Optimum Network Ageing and Battery Sizing for Improved Wind Penetration and Reliability

MOHAMED K. METWALY and JIASHEN TEH, (Member, IEEE)

1Electrical Engineering Department, Faculty of Engineering, Taif University, Taif 21974, Saudi Arabia
2Electrical Engineering Department, Faculty of Engineering, Menoufia University, Shibin El-Kom 32511, Egypt
3School of Electrical and Electronic Engineering, Engineering Campus, Universiti Sains Malaysia (USM), Nibong Tebal 14300, Malaysia

Corresponding author: Jiashen Teh (jiashenteh@usm.my)

The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education, Saudi Arabia, for funding this research work through the project number 284.

ABSTRACT A multiobjective framework that optimises the uprating of the line’s real-time thermal rating and capacity of battery storage against wind curtailment, network ageing and reliability is proposed. The two enhancements are limited to the accumulated expected amount and duration of wind power losses of each wind farm bus. In the framework, actual conductor properties, line failures due to thermal effects, weather data, battery operation policy and wind farm model are considered. The trade-off of the optimisation criteria, the Pareto front, is solved using the non-sorting genetic algorithm and fuzzy decision-making method. Results show that the conductor maximum allowable temperature affects all the three optimisation parameters, but battery efficiency only affects wind curtailment level.

INDEX TERMS Battery energy storage, line rating, reliability, optimisation, ageing, overhead lines, flexibility, Monte Carlo.

I. INTRODUCTION Most countries commit to increasing the penetration of renewable energies, and wind consistently emerges as one of the preferred sources [1]. However, its intermittency remains the main factor that inhibits the widespread penetration of wind farms in power systems. Power gaps created during the coincidence of low wind speed and high energy demand can only be partially met by the remaining generators due to their ramping rate inertia and existing ongoing demands. Excess wind power is generated when wind is curtailed and wasted.

As a result, battery energy storage system (BESS) is normally installed alongside wind farms to address the aforementioned problems [2], [3]. BESS is flexible, and it can be charged/discharged quicker—fast-ramping—than the common large-scale generators, and it has a size that can be easily adjusted by combining small cell-banks together [4]. Owing to its advantages, various reliability studies on the interactions between BESS and power systems are conducted. The component reliability modelling of large-scale BESS consists of multiple modules is performed to demonstrate that configurable battery topology improves the reliability of a power system [5]. The reliability impact of BESS on wind-integrated system is studied based on stochastic unit commitment model and flexible scheduling of the energy storage system [6]. A technique on committing BESS capacity for mitigating the impact of wind intermittency towards the reliability and economy of power systems is modelled [7]. The reliability impact of BESS towards power systems is also modelled alongside demand-side management [8], dynamic thermal rating systems [9] and optimum integrated level of wind farms [10]. Battery degradation has also been considered in designing the coordinated optimization of wind power and BESS [11]. A risk-averse method for heterogeneous energy storage deployment in a residential multi-energy microgrid, considering the diverse uncertainties and multi-energy demand-side management has been proposed before as well [12]. Although the abovementioned studies provide insights into the effects of various battery policies, schedules, technologies and designs towards the power systems, their common drawback is that the size of BESS is never optimised against the level of wind curtailment. At best, various sizes of BESS are studied through trial-and-error to estimate the most suitable capacity, leading to a lack of systematic framework that can specifically quantify the optimum BESS size based on network topology, operations, reliability and economy criteria.

An alternative to BESS is the dynamic thermal ratings of overhead lines (OHL), wherein the thermal behaviour of conductors is utilised to flexibly enhance line ratings to avoid...
limiting wind power flowing into the network [13]. This flexibility is normally achieved via (a) Probabilistic Thermal Rating (PTR) [14], [15], wherein a predefined risk of exceeding the static thermal rating, which is determined based on a set of conservative weather assumptions, is accepted, (b) Real-time Thermal Rating (RTTR) system, which periodically rates line based on existing weather conditions [16]–[18], and (c) Emergency Loading (EL) practices, which are higher than the normal ratings for short and long terms [19]. Among these rating methods, only the RTTR has implementation costs due to the deployment of sensors to record real-time weather conditions [20], [21]. Although at no cost, the PTR and EL methods impose relatively higher network ageing risk due to the probability of exceeding conductors’ maximum designed temperatures (MDT), also known as ‘exceedance’. Exceedance must be quantified to ensure that informed decisions of acceptable network ageing risk are made against acceptable wind curtailment levels. Several studies investigated the ageing of OHL, with only a handful investigated the impact of the ageing towards network reliability. In [14], [15], the OHL ageing caused by the RTTR method and the fuzzy effects of its parameters towards the line failure probability is modelled. In [17], [22], the effects of PTR towards network ageing and reliability are studied. In [23], [24], the ageing risk of distribution cables are examined and ranked for replacement priority. Although these studies modelled the effects of network ageing towards its reliability, this new insight is never utilised for optimising the penetration of wind power. As a result, past wind integration plans ignore network ageing.

