A Quantum-Assisted Boltzmann Machine for Wind Power Probabilistic Learning

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***Abstract*—Accurate probabilistic modeling of renewable power is essential for the secure operation and control of modern power systems. However, learning and modeling the data structure with high accuracy remains challenging due to the inherent spatial-temporal correlations of renewables. To address this issue, we propose a novel quantum-assisted Gaussian-Bernoulli restricted Boltzmann machine (GBRBM), which is intrinsically suitable for continuous wind power modeling. Furthermore, we tailor its negative phase to be directly solvable by quantum computing, thereby accelerating the learning process. Experiments conducted on real quantum hardware validate the cost-effective performance of the proposed method.**

***Index Terms*—Wind power output, probabilistic learning, restricted Boltzmann machine, quantum sampler.**

I. Introduction

Accurate probabilistic learning of renewable power outputs is essential for power forecasting [1] and uncertainty-aware operation [2] in modern power systems. This motivates many researchers to depict the high-dimensional dependency structure of renewables.

As a nonparametric neural network-based method, the restricted Boltzmann machine (RBM) is advocated for learning the joint distribution of uncertain inputs by implicitly capturing statistical dependencies [3]. However, computation of its negative phase requires a computationally intensive sampling procedure that might also lose accuracy under high-dimensional conditions. To address this, quantum techniques have been used and quantum restricted Boltzmann machines (QRBMs) have recently been developed to speed up the sampling procedure while overcoming local optima through a quantum optimization mechanism [4]. However, the existing QBM only applies to discrete variables, which is not the case for the uncertain continuous structure of renewable energy resources, such as wind energy.

To address this challenge, we propose, for the first time, a quantum-assisted GBRBM mechanism for probabilistic wind power learning. Specifically, by tailoring the negative-phase of the GBRBM, we extend the applicability of conventional discrete-only quantum Boltzmann machines to continuous uncertainties, while preserving a structure that remains solvable with quantum computing to accelerate the overall training process. Case studies implemented on real quantum hardware demonstrate the effectiveness of the proposed approach.

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II. Limitation of Traditional GBRBM

We consider the problem of learning dependency structures among multiple wind power outputs. Let $\mathbf{v} \in \mathbb{R}^N$ denote the visible random vector of a GBRBM [5], whose realizations correspond to normalized active power measurements collected from N wind turbines. Fig. 1 provides a conceptual illustration of the probabilistic learning and generation mechanism of the GBRBM. The associated energy function for GBRBM is defined as

$$E_\theta(\mathbf{v},\mathbf{h}) = \frac{1}{2\sigma^2}\|\mathbf{v}-\mathbf{b}\|_2^2 - \frac{1}{\sigma^2}\mathbf{v}^\top\mathbf{W}\mathbf{h} - \mathbf{c}^\top\mathbf{h}, \quad (1)$$

where $\mathbf{h} \in \{0,1\}^M$ denotes binary hidden variables, $\mathbf{W} \in \mathbb{R}^{N\times M}$ is the weight matrix, $\mathbf{b}$ and $\mathbf{c}$ are visible and hidden biases, respectively. $\theta = \{\mathbf{W},\mathbf{b},\mathbf{c}\}$ denotes the parameter set. σ^2 is the variance of the Gaussian visible variables, $\mathbf{v}$. The associated joint probability distribution function (pdf) p_θ is

$$p_\theta(\mathbf{v},\mathbf{h}) = \frac{1}{Z_\theta}\exp\left(-E_\theta(\mathbf{v},\mathbf{h})\right), \quad (2)$$

where $Z_\theta = \int_{\mathbb{R}^N}\sum_{\mathbf{h}}\exp\left(-E_\theta(\mathbf{v},\mathbf{h})\right)\mathrm{d}\mathbf{v}$ is the partition function that ensures the normalization of the joint pdf. The marginal likelihood function is obtained by summing the hidden variables, i.e., $p_\theta(\mathbf{v}) = \sum_{\mathbf{h}} p_\theta(\mathbf{v},\mathbf{h})$.

