MARKOV RELIABILITY MODEL OF A WIND FARM

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Abstract

A Markov reliability model of a wind farm has been built using the example of Anholt wind farm, Denmark. Reliability indicators of wind turbine equipment are calculated as wind speed functions. Basing hourly measurements of the wind speed and the consumed electricity, two samples of duration time of the met and unmet demand of electricity were obtained. It has been found that these samples can be approximated with exponential mixture model of the probability distributions. The wind farm operation process has been approximated with a continues-time 5-states Markov process. As a result, stationary and non-stationary probabilities that the electricity demand will be met by wind power were estimated.

Keywords: wind farm, reliability, availability, met demand, unmet demand, exponential mixture model of distributions, continues-time finite-states Markov process.

1. Introduction

The share of renewable sources in the electricity market is constantly growing, however, at the current stage of development, they cannot guarantee the supply of electricity to consumers. The renewable sources depend on sufficiently significant random factors such as wind speed or insolation intensity. In this regard, it is necessary to use combined power supply systems that include both traditional and renewable energy sources.

A study of the reliability of such systems allows assessing how much power reserve of traditional energy sources is necessary to cover the deficit in the event of insufficient generation of renewable energy sources. It should take into account both instability of wind speed and usual equipment failures. In this paper, one of the most powerful wind farms, the Anholt wind farm in Denmark, is considered as an example. It was built in 2013 and consists of 111 wind turbines Siemens Gamesa Renewable Energy, SWT 3.6-120, the maximum capacity of each of them is 3.6 MW. The whole power plant can generate up to 400 MW, which is about 2.7 % of Denmark's electricity need.

There are numerous studies in literature on reliability models of wind farms and combined energy systems. In [1], a Markov model of combined power gas and thermal networks was built and the reliability of small business supply in Germany during a standard weekend day was investigated. In [2], the optimal parameters of a combine power plant consisting of gas and wind generators were evaluated. Wind energy was accounted for using a probability density, the estimate of which has not been included in this article. In [3, 4, 5], various models of the wind farm reliability were considered. These models take into account that the failure rates of wind turbine equipment are dependent on wind speed. Wind speed values were modelled with the Monte-Carlo method [3, 4] or with Markov chains [5]. In [6], reliability indicators of a wind farm were calculated with probability-generating functions. In [7], generated power of a wind farm was evaluated with a cubic model. The wind speed, as a random variable, was approximated by the Gnedenko-Weibull distribution. The distribution parameters were estimated according to statistical data, and all the measurements were considered independent, i.e. the correlation structure of measurements' series was not taken in account.

The correlation structure of a wind speed time series was studied in [8, 9] and other papers, where the short-terms forecasting problems of wind speed were considered. These problems were solved with neural network models, ARIMA models, etc. These models are not very accurate, so, in this paper, the generated power will be predicted based on real meteorological data. In [10] and [11], wind farm equipment reliability indicators were studied as functions of wind speed based on statistical data.

The models presented in some of the listed articles were utilized in our paper when processing a large amount of statistical data for a specific object – Anholt wind farm. As a result, the statistical patterns were identified, which made it possible to build a Markov model and estimate the reliability indicators of the wind farm.

The paper is organized as follows. In section 2, the reliability indicators of a turbine are estimated as a function of wind speed. In section 3, statistical data and mathematical models are investigated to evaluate the electricity demand and the wind farm capacity to produce it. Then a Markov model of the wind farm operation process has been built and its reliability indicators are estimated. In section 4, the results of the study are summarized.

2. Equipment Reliability of a Turbine

At first, let's estimate equipment reliability indicators of a wind farm. To do this, it is enough to consider any turbine. A stationary availability will be consider as a main reliability indicator:

$$K = \frac{T}{T+R},$$

where T is the mean time between failures (MTBF), R is the mean time to repair (MTTR).

In [10], it is found that the failure rates of wind farm equipment linearly depend on wind speed W in the speed range $W = 7 - 11$ m/s, but the result of extrapolating this dependence to a wider range of real wind speed in the region of Anholt Island is implausible: the failure rate forecast for small wind speeds is negative (Fig. 1). It is natural to assume the equipment does not fail when it is idle, i.e. if wind speed is zero, the failure rate must be zero too. This idea leads us to a quadratic model without a constant:

$$\lambda(W) = b_1 W + b_2 W^2, \quad (1)$$

where $\lambda(W)$ is the failure rate, 1/year, $b_1 = 0.353$ s/(year·m) and $b_2 = 0.0868$ s^2/(year·m^2) are the model coefficients fitted by least squares. Fig. 1 shows this model does not differ from the linear practically in speed range 7–11 m/s.

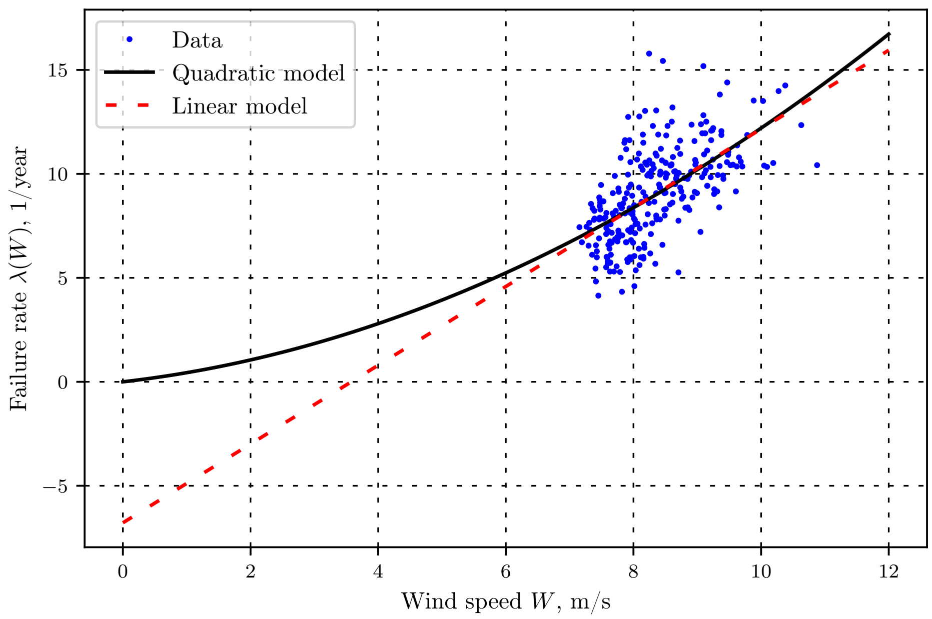

Figure 1: *Dependence of the Failure Rate on Wind Speed*

In [10], the estimations of failure rates (Table 1) and of mean times to repair (Table 2) for various equipment of a wind turbine are presented.