Notwithstanding the work mentioned above and to the best of our knowledge, a lack of framework that integrates informed network ageing model and BESS capacity based on the wind curtailment information is observed. This paper addresses this gap and the followings are the contribution of this paper:

1) A framework that utilises wind curtailment information for optimising OHL ageing and the size of BESS is proposed. This framework can be used by network operators as the new flexibility strategy during planning based on historical data.

2) The proposed framework has a multiobjective optimisation in it that quantifies the capacity of BESS and allowable level of RTTR against wind curtailment, network ageing risk and system reliability.

3) Consequently, the proposed method provides system operators with a new systematic and informed decision-making process that could be combined with existing network management strategies to reconsider the trade-offs between risk and reliability.

II. METHODOLOGY
The proposed methodology uses network operation, OHL plant and weather data in the initialisation and minimisation modules shown in Fig. 1. The network operation data are the topology of the network, reliability information of components, i.e. failure and repair rates, and all technical constraints of the components, i.e. bus voltage limits, maximum and minimum outputs of generators, generation costs, load demand pattern and maximum temperatures of lines and cables. OHL plant data refer to information on the design aspect of the transmission lines, i.e. conductor types, maximum designed temperatures, electrical requirements, physical dimensions and rating approach. Weather data are weather information needed for determining wind power outputs and conductor temperatures of OHLs, i.e. wind speed, wind angle, ambient temperature and solar radiation.

The outputs of the initialisation module—expected wind curtailment level and duration—are used to optimise network ageing, system reliability and wind curtailment in the minimisation module.

A. INITIALISATION MODULE
The initialisation module performs the standard Sequential Monte Carlo (SMC) simulation [25] to create the vast combinations of network failure conditions at each time step, $\Delta t$, over a certain period of simulation, $t$, or until the convergence criteria is met. Within SMC, the common technique of generating component up-down cycles and the AC optimal power flow (ACOPF) based on the standard generation and interruption costs minimisation are used, with generation...
re-dispatch given priority over demand shedding [26]. The weather data input at each \( \Delta t \) are used to determine the RTTRs (based on Line Rating Model) of OHLs at their MDTs to avoid conductor ageing at elevated temperature and the power output of wind farms. No BESS is considered in this module.

During the simulation, this module records the annual probability distributions of wind curtailment (WC in MWh/y) at each wind farm bus, \( b \), and the duration of the wind curtailment (DWC in h/y). These indices are used to estimate the expected wind power curtailment values that must be overcome at each of the wind farm bus. They are called the contractual wind power (CWP), \( P_b^{\text{CWP}} \), such as the following:

\[
P_b^{\text{CWP}} = \frac{1}{Y} \sum_{y=1}^{Y} \left( \frac{\text{WC}_b^y}{\text{DWC}_b^y} \right),
\]

where \( P_b^{\text{CWP}} \) (in MW) is based on the annual \( \text{WC}_b^y \) and \( \text{DWC}_b^y \) of each wind farm bus, \( b \), in each simulated year, \( y \). This formula indicates the expected wind curtailment encountered at each wind farm bus across all \( \Delta t \) in the entire duration of simulation, \( Y \). The values of \( P_b^{\text{CWP}} \) are passed down to the minimisation module, wherein negotiation is performed to determine the acceptable OHL ageing risk and BESS size that provide the optimum wind curtailment level, network ageing and reliability.

**B. MINIMISATION MODULE**

The minimisation module shown in Fig. 1 considers the optimum utilisation of the CWP value to uprate RTTRs of OHLs and to determine the size of BESS against wind curtailment, system reliability and network ageing, which are the three measured indices of the Multi-Objective Optimisation Model. The process starts by randomly assigning \( \alpha \% \) and \( \beta \% \) of CWP from each wind farm as the rated capacity of BESS and to uprate the RTTRs, respectively. Inputs required for the SMC simulation, such as line rating (based on Line Rating Model), line statuses (based on Line Failure Model), BESS size and generation and demand levels obtained from the chronological and reliability data of the power network, are then determined in each time-step, \( \Delta t \), of the SMC. Then, the standard ACOPF is executed until convergence and the indices mentioned earlier are measured and recorded, during which the charges of the BESS are also updated and utilised based on the BESS model.

The wind curtailment index is recorded as the main purpose of the RTTR and BESS is to improve the integration of wind power. In addition, the network ageing and system reliability obtained from the outcomes of the ACOPF are also monitored to present trade-off options with various levels of wind curtailment. The network ageing index described in the Conductor Ageing Model is recorded as OHLs operating with the uprated RTTRs may be overloaded, causing the conductor temperatures to rise beyond its MDTs—the temperature at which the original RTTRs are based on—and subsequently accelerates conductor and network ageing.

As the optimisation proceeds to the next iteration, the new assignments of \( \alpha \) and \( \beta \) are generated based on the genetic algorithm (GA) procedure and the whole process is repeated until convergence.

