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Reliability Synthesis and Prediction for Complex Electromechanical System: A Case Study

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The life test of a complex electromechanical system (CEMS) is restricted by many factors, such as test time, test cost, test environment, test site, and test conditions. It is difficult to realize system reliability synthesis and prediction of a CEMS which consists of units with different life distributions. Aiming at the problems, a numerical analysis method based on the computer simulation and the Monte Carlo (MC) method is proposed. First, the unit's life simulation values are simulated using the MC method with the given each unit's life distribution and its distribution parameter point estimation. Next, using the unit's life simulation values, the CEMS life simulation value can be obtained based on the CEMS reliability model. A simulation test is realized instead of the life test of the CEMS when there are enough simulation values of the CEMS life. Then, simulation data are analyzed, and the distribution of the CEMS life is deduced. The goodness-of-fit test, point estimation and confidence interval of the parameters, and reliability measure are estimated. Finally, as a test example of the wind turbine, the practicability and effectiveness of the method proposed in this paper are verified.

Keywords: Monte Carlo simulation, computer simulation, system reliability prediction, system reliability synthesis, complex electromechanical system

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INTRODUCTION

Complex electromechanical systems (CEMSs) have been used in industry, civil machinery, aerospace, and so on (Mi et al., 2016; Wang et al., 2022). Reliability synthesis and prediction of CEMSs have long been critical issues within the field of reliability engineering. CEMSs are usually composed of optics, machinery, and electricity (Tang et al., 2021). Some CEMSs have very complex structures, some have huge volumes, some have long service life, and some are expensive (Han et al., 2021). Thus, reliability synthesis and prediction of CEMSs only relying on life testing are limited by multiple factors such as test scheme, test site, test time, test cost, and test conditions. However, at the stage of the project demonstration and initial design of CEMSs, reliability synthesis and prediction of CEMSs are necessary (Fuqiu et al., 2020). Therefore, it challenges the realization of reliability synthesis and prediction of CEMSs.

Since Buehler proposed a reliability synthesis method for a series system with two binomial components (Buehler, 1957), scholars from classical, Bayes, and fiducial schools have conducted a lot of research on reliability synthesis and prediction of systems. The classical school put forward the maximum likelihood estimation (MLE) method, modified maximum likelihood estimation (MML) method, sequential reduction (SR) method, combined MML and SR method (CMSR), and so on (Yu et al., 2013). The MLE method is only applicable to large sample tests, and the failure distribution is an unbounded symmetric normal distribution. The MML method is only applicable to binomial (pass–fail) component systems (Fo and Xiong, 2009). The disadvantage of the SR method is that successive compression of test data leads to information loss, resulting in large estimation variance and a more conservative confidence limit of system reliability (Zhu and J Sh, 1990). The algorithm of the CMSR method is complex, and it is not suitable for the system with zero failure number of unit test data. The Bayes method only solves the reliability interval estimation of binomial or exponential approximation for complex systems (Guo and Wilson, 2013). The fiducial method has been proved unsuitable for system reliability evaluation (Zhou and Weng, 1990). Therefore, it is difficult to use the abovementioned methods to synthesize and predict the CEMSs' reliability, and reliability synthesis and prediction of CEMSs are still problems in reliability engineering (Peng et al., 2013). Although the Monte Carlo method can easily deal with the reliability synthesis problem of systems with different unit distributions (Yeh et al., 2010), the simple Monte Carlo method, bootstrap method, double Monte Carlo method, and asymptotic method introduced in many studies can only solve the lower confidence limit of system reliability, and the interval estimation problem of system life distribution types and parameters are unsolved (Meng and Wen-Tao, 2021). Despite decades of research, there is still no general method to realize the reliability synthesis and prediction of CEMSs (Kovacs et al., 2019).

It is well known that a CEMS is composed of several units (subsystems), and the system reliability depends on the reliability of its constituent units (subsystems) (Negi and Singh, 2015), (Liu et al., 2015). When the constituent units' life of CEMS follows different distributions, it is difficult to synthesize and predict the CEMS reliability from units' reliability data information (Weiyan et al., 2009). Hence, some scholars have conducted a lot of correlational research. For example, Guo et al. (2014) analyzed some theories and methods for system reliability synthesis, and the new idea was proposed for the problem aiming at specific engineering backgrounds. Considering that some CEMSs contain outsourced components, Sun et al. (2018) computed system reliability and component importance measures. According to the equal-principle first and second moment of reliability, Yu et al. (2013) investigated Bayes reliability confidence limit for a series-parallel system consisting of different distribution units. Graves and Hamada (2016) evaluated the likelihood for simultaneous failure time data when monitoring was stopped. In view of the lack of reliability data information of CEMSs, Wilson et al. (2006) and Yuan et al. (2019) discussed how to make full use of limited reliability data information of CMESs to synthesize and predict system reliability. Although scholars have discussed the reliability synthesis and prediction of CEMS from many aspects, there are still challenges by many factors such as difficulty in establishing a reliability model for CMES, lack of reliability data information, high test cost, and so on. It is necessary to be studied further.

