|----------------------------------|
| **Index** | **Case 1** | **Case 2** | **Case 3** |
| LOLE (hour/year) | 3.9785 | 0.0310 | 0.0611 |
| LOEE (MWh/year) | 12.1910 | 0.2110 | 0.2902 |
| Healthy (hour/year) | 8328.9715 | 8739.7613 | 8730.0692 |
| Marginal (hour/year) | 334.8145 | 19.4865 | 28.4570 |
| At-risk (hour/year) | 96.2140 | 0.7522 | 1.4738 |

In case 3, the physical power grid is coupled with communication network to obtain real-time monitor and control. Compared with case 2, the value of reliability indexes in case 3 is decreased a little, and the well-being state is slightly deteriorated. This is due to cyber–physical interdependence; thus, the failure on cyber devices can spread to malfunction physical devices, threatening the reliability of CPPS. However, cyber–physical interdependence makes it possible for operators to remotely manage DGs, which is convenient and efficient.

#### 4.2.2. Systems in Isolated State

The router $R1$ becomes faulty, i.e., the substation is disconnected from the systems; thus, the power energy provided results from DGs.

- Case 4: The routers $R2$ and $R4$ are failure free. Segments 1, 2, and 3 are connected.
- Case 5: The router $R2$ is failure free, and router $R4$ fails. Segments 1 and 2 are connected, and segment 3 is isolated.
Case 6: The router $R_2$ fails, and router $R_4$ is failure free. Segment 1 is isolated, and segments 2 and 3 are connected.

Case 7: The routers $R_2$ and $R_4$ fail. Segments 1, 2, and 3 are isolated.

In Table 3, the reliability indexes and well-being state of segments in isolated segments are presented, wherein '/' indicates that the segment has no power energy provided.

| Table 3. Reliability evaluation. |
|----------------------------------|
| **Case 4** Segment 1 Segment 2 Segment 3 |
| **LOLE (hour/year)**       320.4111      320.4111      320.4111  |
| **LOEE (MWh/year)**        4075.0613      2868.2078      6486.5622  |
| **Healthy (hour/year)**    0               0               0  |
| **Marginal (hour/year)**   1084.8313      1084.8313      1084.8313  |
| **At-risk (hour/year)**    7675.1687      7675.1687      7675.1687  |
| **Case 5** **LOLE (hour/year)**       365       365      299.9959  |
| **LOEE (MWh/year)**        5395.8279      3797.8215      5014.8279  |
| **Healthy (hour/year)**    0               0               0  |
| **Marginal (hour/year)**   0               0               1560.0976  |
| **At-risk (hour/year)**    8760            8760      7199.9024  |
| **Case 6** **LOLE (hour/year)**       /       253.5145      253.5145  |
| **LOEE (MWh/year)**        /       1178.5478      2665.3312  |
| **Healthy (hour/year)**    /       2028.7397      2028.7397  |
| **Marginal (hour/year)**   /       646.9134      646.9134  |
| **At-risk (hour/year)**    /       6084.3469      6084.3469  |
| **Case 7** **LOLE (hour/year)**       /       35.5875      299.9959  |
| **LOEE (MWh/year)**        /       847.9200      5014.8279  |
| **Healthy (hour/year)**    /       5929.4250      0  |
| **Marginal (hour/year)**   /       1976.4750      1560.0976  |
| **At-risk (hour/year)**    /       854.1000      7199.9024  |

It is seen in Table 3 that, due to disconnection with substation of four 2 MW transformers, the power energy for systems operation is merely provided by DGs, and the intermittence and uncertainty characteristics of DGs make systems almost in an at-risk state. In case 4 when segments 1, 2, and 3 are connected, the systems are in the marginal state, accounting for 12.38%, and in at-risk state, accounting for 87.62%. This indicates that the power energy provided by DGs cannot meet the demand for all segments, and a power shortage will emerge in the period of peak load.

In cases 5 and 6, when regional segments are connected, the power generation in isolated subsystems, which consist of segment 1 and segment 2, is largely short of the power consumption due to segment 1 containing no DGs and demanding abundant power energy. The isolated sub-systems, which consist of segment 2 and segment 3, can reach a healthy state and a marginal state, indicating that the power generated by DGs can meet the demand of load in a certain period and even attain redundancy. Compared with case 5 and case 6, we can see that rationally partitioning CPPS into isolated sub-systems can decrease the value of LOLE and LOEE and can shorten the period of at-risk state, effectively improving the reliability of isolated sub-systems.