1) **LINE RATING MODEL**

The RTTRs of OHLs are calculated based on the IEEE 738 standard which considers the surrounding weather conditions of the lines as follows:

\[
Q_c(T_c, T_a, v_w, \phi) + Q_r(T_c, T_a) = Q_s + I^2R(T_c),
\]

where the thermal state of the line at any time is balanced by heat losses due to convection, \( Q_c \), and radiation, \( Q_r \), and heat gains caused by solar radiation, \( Q_s \), and current flow, \( I \), which is easily convertible to power rating. The rate of \( Q_c \) is determined by the conductor temperature, \( T_c \), ambient temperature, \( T_a \), wind speed velocity, \( V_w \), and the angle of the incident wind direction with the line, \( \phi \). The rate of \( Q_r \) is controlled by only two parameters, namely, \( T_c \) and \( T_a \). The term \( I^2R(T_c) \) is also known as joule heat gain, formed with a multiplication of \( I \) and conductor resistance, \( R \), which is further affected by \( T_c \).

![FIGURE 2. Back-calculation process of the IEEE 738 standard.](image)

The value of \( T_c \) is usually limited by system operators and the determinant factor that influences OHLs ratings and conductor ageing. Hence, determining the value of \( T_c \) is important but extracting it by rearranging (2) is not possible due to the nonlinearity of the mathematical equation. Instead, its value is estimated with an iteration process shown in Fig. 2, whilst maintaining all other weather parameters until the state of heat balance (HB) is achieved in (2). The iteration process starts by setting \( T_c = T_a \) and increase by \( 0.5 \, ^\circ \text{C} \) after each unsuccessful guess. The iteration is terminated when the successive HB error is less than 1%.

Considering also that an OHL is normally made up of \( n \) number of multiple smaller spans affected by various weather conditions and (2) is applicable in each of the span, the overall loading of the OHL is limited by its smallest current flows, \( I_{\text{min}} \), of all spans, such as the following:

\[
I_{\text{min}} = \min (I_1, I_2, \ldots, I_n).
\]

2) **LINE FAILURE MODEL**

The operating temperature of conductors affects also the probability of line failures due to thermal stress, in addition to its normal random failures and remaining service-life.
A suitable modelling for this phenomenon is known as the Arrhenius model [14] as shown in the following:

\[ L = A \exp \left( \frac{B}{T_c + 273} \right), \]

(4)

where \( L \) is the measure for the average life of the OHL, and \( A \) and \( B \) are empirical constants derived from historical loading data [14].

Given that the SMC is performed in this study, the hourly random statuses of the lines based on the failure rates that consider its thermal stress are required as inputs to the SMC. To achieve such evaluation, the Arrhenius model is fitted into the Weibull distribution to facilitate the generation of the random failures. The reason that the Weibull distribution is chosen is due to its single life measure which matches the one life measure characteristic of the Arrhenius model. Moreover, Weibull distribution is normally used to model the increasing rate of failure with respect to time, which in this study is due to higher thermal stresses and remaining chronological lifespans of the lines. Similar strategy has also been employed before in the modelling of power transformer [27] and cable [23] failures. Given the inverse transformed method normally used in the random generation of component statuses [25], the modified Weibull distribution is as follows:

\[
F(t) = 1 - \exp \left[ - \left( \frac{t}{\theta} \right)^m \right], \\
= 1 - \exp \left[ - \left( \frac{t}{A \exp \left( \frac{B}{T_c + 273} \right)} \right)^m \right],
\]

(5)

where \( \theta \) is the scale parameter equal to \( L \) of (4), and \( m \) is the shape parameter, i.e. the slope or the rate of change of the failure probability with respect to time.

In addition to (5), the conditional probability theory [28] also states that past failures of OHLs have to be considered. As a result, the derivation of the failure probability, \( U \), of the modified Weibull becomes mathematically complex. Thus, its polynomial approximation [29] such as the following is more suitable:

\[
U = \frac{1}{N} \sum_{n=1}^{K} P_n UD_n,
\]

(6)

where \( N \) is the remaining useful time of the OHL minus its operated time, \( T \); \( k \) is the subinterval number of \( N \); \( P_n \) is the probability of OHL failure of each subinterval, \( n \), considering the thermal stress and the length, \( \Delta l \), of the subinteval as shown in (6a); \( UD_n \) is the average duration of \( P_n \), shown in (6b).

\[
P_n = \exp \left( \frac{(T+n-1)\Delta l}{L} \right)^m - \exp \left( \frac{T+n\Delta l}{L} \right)^m - \exp \left( \frac{-T}{L} \right)^m,
\]

(6a)

\[
UD_n = N - (2n-1) \frac{\Delta l}{2},
\]

(6b)

Finally, the failure probability, \( U \), obtained in (6) is used to derive the thermal stress-based failure rate, \( \lambda_L \), of the OHLs as in the following based on the Markov process [28]:

\[
\lambda_L = \frac{\mu U}{1 - U},
\]

(7)

where \( \mu \) is the repair rate of the OHLs, which is normally controllable and is therefore known most of the time.