Table 1: *Failure rates $\bar{\lambda}_i$, 1/year*

Element \ Failure Type	Replacement	Major Repair	Minor Repair	No Cost Data
Blades	0.001	0.010	0.456	0.053
Contactor / Circuit Breaker / Relay	0.002	0.054	0.326	0.048
Controls	0.001	0.054	0.355	0.018
Electrical Components	0.002	0.016	0.358	0.059
Gearbox	0.154	0.038	0.395	0.046
Generator	0.095	0.321	0.485	0.098
Grease / Oil / Cooling Liq.	0	0.006	0.407	0.058
Heaters / Coolers	0	0.007	0.190	0.016
Hub	0.001	0.038	0.182	0.014
Other Components	0.001	0.042	0.812	0.150
Pitch / Hyd	0.001	0.179	0.824	0.072
Power Supply / Converter	0.005	0.081	0.076	0.018
Pumps/Motors	0	0.043	0.278	0.025
Safety	0	0.004	0.373	0.015
Sensors	0	0.070	0.247	0.029
Service Items	0	0.001	0.108	0.016
Tower / Foundation	0	0.089	0.092	0.004
Ransformer	0.001	0.003	0.052	0.009
Yaw System	0.001	0.006	0.162	0.020

Table 2: *Mean times to repair R_i, hours*

Element \ Failure Type	Replacement	Major Repair	Minor Repair	No Cost Data
Blades	288	21	9	28
Contactor / Circuit Breaker / Relay	150	19	4	5
Controls	12	14	8	17
Electrical Components	18	14	5	7
Gearbox	231	22	8	7
Generator	81	24	7	13
Grease / Oil / Cooling Liq.	–	18	4	3
Heaters / Coolers	–	14	5	5
Hub	298	40	10	8
Other Components	36	21	5	8
Pitch / Hyd	25	19	9	17
Power Supply / Converter	57	14	7	10
Pumps/Motors	–	10	4	7
Safety	–	2	2	2
Sensors	–	6	8	8
Service Items	–	2	7	9
Tower / Foundation	–	7	5	6
Ransformer	1	26	7	19
Yaw System	49	20	5	9

The failure rate of turbine subsystems should be as dependent on the wind speed as the failure rate of the whole turbine. Assuming that this dependence has the form (1), then it can be estimated using

$$\lambda_i(W) = \frac{\bar{\lambda}_i}{\sum\limits_k \bar{\lambda}_k} \lambda(W).$$

Let the equipment failures be independent. Then simultaneous failures of different elements are unlikely, they can be neglected. Therefore, the mean time to repair of the whole turbine can be calculated with the law of total probability:

$$R = \sum_k R_k p_k,$$

where p_k is the conditional probability of a failure of the k-th subsystem, if there is a failure of the whole turbine. These probabilities can be estimated as the multinomial distribution parameters:

$$p_k = \frac{\lambda_k(W)}{\sum\limits_i \lambda_i(W)} = \frac{\bar{\lambda}_k}{\sum\limits_i \bar{\lambda}_i}.$$

Remark. Assuming the failure flow is Poisson, i.e. the time between failures is exponentially distributed, then this result can be obtained more rigorously:

$$p_k = \mathrm{P}\{\xi_k < \xi_i, \forall i \neq k\} = \int\limits_0^\infty \prod_{i\neq k} \big(1 - F_i(t)\big)\, dF_k(t) = \int\limits_0^\infty \prod_{i\neq k} e^{-\lambda_i(W)t}\, \lambda_k(W) e^{-\lambda_k(W)t}\, dt = \frac{\bar{\lambda}_k}{\sum\limits_i \bar{\lambda}_i},$$

where ξ_j is the time between failures of the subsystem j, $F_j(t)$ is the cumulative distribution function of ξ_j.

In spite of the fact that the failure rates of the subsystems depend on wind speed, the probability p_k does not depend on it under assumption about equality of wind speed influence on all the equipment is true.

Thus, the mean time to repair of a turbine is

$$R = \frac{\sum_k R_k \bar{\lambda}_k}{\sum_i \bar{\lambda}_i} = 0.00153 \text{ years} = 13.5 \text{ hours}.$$

To estimate the mean time between failures, we will consider a wind turbine operation process, i.e. the number of work-repair cycles, as a renewal process. The mean number of failures to a point in time t is a renewal function $H(t)$, that, according elementary renewal theorem [12], is

$$H(t) \approx \frac{t}{T+R}.$$

If $t \to \infty$, then $\frac{H(t)}{t}$ is approximately equal to the failure rate $\lambda(W)$, so

$$T \approx \frac{1}{\lambda(W)} - R,$$

which implies

$$K(W) = 1 - \lambda(W)R = 1 - 0.000542\,W - 0.000133\,W^2. \tag{2}$$

3. Markov Modelling of Electricity Supply and Demand

We will use a continuous-time finite state Markov process to model a wind farm operation. Let consider a model with two states: in the state 0, the wind farm fully provides its consumers, and in state 1, there is not enough wind energy, it is necessary to use gas, coal, etc. Such model is correct, if the residence time of the process in each state is well approximated with the exponential law. To prof this assumption a large amount of statistical data was researched. We have used only open information sources, so it took some calculations to estimate the residence time distribution laws.

