57º SBPO
SIMPÓSIO BRASILEIRO DE PESQUISA OPERACIONAL
Gramado • RS
DE 5 A 9 DE OUTUBRO DE 2025

Application of Quantum Bayesian Network in the Reliability Analysis of Offshore Wind Turbine Generator

Samuel Bezerra da Gama Neto[1]
samuel.gneto@ufpe.br
Isis Didier Lins[1,2]
isis.lins@ufpe.br
Gustavo de Novaes Pires Leite[3]
gustavonovaes@recife.ifpe.edu.br
Alvaro Antonio Ochoa Villa[3]
ochoaalvaro@recife.ifpe.edu.br
Márcio José das Chagas Moura[1,2]
marcio.cmoura@ufpe.br

[1]Universidade Federal de Pernambuco, Cidade Universitária, s/n, Recife, CEP 50740-550, Brasil
[2]Centro de Estudos e Ensaios em Risco e Modelagem Ambiental (CEERMA)
[3]Instituto Federal de Educação, Ciência e Tecnologia de Pernambuco, Campus Recife, Brasil

ABSTRACT

As energy demand grows worldwide and the impact of climate change, renewable energy sources have become increasingly prominent in the global energy transition, especially offshore wind farms, which benefit from stronger wind conditions. However, due to the effects of wind and waves on wind turbines, assessing their reliability is essential. In this study, quantum computing was employed as an alternative approach to estimate the probabilities in a Bayesian Network model of a floating offshore wind turbine generator. The quantum version of the model was implemented on a quantum circuit with 22 qubits, simulating service times of up to 10 years, with 10 executions performed for each service time using a quantum simulator. The results, when compared to the exact solution, showed error values close to zero, indicating that quantum computing can be effective for applications of this nature.

KEYWORDS. Offshore Wind Turbine. Quantum Bayesian Network. Quantum inference.

Paper topics (SE-QPO - Quantum Methods and their Applications in Operational Research, EN&PG - OR in the Energy, Oil and Gas Area)

1. Introduction

Over the years, wind energy has increased its contribution to global electricity generation. By 2030, renewable energy sources are expected to account for 46% of the total electricity produced worldwide, with wind and solar together contributing around 30% [IEA 2024]. Wind energy is generated by converting the kinetic energy of the wind into electrical power through the use of wind turbines. As a renewable energy source, wind energy has significantly contributed to reducing the dependence on fossil fuels. However, due to its intermittent nature, ensuring the reliability and cost-effectiveness of wind turbines throughout their operational lifetime is essential to maintain competitiveness in the energy market [Sayed et al. 2023].

Despite the maturity of onshore wind farms, offshore wind energy has a promising future due to its capability of harnessing stronger and reliable winds, greater availability of space, and reduced conflicts [Jung et al. 2024]. To explore wind in deep water, floating offshore wind turbines (FOWTs) have been increasingly investigated as a viable solution. In this context, several studies have focused on the performance improvement and reliability analysis of FOWTs, such as aerodynamic and wake analysis under pitch motion [Fu et al. 2023], fatigue life assessment due to wake effects and yaw misalignment [Tao et al. 2023], and pitch fault detection [Wang et al. 2024].

Quantum computing (QC) offers new possibilities for solving complex problems by exploiting fundamental principles of quantum mechanics, as superposition and entanglement [Golestan et al. 2023]. This technology is gaining attention in the wind energy sector, with research on fault detection [Correa-Jullian et al. 2022], wind speed forecasting [Hong et al. 2024], and optimization of wind farm layout [Kagemoto 2024]. Thus, this study focuses on applying QC to the reliability analysis of the FOWT generator through a quantum variant of a Bayesian Network following the procedure proposed by [Borujeni et al. 2021].

2. Quantum Bayesian Network

Bayesian Networks (BNs) are probabilistic graphical models representing knowledge over a set of variables X from an uncertain domain. The qualitative part of a BN is described by a directed acyclic graph (DAG), where the nodes represent the variables and the edges correspond to the dependencies between the variables. In addition, the quantitative part is given by assigning the marginal probabilities of independent variables and the conditional probability of a variable given its parents with the Conditional Probability Table (CPT) provided by $P(X_i|parents(X_i))$, for $i = 1, \dots, n$, in which n is the number of nodes (or variables) in the BN.

The BN functions as a predictive model by the joint probability $P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i|parents(X_i))$ or can be used for inference analysis based on Bayes' Theorem $P(X_i|E) = P(E|X_i)P(X_i)/P(E)$, which allows the calculation of posterior probabilities, such as the probability of a generator failure given evidence of a wind turbine failure.