The presented line failure model works based on the conductor operating temperature, \( T_c \), of the previous time step, \( \Delta t \). As a result, the random statuses of lines in the first hour of the SMC is initialised without considering the conductor thermal effect based on the classical reliability method [25], [28].

3) BESS MODEL

In a wind-integrated power network where a percentage of the power supply by the conventional generator units (CGUs) have been replaced by wind farms, the surplus wind power of each wind farm bus, \( \text{SGW}_b^i \), at a particular hour \( i \) is as follows:

\[
\text{SGW}_b^i = \text{TGW}_b^i - \text{OGW}_b^i,
\]

(8)

where \( \text{TGW}_b^i \) and \( \text{OGW}_b^i \) are the total and output wind power of each wind farm bus, respectively.

Then, for simplicity, BESSs used in this study are all considered to be located at the wind farm buses and owned and operated by wind farm owners. Other possible BESS operating strategies are not explored here as the focus of this study is to demonstrate the methodology for optimising the utilisation of CWP to improve battery sizing and network ageing. In the considered scenario, wind farms and CGUs participate in the open electricity market and compete to supply electricity. When a surplus wind power exists, the entirety of it is stored in the BESS for later usage. On the contrary, when wind farms need power support due to demand spike or loss of generators, the earlier stored charges of the BESSs are discharged to supplement the additional required wind power. Based on this description, the state-of-charge (SOC) of the BESS at each hour, \( \text{SOC}_{i+1} \), is updated as follows:

\[
\text{SOC}_{i+1} = \begin{cases} 
\text{SOC}_i + \text{SGW}_b^i \times C & \text{SGW}_w > 0 \\
\text{SOC}_i - \text{OGW}_b^i \times C & \text{SGW}_w < 0,
\end{cases}
\]

(9)

where \( \text{OGW}_b^i \) is the power discharged by BESSs based on the calculation of the ACOPF at every hour. \( C \) is the C-rate governing the linear charging/discharging rate of the BESS. For example, a fully charged 1 C battery rated at 1 Ah will discharge 1 A for an hour; the same battery with 0.5 C will provide 500 mA for two hours, and at 2 C it delivers 2 A for 30 minutes. The first line of (9) describes the charging of the BESS with surplus wind power, which could be due to a congested transmission network that is unable to accept more wind power than that has already been generated, or the coincidence of low demand levels and high wind power outputs. The second line describes the discharging of BESS when the opposite happens, i.e. uncongested power network and/or the coincidence of high load demands and low wind power outputs.
4) WIND FARM MODEL

Wind farms are made up of multiple smaller wind turbines. Given that the fluctuation of winds received by all wind farms is negligible within a region, all wind turbines coming from the same wind farm are considered to receive the same amount of wind. Thus, the total power of a wind farm, $P_w^T$, is the multiplication of the power generated by a wind turbine with the number of wind turbine required to achieve a particular maximum wind farm capacity. The wind power generated by a wind turbine of a wind farm at a certain bus $b$, $P^T_b$, is as follows [30]:

$$
P^T_b = \begin{cases} 
0 & 0 \leq V_w < V_{ci} \\
(A + BV_w + CV_w^2)P_r & V_{ci} \leq V_w < V_r \\
P_r & V_r \leq V_w < V_{co} \\
0 & V_w \geq V_{co},
\end{cases}$$

(10)

where $P_r$ is the wind turbine rated capacity; $V_{ci}, V_r$ and $V_{co}$ are the cut-in, rated and cut-out wind speed of the turbine respectively. $A, B$ and $C$ are constants which can be obtained from [9].

A survey of a long term operational records [31] of the commonly used wind turbines at Denmark, Germany and Sweden was performed to extract the reliability data of wind turbines. The survey reveal that a 5 MW directly-driven-wind turbine is the most commonly used wind turbines at Denmark, Germany and Sweden was performed to extract the reliability data of wind turbines. The survey reveal that a 5 MW directly-driven-wind turbine is the most common type of wind turbine used in these regions. The survey also revealed that the reliability data of wind turbines is available from [31].

5) CONDUCTOR AGEING MODEL

OHLs enter the ageing temperature, $T_{age}$, when the conductor temperatures, $T_c$, increased beyond their MDTs and this crossover is known as exceedance. The accelerated conductor ageing due to the exceedance is also known as the elevated temperature creep, $\varepsilon_c$, in the IEEE 1283 standard [32]. This creep rate is unique for different types of conductors. In this study, only the Aluminum Conductor Steel Reinforced (ACSR) conductors are considered, and the following is its creep equation:

$$
\varepsilon_c = 0.24 \left(\% RS\right)^{1.3} T_c^{1.4} T_{100}^{0.16},
$$

(11)

where $RS$ is the percentage remaining strength of the ACSR, and $T$ is the number of equivalent hours of operating at $T_c$. $RS$ is further expanded as the following [33]:

$$
RS = RS_{al} \left(\frac{STR_{al}}{STR_T}\right) + 109 \left(\frac{STR_{st}}{STR_T}\right),
$$