3.1. Estimation of Power Dependent on Wind Speed

Using experimental data from [13], a model of the dependence of the turbine power on the wind speed $P(W)$ in MW has been fitted with least squares given by (3) and represented at Fig. 2.

$$P(W) = 3.6\left(1 - e^{-\exp(-7.6+0.23W)W^{2.5}}\right). \tag{3}$$

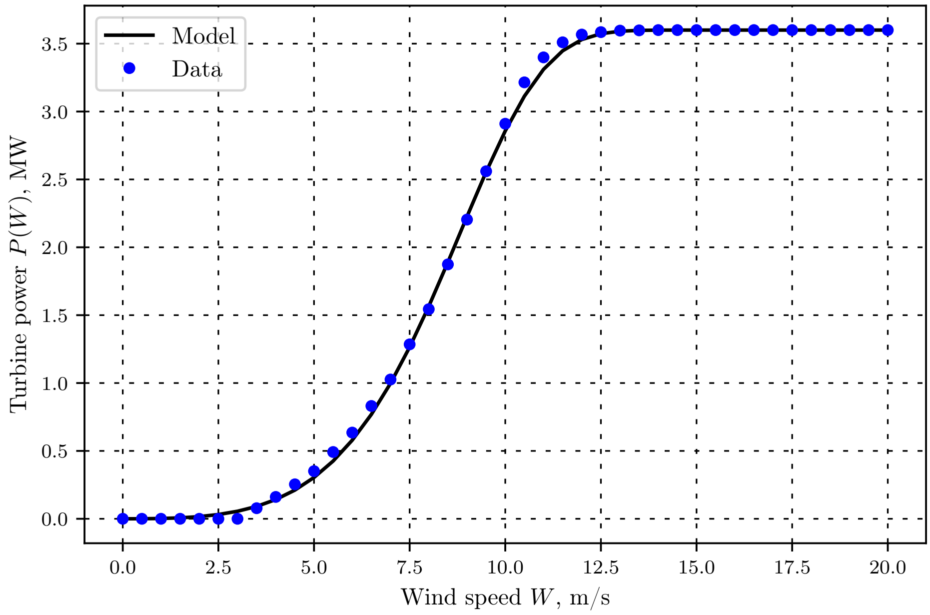

Figure 2: *Power Curve of the Turbine Siemens Gamesa Renewable Energy, SWT 3.6-120 [13]*

The wind speed is measured at the weather vane height, $h = 10$ m [14], and the power depends on the wind speed at the height of the turbine blades, i.e. at an altitude $z = 90$ m. To recalculate the wind speed, we will utilize the logarithmic model from [15]:

$$W = W_h \frac{\ln z - \ln z_0}{\ln h - \ln z_0}, \tag{4}$$

where $z_0 = 0.0002$ m is the roughness length [16]. Thus, knowing the wind speed at the height of the blades we can evaluate the power generated by a turbine.

The total generated power of the wind farm is equal to $N\,P(W)$, where N is a number of operable turbines, which may be less, than the nominal count $n = 111$ due equipment failures of some turbines. The random variable N has binomial distribution with a "success" probability $K(W)$, which may be calculated by the formula (2). To obtain a lower limit of the total generated power it is necessary to take a significance level $1 - \alpha$ and calculate a left quantile N_α. The number of the turbines is large enough, so the distribution of the variable N may be approximated by the normal law. Therefore, the low limit of the number of operable turbines is evaluated by

$$Z(W) = n\,K(W) + z_\alpha \sqrt{n\,K(W)\big(1 - K(W)\big)},$$

where z_α is a standard normal quantile. In this case, the real number of operable turbines will not be less $Z(W)$ with the probability $1 - \alpha$.

Thus, a lower limit of the power generated by the wind farm is

$$P_{Anholt}(W) = Z(W)P(W). \tag{5}$$

3.2. Met and Unmet Demand periods

The electricity generated by Anholt wind farm goes to the total network in Denmark, so it is impossible to point, what consumers receive this energy. That's why we have to evaluate the electricity demand from Anholt as a share of the national demand, assuming it corresponds to the share of the installed capacity of the Anholt wind farm ($Q_{Anholt} = 400$ MW) in the total installed capacity $Q_{Denmark}$ of all the power plants in Denmark. In open access, there is information about the total installed capacity between 1990 and 2018 [17]. To predict the total installed capacity $Q_{Denmark}(y)$ for 2019 and 2020, a logarithmic model was used (Fig. 3):

$$Q_{Denmark}(y) = a_0 + a_1(y - 1989) + a_2 \ln(y - 1989),$$

where y is the time in years and the coefficients $a_0 = 8749.25$, $a_1 = 88.25$, $a_2 = 967.3$ are fitted by least squares.