In order to solve the above problems and realize the reliability synthesis and prediction of CEMS, a numerical analysis method based on the computer simulation and the Monte Carlo (MC) method is proposed in this article. The remainder of this article is organized as follows: In **Section 2**, we propose a method to obtain the life simulation values for the constituent units of CEMS when the life distribution types and distribution parameters of constituent units are known. In **Section 3**, we take a method to obtain the system life simulation value from the units' life simulation values. One system life simulation value represents a reliability test of CEMS. Computer simulation can be realized instead of life test when there are enough system life simulation values. In **Section 4**, we carry out the initial selection of CMES life distribution types and goodness-of-fit test. In **Section 5**, a case study of a CMES is presented to demonstrate the effectiveness of our proposed method. Finally, conclusions are made in **Section 6**.

LIFE SIMULATION VALUES FOR THE CONSTITUENT UNITS OF COMPLEX ELECTROMECHANICAL SYSTEMS

It is assumed that a CEMS is composed of n different life distribution units, and the life distribution and the appropriate parameters of each constituent unit are known. The life simulation values for n units are generated using the random variable simulation conversion equation and through Monte Carlo simulation (Yoshida and Akiyama, 2011; Wang et al., 2012; Zhang et al., 2014). According to the common distributions in engineering, such as the exponential distribution, Weibull distribution, normal distribution, logarithmic normal distribution, extreme value distribution, Gamma distribution etc., the respective random variable simulation conversion equations $g(\vartheta_i)$ are deduced and listed in **Table 1**. If a unit is subject to any other distribution, its random variable simulation conversion equation can be solved similarly using the inverse function method.

In order to ensure that all units are independent of each other, the pseudo-random number is computer-generated for each unit and subject to 0-1uniform distribution.

$$\vartheta_i = \mathrm{RND}(1) \quad i = 1, 2, \cdots, n.$$

According to the life distribution and parameters of each constituent unit, the life simulation value t_i for the corresponding unit can be obtained through logical operation.

$$t_i = g(\vartheta_i) \quad i = 1, 2, \cdots, n.$$

In this way, a set of life simulation values of n units can be obtained, and the first simulation values are completed. The m groups of life simulation values are obtained after m cycles.

LIFE SIMULATION VALUES FOR THE COMPLEX ELECTROMECHANICAL SYSTEMS

For the CEMS composed of n units, the life simulation value for each unit can be obtained through each simulation, and they are

TABLE 1 | Conversion formulas of different distributions.

Probability density function	Distribution function	Conversion formula $g(\vartheta_i)$
$f_e(t) = \lambda e^{-\lambda(t-t_0)}$	λ t_0	$t = -\frac{\ln(\vartheta)}{\lambda} + t_0$
$f_w(t) = \frac{m(t-t_0)^{m-1}}{\eta^m} e^{-(\frac{t-\gamma}{\eta})^m}$	m η t_0	$t = \eta(-\ln\vartheta)^{1/m} + t_0$
$f_N(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}}$	μ σ	$t_1 = \sqrt{-\ln\vartheta_1}\sin 2\pi\vartheta_2$ $t_2 = \sqrt{-\ln\vartheta_1}\cos 2\pi\vartheta_2$
$f_L(t) = \frac{1}{\sqrt{2\pi}\sigma_L t} e^{-\frac{(\ln t-\mu_L)^2}{2\sigma_L^2}}$	μ_L σ_L	$t_1 = e^{\sqrt{-\ln\vartheta_1}\sin 2\pi\vartheta_2}$ $t_2 = e^{\sqrt{-\ln\vartheta_1}\cos 2\pi\vartheta_2}$
$f_m(t) = \frac{1}{\sigma_m} e^{\frac{t-\mu_m}{\sigma_m}} e^{-e^{\frac{t-\mu_m}{\sigma_m}}}$	μ_m σ_m	$t = \mu_m + \sigma_m \ln(-\ln\vartheta)$
$f_M(t) = \frac{1}{\sigma_M} e^{-\frac{t-\mu_M}{\sigma_M}} e^{-e^{\frac{t-\mu_M}{\sigma_M}}}$	μ_M σ_M	$t = \mu_M - \sigma_M \ln(-\ln\vartheta)$
$f_\Gamma(t) = \frac{\lambda_\Gamma^\alpha t^{\alpha-1}}{\Gamma(\alpha)} e^{\lambda_\Gamma t}$	λ_Γ α	$t = -\frac{\ln(\vartheta_1,\ldots,\vartheta_\alpha)}{\lambda_\Gamma\Gamma(\alpha)}$