In this study, the quantum model was applied based on the fault tree (FT) approach for the FWOT generator described by [Kang et al. 2019], and evaluated as a BN problem by [Li et al. 2020], as shown in Figure 1. The failure probabilities of the root nodes were obtained using the failure rates presented in Table 1, assuming an exponential distribution, following $P = 1 - e^{-\lambda t}$.

Table 1. Identification of events and failure rates of the root nodes for the wind turbine generator.

Event	Failure rate (h^{-1})	Event	Failure rate (h^{-1})
GN: Generator		B4: Asymmetry	5.85E-6
I1: Rotor and stator failure		B5: Structural deficiency	1.17E-6
I2: Bearing failure		B6: Abnormal vibration	2.14E-6
I3: Abnormal signals		B7: Abnormal instrument reading	2.17E-6
I4: No centricity generation		B8: Fail to synchronize	3.61E-6
I5: Overheating		B9: Broken bars	2.10E-7
B1: Measurement facilities failure	1.63E-5	B10: Fail to start on demands	2.89E-6
B2: Wire failure	1.00E-7	B11: Sensor failure	7.08E-6
B3: Leak	8.40E-5	B12: Temperature above limitation	7.20E-7

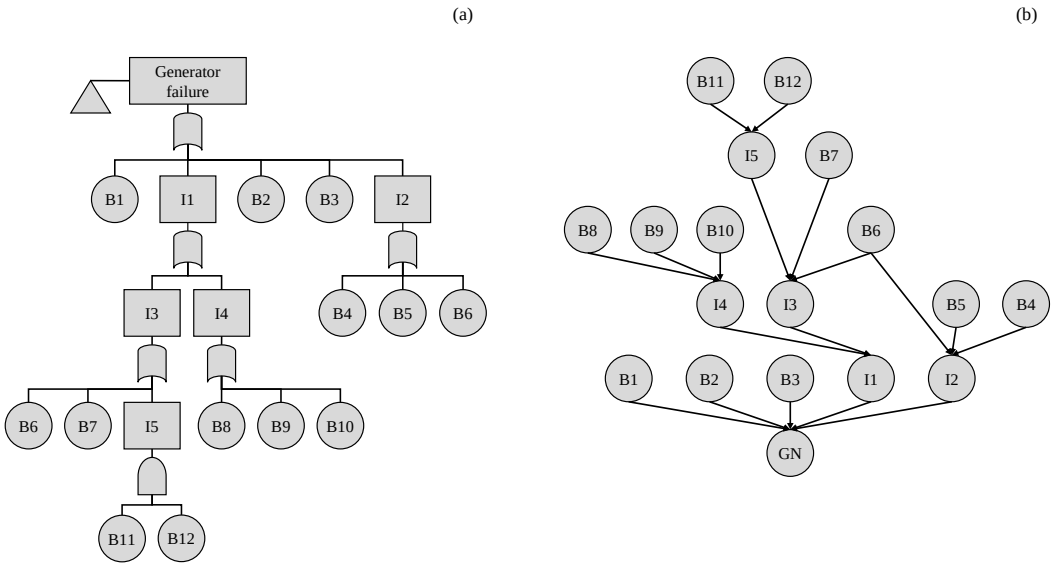


Figure 1. Models of failure analysis for the wind turbine generator (a) FT model; (b) BN model.

The Quantum Bayesian Network (QBN) leverages quantum circuits to perform probabilistic inference. The number of qubits required to represent the BN is given by $N_{qubits} = n + max\big(parents(X_1), parents(X_2), \cdots, parents(X_n)\big) - 1 = 22$. To construct the quantum circuit, the primary quantum gates used are the rotation-Y gate, which encodes the marginal probabilities of the root nodes using $\theta_i = 2 \cdot arctan\sqrt{P(X_i = 1)/P(X_i = 0)}$, and a combination of controlled-NOT and controlled-rotation-Y gates to encode the conditional probabilities of variables with more than two parent nodes.

3. Results and Discussion

To implement the QBN, the Python library Qiskit was used. A quantum circuit with 22 qubits was executed with 20,000 shots and repeated 10 times to compute the average marginal probabilities over a service time of up to 10 years, as illustrated in Figure 2.

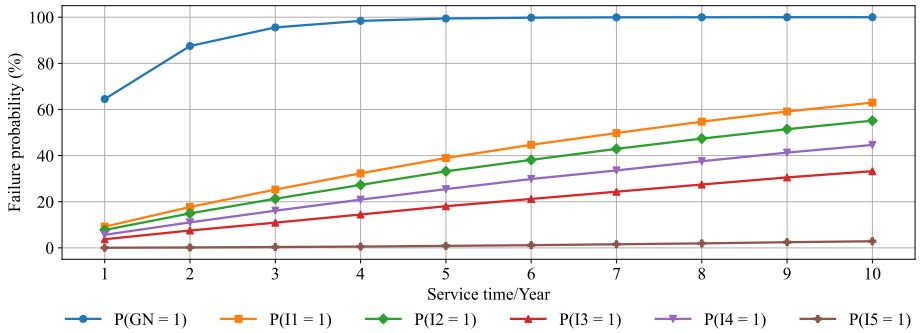


Figure 2 – Mean marginal probabilities of the child nodes from the QBN.