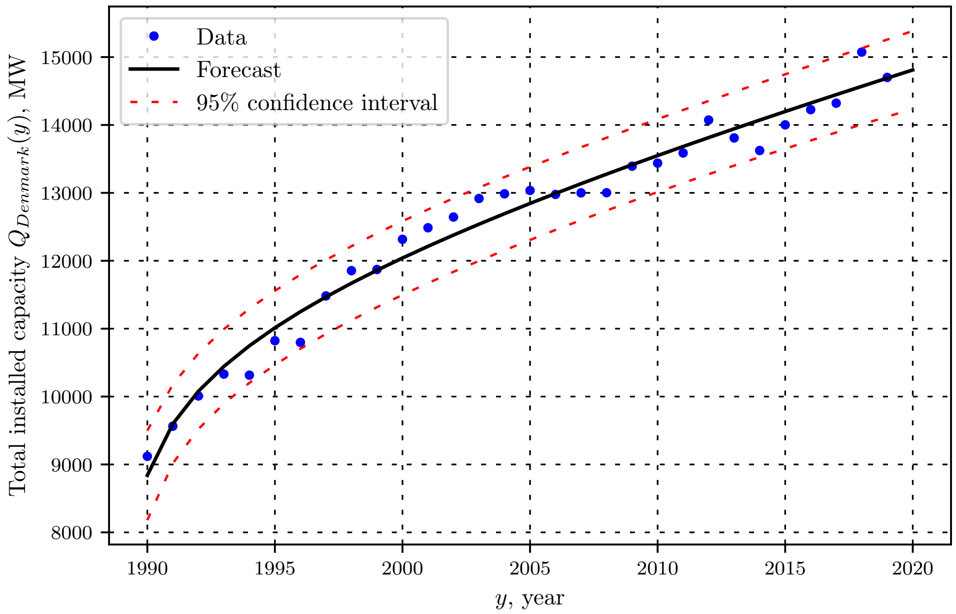

Figure 3: *Total Installed Electricity Capacity in Denmark*

According to this model, the total installed capacity was 14700 MW in 2019 and 14800 MW in 2020, so the Anholt share is evaluated as 2.72% and 2.70%, respectively.

Using hourly data on total electricity consumption in Denmark [18], we have obtained an evaluation of the electricity demand for the wind farm under study:

$$C_{Anholt}(t) = \frac{Q_{Anholt}}{Q_{Denmark}(y)} C_{Denmark}(t),$$

where t is the time in hours, $y = y(t)$ is the time in years, $C_{Denmark}(t)$ is the total electricity consumption in Denmark, MWh.

Using hourly data on wind speed in Anholt Island at the height $h = 10$ m we have obtained $W(t)$ – the wind speed at the height of the turbine blades for every hour t by the Eq. (4). Then by Eq. (5), we have calculated the power $P_{Anholt}(t) = P_{Anholt}(W(t))$ generated by all the turbines of the Anholt wind farm. A positive expression $P_{Anholt}(t) - C_{Anholt}(t)$ determines met demand periods, and a negative determines unmet ones. Fig. 4 shows a data fragment from March 28 to April 2, 2016.

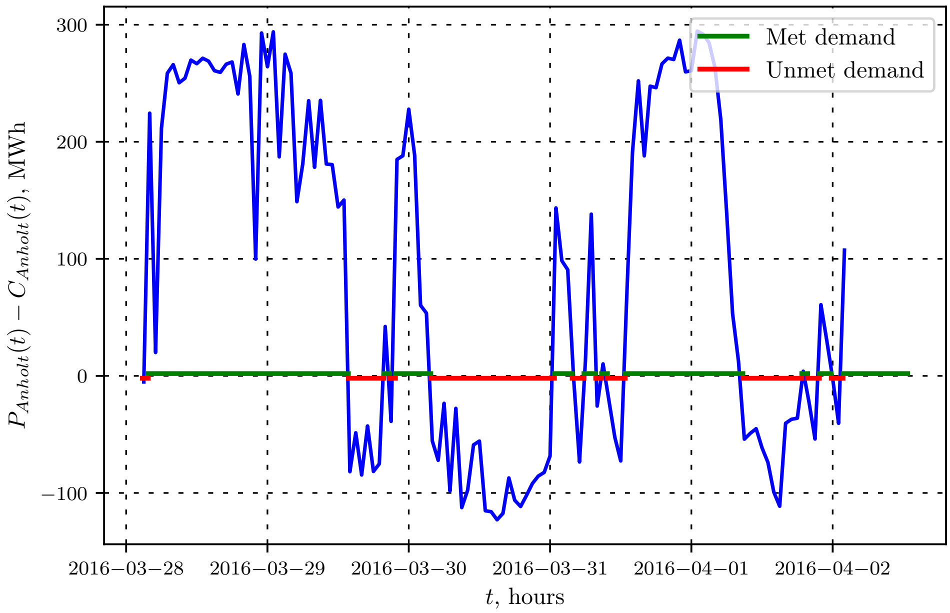

Figure 4: *Periods of Met and Unmet Demand*

The duration of the periods depends mainly on fluctuations in generated power, i.e. on wind speed. Although the demand fluctuations have 3 cycles (daily, weekly and seasonal), their amplitude is much less, than that of the power fluctuations. Fig. 5 shows a data fragment from January 9 to 21, 2016.

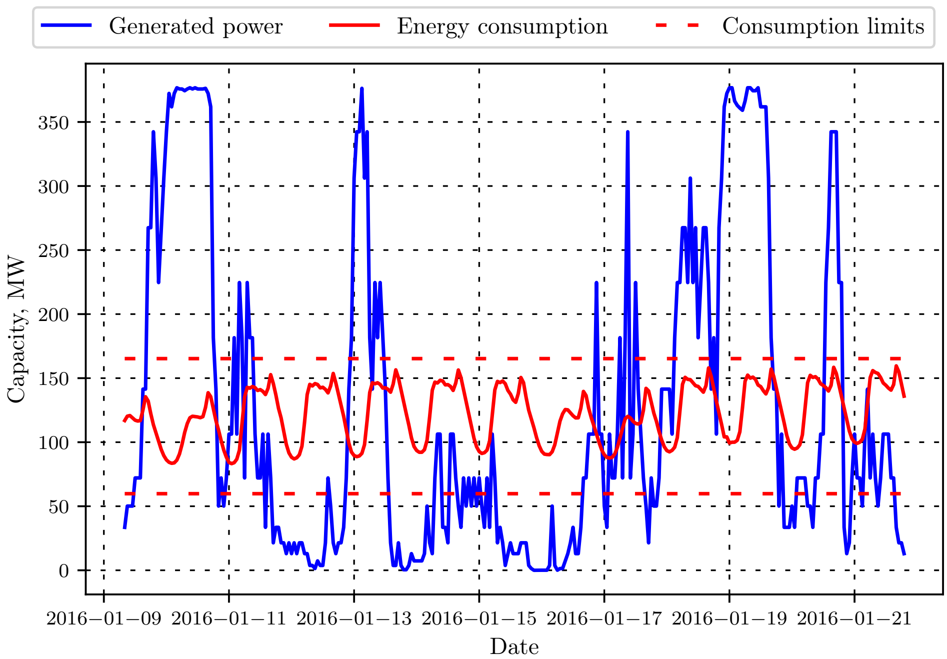

Figure 5: *Comparison of the Fluctuations' Amplitude in Supply and Demand*

After processing the data for 2016 – 2020, we have obtained two samples: the periods of met and unmet demand (the sample sizes are 2015 and 2016 observations, respectively). These measurements are weakly correlated with each other (Fig. 6)), so we will consider them as independent observations.