Given the observed $\mathbf{v}$, we maximize the log-likelihood function to train the GBRBM as follows:

$$\max_\theta\ \log p_\theta(\mathbf{v}) = \max_\theta\ \log\sum_{\mathbf{h}}\frac{1}{Z_\theta}\exp\left(-E_\theta(\mathbf{v},\mathbf{h})\right). \quad (3)$$

Taking the gradient of the log-likelihood function with respect to θ yields a positive-negative phase decomposition [5] as

$$\begin{aligned}\nabla_\theta \log p_\theta(\mathbf{v}) &= \mathbb{E}_{p_\theta(\mathbf{h}|\mathbf{v})}\left[-\nabla_\theta E_\theta(\mathbf{v},\mathbf{h})\right] \\ &\quad - \mathbb{E}_{p_\theta(\mathbf{v},\mathbf{h})}\left[-\nabla_\theta E_\theta(\mathbf{v},\mathbf{h})\right],\end{aligned} \quad (4)$$

where $\nabla_\theta = \frac{\partial}{\partial\theta}$ denotes the gradient operator with respect to θ. Here, in (4), the first term is the positive phase, while the second term is the negative phase. In the positive phase, the expectation is taken with respect to the conditional pdf $p_\theta(\mathbf{h} \mid \mathbf{v})$, where $\mathbf{v}$ are given as the observed power measurements. Then, the hidden variables, $\mathbf{h}$, become conditionally independent and can be directly sampled in practice.

Remark 1: In contrast to the previously mentioned easily sampled positive phase, the negative phase requires computing an expectation with respect to the joint pdf, $p_\theta(\mathbf{v},\mathbf{h})$, where both visible and hidden variables vary. This necessitates the *reliance on more computationally intensive sampling methods, such as Gibbs sampling or Markov chain Monte Carlo. Moreover, for high-dimensional dependent data structures, such as highly correlated wind, these samplers converge slowly and may lead to biased estimates. Consequently, negative-phase sampling can be both computationally expensive and inaccurate, which challenges the practical application of GBRBM [3], [5]. This difficulty motivates the reformulation of the negative phase in the following section.*

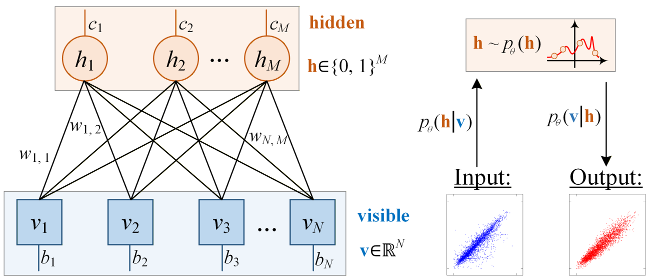

Fig. 1. Visualization of probabilistic generative modeling of wind power using a GBRBM.

III. The Proposed Method

Now, we present the proposed quantum-assisted GBRBM training method for probabilistic wind power learning.

A. Motivation for Designing a Hidden-Only Structure

As shown in Table I, there is a fundamental mismatch in current RBMs between quantum sampling needs and wind power modeling. Standard RBM and QRBM use binary energy functions, making them quantum-compatible but unsuitable for continuous wind data. In contrast, GBRBMs fit continuous wind power outputs, yet their negative phase involves continuous variables, which is incompatible with quantum sampling.

TABLE I
Comparison of RBM-based methods under wind power modeling

Method	Model ($\mathbf{v}$-$\mathbf{b}$)	Quantum sampling	Wind power
RBM	Binary-Binary	✗	✗
QRBM	Binary-Binary	✓	✗
GBRBM	Continuous-Binary	✗	✓
Ours	Continuous-Binary	✓	✓

A straightforward remedy would be to discretize continuous variables, but this leads to a rapid increase in the number of binary units and quickly becomes impractical for current quantum hardware. Therefore, enabling quantum-assisted training for GBRBMs requires a reformulation of the negative phase that removes continuous visible variables from sampling while preserving the underlying statistical dependencies. This motivates us to analytically eliminate visible variables in the negative phase, producing an equivalent hidden-only energy function defined over binary variables only.