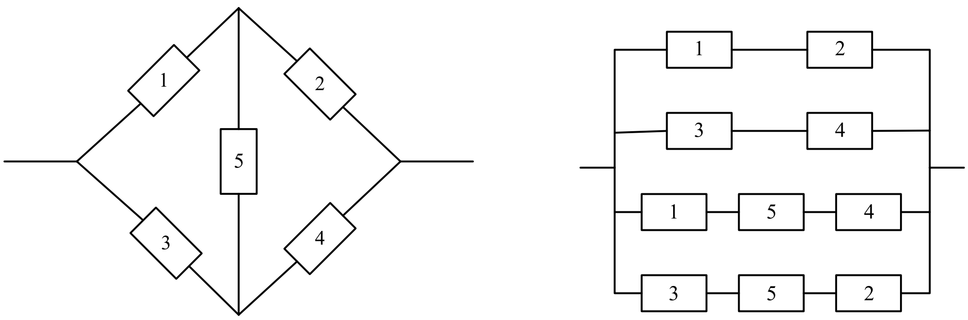

FIGURE 1 | Minimal path sets of typical system.

denoted by $t_{j1}, t_{j2}, \cdots, t_{jn}$. According to the reliability logical relationship between the CEMS and each component unit, the life simulation values for the CMES are obtained on the minimal path set method (Cancela et al., 2013; Schallert, 2014).

$$\boldsymbol{S} = \overset{q}{\underset{h=1}{\cup}} \boldsymbol{S}_h = \overset{q}{\underset{h=1}{\cup}} \left[\underset{x_i, x_j, \cdots \in S_h}{\cap} \left(x_i, x_j, \cdots \right) \right], \tag{1}$$

where S denotes the CEMS, q denotes the number of the minimum path sets in the CEMS, $h = 1, 2, \cdots, q$, and $S_h = (x_i, x_j, \cdots)$, $x_i, x_j \ldots$ is all the units in a minimum path set.

Therefore, the life simulation value t_S for a CEMS can be obtained through logical operation after each simulation.

$$t_S = \underset{1<h<q}{max}\left(t_{S_h}\right) = \underset{1<h<q}{max}\left[\underset{t_i, t_j \ldots \in S_h}{min}\left(t_i, t_j, \ldots\right) \right], \tag{2}$$

where t_S is the life simulation value for the CEMS, $t_i, t_j \ldots$ is the life simulation value for each unit in the minimum path set, and t_{S_h} is the life simulation value for the hth minimum path set.

The minimal path sets of the typical system are shown in **Figure 1**, and the system has four minimum path sets: (x_1, x_5, x_4), (x_2, x_5, x_3). The life simulation values for the system are obtained by the following equation (Hong-Bo and Guo, 2009):

$$t_S = \max\left[\min(t_1, t_2),\ \min(t_3, t_4), \min(t_1, t_5, t_4),\ \min(t_3, t_5, t_2)\right]. \tag{3}$$

In general, the CEMS is usually considered to be composed of several simple serial or parallel subsystems, and the following equations are established:

$$t_{Sk} = \underset{t_i, t_j \ldots \in S_k}{min}\left(t_i, t_j, \ldots\right), \tag{4}$$

$$t_{Sl} = \underset{t_i, t_j \ldots \in S_l}{\max}\left(t_i, t_j, \ldots\right), \tag{5}$$

where t_{Sk} is the life simulation value for the serial subsystem and t_{Sl} is the life simulation value for the parallel subsystem.

For any CEMS, the simulation value array $T(r \times n)$ for the units can be obtained by carrying out r simulations over n component units.

$$T(r \times n) = \begin{vmatrix} t_{11}, t_{21}, \cdots, t_{n1} \\ t_{12}, t_{22}, \cdots, t_{n2} \\ \vdots \\ t_{1r}, t_{2r}, \cdots, t_{nr} \end{vmatrix}. \tag{6}$$

Each simulation can yield a set of life simulation values for the units, and one life simulation value for the system can be obtained by **Eq. 2**. If r simulations are performed, r life simulation values can be obtained, namely, $t_{S1}, t_{S2}, \ldots, t_{Sr}$, and t_{Sr} is equivalent to the full life test over r CEMSs. If r is large enough, the life distribution types for CEMSs can be counted and deduced from $t_{S1}, t_{S2}, \ldots, t_{Sr}$. Therefore, the probability estimation for the reliability measures of the CEMS is taken.

INITIAL SELECTION OF LIFE DISTRIBUTION TYPES FOR THE COMPLEX ELECTROMECHANICAL SYSTEMS AND GOODNESS-OF-FIT TEST

In order to determine the life distribution types for the system, this thesis makes use of the probability graph estimation method and goodness-of-fit test method. First, the probability graph for common distributions is designed and constructed on the computer, and $t_{S1}, t_{S2}, \ldots, t_{Sr}$ is drawn and fit on the probability graph. Then, the residual sum of squares under each distribution is calculated, and the distribution whose residual sum of squares is minimal is selected as the initial distribution. Finally, the Pearson χ^2 goodness-of-fit test is performed (Praks and Gono, 2011; Aguwa and Sadiku, 2012), and the life distribution type for the system is determined after the hypothesis test is accepted.