(12)

such that:

$$
RS_{al} = \begin{cases} 
\gamma t^\rho & if \gamma < 100 \\
100t^\rho & otherwise
\end{cases},
$$

(12a)

$$
STR_{al} = \pi \eta_{al} S_{al} d_{al} k_{al}/4,
$$

(12b)

$$
STR_{st} = \pi \eta_{st} S_{st}^{1%} d_{st} k_{st}/4,
$$

(12c)

where in (12), $RS_{al}$ is the remaining strength of the aluminum strand of the ACSR; $STR_{al}$ and $STR_{st}$ are the strength of the aluminum and steel strands of the ACSR, respectively. Hence, $STR_T = STR_{al} + STR_{st}$ is the total strength of the ACSR. In (12a), further expansions of the variables are

$$
\gamma = 134 - 0.24 T_c \quad and \quad \rho = (0.241 - 0.00254 T_c)/d_{al},
$$

where $d_{al}$ is the aluminum strand diameter of the ACSR. The remaining variables in (12b) and (12c) of the ACSR are as follows: $\eta_{al}$ and $\eta_{st}$ are the number of aluminum and steel strands, respectively; $d_{al}$ is the diameter of the steel strand; $S_{al}$ and $S_{st}^{1%}$ are the average breaking stress of the aluminum strand and the average breaking stress of steel strand at 1% extension, respectively; and $k_{al}$ and $k_{st}$ are the reduction factors of aluminum and steel strands, respectively. Based on the specific conductor of the ACSR, the SI unit values of all the previously mentioned variables can be found in [34], [17].

A unique feature of the ACSR is that $T_{age} = 95^\circ C$ and exceedence therefore occurs as long as $T_c > 95^\circ C$. Hence, to obtain comparable results among various creeps, $\varepsilon_c$, occur at different temperatures, all $\varepsilon_c$ at different $T_c$ are converted to the equivalent ageing at $T_c = 100^\circ C$, as follows:

$$
t_{100} = \left(\frac{0.24 \left(\% RS\right)^{1.3} T_c^{1.4} T_{100}^{0.16} - 1}{0.24 \left(\% RS\right)^{1.3} T_{100}^{1.4}}\right)^{6.25}
$$

$$
= \left(\frac{\varepsilon_c T_c}{\varepsilon_c 100}\right)^{6.25},
$$

(13)

where the variables with the equivalent values at 100°C have the subscript ‘100’, and the remaining variables at their original $T_c$ have the subscript with the same notation.

The Expected Total Network Ageing (ETNA), which quantifies the risk of CWP utilisation for additional network flexibility, is determined by summing all distinct ageing events, $N_{age}$, of all OHLs, $N_{OHL}$, in all simulations, $N_Y$, as follows:

$$
ETNA = \frac{1}{Y} \sum_{y=1}^{N_Y} \sum_{j=1}^{N_{OHL}} \sum_{i=1}^{N_{age}} \left(\frac{E_{T_{c,i}}}{\varepsilon_{c,100}}\right)^{6.25} h/y.
$$

(14)

6) MULTI-OBJECTIVE OPTIMISATION MODEL

The total Expected Wind Energy Curtailment (EWEC), Expected Energy Not Supplied (EENS), i.e. the system reliability, and Expected Total Network Ageing (ETNA) are the three conflicting objectives used to guide the optimisation process in this study. Due to the complex relationship among these indices as the utilisation ratio of $\alpha$ and $\beta$ changes, they are suitable to be solved and minimised as a multi-objective optimisation problem during each $\Delta t$, as follows:

$$
\min \left[ \begin{array}{c} f_1 \\ f_2 \\ f_3 \end{array} \right] = \min \left[ \begin{array}{c} \text{EWEC} \\ \text{EENS} \\ \text{ETNA} \end{array} \right] \begin{array}{c} (\alpha_b, \beta_b) \\ b \in \Omega_B \end{array},
$$

(15)

subject to: $0 \leq \alpha_b \leq 1$, $\alpha_b + \beta_b = 1$, (15a)

where $\Omega_B$ is the set of all wind farm buses and the values of $\alpha_b$ and $\beta_b$ of each wind farm bus are selected independently of each other. A special case where network ageing risk is not
limited is when $\beta_b = 1$, whereas $\beta_b = 0$ means that the risk of network ageing is not permitted and completely mitigated.

