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Artificial Neural Network Application to Power System Planning and Security Improvement Scheme

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ABSTRACT: Co-ordinately embedding machine learning and optimization in the Monte Carlo simulation is proposed as a new framework for reliability evaluation, which is becoming more challenging due to the joining of variability and intermittency of the renewable generation and components' ageing. As a machine learning method, the dynamic Bayesian belief network predicts the renewable outputs by generating their probability distributions through historical data to overcome the defect of rarely grasping the low-probability events in the traditional methods, which either predict a single-point value or presume a parametric probability distribution. As the internal operation module of the framework, the rolling-horizon unit commitment maintains the complexity of the operation model and meantime punctually updates the predicted renewable generation and the components' ageing. The dynamic Bayesian belief network and the rolling-horizon unit commitment traverse time step after time step throughout the horizon, and thus form one bid of the Monte Carlo simulation. In each time step, the dynamic Bayesian belief network extracts the probability distributions of the renewable generation, from which the boundary of the commitment is sampled, and the impact of scheduling the generators on their ageing is then accumulated from the commitment. The proposed framework has its effectiveness proved on a microgrid.

KEYWORDS: Ageing, Dynamic Bayesian Belief Network, Monte Carlo Simulation, Reliability, Rolling horizon Unit Commitment.

I. INTRODUCTION

Reliability evaluation of power system involves calculating the system's ability of serving the load demand in case of component outages during operation. It is usually realized by calculating specific indices of load serving from an operation model, such as optimal power flow [1]– [3] economic dispatch [4] and unit commitment (UC) [5], [6]. In recent years, power systems have seen increasing penetration of renewable energy sources whose output are weather dependent and hence difficult to accurately predict, leaving the traditional generators to absorb its variability and intermittency, and rendering the grid less reliable. On the bright side, machine learnings as more powerful tools have weighed in to counteract the negative effect caused by the inaccurate prediction of renewable generation, suggesting an upgrade of reliability evaluation to integrate machine learning. Variable and intermittent renewable generation also requires the dispatchable generators to react with enough flexibility, suggesting embedding unit commitment, a more accurate operation model but also more complex optimization, into reliability evaluation. A reliability framework composed of both machine learning and optimization is thus promised [7].

Modelling the renewable generation is the preliminary step of analysing the reliability of renewableintegrated systems. Many different models have appeared prior to machine learning [8], including roughly two types, the deterministic prediction and the probabilistic prediction [9]. The deterministic prediction (or spot prediction) concretes reliability evaluation only on several events of high probability [10], [11]. These methods are simple and convenient to apply, but have a notable defect of being incapable of dealing with uncertainty, for they rarely grasp the low-probability events which are actually vital to reliability evaluation. Probabilistic modelling techniques are considered more effective in that they model the renewable generation as a random variable having a specified probability distribution function, which can be further put in two main groups according to approaches used to construct the predictive distribution functions, namely those using the parametric approaches and those using the non-parametric



approaches [9]. The parametric methods assume the sources of uncertainties to follow predefined distributions, e.g. Weibull distribution [12] and Gaussian distribution [13]. Their advantage lies in that only a few parameters are needed to define the distribution shape, allowing for simplified estimation and light computation, but a fixed, sometimes inappropriate, selection of the distribution may bring about a poor prediction, especially along the tail of the distribution [14]. The nonparametric methods do not make strong presumptions about the underlying distributions of the renewable generation, but rather track the characteristics of the historical data. A widely used traditional non-parametric method is the kernel density estimation which statistically estimates the probability distribution of the wind prediction error [15]. Still, the traditional methods need complex mathematical calculations and cannot express the relationship between events directly.

To overcome the drawbacks of the aforementioned methods, machine learnings that deal with big data without making assumptions of their distributions have emerged as a new family of non-parametric methods [16], [17]. As typical machine learning tools, the Bayesian belief network (BBN) [18] and its upgrade, the dynamic Bayesian belief network (DBBN) that describe dependencies between events, have played great roles in probabilistic predicting methodologies, e.g. a dynamic probabilistic reserve sizing method with DBBNs in [19]. The DBBNs therein describe the dependencies between events based on directed acyclic graphs and use conditional probability tables to form the joint probability distribution of weather conditions and the renewable generation.

The operation model that conducts the matching between the generation and demand is an essential module of reliability evaluation. To evaluate the supply capability under probabilistic realizations of varied renewable generation and component conditions, appropriate reliability assessment algorithms should be selected, mainly including two groups, namely analysis method and simulation-based method. Analysis method is capable of providing an accurate and direct way for reliability assessments [20], [21], but at an extremely high computational expense that is not suitable for large-scale power systems.

The simulation-based method embeds the operation model in an iterative simulation framework like the Monte Carlo simulation and then calculates the mathematical expectation of reliability indices from sampled scenarios. For example, a probabilistic method for evaluating load shedding at isolated time steps is embedded in the Monte Carlo simulation and applied for power grid reliability evaluation with multi-energy storage system in [22]. The Monte Carlo based day-ahead unit commitment is applied in reliability assessment of power systems with wind power generation in [23] and optimal reliability planning for a composite power system in [24]. Some literature assesses the reliability by combining multiple operation models in the Monte Carlo simulation, for example, the DC optimal power flow and economic dispatch models established to calculate the load shedding considering common-cause and cascading outages in [25]. A Monte Carlo based operation model is applied to improve system security and reliability in [26]. Series of scenarios therein are clustered: extreme scenarios are solved by a day-ahead UC model for ensuring high robustness and typical scenarios are solved by an economic dispatch model for improving the economy.