Data Processing and Initial Selection of Distribution Types

The basic principle for the probability idea design is to linearize the distribution function, and **Table 2** shows the linearized conversion equations for seven common distributions. The system life data are drawn in the new coordinate system, respectively. According to the discretization of the fitting line, the life distribution types for the system are initially decided.

TABLE 2 | Design of different probability plots.

Distribution functions	X–Y coordinate transformation
$F_e(t) = 1 - \exp[-\lambda(t - t_0)]$	$Y = \ln\frac{1}{1 - F_e(t)}$ $X = t - t_0$
$F_w(t) = 1 - \exp[-(\frac{t-t_0}{\eta})^m]$	$Y = \ln\ln\frac{1}{1 - F_w(t)}$ $X = \ln(t - t_0)$
$F_N(t) = \frac{\int_0^t e^{-\frac{(x-\mu)^2}{2\sigma^2}}dx}{\sigma\sqrt{2\pi}} = \Phi(u)$	$Y = u_\alpha \to \Phi(u_\alpha)$ $X = t$
$F_L(t) = \frac{\int_0^t e^{-\frac{(\ln x-\mu_L)^2}{2\sigma_L^2}}dx}{\sigma_L\sqrt{2\pi}} = \Phi(u_L)$	$Y = u_{L\alpha} \to \Phi(u_{L\alpha})$ $X = \ln t$
$F_m(t) = 1 - \exp[-e^{(\frac{t-\mu_m}{\sigma_m})}]$	$Y = \ln\ln\frac{1}{1 - F_m(t)}$ $X = t$
$F_M(t) = \exp[-e^{-(\frac{t-\mu_M}{\sigma_M})}]$	$Y = \ln\frac{1}{\ln[1/F_M(t)]}$ $X = t$
$F_\Gamma(t) = \frac{1}{\Gamma(\alpha)}\int_0^{\lambda_\Gamma t} x^{\alpha-1}e^{-x}dx$	$Y = F_\Gamma(t)$ $X = \lambda_\Gamma t$

To improve the accuracy of statistical inference, the value of r is relatively larger. To reduce the amount of calculation, the life simulation values for the system t_{Sj}, $(j = 1, 2, \ldots, r)$ are arranged in ascending order of time.

$$t_{s(1)} \le t_{s(2)} \le \ldots \le t_{s(j)} \le \ldots \le t_{s(r)}.$$

Then $[t_{s(1)}, t_{s(r)}]$ is evenly divided into p intervals, and p can be determined according to the number of simulations, r, generally $p = 20 \sim 100$. The time interval is calculated as follows:

$$\Delta t_{S,k} = t_{S,k+1} - t_{S,k} \quad k = 1, 2\cdots, p, \tag{7}$$

where $t_{S,k+1}, t_{S,k}$ is the boundary of the kth interval and $\Delta t_{S,k}$ is the kth interval space.

The median $\bar{t}_{S,k}$ of all intervals is denoted as follows:

$$\bar{t}_{S,k} = t_{S,k} + \frac{\Delta t_{S,k}}{2}. \tag{8}$$

The frequency number of the life simulation value for the system in the kth interval $[t_{S,k+1}, t_{S,k}]$ is denoted as r_k. $\bar{t}_{S,k}$, and the corresponding cumulative failure probability constitutes p scattered data pairs $[F(\bar{t}_{S,k}), \bar{t}_{S,k}]$.

$$\left[F(\bar{t}_{S,k}) = \frac{1}{r}\left(\sum_{i=1}^{k} r_i - \frac{r_k}{2}\right), \bar{t}_{S,k} = t_{S,k} + \frac{\Delta t_{S,k}}{2}\right]. \tag{9}$$

Each scattered data pair $[F(\bar{t}_{S,k}), \bar{t}_{S,k}]$ corresponds to 1 point on the probability graph, and the least square method is used to fit the straight line.

$$Y_j = a_j + b_j X_j \quad j = 1, 2, \cdots, q,$$

where a_j and b_j are the linear parameters of the fitting line, and q is the number of the selected probability graphs.a_j and b_j and the residual sum of squares Q_j are calculated on the probability graph, respectively.

$$\begin{cases} b_j = \dfrac{p\sum_{k=1}^{p} X_{jk}Y_{jk} - \sum_{k=1}^{p} X_{jk}\sum_{k=1}^{p} Y_{jk}}{p\sum_{k=1}^{p} X_{jk}^2 - \left(\sum_{k=1}^{p} X_{jk}\right)^2}, \\ a_j = \dfrac{1}{p}\left[\sum_{k=1}^{p} Y_{jk} - b_j\sum_{k=1}^{p} X_{jk}\right] \end{cases} \tag{10}$$

$$Q_j = \sum_{k=1}^{p}\left(Y_{jk} - a_j - b_j X_{jk}\right)^2, \tag{11}$$

where X_{jk} and Y_{jk} are the horizontal and vertical coordinate of the kth data point.

The values of Q_j on different distribution probability graphs are compared, and the distribution corresponding to the minimum value of Q_j is selected as the initial life distribution for the CEMS.