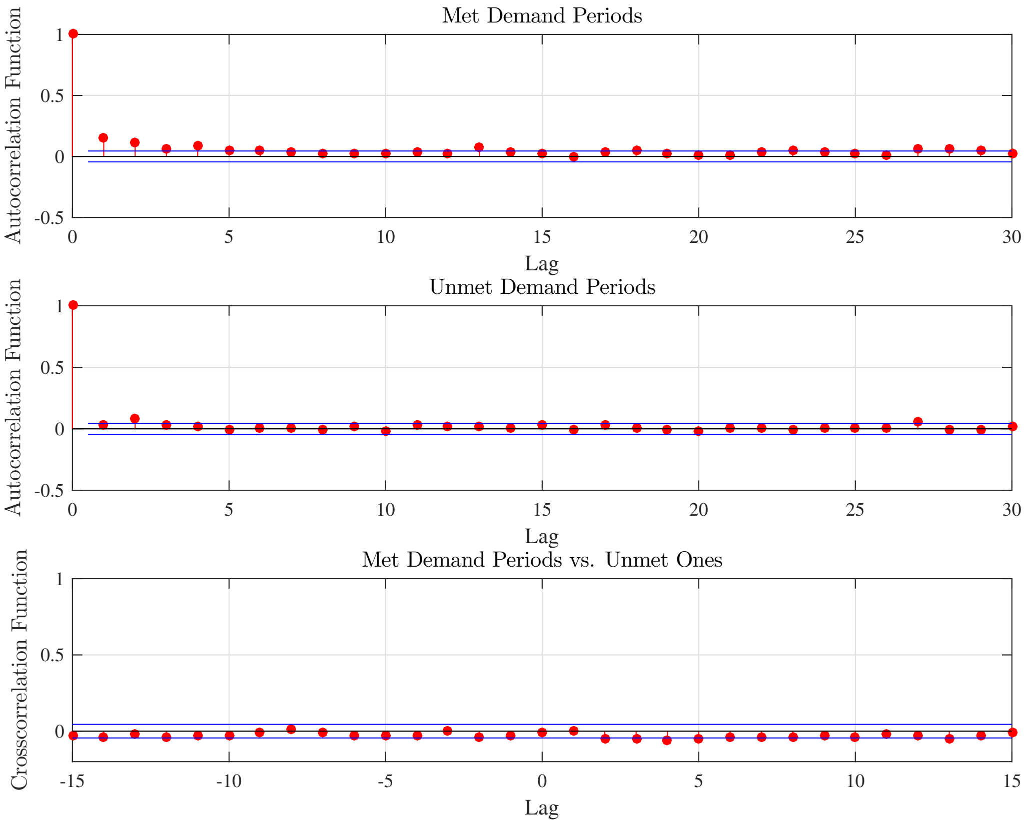

Figure 6: *Correlation Functions of the Periods*

The data may be described by the exponential mixture model, for which the probability density functions have the form

$$f(t) = \sum_{i=1}^{k} \frac{v_i}{\mu_i} e^{-\frac{t}{\mu_i}}.$$

The parameters μ_i are expectations of exponential distributions, from which the mixture model consists, and v_i are weight parameters of them. To estimate these parameters, the expectation-maximization algorithm (EM-algorithm) [19] was applied. It is a modification of the maximum likelihood method adapted for mixture distribution models. The model parameters for the met demand periods distribution are

$$\begin{aligned} \vec{v} &= [0.63,\ 0.19,\ 0.18]; \\ \vec{\mu} &= [2.2,\ 11.0,\ 43.6] \text{ hours}, \end{aligned}$$

and these ones for the unmet demand periods distribution are

$$\begin{aligned} \vec{v} &= [0.66,\ 0.34]; \\ \vec{\mu} &= [2.4,\ 24.0] \text{ hours}. \end{aligned}$$

Figures 7 and 8 show histograms and probability plots validating the models. The formal χ^2-test has not confirm goodness of fit of these models, because the samples are too large, and the test founds insignificant deviations of an empirical distribution from a hypothetical one. But if we reduce the sample size by 4 times (up to 500) by randomly discarding a part of the observations, the p-values will be 0.8 for met and 0.2 for unmet demand periods, that is, much greater than the significance level $\alpha = 0.05$.