B. Hidden-Only Energy Reformulation

To eliminate continuous visible variables in (1), we first integrate the joint pdf, $p_\theta(\mathbf{v},\mathbf{h})$, with respect to $\mathbf{v}$, to get the marginal pdf $p_\theta(\mathbf{h})$ as

$$p_\theta(\mathbf{h}) \propto \int_{\mathbb{R}^N} \exp(-E_\theta(\mathbf{v},\mathbf{h}))\, \mathrm{d}\mathbf{v}. \tag{5}$$

Substituting $E_\theta(\mathbf{v},\mathbf{h})$ in (1) into (5), we obtain

$$p_\theta(\mathbf{h}) \propto \exp\left(\mathbf{c}^\top\mathbf{h}\right)\int_{\mathbb{R}^N} \exp\left(-\frac{\|\mathbf{v}-\mathbf{b}\|_2^2}{2\sigma^2}+\frac{\mathbf{v}^\top\mathbf{W}\mathbf{h}}{\sigma^2}\right)\mathrm{d}\mathbf{v}. \tag{6}$$

To facilitate analytical integration with respect to $\mathbf{v}$, we rewrite the exponent as a quadratic function of $\mathbf{v}$ and collect all $\mathbf{v}$-dependent terms of (6). Accordingly, we define

$$f(\mathbf{v},\mathbf{h}) = -\frac{1}{2\sigma^2}\|\mathbf{v}-\mathbf{b}\|_2^2+\frac{1}{\sigma^2}\mathbf{v}^\top\mathbf{W}\mathbf{h}, \tag{7}$$

By expanding $\|\mathbf{v}-\mathbf{b}\|_2^2$ in (7), we have

$$f(\mathbf{v},\mathbf{h}) = -\frac{1}{2\sigma^2}\mathbf{v}^\top\mathbf{v}+\frac{1}{\sigma^2}\mathbf{v}^\top\left(\mathbf{b}+\mathbf{W}\mathbf{h}\right)-\frac{1}{2\sigma^2}\mathbf{b}^\top\mathbf{b}. \tag{8}$$

Note that the last term $-\frac{1}{2\sigma^2}\mathbf{b}^\top\mathbf{b}$ is independent of $\mathbf{v}$ and can be included in the partition function Z_θ. Hence, by isolating the $\mathbf{v}$-dependent terms and completing the square, (8) can be rearranged as

$$f(\mathbf{v},\mathbf{h}) = -\frac{\|\mathbf{v}-(\mathbf{b}+\mathbf{W}\mathbf{h})\|_2^2}{2\sigma^2}+\frac{\|\mathbf{b}+\mathbf{W}\mathbf{h}\|_2^2}{2\sigma^2}-\frac{\mathbf{b}^\top\mathbf{b}}{2\sigma^2}. \tag{9}$$

The first term in (9) is a standard Gaussian kernel in $\mathbf{v}$. Specifically, for any $\mathbf{b}+\mathbf{W}\mathbf{h}\in\mathbb{R}^N$, it holds that $\int_{\mathbb{R}^N}\exp\left(-\frac{\|\mathbf{v}-(\mathbf{b}+\mathbf{W}\mathbf{h})\|_2^2}{2\sigma^2}\right)\mathrm{d}\mathbf{v}=(2\pi\sigma^2)^{\frac{N}{2}}$, which is a constant independent of $\mathbf{h}$. Applying this to (9), all $\mathbf{v}$-dependent terms can be analytically integrated, resulting in a constant factor independent of $\mathbf{h}$. Then, (6) can be written as

$$p_\theta(\mathbf{h}) \propto \exp\left(\mathbf{c}^\top\mathbf{h}+\frac{1}{2\sigma^2}\|\mathbf{b}+\mathbf{W}\mathbf{h}\|_2^2\right). \tag{10}$$

Expanding the quadratic term $\|\mathbf{b}+\mathbf{W}\mathbf{h}\|_2^2$ in (10) yields

$$p_\theta(\mathbf{h}) \propto \exp\left(\underbrace{\left(\mathbf{c}+\frac{1}{\sigma^2}\mathbf{W}^\top\mathbf{b}\right)^\top\mathbf{h}+\frac{1}{2\sigma^2}\mathbf{h}^\top\mathbf{W}^\top\mathbf{W}\mathbf{h}}_{-E_\theta^{\mathrm{eff}}(\mathbf{h})}\right). \tag{11}$$

Now, (11) is the pdf whose corresponding energy function $E_\theta^{\mathrm{eff}}(\mathbf{h})$ consists only of binary hidden variables.

C. Quantum-Assisted Negative Phase Sampling

Now, it is very interesting to note that the hidden-only distribution in (11) naturally corresponds to an Ising model, an energy-based model originally describing interacting spin systems. Its energy is defined on binary spin variables $\mathbf{s}\in\{-1,+1\}^M$ with linear and pairwise interaction terms [6] as

$$E(\mathbf{s}) = -\boldsymbol{\alpha}^\top\mathbf{s}-\frac{1}{2}\mathbf{s}^\top\mathbf{J}\mathbf{s}, \tag{12}$$

where $\boldsymbol{\alpha}$ denotes external fields and $\mathbf{J}$ represents pairwise couplings between spins.