These studies embed the day-ahead operation models in Monte Carlo simulation such that the entire 24-hour scheduling forms one round of simulation. However, the day-ahead UC suffers from the inaccuracy prediction of renewable generation, and the farther ahead the prediction targets, the more unneglectable the inaccuracy becomes. Therefore, the prediction horizon has to be shortened to reduce the prediction error, which interacts with the hour-ahead variant of the UC [5], [27], termed “step-by-step” unit commitment hereafter. Whereas the step-by-step UC schedules the generators for the next hour with the renewable generation more accurately predicted, and continues hour after hour sequentially, its drawback lies here — the operation model is over-simplified rendering the result local optimum. To compromise between the accuracy of prediction and the optimality of operation, the rolling-horizon unit commitment (RH-UC) that searches for the optimal trajectory in a small number of forthcoming time intervals and only implements the actions for the current has been accepted [28]. Though the RH strategy has been applied to some optimal operations with renewable integration [29],[30], their merit to reliability evaluation has yet to be exploited.

In response to call for both effective prediction of renewable energy and an optimal operation model, a reliability evaluation framework that embeds DBBN and RH-UC in the sequential Monte Carlo simulation is established. The big-data-driven DBBN, a machine learning tool, predicts the solar and wind generation by representing uncertainties directly through the graphical structure. The RH-UC strategy replaces the day-ahead or step-by-step UCs to realize its value in reliability evaluation for the first time in this work, and is extended to cooperate with a double-layer storage operation model for power systems with storage installed. The generator’s outage is determined by a sampling method with the proportional hazard model. In each time step, the DBBNs generate the boundary condition of UC problems and the solution of RHUC accumulate the outage rate for the proportional hazard model. The three aspects iterate one



after another and are all embedded in the hourly steps of sequential Monte Carlo simulation. The contributions are expected as follows:

- 1) Apply the data-driven machine learning tool, DBBN, to reliability evaluation.
- 2) Introduce the rolling-horizon unit commitment to balance the accuracy of prediction and optimality of system operation, which incorporates the storage dispatch.
- 3) Develop a sequential Monte Carlo simulation framework that interacts both DBBNs and the rolling horizon unit commitment, i.e. machine learning and optimization.

II. BACKGROUND ON BAYESIAN NETWORKS

The Bayesian belief network as one of the most effective ways to predict the uncertainty is briefed as the background for the dynamic Bayesian belief network which is actually used by the proposed model; details of both are referred to [31].

A. Bayesian Belief Networks

Ever since it was proposed by Pearl in 1986 [32], the Bayesian belief networks (BBNs) have been effectively applied to investigate the causal relationships between special events of the system and solve problems of stochastic phenomena. A BBN consists of two parts, one being the network structure diagram, the other being the conditional probability tables (CPTs). The network structure diagram is a directed acyclic graph composed of nodes and arcs, which are used to reflect conditional dependency between random events. An arc starts at a parent node and ends at a child node, representing along the direction of the arc, the event represented by the parent node affects that by the child node. As the structure diagram plots the relationships of the events, the CPTs attached to each node quantify them, by providing the conditional probability between a child node and all its parents obeying the Bayes theorem, i.e. the probability of x given y is $P(x|y) = P(xy)/P(y)$.

B. Dynamic Bayesian Belief Networks

Whereas BBNs are advantageous to predict event X based on condition Y in a large volume, they only define an event's dependency on other events of a single time step, while most random events are actually led to by multiple events, each lasting a sequence of time steps. To capture how the events change over time, the static BBN is upgraded to the dynamic

BBN (DBBN) to explicitly depict dependencies of each event on others, each defined as a time series. The DBBN traces all events as time forwards and keeps reflecting the temporal dependency within each event in its prediction of a specific event of interest.

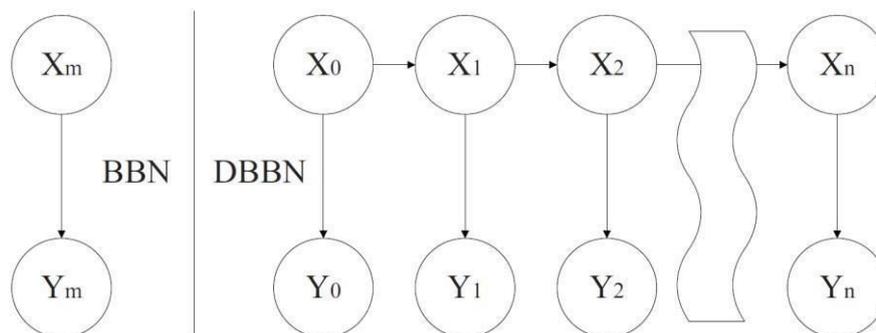


Figure 1. BBN vs DBBN.