**Objective 1:** Minimise EWEC of the wind farms:

$$\min f_1 = \min \left[ \text{EWEC} \right] = \min \left[ \frac{1}{Y} \sum_{y=1}^{Y} \sum_{b=1}^{N_b} \left( P_{\text{Gen}}^b - P_{\text{Sav}}^b - P_{\text{Del}}^b \right) \right],$$

such that: $P_{\text{Sav}}^b \leq \alpha_b P_{\text{CWP}}^b$,  \hfill (16a)

where $P_{\text{Gen}}^b$, $P_{\text{Sav}}^b$ and $P_{\text{Del}}^b$ are the total wind power generated, saved by BESS and delivered into the network. $N_b$ is the total number of wind farm bus. As the selection of $\alpha_b$ becomes larger, $P_{\text{Sav}}^b$ increases due to larger BESS provided that similar or better C rating is used, and the value of EWEC drops eventually. Similarly, the increment of $\beta_b$ uprates the original RTTRs, leading to more $P_{\text{Del}}^b$ and lower EWEC.

**Objective 2:** Minimise EENS of the power network:

$$\min f_2 = \min \left[ \text{EENS} \right] = \min \left[ \frac{1}{Y} \sum_{y=1}^{Y} \sum_{l=1}^{N_L} \left( P_{\text{Total}}^l - P_{\text{Met}}^l \right) \right],$$

where $P_{\text{Total}}^l$ and $P_{\text{Met}}^l$ are the total load demanded and satisfied at each load bus, $L$, respectively, by having various sizes of or no BESS, under the original ($T_c = 95^\circ$C) or uprated ($T_c > 95^\circ$C) RTTR conditions, of which only the conductor ageing occurs in the latter. $N_L$ is the total number of load bus.

**Objective 3:** Minimise ETNA of the power network by controlling $\beta_b$ of each wind farm bus. Note that the CWP of wind farms is divided equally among the lines with outgoing power flow that are connected to the wind farm buses; the portion of the utilised $\beta_b$ on the connected line $l$ is noted as $\beta_{b,l}$. Moreover, the lines that are connected to two wind farm buses are allowed to have their RTTR uprated from both of the buses. The increased in RTTR of line is expressed as $\Delta P_{b,l} = \beta_{b,l} P_{\text{CWP}}^b$ and the following is the third objective function:

$$\min f_3 = \min \left[ \text{ETNA}(\Delta P_{b,l} = \beta_{b,l} P_{\text{CWP}}^b) \right],$$

where the formulation of the ETNA is from (7) but based on the uprated RTTR conditions.

In each iteration of the optimisation, the standard ACPF [26] considering the network constraints such as the rating limits, voltage limits and generation limits is performed after assigning the utilisation ratio of $\alpha_b$ and $\beta_b$ at each wind farm bus. Moreover, the following constraints are observed due to deployments of BESS, RTTR and wind farms:

$$F_{l_{\text{RTTR}}} \leq R_{l_{\text{RTTR}}}, \quad l \in \Omega_L, \hfill (19)$$

$$\text{SOC}_{\text{min}} \leq \text{SOC}_i \leq \text{SOC}_{\text{max}}, \quad i \in \Omega_{\text{BESS}}, \hfill (20)$$

$$0 \leq P_b \leq P_b^W, \quad b \in \Omega_B \hfill (21)$$

where $F_{l_{\text{RTTR}}}$ is the power flow of line $l$, limited by the sum of its original RTTR, $R_l$, and its enhancement, $\Delta P_{b,l}$. $\Omega_L$ is the set of all lines; $\text{SOC}_{\text{min}}$ and $\text{SOC}_{\text{max}}$ are the minimum and maximum capacity of the BESS, such that $\text{SOC}_{\text{max}}^i = \alpha_b P_{\text{CWP}}^b$ and $\text{SOC}_{\text{min}}^i = 0.2 \text{SOC}_{\text{max}}^i$, $\Omega_{\text{BESS}}$ is the set of all BESS and all wind farms busses are candidates for hosting BESS; $P_b^W$ is wind power output limited by the maximum wind farm capacity, $P_b^W$; $\Omega_{\text{B}}$ is the set of all wind farm busses.

Owing to the non-linear and non-convex nature of the optimisation and the Pareto optimality factor, i.e. none of the indices can be improved without degrading the value of the other, the optimisation is solved based on the common operations of the non-sorting genetic algorithm (NSGA) [35], i.e., mutation, crossover and selection. Outcomes of the optimisation are a range of solutions known as the Pareto front, and further decision making process is performed to select the most desirable one. The Fuzzy method is used to perform the selection as it works well due to its inherent ability to model and rank the quality of desirability, as follows:

$$\mu_{f_i}(x) = \begin{cases} 0 & \text{if } f_i(x) = f_i^{\text{max}} \\ \frac{f_i^{\text{max}} - f_i(x)}{f_i^{\text{max}} - f_i^{\text{min}}} & f_i^{\text{min}} \leq f_i(x) \leq f_i^{\text{max}} \\ 1 & \text{if } f_i(x) = f_i^{\text{min}} \end{cases}, \hfill (22)$$

where $\mu_{f_i}(x)$ is the relative distance of a solution, $x$, between the maximum, $f_i^{\text{max}}$, and minimum, $f_i^{\text{min}}$, values of the optimised objective function, $f_i$, such that $x \in \Omega_x$ with $\Omega_x$ being the set of all solution. Then, the minimum sum of distance between $\mu_{f_i}(x)$ and the assigned desirability, $\mu_i$, of the three objectives is selected as the final solution, as follows:

$$\min \sum_{x \in \Omega} \left[ \sum_{i=1}^{3} \left| \mu_i - \mu_{f_i}(x) \right|^n \right] \hfill (23)$$

where $n$ is an integer between 1 and $\infty$; larger values of $n$ reduce the sensitivity of the final solution towards it.