Pearson χ^2 Goodness-of-Fit Test

The goodness-of-fit test should be performed after the initial distribution is determined.

The initial distribution function as $F_x(t)$ is set, and the sample observation is the median value of p intervals, $\bar{t}_{S,1}, \bar{t}_{S,2}, ..., \bar{t}_{S,p}$. The Pearson χ^2 goodness-of-fit test is performed as follows:

1) The hypotheses are established.

The original hypothesis H_0: the sample is from $F_x(t)$, and the alternative hypothesis: the sample is not from $F_x(t)$.

2) The point estimate value $\widehat{\theta_x}$ (or $\hat{\theta}_{x1}, \hat{\theta}_{x2}, \ldots, \hat{\theta}_{xl}$) of $F_x(t)$ is estimated using the probability graph method.

The probability for p intervals is calculated as follows:

$$P_k = F_x\left(\bar{t}_{S,k+1}, \hat{\theta}_x\right) - F_x\left(\bar{t}_{S,k}, \hat{\theta}_x\right) \quad k = 1, 2\cdots, p. \tag{12}$$

3) The Pearson χ^2 test statistics is calculated by

$$\chi^2 = \sum_{k=1}^{p} \frac{(r_k - r p_k)^2}{r p_k}. \tag{13}$$

4) When the confidence probability γ is given, the following formula holds:

$$P\left[\chi^2 \le \chi^2_\gamma(v)\right] = \gamma, \tag{14}$$

where v is the degree of freedom, $v = p - 1 - l$, and l is the number of parameters of initial distribution.

If $\chi^2 \le \chi^2_\gamma(v)$, the original hypothesis is accepted at a high probability, and then, the sample can be identified from $F_x(t)$. Otherwise, the original hypothesis shall be rejected.

To facilitate the computer analysis, the Fisher approximation of $\chi^2_\gamma(v)$ is given

$$\chi^2_\gamma(v) \approx \frac{1}{2}\left[\sqrt{2v - 1} + u_\gamma\right]^2, \tag{15}$$

where u_γ is the γ quantile of the standard normal distribution, which can be approximated as follows:

$$u_\gamma \approx \frac{a_0 + a_1 z}{1 + b_1 + b_2 z^2}, \tag{16}$$

where $a_0 = 2.3075$; $a_1 = 0.2706$; $b_1 = 0.9922$; $b_2 = 0.0448$; and $z = \sqrt{\ln(1-\gamma)^{-2}}$.

ENGINEERING APPLICATION–SYSTEM RELIABILITY PREDICTION ON WIND TURBINE

An MW wind turbine unit is mainly composed of impeller, gearbox, generator, yaw system, pitch system, brake system, lubrication system, electrical system, and frequency converter in serial connection, and its reliability block diagram (RBD) is shown in **Figure 2**.

The given life distributions and parameters for all components in the wind power generator unit are listed in **Table 3** (Tavner et al., 2007; Spinato et al., 2009; Guo et al., 2012).

According to the relevant parameters of each unit listed in **Table 3**, the life simulation value for each unit is generated using the simulation conversion equation in **Table 1**. We set $r = 500$, and the 500 life simulation values for units are obtained as listed in **Table 4** (excerpt). 500 life simulation values for the system are obtained through logical operation.

1) Initial selection of the life distribution types for the wind turbine.

The characteristic data in **Table 5** are processed using probability graph estimation to get the residual sum of squares under different distributions, Q_j, as listed in **Table 6**.

It is shown in **Table 6** that the residual sum of squares for the two-parameter Weibull distribution was the least, and it can be used as the initial distribution.

2) Goodness-of-fit test for the initial distribution.

According to the probability graph estimation, $m = 1.1925$, $\eta = 13207h$, the Pearson χ^2 test statistics is obtained from **Eqs 12** and **13**:

$$\chi^2 = 58.7058.$$

Given the confidence probability $\gamma = 0.9$, $\chi^2_{0.9}(47)$ is obtained from **Eq. 15**.

$$\chi^2_{0.9}(47) = 60.0312.$$

We can obtain χ^2 less than $\chi^2_{0.9}(47)$.

$$\chi^2 < \chi^2_{0.9}(47).$$

The hypothesis test is passed at a high probability, and then the life data of this wind turbine follows the two-parameter Weibull distribution, the distribution parameters, the point estimation and the interval estimation of reliability measures can be further solved.