The upgrade of BBN into DBBN is conceptualized in Fig. 1, wherein it is assumed for simplicity that node (event) Y has only one parent node (event), X . On the left side, the BBN describes event y_m being affected by event x_m at a single time step, while on the right side, the DBBN has event y_n being impacted by a series of events x_0, x_1, \dots, x_n . In each time step of the DBBN, the variables and their corresponding probabilities are affected by the previous events, except the initial step when the probability distributions are arbitrarily assigned, returning the conditional probability:



$$P(y_n, x) = P(x_0) \left[\prod_{t=1}^{n-1} P(x_t | x_{t-1}) \right] P(y_n | x_n), \quad (1)$$

where $P(x_0)$ is the initial state distribution prior to the starting point of the process, $P(x_t | x_{t-1})$ is the state transition rate between adjacent time steps. Three steps precede the use of a DBBN to predict the renewable generation.

- 1) Modelling: extract the factors relevant to the prediction from the observed data and initialize the structure diagram.
- 2) Pruning: for each event y , apply sensitivity analysis to find out those of its parent nodes that are important for deriving it, and remove the less important ones from the DBBN. Too many nodes will cause redundancy for the network and make it difficult to train. Naive Bayesian classification algorithm [33] is applied in sensitivity analysis, which helps to identify the input variables that have the most impact on the target variable.
- 3) Training: assign values to the parameters of DBBN with observed historical data by maximum likelihood estimation.

III. RELIABILITY EVALUATION

The framework used for reliability evaluation is built up by the Monte Carlo simulation. In each sample, a sequential process is applied to match the generation with the demand. In each time step, the DBBNs predict the renewable generation and form the boundary conditions of unit commitment by the sampling method. Then the RH-UC is conducted and the result is applied to calculate the cumulative probability of the generator outage. The forced outage rate and the sampling method as well as the RH-UC is presented as modules of the reliability evaluation, followed by the proposed framework of reliability evaluation.

A. Forced Outage Rate of the Generators

Generators in operation are subject to random outages in different operating and real-time loading conditions, among which ageing is a key contributor — a severely aged generator is more likely to break down. The ageing process fits into the Weibull distribution, a commonly used distribution for equipment ageing. In the ageing process, the forced outage rate of the equipment accumulates over time, which is described with the proportional hazard model [34],

$$h(t, Z(t)) = a^{-b} \cdot b \cdot t^{b-1} \cdot e^{\gamma_1 Z_1(t) + \gamma_2 Z_2(t)^2} \quad (2)$$

where a depicts the scale, and b the shape of the distribution. This exponential function aims to quantify the impact of two influencing factors, namely the temperature condition and the loading rate, assigned respectively as covariates $Z_1(t) \in \{0, 1, 2\}$ and $Z_2(t) \in [0, 1]$ with coefficients γ_1 and γ_2 . $Z_1(t)$ is a discrete variable with value 0 for normal temperature, 1 for hot weather, and 2 for severe weather, while $Z_2(t)$ is squared to emphasize the huge impact of overloading on generator.

Consider a component that has remained reliable until t_0 , the probability of its survival at time t can be calculated as

$$R(t | t_0) = P(T > t | T > t_0) = e^{-\int_{t_0}^t h(x, Z(x)) dx} \quad (3)$$

The hourly outage probability $F(t)$ is

$$\begin{aligned} F(t) &= 1 - R(t) \\ &= 1 - R(t | t-1)R(t-1) \\ &= 1 - R(t | t-1)(1 - F(t-1)) \\ &= 1 - e^{-\int_{t-1}^t h(x, Z(x)) dx} \\ &\quad + F(t-1)e^{-\int_{t-1}^t h(x, Z(x)) dx}, \end{aligned} \quad (4)$$



which is a recursive process in that the outage probability of a generator of the present time is determined by its outage probability and its output of the last time step.

B. Sampling Method

At each time step before the unit commitment is conducted, its conditions have to be determined first, including both the renewable generations and the generator outage states which can be collected with the sampling method. As stated in section III-A, the outage probability is determined by its previous outage probability and the output at the last time step. Given that a component has survived until time t_m , the proposed sampling process includes three steps:

- 1) Accumulate the outage probability $F(t_m)$ according to (4).
- 2) Randomly pick u from the uniform distribution $U(0, 1)$, which serves as an arbitrary probability.
- 3) Compare u with the outage probability $F(t_m)$: if $u < F(t_m)$, the generator is regarded failed and the outage is assumed to last from t_m through $t_m + T_r - 1$, after which it will be fully repaired with its accumulated outage rate cleared, i.e., $F(t_m + T_r)$ reset to zero.

Sampling the renewable generation undergoes a similar process. Given a renewable energy source follows a probability distribution from the DBBN at time t_m , the sampling process is as follows:

- 1) Calculate the cumulative distribution function $P(t_m, v)$ using the probability distributions $p(t_m, v)$,

$$P(t, v) = \sum_{i=0}^{i=v} p(t, i). \tag{5}$$

- 2) Randomly pick u from the uniform distribution $U(0, 1)$.
- 3) Compare u with the cumulative probability $P(t_m, v)$. If u falls in the interval $[P(t_m, v_i), P(t_m, v_{i+1})]$, the generation of this renewable energy is assumed to be v_i .

The UC and the sampling process are executed alternatively throughout the time horizon. Random outages and renewable generation affect the unit commitment in contrary ways. Random outage shifts loading to the remaining units and aggravates their ageing, while the renewable generation hands over load from traditional units and thus alleviates ageing.