**III. RESULTS AND DISCUSSIONS**

The proposed optimisation is applied onto the IEEE 24-bus Reliability Test Network (RTN) with 3 pu demand and generation levels [36]. The RTN is modified with 100% wind penetration level in all its 10 generation buses and all OHLs are ACSR conductor. The settings for the base case study are as follows: (1) each wind farm bus is a candidate for installing BESS rated at 1 C of which its capacity is determined in the optimisation, and (2) the maximum allowable conductor temperature, $T_c$, is limited to 119$^\circ$C during the optimisation, which is 25% higher than $T_{\text{age}} = 95^\circ$C, the temperature at which the ACSR conductors in the RTN start to age.

Weather data is obtained from the British Atmospheric Data Center (BADC) in hours for 2016 and overlaid on all lines and wind farms. The weather data is used to determine the wind power outputs and initial RTTRs of lines prior to the optimisation based on the line rating model given in section II.B with $T_c = T_{\text{age}} = 95^\circ$C for ensuring the maximum line rating before ageing sets in. The RTN is divided into two voltage zones and each has different conductor types. The Drake and Lapwing ACSR are used in the lower 138 kV
and higher 230 kV portion of the network, respectively. Due to the lack of OHL ageing data, all lines have equal ageing criticality, in which $\beta_b$ of all wind farm buses are allowed to vary freely in between 0 and 1 which are shared equally among all outgoing lines. Moreover, all lines are considered to have a remaining useful life of 40 years. The simulation stopping criteria are 5% EENS covariance or 2500 simulation years, whichever comes first.

The CWP values, $p_{CWP, b}$, identified in the initialisation module (section II.A) are shown in Fig. 3, which are used in the optimisation against EWEC, EENS and ETNA.

![FIGURE 3. Contractual wind power (CWP) of generation busses.](image)

![FIGURE 4. Pareto front of EENS versus ETNA.](image)

![FIGURE 5. Pareto front of EWEC versus ETNA.](image)

**A. OPTIMISED CWP UTILISATION RATIO ($\alpha_b$ AND $\beta_b$)**

The Pareto solutions of the proposed optimisation are shown in Fig. 4 and 5. Fig. 6 shows the 3D plot of the Pareto front. In general, the results show that EENS and EWEC are inversely related to ETNA. Higher ETNA values indicate that the utilisation ratio of the CWP value is biased for more uprating of lines’ RTTR, and therefore the lines are more heavily loaded, leading to higher conductor temperature that eventually causes more line ageing. At the same time, higher line ratings also increase the power transfer capability of the network which enables more load demand to be met by wind farms, subsequently reduces the overall EENS of the system as shown in Fig. 4. On the contrary, to achieve smaller ETNA which reduces network ageing, the optimisation compensates by increasing EENS due to smaller line ratings which inhibits the capability of the network in matching power supplies and demands. The main reason that the EENS drops in Fig. 4 is due to higher ETNA cases which allow more wind energy to be injected into the network when high demand is observed. Consequently, the rate of wind energy utilisation increases and the EWEC drops as shown in Fig. 5. On the contrary, as the ETNA reduces, less wind power can be injected into the network and extra wind energy has to be stored in the BESS. The remaining wind energy not stored due to fully charged BESSs is curtailed, which leads to higher EWEC.

An optimum Pareto solution is selected based on the fuzzy method described in (21) and (22) without specifying preferences in all the three indices, i.e. $\mu_1 = \mu_2 = \mu_3 = 0.5$. In other words, one of the solutions of the Pareto front for the CWP utilisation ratio that produces the most balance—middle value—indices is selected when no bias is granted to any of the indices. The selected $\alpha_b$ and $\beta_b$ values of each wind farm bus are shown in Fig. 7, which indicates that wind farm buses 1, 2, 7 and 13 utilise most of their CWP to install BESS ($\alpha_b > 0.5$), whereas the remaining buses dedicate most of their CWP to uprate RTTRs ($\beta_b > 0.5$). The cumulative installed BESS capacity on all wind farm buses is approximately 2682 MW, accounting for 48.53% of the total CWP. In practice, the preference value mentioned earlier can be adjusted based on the priority of the utility towards any particular index.