We set $\bar{t}_{S,1}, \bar{t}_{S,2}, ..., \bar{t}_{S,p}$ as a complete sample, the likelihood function for the two-factor Weibull distribution can be expressed as

$$L(m, \eta) = \prod_{k=1}^{p} \frac{m}{\eta}\left(\frac{\bar{t}_{S,k}}{\eta}\right)^{m-1} \exp\left[-\left(\frac{\bar{t}_{S,k}}{\eta}\right)^m\right]. \tag{17}$$

The logarithm is taken from

$$\ln L(m, \eta) = p \ln\frac{m}{\eta} + (m-1)\sum_{k=1}^{p} \ln\frac{\bar{t}_{S,k}}{\eta} - \sum_{k=1}^{p}\left(\frac{\bar{t}_{S,k}}{\eta}\right)^m. \tag{18}$$

The constraint conditions are set as

$$\frac{\partial \ln L}{\partial m} = 0, \quad \frac{\partial \ln L}{\partial \eta} = 0.$$

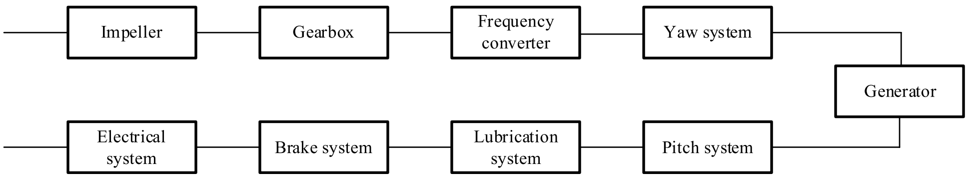

FIGURE 2 | Reliability block diagram of the wind turbine.

TABLE 3 | Distribution parameters of the units.

Component	Distribution	Mean value μ	Standard deviation σ	Scale parameter η	Shape parameter m
Blade	Normal distribution	42000	663	—	—
Gearbox	Logarithmic normal distribution	11	1.2	—	—
Generator	Weibull distribution	—	—	76000	1.2
Yaw system	Extreme maximum value distribution	65000①	370②	—	—
Pitch control system	Normal distribution	84534	506	—	—
Brake system	Exponential distribution	120000	—	—	—
Lubrication system	Weibull distribution	—	—	66000	1.3
Electrical system	Weibull distribution	—	—	35000	1.5
Frequency converter	Exponential distribution	45000	—	—	—

① denotes the location parameter of the maximum value distribution, and ② denotes the scale parameter of the maximum value distribution.

TABLE 4 | Units' life simulation data (*h*).

Times	Impeller	Gearbox	Generator	Pitch control system	Yaw system	Brake system	Lubrication system	Electrical system	Frequency converter
1	43311	40009	74395	65193	84351	20324	50765	48938	55911
2	42201	16828	185946	65318	84236	4826	39547	19360	23634
3	41248	48744	86633	64261	84653	123818	63409	6771	14843
4	41940	58750	1673	65331	84583	45553	116354	24337	59810
5	42013	14828	35490	65000	85129	99210	106863	57828	5754
6	42133	125633	75981	64158	85021	101249	9013	36303	13516
7	43656	175291	41034	64586	84203	37468	14264	6903	9821
8	42372	28295	175973	64914	84273	21075	91015	11582	162175
9	41716	363928	38274	65426	85453	125173	44053	59533	47344
10	42558	47368	6393	65447	83788	20456	81417	57654	94197
11	42667	70521	22551	64348	85127	57006	41832	68821	9781
12	41678	24014	37799	65466	84852	8933	65919	49767	286468
13	41753	19934	28705	65425	84414	297109	49832	27628	33671
14	43029	21064	40274	64849	84405	51099	65566	24296	10853
15	42602	57290	33770	65176	85297	172179	89127	21851	18474
16	41605	56145	139157	64305	84050	38637	98599	31637	16932
17	42969	17676	56570	64777	84433	57656	51311	3445	66923
18	41590	372267	207061	65335	84546	34188	11249	16269	104821
19	41921	30931	21816	65167	85164	65177	3692	50081	26140
20	42121	137379	28842	65431	86255	85724	30947	19872	7451
21	43323	34659	104992	65024	85339	50258	104110	5776	29574
22	41598	1375050	40966	63774	84082	4140	16036	2046	29741
23	42661	36847	14916	65236	83399	20625	37707	9471	8159
24	41058	179747	8944	65370	84464	61753	104395	19642	70728
25	41747	18501	76860	65047	84158	120728	7691	37303	1066
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
500	42109	283068	46822	64981	84803	93965	1632	39312	7857

Setting p = 50, *we can get 50 characteristic data as listed in* ***Table 5***.

TABLE 5 | The system simulation life data.

Sequence number	Data		Sequence number	Data		Sequence number	Data	
	r_k	$\bar{t}_{S,k}$		r_k	$\bar{t}_{S,k}$		r_k	$\bar{t}_{S,k}$
1	11	250	18	10	8750	35	9	20000
2	13	750	19	10	9250	36	8	21000
3	16	1250	20	16	9750	37	10	22000
4	5	1750	21	9	10250	38	5	23000
5	14	2250	22	8	10750	39	12	24000
6	15	2750	23	13	11250	40	5	25000
7	13	3250	24	18	11750	41	6	26250
8	14	3750	25	14	12250	42	7	27750
9	13	4250	26	4	12750	43	6	29250
10	9	4750	27	7	13250	44	4	30750
11	15	5250	28	8	13750	45	2	32000
12	18	5750	29	7	14250	46	3	34000
13	12	6250	30	6	15000	47	5	36000
14	18	6750	31	13	16000	48	4	38000
15	10	7250	32	15	17000	49	5	40000
16	15	7750	33	16	18000	50	9	42000
17	7	8250	34	8	19000			

TABLE 6 | The life distribution deduction result.