C. Rolling-Horizon Unit Commitment

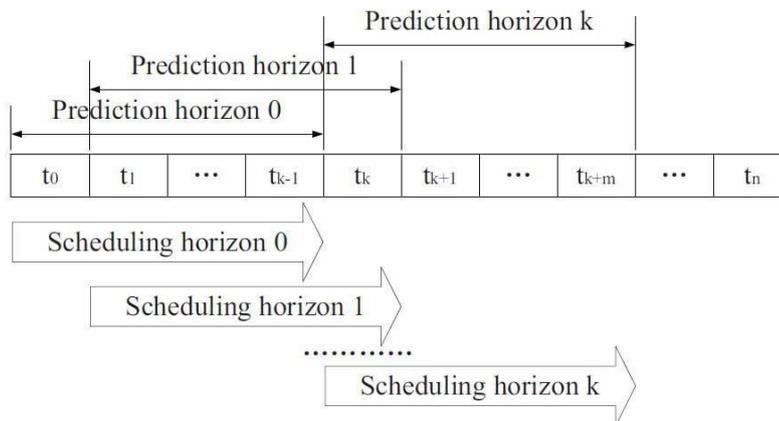


Figure 2 : Demonstration of the rolling-horizon unit commitment

Day-ahead unit commitment suffers from the inaccuracy of the prediction of the renewable generation, which becomes notable when the prediction is carried out more than 4 hours ahead. The RH strategy counteracts the accuracy issue of the prediction by searching for and updating the optimal trajectory only for a smaller number of the forthcoming time intervals at each time step, while only implementing the actions for the current time step. Denoting the present time



step as t_0 and the narrower time horizon of interest as t_m , RH-UC demonstrated in Fig. 2 is composed of the following steps [28]:

- 1) Solve the unit commitment within time range $[t_0, t_{0+m}]$.
- 2) Implement the resulted optimization strategy for the current step t_0 , e.g., the output of generator i at time t_0 set to $\widehat{P}_i^{t_0}$.
- 3) Update system information including the load and renewable energy and update the boundary of unit commitment.
- 4) Increment t to $t + 1$, and go to step 1.

The formulation of the RH-UC in detail follows that of the ordinary UC in [35], except for fitting the objective function and constraints into a narrower time horizon. Note that the generator must be off-line if it fails, and once it does, it has to be exempted from meeting the constraints of maximum ramp-down rate and minimum uptime. Consequently, these constraints have to be relaxed when outages happen, which are designed as follows:

$$u_{gt} \leq 1 - \sum_{i=t-T_r+1}^t out_{gi} \quad \forall g, t, \tag{6}$$

$$p_{g,t-1} - p_{gt} \leq RD_g + M_1 \times out_{gt} \quad \forall g, t, \tag{7}$$

$$\sum_{i=t-TU_g+1}^t v_{gi} \leq u_{gt} + M_2 \times \sum_{i=t-TU_g+1}^t out_{gi} \tag{8}$$

$$\forall g, t \in [TU_g, T].$$

Here, (6) determines the on/off status of the failed unit, with binary variable out_{gi} denoting the outage status of the unit g for hour i , 1 for failure and 0 otherwise, u_{gt} denoting the on/off status, 1 for online, (7) relaxes the ramp down constraints when outages occur, with M_1 being a big value, and similarly, (8) relaxes the minimum uptime constraints, with M_2 being another big value, and v_{gi} denoting the turn on status, which takes the value of 1 if the unit is turned on for hour i .

D. Double-Layer Storage Dispatch

The storage dispatch rules for the ordinary UC can be directly inherited into a narrower time horizon and applied to RH-UC, but will not allow the storage for peak shifting and valley filling, for it is prohibited by the narrower horizon from foreseeing the daily trend of load curve, i.e., the peaks and valleys that exhibit over the full horizon. To overcome this shortage, the storage-integrated operation adopts a doublelayer model. A day-ahead unit commitment has to be run before the RH-UC to determine the crude state of charge (SOC) of the storage, only after which the RH strategy will be carried out to ensure the storage can smooth the real-time fluctuation of renewable generation and improve the reliability by taking over load when the generator fails.

Day-ahead dispatch. The storage operation in day-ahead unit commitment can be expressed as:

$$soc_t = soc_{t-1} + pc_t \times \eta_c - pd_t / \eta_d \quad \forall t, \tag{9} \quad pc_t$$

$$\leq pc_{\max} \quad \forall t, \tag{10} \quad pd_t \leq pd_{\max} \quad \forall$$

$$t, \tag{11}$$

$$soc_{\min} \leq soc_t \leq soc_{\max} \quad \forall t, \tag{12}$$

$$soc_{initial} = soc_m, \tag{13}$$

which describes the change of state-of-charge (9), bounds of charge power pc (10), discharge power pd (11), and soc (12), and the equality of soc levels at the start and end of the horizon (13). The day-ahead dispatch also balances generation and load by renewable generation from day-ahead forecasting and the storage system:



$$\sum_g P_{g,t} + P_{solar,t} + P_{wind,t} - pc_t + pd_t = D_t - loss_t \quad \forall t. \tag{14}$$

Rollinghorizon strategy. Besides constraint (9)-(14) which is directly inherited into a narrower time horizon and applied in RH-UC, constraint (15) is also added to RH-UC to make sure the RH strategy follow the crude trend of *soc* determined by day-ahead dispatch,

$$-\alpha \times soc_{max} \leq soc_t - soc_{ref} \leq \alpha \times soc_{max} \quad \forall t. \tag{15}$$