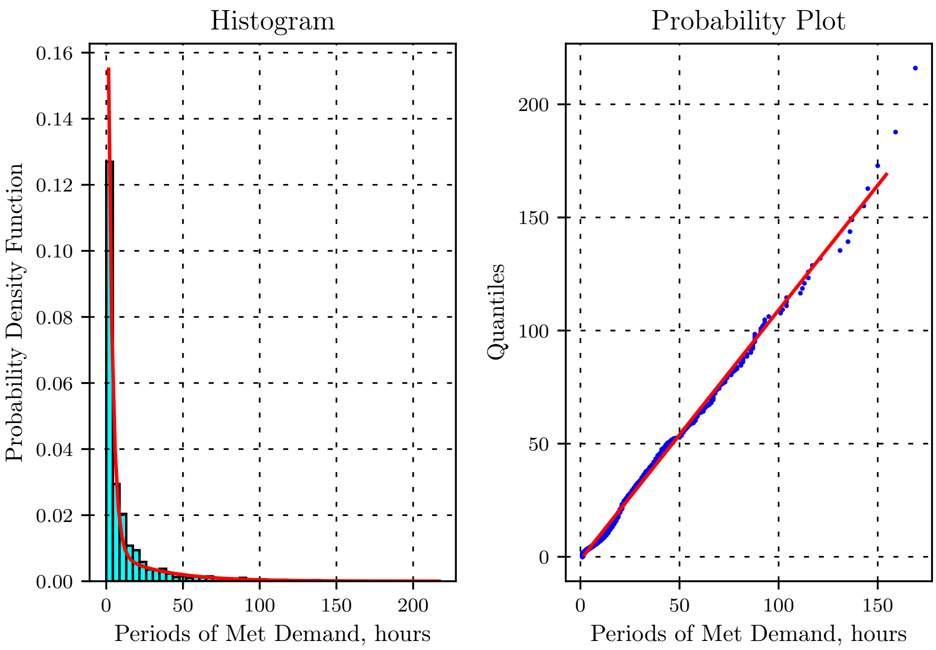

Figure 7: *Distribution Low of Met Demand Periods*

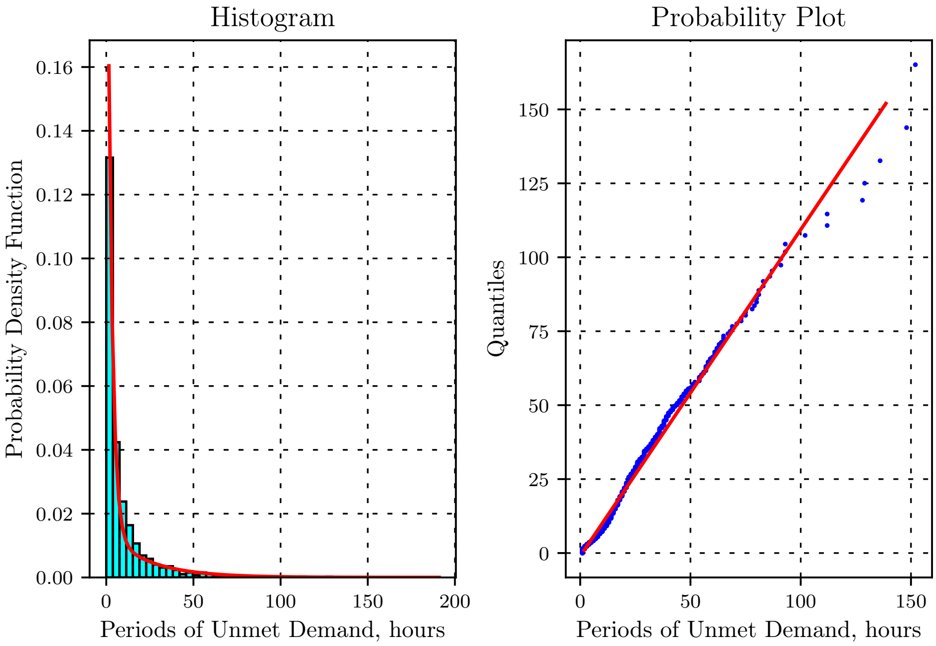

Figure 8: *Distribution Low of Unmet Demand Periods*

3.3. The Model

The exponential mixture model can be interpreted as follows: every real process state (0 – for met demand and 1 – for unmet one) consists from several fictive (3 or 2, respectively) states. The residence time in each of them has an exponential distribution. Let's number the fictive states: 0, 1 and 2 are the numbers of met demand states (shown by green vertices on the transition graph in Fig. 9), 3 and 4 are the numbers of unmet demand states (shown by red vertices on the transition graph in Fig. 9).

The transition rates are inversely proportional to the mean residence times in the states from which the process leaves, and are directly proportional to the weight coefficients of the states into which the process comes:

$$\lambda_{ij} = \frac{v_j}{\mu_i}, \quad i,j = \overline{0,4}.$$

Let's write the transition rates estimated by the data in the matrix form:

$$\Lambda = [\lambda_{ij}] = \begin{bmatrix} 0 & 0 & 0 & 0.30 & 0.15 \\ 0 & 0 & 0 & 0.06 & 0.03 \\ 0 & 0 & 0 & 0.02 & 0.01 \\ 0.26 & 0.08 & 0.07 & 0 & 0 \\ 0.03 & 0.01 & 0.01 & 0 & 0 \end{bmatrix}$$

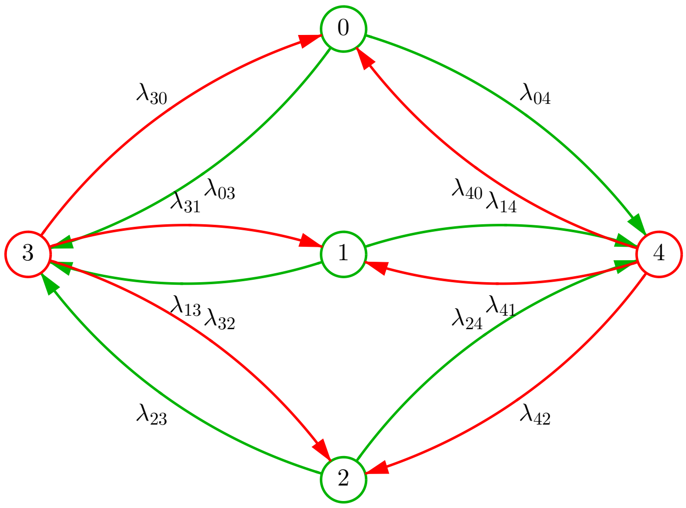

Figure 9: *Transition Graph of the Markov Model*

Because the residence time of every fictive states has approximately an exponential distribution, the process of transitions between them can be modelling as a Markov one. Therefore, the vector of the state probabilities $\vec{p}(t)$ is the solution of Kolmogorov system of equations [20]:

$$\frac{d\vec{p}}{dt} = \Lambda'\vec{p}, \quad \sum_{i=0}^{4} p_i(t) = 1. \tag{6}$$

A detailed derivation of this equation one can be find in numerous textbooks, for example in [21].