Distribution	Normal distribution	Exponential distribution	Weibull distribution	Logarithmic normal distribution	Extreme minimum value distribution	Extreme maximum value distribution
Q_j	14.3679	0.9514	0.1737	19.2132	9.6881	1.3746

The likelihood equations are established and arranged as

$$\begin{cases} \dfrac{\sum\limits_{k=1}^{p}(\bar{t}_{S,k})^m \ln \bar{t}_{S,k}}{\sum\limits_{k=1}^{p}(\bar{t}_{S,k})^m} - \dfrac{1}{m} = \dfrac{1}{p}\sum\limits_{k=1}^{p}\ln \bar{t}_{S,k} \\ \eta^m = \dfrac{1}{p}\sum\limits_{k=1}^{p}(\bar{t}_{S,k})^m \end{cases}, \tag{19}$$

$\bar{t}_{S,1}, \bar{t}_{S,2}, \cdots, \bar{t}_{S,50}$ are substituted into **Eq. 19** to solve the maximum likelihood estimation for the parameter m, η.

$$\begin{cases} \hat{m} = 1.2427 \\ \hat{\eta} = 13114 \end{cases}.$$

Therefore,

$$\bar{T}_S = \hat{\eta}\Gamma\left(1 + \frac{1}{\hat{m}}\right), \tag{20}$$

where $\bar{T}_S$ is the maximum likelihood estimation for the average life of the wind turbine.

As $\hat{m} > 1$, gamma function can be approximated as

$$\Gamma\left(1 + \frac{1}{\hat{m}}\right) \approx 1 - 0.5748646\frac{1}{\hat{m}} + 0.9512363\left(\frac{1}{\hat{m}}\right)^2$$
$$-0.6998588\left(\frac{1}{\hat{m}}\right)^3 - \tag{21}$$
$$0.6998588\left(\frac{1}{\hat{m}}\right)^3 + 0.4245549\left(\frac{1}{\hat{m}}\right)^4 - 0.1010678\left(\frac{1}{\hat{m}}\right)^5.$$

If $\hat{m} \le 1$, the calculation can be simplified using the recursive equation and $\bar{T}_S$ can be calculated as follows:

$$\bar{T}_S = 12287.02h.$$

With the given t value, the maximum likelihood estimation for the reliability function $R(t)$ is

$$\hat{R}_S(t) = \exp\left[-\left(\frac{t}{\hat{\eta}}\right)^{\hat{m}}\right]. \tag{22}$$

Therefore, the maximum likelihood estimation for the failure rate function $\lambda(t)$ is

$$\hat{\lambda}_S(t) = \frac{\hat{m}}{\hat{\eta}}\left(\frac{t}{\hat{\eta}}\right)^{\hat{m}-1}. \tag{23}$$

If the confidence probability is set as $1-\alpha$, the confidence interval for the distribution parameter m, η is

$$\begin{cases} m_L = \hat{m}\exp\left(-u_{1-\frac{\alpha}{2}}\dfrac{1.0490}{\sqrt{p-1}}\right) \\ m_U = \hat{m}\exp\left(u_{1-\frac{\alpha}{2}}\dfrac{1.0490}{\sqrt{p-1}}\right) \end{cases}, \tag{24}$$

$$\begin{cases} \eta_L = \hat{\eta}\exp\left(-u_{1-\frac{\alpha}{2}}\dfrac{1.0810}{\hat{m}\sqrt{p-1}}\right) \\ \eta_U = \hat{\eta}\exp\left(u_{1-\frac{\alpha}{2}}\dfrac{1.0810}{\hat{m}\sqrt{p-1}}\right) \end{cases}, \tag{25}$$

TABLE 7 | The confidence interval for the distribution parameter and lower confidence limit for the average life of the wind turbine under different confidence probabilities.

$1-\alpha$	m_L	m_U	η_L	η_U	$(\bar{T}_S)_L$
0.9	0.9712	1.4374	10689.6575	16088.1672	10015.5596
0.8	1.0256	1.4491	11183.3236	15377.9862	10478.0948
0.7	1.0639	1.4575	11529.2156	14916.6259	10802.1745

Given the t value, the lower confidence limit (1 − α) for the reliability of the wind turbine is approximated.