E. Framework of the Reliability Evaluation

The proposed reliability evaluation is based on Monte Carlo simulation, as shown in Fig. 3. Along the time axis of each run of the simulation, the RH-UC is sequentially solved interactively with DBBNs and the sampling method. In each time step, the DBBNs extract the probability distributions of the solar and wind generations; then, according to the probability distributions, the renewable generations are sampled as the realized boundary of the UC problem of the present time step; after that, the UC is solved to calculate the load shedding; finally, the impact of committing the generators on their ageing conditions is accumulated. Within the Monte Carlo framework, the above sequential simulation process is repeated until the convergence condition is met to ensure that the generated samples are able to represent the global feature.

The convergence condition is labelled with the coefficient of variation (CV) which measures the variability in Monte Carlo simulation and judges whether the samples are enough to represent the global feature of system reliability [36]. Loss of load probability (LOLP) and expected energy not supplied (EENS) are chosen as the reliability index to describe the supply capability of the system, and the CV with LOLP is used to determine the termination condition for simulations:

$$CV = \sqrt{\frac{1}{n(n-1)} \sum_{k=1}^n (LOLP_k - \overline{LOLP})^2 / \overline{LOLP}^2}. \tag{16}$$

Given varying initial states and random sampling results, the RH-UC in each round of the Monte Carlo simulation returns different solutions, leading to different values of LOLP. However, the Monte Carlo simulation pertains to the overall performance by taking the average of results of all simulations. The entire reliability evaluation framework is explained in more detail below: The entire reliability evaluation framework is explained in more detail below:

- 1) The weather conditions, the parameters of the components and the load are gathered and processed. The initial states of all components are regarded in the normal state.
- 2) The sequential simulation process of DBBNs, sampling method and RH-UC are conducted as follows:
 - a) Generate the probability distributions of solar and wind outputs using DBBNs.
 - b) Sample renewable generations and component states.
 - c) Conduct UC at time *t* with the horizon [*t*, *t* + *T_H*].
 - d) Implement the optimization result of RH-UC at time *t*.
 - e) Accumulate the outage probability at the end of *t*.
 - f) Repeat steps (a) to (f) until the optimization horizon is concluded for this scenario.
 - g) Calculate the LOLP of this scenario.
- 3) If the CV is larger than a pre-set critical value δ , go to (1) for a new scenario.

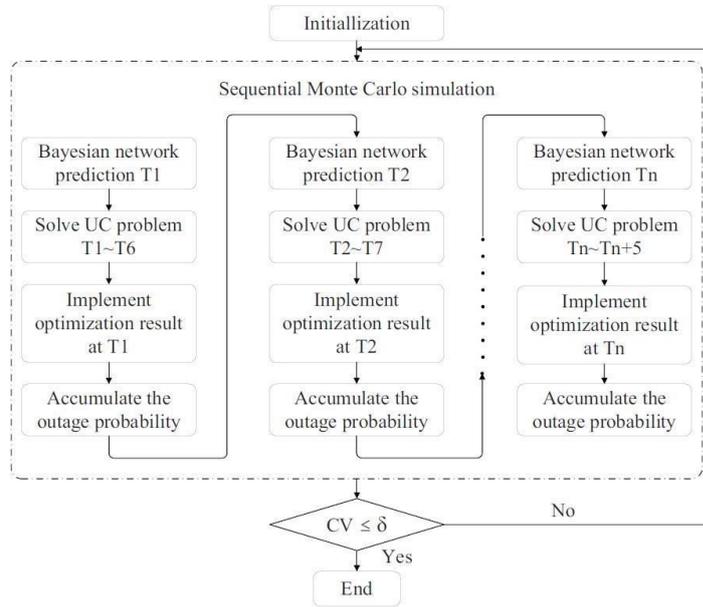


Figure 3 : Algorithm flow of the proposed reliability evaluation

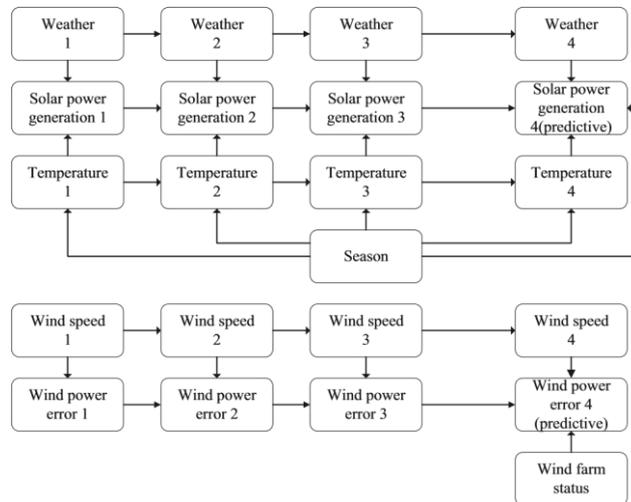


Figure 4 : DBBNs for solar and wind prediction.