In case 7, each segment in CPPS forms an isolated sub-system. The period of an at-risk state of segment 2 is 854.1 h each year, while in segment 3, it is 7199.9024 h. The power generated in segment 2 can almost become self-sufficient, while in segment 3, it is severely insufficient. This is due to the load of segment 3 being around two times that of segment 2, but the power generation of the DGs equipped are not proportionally increased.
4.3. DGs Suffering Cyber Attacks

The circuit breakers along with routers connected to them are failure free, and the CPPS is in the connected state. The routers connected to DGs are attacked by a hacker, while other devices follow MTTF and MTTR.

Case 8: The routers R7 and R8 are attacked, and two wind turbines quit running.
Case 9: The router R5 is attacked, and the photovoltaic panel quits running.
Case 10: The router R3 or R6 is attacked, and one diesel generator quits running.
Case 11: The routers R3 and R6 are attacked, and two diesel generator quit running.

In Table 4, attacking diesel generators causes more serious effect on CPPS than attacking other DGs including wind power and solar power. First, the rated power of a diesel generator is far larger than that of wind turbines and photovoltaic panels. Second, the output power of wind turbine and photovoltaic panel is uncertain, which is merely used as the complement. Third, a diesel generator not only provides power energy to CPPS but also is in charge of balancing the voltage fluctuation caused by wind turbines and photovoltaic panels. Obviously, the shutdown of diesel generators causes a more serious effect on the reliability of CPPS. Compared with case 3 in which CPPS is failure free, the LOLE of CPPS suffering cyber attacks is at least increased by 59.74%, and the greatest increase is up to 1278.89%. Meanwhile, the LOEE is at least increased by 104.79%, and the greatest increase is up to 3145.35%. In detail, the period of healthy state is decreased, and the period of marginal states and at-risk states is increased differently due to the attack targets.

| Index           | Case 8 | Case 9 | Case 10 | Case 11 |
|-----------------|--------|--------|---------|---------|
| LOLE (hour/year)| 0.2112 | 0.0976 | 0.2864  | 0.8425  |
| LOEE (MWh/year) | 0.6777 | 0.5943 | 1.8427  | 9.4180  |
| Healthy (hour/year) | 8726.4437 | 8728.1068 | 8634.1879 | 8380.6360 |
| Marginal (hour/year) | 28.4625  | 29.5473 | 117.8001 | 359.1385 |
| At-risk (hour/year) | 5.0938   | 2.3459  | 8.0120  | 20.2255 |

In case study, it is indicated that disintegrating CPPS into isolated state can effectively destroy its reliability. Moreover, cyber attack can sharply destroy the well-being criteria and reliability indexes of CPPS, especially the attack targeted at diesel generators. Based on the research results, more defense should be established to prevent CPPS disintegrating into isolated state. Furthermore, the defense from cyber attack should also be noticed, and the coordination of both the cyber and physical sides in CPPS should be considered more.

5. Conclusions and Discussion

In this paper, we introduced the model of CPPS and its coupling mechanism in operation and further analyzed the propagation mechanism of cascading failure within and across a physical power grid and communication network. Considering the uncertainty of power generated on the supply side, the hourly output power of DGs including wind turbine and photovoltaic panel is modeled and one typical day for each quarter is chosen to represent four seasons in a year. On the demand side, the load profile for usage of household and charging of PHEVs is modeled based on historical data concerning human behaviors and habits.

The simulation result indicates that introducing DGs can effectively reduce the value of LOLE and LOEE, and can enhance the period of healthy and marginal states to improve the reliability of CPPS both in the connected state and the isolated state. Compared with aging failure, cyber attacks can sharply impair the reliability of CPPS, wherein attacking diesel generators causes more serious damage on CPPS than attacking wind turbines and photovoltaic panels. In detail, the LOLE of CPPS suffering cyber attacks is at least increased by 59.74%, and the greatest increase is up to 1278.89% compared with case 3 in which the CPPS is failure free. Meanwhile, the LOEE is at least increased by 104.79%, and the greatest increase is up to 3145.35%.
In CPPS, a diesel generator as the dispatchable DG can effectively balance the voltage fluctuation and can reduce uncertainties brought by other DGs, but this is not economical, and equipping energy storage systems to store the redundant power generated by DGs is the optimal option. Furthermore, the research on location of DGs is still an interesting filed.

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