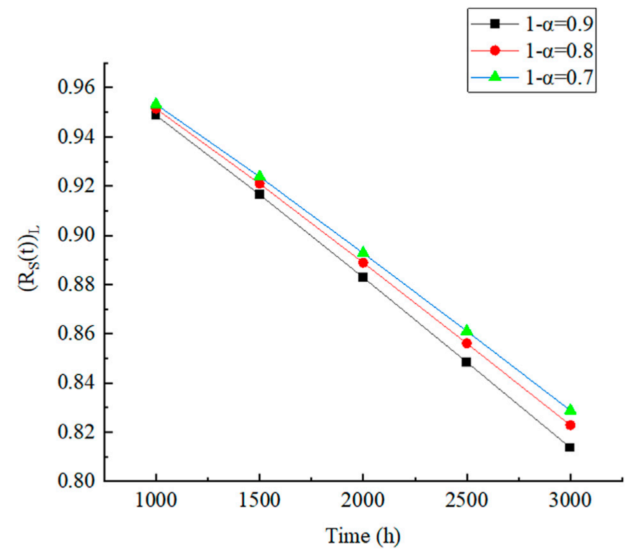

FIGURE 3 | Reliability lower confidence limit (1 − α) of the wind turbine under different confidence probabilities and life.

where $u_{1-\frac{\alpha}{2}}$ is the quantile of standard normal distribution, and it can be calculated by **Eq. 16**.

To simplify the calculation, the shape parameter m can be taken as its maximum likelihood estimation, and it is taken as $\hat{m} = 1.2427$.

When the given confidence probabilities $1-\alpha$ are 0.9, 0.8, and 0.7, respectively, the confidence interval for the distribution parameter m, η, and lower confidence limit for the average life of the wind turbine are shown in **Table 7**.

$$(R_S(t))_L = \exp\left[-\left(\frac{t}{\eta_L}\right)^{\hat{m}}\right]. \tag{26}$$

The upper confidence limit $(1-\alpha)$ for its failure rate is approximated as

$$(\lambda_S(t))_U = \frac{\hat{m}}{\eta_L}\left(\frac{t}{\eta_L}\right)^{\hat{m}-1} \Big/ \mathrm{h}, \tag{27}$$

when t is 1000, 1500, 2000, 2500, and 3000h, and the confidence probabilities $1-\alpha$ are 0.9, 0.8, and 0.7, respectively, the reliability lower confidence limit $(1-\alpha)$ and failure rate upper confidence

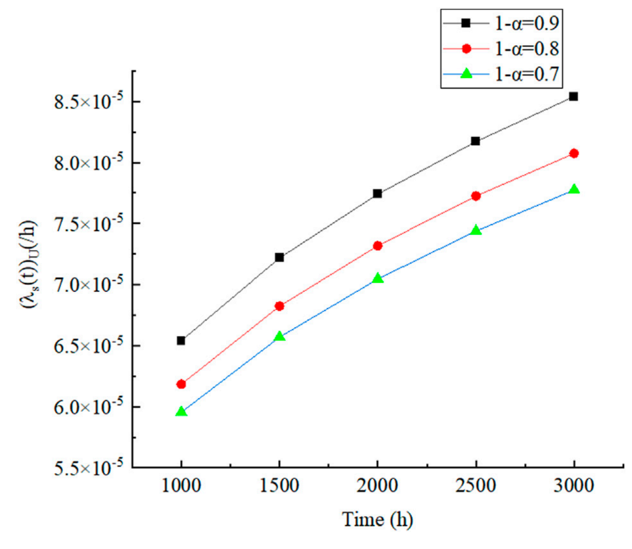

FIGURE 4 | Failure rate upper confidence limit (1 − α) of the wind turbine under different confidence probabilities and life.

limit $(1-\alpha)$ of wind turbine are shown in **Figure 3** and **Figure 4**, respectively.

It can be seen from **Figure 3** and **Figure 4** that all lower limits of reliability $(R_S(t))_L$ show a downward trend, while all failure rates show an upward trend under different confidence probabilities.

CONCLUSION

For the CEMS with many limiting factors, this article presented a method of replacing life test with computer analog simulation for CEMS. The life simulation values of system constituent units of CEMS could be obtained by their life distribution types and relevant distribution parameters. The life simulation values of CEMS were obtained according to the reliability logic relationship and reliability logic block diagram of the CEMS, and the simulation was instead of the life test of CEMS when the simulation times were enough. The method proposed in this thesis was of great significance to save test time and test cost, especially for the CEMSs that could not carry out reliability life test.

The method proposed in this thesis could solve the problems of system reliability synthesis and prediction of CEMS with different distributions of units. When the "pyramid model" was used for system reliability level by level synthesis and prediction. Compared with the traditional life test method of CMES, it could save a lot of test cost, test time, test site, and so on. This approach could be applied to the early program design, prototype development, trial production, and other stages of production. In engineering applications, the CMES reliability logic block diagram could be drawn by computer, and all the smallest path sets could be obtained by the node traversal optimization algorithm. Therefore, it has obvious application value in engineering.

Finally, the proposed method was applied to the wind turbine, and the reliability lower confidence limit $(1-\alpha)$ and failure rate upper confidence limit $(1-\alpha)$ of wind turbine were calculated with given the life time t. The method is also applicable to other CEMSs and can be utilized to provide guidance for system design, maintenance planning, and so on. This paper provides an effective and flexible method for reliability synthesis and prediction of CEMS, which can be easily implemented in engineering practices.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

CY: writing, reviewing, and editing, YG: reviewing and drawing, and XY: funding acquisition.

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