IV. CASE STUDY

A case study is performed on a microgrid with eight generators as shown in Table I. The maximum generations of the solar and wind energy are 450MW, accounting for about 25% of the 1700MW peak load. The DBBNs used to predict the solar and wind generations are trained with historical data of wind speed and solar radiation in Shanghai, China for three years from 2015 to 2017 [37], [38]. The RH-UC is formulated with a weekly full horizon (168 hourly time steps) and a six-hour rolling horizon, which is solved as a mixed integer linear program with CPLEX 12.8, and programmed in the Python environment together with the DBBNs.

A series of events related to renewable generation are preselected from the historical data to construct the network structure diagram by setting the relevant events as the parent nodes and the renewable generation as the child, as Fig. 4 shows.

Table 1 : Parameters of the Generators

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8
Max Gen (MW)	425	365	220	210	165	158	90	87
Min Gen (MW)	100	140	78	52	54	39	17	15
Ramp Up/Down (MW)	212/83	150/198	101/96	95/101	58/78	50/60	40/24	60/45
Min on/off (h)	15/9	15/8	6/7	5/4	5/3	4/2	3/2	3/2

By feeding the historical data in sequence to the model, the parameters of the DBBN are estimated by using the maximum likelihood estimation so that they accurately reflect the conditional probability between nodes. After the DBBNs are trained with the three-year-long big data, they are ready to produce the sequential renewable generations.

A. Computational Efficiency of Proposed Framework

DBBN is assessed in the proposed reliability evaluation framework against a three-layer artificial neural network, a proved efficient spot prediction method, for its computational efficiency. It takes the framework with DBBN 234 rounds of simulations to meet the convergence criterion of the Monte Carlo simulation, i.e. the CV of the LOLP dropping below 0.02 after 234 rounds of simulations, while the spot prediction needs 93 rounds for the same convergence criterion, data provided in Table II. When the spot estimation is also run for 234 rounds, it achieves a lower CV, namely 0.0113, but the LOLP stays higher 0.02161 than that for the DBBN. In each round of simulation, the average time of running the DBBNs with the UC is about 8.2 seconds, which is slightly longer than that of the point prediction model, indicating that the DBBN as a machine learning technique takes longer computation time for better quality than a regular method. Whereas tens of minutes is not a long period for reliability evaluation, each of the Monte Carlo simulations is mutually independent, allowing for parallel computation to further decrease the computation time. In general, the proposed framework would provide a reliable solution within a reasonable CPU time.

Table 2 : Comparison Of Computational Efficiency

Method	No. of simulations	Time	LOLP	CV
Point Estimation	93	10 min	0.02186	0.0199
Point Estimation	234	28 min	0.02161	0.0113
DBNNs	234	32 min	0.02092	0.0199

B. Renewable Prediction with DBBN

The performance along the reliability index, i.e., LOLP, of both methods shown in Fig. 5 illustrates the accuracy of both methods, as they are run for the same number of simulations, namely 234, to make them comparable in accuracy. The actual case in which the weather condition is observed afterwards and the reliability index is calculated by the RH strategy is also shown in Fig. 5 as a reference. While both methods qualify for reliability evaluation with a certain accuracy because LOLP of the actual case is contained in their ranges, and the average result of DBBN achieves a much lower relative error, 0.4% vs. 3.7% achieved by the point estimation. Moreover, the DBBN method can generate more scenarios with a wider LOLP range, namely from 0 to 0.0428, indicating that it will succeed when the spot prediction may fail under extreme conditions. It is worth noting that some low probability scenarios that get missed in the sampling process might contribute to errors in reliability evaluation. Tightening the convergence condition of the sampling method to ensure that enough scenarios are well considered is one of the solutions, which, however, may cause a heavy computational burden, sacrificing efficiency. An alternative choice can be expected from the Monte Carlo integrated cross-entropy method that increases the sampling probability of rare events [39].

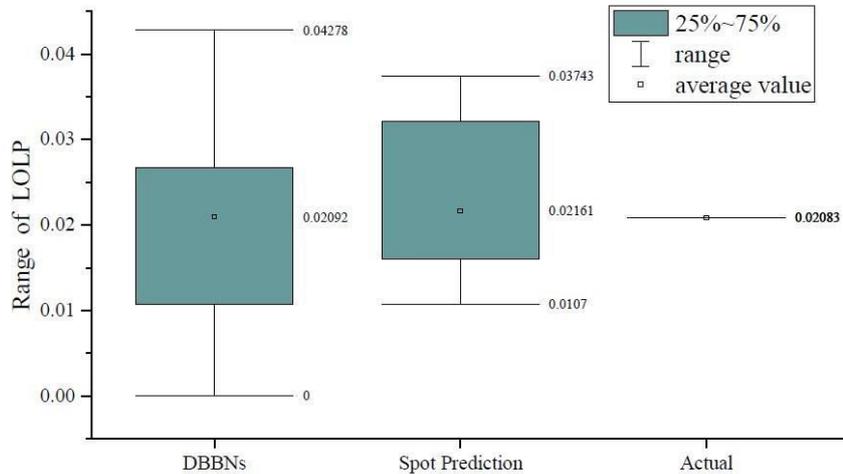


Figure 5 : Distribution of LOLP sampled by two algorithms against actual

C. Unit Commitment Mechanisms

As mentioned above, the step-by-step unit commitment breaks down the ordinary day-head UC together with its objective function and constraints into a series of them over single time steps [27], which unavoidably lands in local optimum for system operation. On the other hand, the day-ahead UC, though being able to find the global optimum for system operation, does not update the weather conditions during its running. The proposed method uses the RH-UC instead to balance operational optimality and punctuality of updating the weather conditions.