An example of the impact of such allocations of CWP utilisation onto the power flow and line ageing risk criticality is
and sensitivity of varying limit are never investigated. This section addresses this by evaluating the effects of decreasing the percentage limit by 1% each time, whilst maintaining all other settings and the result is shown in Fig. 9. The results show that as the allowable limit of $T_c$ becomes higher, the values of ETNA increase exponentially. However, this unlocks more network capacity which also allows EENS and EWEC to decrease at the same time. Overall from the 1% to 25% temperature limits, the EENS reduces by 76.3% in total from approximately $2.88 \times 10^5$ MWh/y to $6.83 \times 10^4$ MWh/y, whereas the EWEC reduces more by 81.4% from approximately $2.66 \times 10^6$ MWh/y to $4.95 \times 10^5$ MWh/y. This shows that EWEC is more sensitive towards the temperature change than EENS as the optimisation is performed based on the utilisation of wind curtailment which its main purposed is to improve wind penetration level.

C. EFFECTS OF BESS C-RATE

In the base case, the limit of conductor temperature, $T_c$, is fixed at 25% higher than $T_{age} = 95^\circ$C and the effects

**FIGURE 9.** Effects of maximum allowable conductor temperature towards ETNA, EENS and EWEC.

**FIGURE 10.** Effects of BESS C-rate towards EWEC, EENS and ETNA.
mainly limited due to network topology. Therefore, BESS effectively arrests wind curtailment, and investing in a battery with higher C-rate is critical for arresting wind curtailment which is one of limiting factors in the optimisation in this study.

IV. CONCLUSION
A multiobjective optimisation methodology in utilising the CWP values for minimising wind curtailment, network ageing and reliability is proposed. The method is applied on every wind farm bus, and it gives network operators the flexibility to adjust the indices by varying the $\alpha_c$ and $\beta_h$ values. As a result, the contribution of the CWP values towards uprating RTTRs and assigning BESS capacity is optimised. Results show that the proposed method is balanced as ETNA, EWEC and EENS are considered together. Moving forward, new and specific OHL health indices, extreme weather and hostile working conditions can be incorporated to ensure the robustness of the proposed framework.

REFERENCES
[1] H. Abunima, J. Teh, C.-M. Lai, and H. Jabir, “A systematic review of reliability studies on composite power systems: A coherent taxonomy motivations, open challenges, recommendations, and new research directions,” Energies, vol. 11, no. 7, p. 1749, Jul. 2018.
[2] F. Mohamad and J. Teh, “Impacts of energy storage system on power system reliability: A systematic review,” Energies, vol. 11, no. 9, p. 2278, Aug. 2018.
[3] F. Mohamad, J. Teh, C.-M. Lai, and L.-R. Chen, “Development of energy storage systems for power network reliability: A review,” Energies, vol. 11, no. 9, p. 2278, Aug. 2018.
[4] A. Bani Ahmad, C. A. Ooi, D. Ishak, and J. Teh, “State-of-Charge balancing control for ON/OFF-line internal cells using hybrid modular multi-level converter and parallel modular dual L-Bridge in a grid-scale battery energy storage system,” IEEE Access, vol. 7, pp. 131–147, 2019.
[5] M. Liu, W. Li, C. Wang, M. P. Polis, L. Y. Wang, and J. Li, “Reliability evaluation of large-scale battery energy storage systems,” IEEE Trans. Smart Grid, vol. 8, no. 6, pp. 2733–2743, Nov. 2017.
[6] N. Li, C. Uckun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, “Flexible operation of batteries in power system scheduling with renewable energy,” IEEE Trans. Sustain. Energy, vol. 7, no. 2, pp. 685–696, Apr. 2016.
[7] C. Liang, P. Wang, X. Han, W. Qin, Y. Jia, and T. Yuan, “Battery energy storage selection based on a novel intermittent wind speed model for improving power system dynamic reliability,” IEEE Trans. Smart Grid, vol. 9, no. 6, pp. 6084–6094, Nov. 2018.
[8] J. Teh, “Adaptability assessment of wind integrated generating systems incorporating demand response and battery energy storage system,” Energies, vol. 11, no. 10, p. 2649, Oct. 2018.
[9] J. Teh and C.-M. Lai, “Reliability impacts of the dynamic thermal rating and battery energy storage systems on wind-integrated power networks,” Sustain. Energy, Grids Nets., vol. 20, Dec. 2019, Art. no. 100268.
[10] F. Mohamad, J. Teh, and H. Abunima, “Multi-objective optimization of Solar/Wind penetration in power generation systems,” IEEE Access, vol. 7, pp. 169094–169106, 2019.
[11] Y. Wang, Z. Zhou, A. Botterud, K. Zhang, and Q. Ding, “Stochastic coordinated operation of wind and battery energy storage system considering battery degradation,” J. Mod. Power Syst. Clean Energy, vol. 4, no. 4, pp. 581–592, Oct. 2016.
[12] Z. Li, Y. Xu, X. Feng, and Q. Wu, “Optimal stochastic deployment of heterogeneous energy storage in a residential multi-energy microgrid with demand-side management,” IEEE Trans. Ind. Informat., early access, Feb. 2020.