Applying the standard affine transformation $\mathbf{h} = (\mathbf{s}+\mathbf{1})/2$, where $\mathbf{1}$ is the vector of all the ones, the energy function $E_\theta^{\text{eff}}(\mathbf{h})$ can be equivalently rewritten in the Ising form as

$$E_\theta^{\text{eff}}(\mathbf{s}) = -\Bigg(\underbrace{\frac{1}{2}\left(\mathbf{c}+\frac{1}{\sigma^2}\mathbf{W}^\top\mathbf{b}\right)+\frac{\mathbf{W}^\top\mathbf{W}\mathbf{1}}{4\sigma^2}}_{\alpha}\Bigg)^\top \mathbf{s} - \mathbf{s}^\top \underbrace{\frac{1}{8\sigma^2}\mathbf{W}^\top\mathbf{W}}_{\frac{1}{2}\mathbf{J}}\,\mathbf{s} + C, \tag{13}$$

where $C = -\frac{1}{2}\left(\mathbf{c}+\frac{1}{\sigma^2}\mathbf{W}^\top\mathbf{b}\right)^\top \mathbf{1} - \frac{1}{8\sigma^2}\,\mathbf{1}^\top\mathbf{W}^\top\mathbf{W}\,\mathbf{1}$ collects all terms independent of $\mathbf{s}$ and thus does not affect the relative energy differences among spin configurations, nor the resulting sampling behavior.

Until now, we have reformulated the negative-phase distribution of the GBRBM into an explicit Ising energy function that is naturally solvable by the Ising-based quantum hardware, such as a CIM [6], [7]. More specifically, in a CIM, Ising spins are represented by the phase states of coupled optical parametric oscillators, whose dynamics implement an analog physical process for sampling low-energy configurations of Ising Hamiltonians [7], [8]. In this work, the CIM is employed exclusively to generate samples for the negative phase, while all parameter updates and gradient computations are performed in a classical manner. Such a hybrid learning strategy effectively accelerates the most time-consuming component of GBRBM training, while potentially benefiting from non-local sampling offered by quantum hardware.

Remark 2: The proposed reformulation enables quantum-assisted negative-phase sampling for GBRBMs without discretizing the continuous visible variables, thereby avoiding combinatorial blow-up and information loss. Moreover, it allows the integration of quantum hardware, such as a CIM, into the sampling process, providing an alternative to classical sampling schemes [7].

IV. Case Studies

In this section, the proposed method is evaluated using real quantum hardware provided by a CIM from Beijing QBoson using Kaiwu SDK [9]. Wind power data are obtained from the SDWPF dataset [10]. The comparisons include the classical GBRBM trained using Gibbs sampling and a RealNVP-based normalizing flow. To test the scalability of the proposed method, four test cases with increasing system sizes are considered, involving 5, 10, 15, and 20 wind turbines, respectively. For both GBRBM and the proposed RBM, to ensure comparable model capacity, the number of hidden units is set according to the system size: 128 for the 5- and 10-turbine cases, and 256 for the 15- and 20-turbine cases. The learning rate is adjusted based on the problem scale, with values of 0.003, 0.002, and 0.001 for the 5-, 10-, and 15/20-turbine cases, respectively. For the 5- and 10-turbine cases, the batch size is set to 128 and the number of training epochs is 200, while for the 15- and 20-turbine cases, the batch size is set to 256 and the number of training epochs is increased to 300. The energy distance (ED) and the Wasserstein distance (WD) are adopted to evaluate the similarity between the learned and true distributions, as they effectively capture statistical properties of wind power data.

A. Computing Efficiency

Fig. 2 illustrates the computational runtime of the classical GBRBM and the proposed method as the number of wind turbines increases. For the classical GBRBM, the runtime grows rapidly with the system size, reflecting the increasing cost of repeated negative-phase sampling in high-dimensional settings. By contrast, the proposed quantum-assisted method exhibits a markedly slower rate of runtime growth as the system scale increases, indicating that offloading negative-phase sampling to quantum hardware effectively mitigates the dominant computational bottleneck. Overall, these results demonstrate the scalability of the proposed approach for large-scale probabilistic learning of wind power.