3.4. Model Investigation

To obtain an unique solution, it is necessary to set an initial condition by choosing one of the fictive states as the starting. With operational control at some time point t, we can attribute the last completed period to one of the fictitious states, because the EM-algorithm allows both estimating the parameters of a mixture of distributions and classifying observations.

The analytical solution of the system (6) is very cumbersome and is not presented here. It is recommended to apply numerical methods for solving the system (6), for example an explicit Runge-Kutta method.

The probabilities of the real states (0 – the met demand, 1 – unmet demand) are the sums of the fictive state probabilities:

$$\begin{aligned} p_0^*(t) &= \mathbf{P}\{P_{Anholt} \geq C_{Anholt}\} = p_0(t) + p_1(t) + p_2(t), \\ p_1^*(t) &= \mathbf{P}\{P_{Anholt} < C_{Anholt}\} = p_3(t) + p_4(t). \end{aligned}$$

Fig. 10 shows the plot of the met demand probability for various initial states. Green curves are for met demand initial states, red ones are for unmet demand initial states.

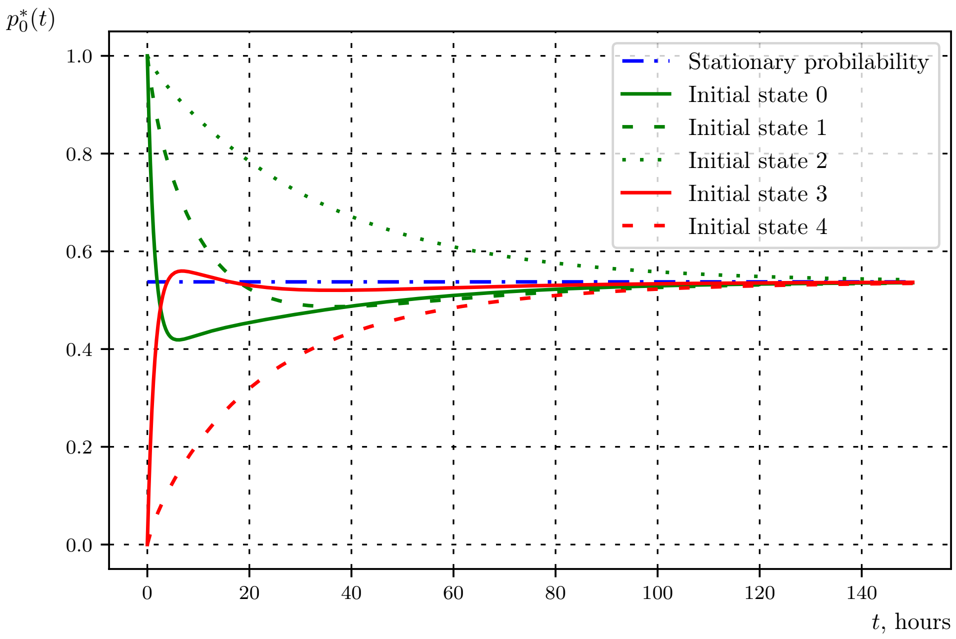

Figure 10: *Met Demand Probabilities for Various Initial States*

The stationary state probabilities $\vec{p} = \lim_{t\to\infty} \vec{p}(t)$ can be obtain form the system (6) by setting

$$\frac{d\vec{p}}{dt} = \vec{0}, \text{ i.e. } \Lambda'\vec{p} = \vec{0}.$$

This is a system of linear algebraic equations. The rank of the system matrix is 4, which is 1 less than the number of states, but with the normalisation condition $\sum p_i = 1$, the system has the full rank and its unique solution is presented in Table 3.

Table 3: *Stationary Probabilities of the Process States*

i	0	1	2	3	4
p_i	0.066	0.099	0.373	0.075	0.387

The process converges to the stationary one, but does not it very quickly: only in 120 hours after a start time point, the state probabilities differ from its stationary values less than 0.01.

The stationary probability of the met demand does not depend on an initial state and is

$$p_0^* = p_0 + p_1 + p_2 \approx 0.537.$$

This value differs little from the total share of the met demand time for the studied period, which indicate the adequacy of the constructed model:

$$\frac{T_0^*}{T_0^* + T_1^*} \approx 0.544,$$

where T_0^* is the total time of the met demand, T_1^* is the total time of the unmet demand.

Thus, the power of the wind farm is insufficient to meet the electricity demand on average 54% of the time. At the rest of the time consumers have to use other energy sources additionally. At the same time, the amount of energy generated during the periods of met demand is much greater than the required one. Although an industry technology for long-term storage of electricity, for example in the hydrogen form, has not yet been developed by now, investigations in this direction are being actively pursued. Conservation of energy during the period when it is generated in excess would make it possible to cover its deficit during periods of weak wind.

4. Conclusion

The electricity provision to consumers is determined both by the reliability of wind farm equipment and by weather conditions. This paper presents a mathematical model that makes it possible to assess the reliability indicators, such as failure rate, mean time to repair, and availability, based on the statistical data. The assessment took into account the dependence of the indicators on wind speed.

Based on statistical data and the already known mathematical models, the distributions of the met and unmet demand periods have been investigated. Using hourly data over 5-years period, we have found out that these distributions can be approximated by exponential mixture model, and, therefore, the process of the wind farm operation can modelled as a Markov process.

Thus, the model of the wind farm operating process taking into account both the random nature of wind speed as an energy source and usual failures of equipment is built. The main result of the study is the estimation of stationary probability of the met demand: it is approximately 0.537. It means that the power of the wind farm is insufficient to meet the electricity demand on average 54% of the time.