To compare the results obtained using the QBN approach, the exact solution was also computed. The root mean square error (RMSE) was then computed for each service time and each marginal probability by $\sqrt{(1/n_{run}) \cdot \sum_{i=1}^{n_{run}} (y - \tilde{y}_i)^2}$. The RMSE for the generator failure $P(GN = 1)$, reached the maximum value (0,811) at 1-year service time and the minimum value (0,004) for 10-year service time compared with predictions of the marginal probabilities of intermediate events. Considering only the intermediate events, the maximum RMSE value was for

bearing failure $P(I2 = 1)$, with 0.435 for 5-year service time and the lowest RMSE was for overheating with 0.013 for 1-year service time. However, the RMSE values close to zero indicate that the QBN approach was effective in representing a BN problem within the context of a FOWT.

4. Conclusion

This study demonstrated the feasibility of applying QC to the reliability analysis of a FOWT generator by implementing a QBN model. The QBN was constructed based on an FT with 22 qubits in the quantum circuit, evaluating the marginal failure probabilities over different service times. The results of 10 simulations showed that the approach achieved consistent results compared with the exact solution, with RMSE values close to zero in most cases. Future research should focus on the application of amplitude amplification techniques to estimate the conditional probabilities of rare events, which are difficult to observe using the standard QBN approach.

Acknowledgements

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001 and by the *Conselho Nacional de Desenvolvimento Científico e Tecnológico* (CNPq) – 409701/2022-0, 310892/2022-8, 308924/2021-5.

References

Borujeni, S. E., Nannapaneni, S., Nguyen, N. H., Behrman, E. C., & Steck, J. E. (2021). Quantum circuit representation of Bayesian networks. Expert Systems with Applications, 176, 114768.

Correa-Jullian, C., Cofre-Martel, S., San Martin, G., Lopez Droguett, E., de Novaes Pires Leite, G., & Costa, A. (2022). Exploring quantum machine learning and feature reduction techniques for wind turbine pitch fault detection. Energies, 15(8), 2792.

Fu, S., Li, Z., Zhu, W., Han, X., Liang, X., Yang, H., & Shen, W. (2023). Study on aerodynamic performance and wake characteristics of a floating offshore wind turbine under pitch motion. Renewable Energy, 205, 317-325.

Golestan, S., Habibi, M. R., Mousavi, S. M., Guerrero, J. M., & Vasquez, J. C. (2023). Quantum computation in power systems: An overview of recent advances. Energy Reports, 9, 584-596.

Hong, Y. Y., Rioflorido, C. L. P. P., & Zhang, W. (2024). Hybrid deep learning and quantum-inspired neural network for day-ahead spatiotemporal wind speed forecasting. Expert Systems with Applications, 241, 122645.

IEA. Renewables (2024). Analysis and Forecast to 2030. International Energy Agency: Paris, France.

Jung, C., Sander, L., & Schindler, D. (2024). Future global offshore wind energy under climate change and advanced wind turbine technology. Energy Conversion and Management, 321, 119075.

Kagemoto, H. (2024). Possible application of quantum computing in the field of ocean engineering: optimization of an offshore wind farm layout with the Ising model. Journal of Ocean Engineering and Marine Energy, 1-10.

Kang, J., Sun, L., & Soares, C. G. (2019). Fault Tree Analysis of floating offshore wind turbines. Renewable energy, 133, 1455-1467.

Li, H., Soares, C. G., & Huang, H. Z. (2020). Reliability analysis of a floating offshore wind turbine using Bayesian Networks. Ocean Engineering, 217, 107827.

Sayed, E. T., Olabi, A. G., Alami, A. H., Radwan, A., Mdallal, A., Rezk, A., & Abdelkareem, M. A. (2023). Renewable energy and energy storage systems. Energies, 16(3), 1415.

Tao, T., Long, K., Yang, T., Liu, S., Yang, Y., Guo, X., & Chen, M. (2023). Quantitative assessment on fatigue damage induced by wake effect and yaw misalignment for floating offshore wind turbines. Ocean Engineering, 288, 116004.

Wang, Y., Wen, C., & Wu, X. (2024). Fault detection and isolation of floating wind turbine pitch system based on Kalman filter and multi-attention 1DCNN. Systems Science & Control Engineering, 12(1), 2362169.