The RH- and step-by-step UCs share the same problem settings including the weather conditions and generator parameters. As UC is solved within a Monte Carlo simulation framework, results corresponding to different scenarios will be produced. It is then important to note that although different scenarios are created for both strategies in each sample, for they have different mechanisms, the number of scenarios is made large enough to expose the probability distribution, which makes the two strategies comparable.

The results from both strategies with DBBNs creating the same distribution of renewable generations are shown in Fig. 6. The lower bound of the total cost corresponds to the best scenario where the renewable generation is high and outages seldom happen, which sees the RH strategy outperforms the step-by-step one. The worst scenario corresponds to the upper bound of the total cost, where the RH strategy proves much more advantageous in saving operation cost, while the step-by-step strategy shows deficient faced with the extreme condition. Detailed numbers for cost compositions, and reliability and computational indices are given in Table III. RH-UC costs slightly lower than step-by-step UC in terms of both the fixed and the variable parts of the operation cost, and saves even more for the start cost (397802 vs 222744), indicating it schedules turn-on and shut-off of generators less frequently. The RH strategy even achieves a lower LOLP, proving its better performance in improving system reliability. The synchronous reliability improvement and a lower operation cost come at a price: its computational burden is heavier than that of the step-by-step UC, for in each time step it involves six times the number of variables and constraints of the latter, which results in longer computational time for the RH strategy, namely about 8.2 seconds per simulation, about 4 times longer than that of the step-by-step one. Still, the 32-min total time is acceptable for system reliability evaluation.

Table 3 : Cost of Operation, and Reliability and Computational Indices of Both Strategies

Strategies	Average total cost (\$)	Variable cost (\$)	Fixed cost (\$)	Start cost (\$)	LOLP	EENS	No. of simulations	Time
Step-by-step	14119031	8627996	147356	397802	0.0334	0.00459	157	6 min
Rolling-horizon	13638608	8448446	146386	222744	0.0208	0.00120	234	32 min



Table 4 : Difference of the Cumulative Total Cost

Time of day	1	2	3	4	5	6	7	8	9	10	11	12
Difference (\$)	0	0	0	0	-32	-9	67	197	303	26046	56091	57983
Time of day	13	14	15	16	17	18	19	20	21	22	23	24
Difference (\$)	48314	50171	52303	53484	28084	28363	27348	159645	161421	162842	163258	163266

A closer observation of both strategies is offered by their application in a special scenario where the 24hour full horizon with the renewable generations of the highest probability. Fig. 7 shows the accumulative total cost of both strategies in each time step, and the blue line shows the difference between them. As can be seen here, the total cost of

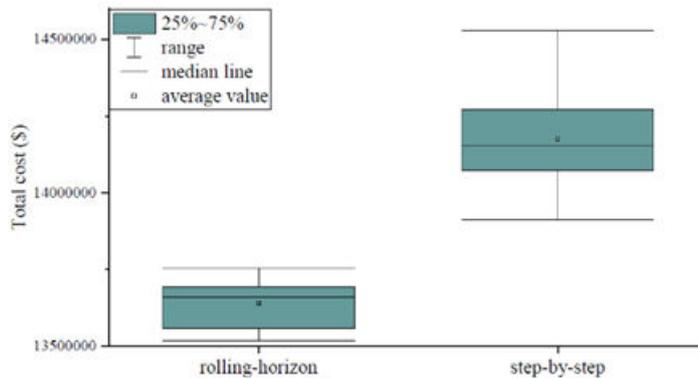


Figure 6 : Distribution of total cost achieved by two strategies

the step-by-step strategy remains the same as that of RH strategy in the first four steps.

Despite it reaches a lower cost at the fifth step (see exactly in Table IV), its accumulative cost till the seventh hour becomes higher, indicating with the two consecutive steps, i.e., the fifth and sixth, jointly considered, the step-by-step strategy shows less economic. Such comparison points to the fact that the step-by-step strategy is a local optimization, which may arrive at lower costs in individual steps, but misses the better solution throughout the entire horizon. Another finding is that there is a huge increment of cost by the step-by-step strategy at 11 am and 8 pm, when the demand rises rapidly, indicating the step-by-step strategy performs poorly when load changes intensely.

The generation patterns of both strategies are laid out unit by unit in Fig. 8, which help to explain the accumulative cost difference of all steps. The step-by-step strategy turns off generator 6 at the fifth hour and increases the output of generator 2, while the RH strategy, being able to foresee conditions of the next six steps including especially a sharp

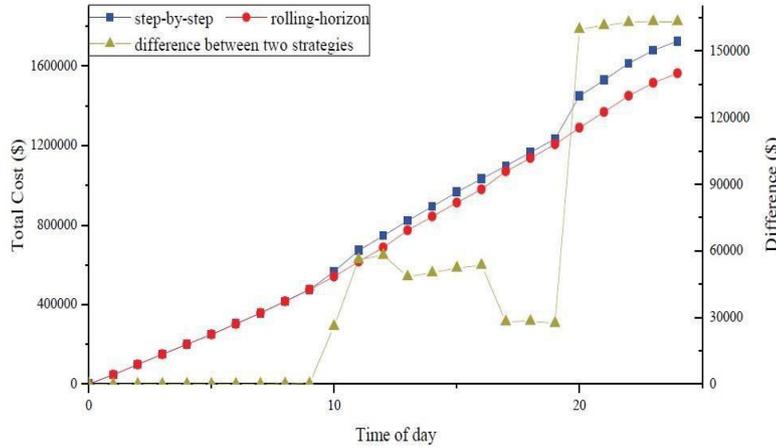


Figure 7 : Per-hour comparison of total cost of both strategies

load increment at 10th hour, keeps generator 6 at its minimum level allowing for its potential output, which would otherwise have to stay offline due to the minimum off-time constraint. The rolling-horizon strategy thusly avoids turning on and off the generators frequently and results in a lower start cost.