The amount of energy generated during the periods of met demand is much greater than the required one. Therefore, it is profitable to build an energy storage to save the energy excess. The author intends to study a reliability problem about a rational storage volume.

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References

[1] Gaudenz, K. and Göran, A. (2006). The influence of combined power, gas, and thermal networks on the reliability of supply. The Sixth World Energy System Conference, Torino, Italy, July 10-12.

[2] Chen, Sh., Sun, G., Wei, Zh., Chen, Sh. and Li, Y. (2016). Multi-time Combined Gas and Electric System Optimal Power Flow Incorporating Wind Power. Energy Procedia. 100. 111-116. doi:10.1016/j.egypro.2016.10.147.

[3] Kim, H., Singh, C. and Sprintson, A. (2012). Simulation and Estimation of Reliability in a Wind Farm Considering the Wake Effect. IEEE Transactions on Sustainable Energy, 3, PP. 274–282.

[4] Nath, A., Paul, S., Rather, Z. and Mahapatra, S. (2019). Estimation of Offshore Wind Farm Reliability Considering Wake Effect and Wind Turbine Failure. 3866-3871. doi:10.1109/ISGT-Asia.2019.8880887.

[5] Nguyen, N. and Almasabi, S. and Mitra, J. (2019). Impact of Correlation Between Wind Speed and Turbine Availability on Wind Farm Reliability. IEEE Ransactions on Industry Applications. PP. 1-1. doi:10.1109/TIA.2019.2896152.

[6] Fazio, A.R., Russo, M. (2009). Wind farm modelling for reliability assessment. Renewable Power Generation, IET. 2. PP. 239 – 248. doi:10.1049/iet-rpg:20080005.

[7] Goldaev, S.V. and Radyuk, K.N. (2015). Raschet proizvoditel'nosti vetroenergeticheskoj ustanovki bol'shoj moshchnosti po usovershenstvovannoj metodike [Calculation of the ca-

pacity of a high power wind power plant using an improved procedure]. Izvestiya Tomskogo politekhnicheskogo universiteta. Inzhiniring georesursov. Vol. 326. № 8. (In Russian)

[8] Rakhmanov, N.R., Kurbatski, V.G., Guliev, G.B. and Tomin, N.V. (2015) Kratkosrochnoe prognozirovanie vyrabotki moshchnosti vetroenergeticheskih ustanovok dlya obespecheniya nadyozhnosti elektricheskih setej [Short-term forecasting of power generationwind power plants to ensure the reliability of electrical networks]. Metodicheskie voprosy issledovaniya nadezhnosti bol'shih sistem energetiki. Vypusk 66. Aktual'nye problemy nadezhnosti sistem energetiki [Methodological issues of reliability research large energy systems. Issue 66. Actual problems of reliability of energy systems]. Minsk, BITU, PP. 397-403 (In Russian).

[9] Kurbatsky, V.G. and Tomin, N.V. (2009). Use of the "ANAPRO" software to analyze and forecast operating parameters and technological characteristics on the basis of macro applications. 1 – 8. doi:10.1109/PTC.2009.5281905.

[10] Carroll J., McDonald A. and McMillian D. (2014). Reliability comparison of wind turbines with DFIG and PMG drive trains. IEEE Rans. Energy Convers., vol. PP, pp. 1–8, Dec.

[11] Wilson, G. and Mcmillan, D. (2014). Assessing Wind Farm Reliability Using Weather Dependent Failure Rates. Journal of Physics: Conference Series. 524. 012181. doi:10.1088/1742-6596/524/1/012181.

[12] Sevastýanov, B.A. (1975). Renewal theory. J. Math. Sci. 4, PP. 281—302. doi:10.1007/BF01097185

[13] The wind power. Wind Energy Market Intelligence. [online]. URL: https://www.thewindpower.net/turbine_en_79_siemens_swt-3.6-120.php. [Accessed 1 November 2021].

[14] National Centers for Environmental Information.[online] Data URL: https://www.ncei.noaa.gov/access/search/data-search/global-hourly. Description URL: https://www.ncei.noaa.gov/data/global-hourly/doc/isd-format-document.pdf. [Accessed 1 November 2021].

[15] Ryhlov, A.B. (2011) Ocenka parametrov zakonov izmeneniya srednej skorosti vetra s vysotoj v prizemnom sloe atmosfery na yugo-vostoke evropejskoj chasti Rossii dlya resheniya zadach vetroenergetiki [Estimation of the parameters of the laws of variation of the average wind speed with height in the surface layer of the atmosphere in the southeast of the European part of Russia for solving the problems of wind power]. Izv. Sarat. un-ta Nov. ser. Ser. Nauki o Zemle, №2.

[16] Mlyavaya, G.V. (2014). Vliyanie parametrov sherohovatosti podstilayushchej poverhnosti na skorost' vetra [Influence of the roughness length of an underlying surface on wind speed]. Ecologia i Geografia. №2 (323). PP. 181 -– 187.

[17] Un data. A world of information.[online]. URL: https://data.un.org. [Accessed 1 November 2021].

[18] Energi data service. Production and Consumption – Settlement. [online] URL: https://www.energidataservice.dk/tso-electricity/productionconsumptionsettlement. [Accessed 1 November 2021].

[19] Sundberg, R. (1976). An iterative method for solution of the likelihood equations for incomplete data from exponential families. Communications in Statistics – Simulation and Computation. 5 (1): 55–64. doi:10.1080/03610917608812007.

[20] Kolmogoroff, A. (1931) Über die analytischen Methoden in der Wahrscheinlichkeitsrechnung. Math. Ann. 104, 415–458 . https://doi.org/10.1007/BF01457949 (In German).

[21] Rykov V.V., Itkin V.Yu. (2016) Nadyozhnost' tekhnicheskih sistem i tekhnogennyj risk (Reliability of technical systems and technogenic risk). Moscow: INFRA-M. 192 P. (In Russian).