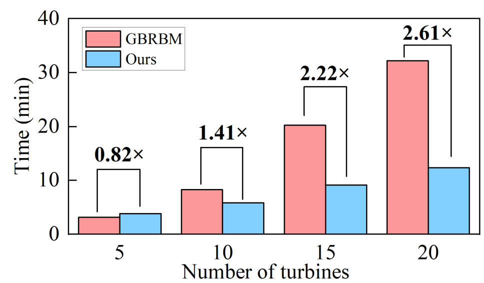

Fig. 2. Runtime comparison between the classical GBRBM and the proposed method under different numbers of turbines. The annotations indicate the speedup factor of our proposed method compared to the traditional GBRBM method.

B. Accuracy Tests

Table II summarizes the performance of the classical GBRBM, the proposed method, and a RealNVP-based normalizing flow in 5-, 10-, 15- and 20-turbine settings. Both GBRBM and the proposed method yield comparable accuracy, as evidenced by similar ED and WD values, indicating that the proposed quantum-assisted training preserves the original GBRBM's modeling capability. Meanwhile, the proposed method consistently achieves slightly lower ED and WD across different system sizes, with the improvement becoming more noticeable in larger cases. As a representative modern generative baseline, the RealNVP model achieves competitive performance in 5-turbine case and often achieves lower ED values, but its advantage is not consistently maintained as the system size increases, especially in terms of WD. These results indicate that the proposed method achieves stable and competitive performance across scales with improved computational efficiency.

TABLE II
Performance comparison for ED ($\times 10^{-4}$) and WD ($\times 10^{-3}$)

Method	5 Turbines		10 Turbines		15 Turbines		20 Turbines	
	ED	WD	ED	WD	ED	WD	ED	WD
RealNVP	5.84	5.65	6.86	4.24	10.32	7.81	11.96	9.82
GBRBM	5.95	5.70	6.86	4.13	10.43	7.67	12.14	9.59
Ours	5.94	5.68	6.80	4.02	10.21	7.60	12.02	9.37

C. Discussion

1) Discussion on Computational Scalability: The sampling dimension is reduced from $\mathcal{O}(N+M)$ to $\mathcal{O}(M)$, and the computational burden shifts from iterative sampling to polynomial matrix operations. Specifically, the classical negative phase requires repeated sampling in a high-dimensional joint continuous-discrete space, whereas the proposed method operates on a hidden-only distribution, removing the continuous component from the sampling loop. This structural reformulation alleviates the difficulty of high-dimensional joint sampling and leads to more favorable scaling behavior, consistent with the slower runtime growth observed in Fig. 2.

2) Discussion on Sampling Mechanism: The sampling process can be interpreted through an energy landscape, where each configuration corresponds to an energy value. In wind power modeling with multiple turbines, such landscapes are typically highly complex due to strong spatial correlations. Classical sampling methods, such as Gibbs sampling, update variables sequentially based on conditional distributions [3], [5], resulting in incremental exploration and limited coverage within a finite number of iterations. In contrast, the proposed method employs CIM-based quantum dynamic sampling, where coupled oscillators evolve collectively and update multiple variables simultaneously [7], [8], enabling more efficient transitions across the energy landscape. This difference improves exploration efficiency and is consistent with the results in Table II.

3) Discussion on Hardware Limitations: Current CIM platforms are subject to hardware noise and limited qubit counts, which may affect practical performance. In particular, hardware noise during the evolution process may introduce variability across repeated runs, affecting the stability of the sampling results. Meanwhile, the executable problem size is constrained by the number of available qubits, since each hidden unit corresponds to one Ising spin in the reformulated model, and the required number of hidden units typically increases with the data dimensionality and modeling complexity. Despite these limitations, the real quantum device tests already demonstrate excellent performance for our proposed method. These results are expected to improve further as quantum hardware advances.

V. Conclusion

This paper presents a quantum-assisted training method that alleviates the negative-phase sampling bottleneck in GBRBMs for probabilistic wind power learning. The results obtained on real quantum hardware demonstrate the excellent performance of the proposed approach.

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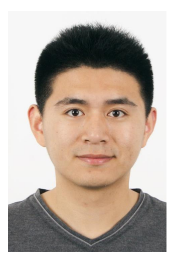

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