D. Impact of System Configuration and Load Condition

Two more cases are studied to verify the proposed framework under different system configurations and load conditions, as opposed to the base case considering the forced generator outages only.

- Case (Storage): An energy storage system is installed in the microgrid, which incorporates with the generators in the way of storage-integrated unit commitment as defined (9)-(15). The parameters of storage are given in Table V.
- Case (Load): Forced load outages are meantime taken into account with the generator outages. The total load is composed of ten users of microgrid with the unexpected load outages rate of each one being 0.1% per hour.

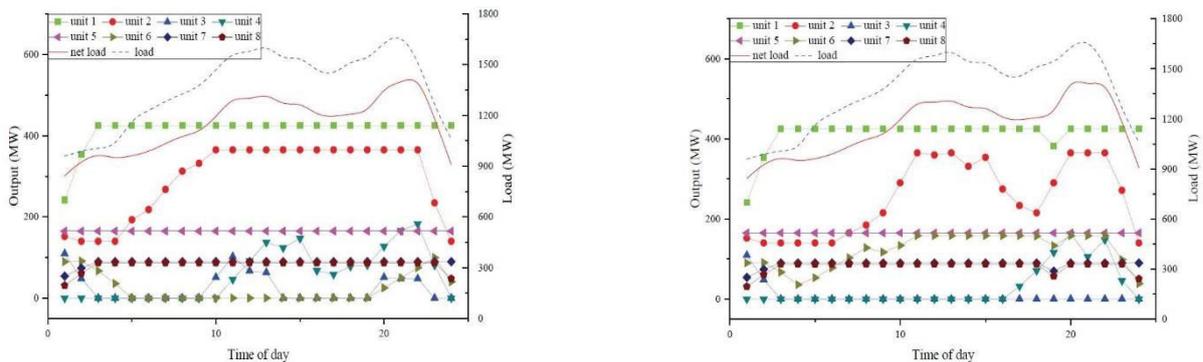


Figure 8 : Generation patterns of both strategies (a) Step-by-step (b) Rolling Horizon

The results of the two cases are listed, and part of those of the base case are repeated, in Table VI. The computation time for such scenario-based problems depends on the number of simulations. Base case and case S share nearly the same number of simulations, while case L, having more uncertain factors of load outages brought in, needs to run more scenarios before convergence. The comparison between case S and the base case shows that the storage can further reduce the cost, especially the start cost of the generators, which may result from the energy-shifting function of storage. The storage also helps to improve the reliability, indicated by the drop of reliability indices, namely LOLP and EENS, proving it can take over a portion of load when the generators fail.

Table 5 : Parameters of the Storage

η_c	η_d	SOC_{max}	SOC_{min}	$SOC_{initial}$	PC_{max}	PD_{max}
0.95	1	150	30	45	30	30

The unexpected load outages in Case L make the system less reliable as the reliability indices of this case rise from the base, LOLP of 0.0485 and EENS of 0.00399 as shown in Table VI. The more load shedding and higher penalty for loss of load also raise the total cost of Case L in spite of a slightly lower cost from the generators.

Table 6 : Reliability and the Corresponding Operation of the Three Cases

Cases	Average total cost (\$)	Variable cost (\$)	Fixed cost (\$)	Start cost (\$)	penalty cost (\$)	LOLP	EENS	No. of simulations
Base	13638608	8448446	146386	222744	64553	0.0209	0.00120	234
S	13300654	8278219	140600	25127	51769	0.0186	0.00093	248
L	13733554	8404795	145816	221697	214356	0.0485	0.00399	326

IV. CONCLUSION

A novel Monte Carlo framework is developed to conduct reliability evaluation of power systems subject to both the variable and intermittent renewable energy and the ageing of generators. The proposed framework uses DBBN, a machine learning method, to generate the probability distributions of solar and wind energy, from which the boundary conditions of the unit commitment are sampled. The rolling-horizon unit commitment, naturally an optimization, is introduced as the internal operation model to match the demand with the generation considering the random outages picked by the proportional hazard model. The machine learning and optimization interact with each other in each time step to form a proactive and sequential reliability evaluation framework.

In its comparison with the step-by-step unit commitment, the rolling-horizon strategy proves more effective in this reliability evaluation framework and thus gains a superior operation schedule to avoid underestimation of the grid reliability. The simulation also shows that the DBBNs cooperated with unit commitment can describe more scenarios including those when the renewable generation is deficient, and avoid overestimating the reliability. Although this framework is proposed for and demonstrated with reliability evaluation here, it can also be incorporated with other evaluations like the resilience assessment.

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