Reliability Based Framework for Cost-Effective Replacement of Power Transmission Equipment

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***Abstract*—This paper presents a probabilistic framework for making decisions about the replacement of ageing power equipment. The framework involves three steps: first, to identify the most important and critical components of the system for overall system reliability; secondly, to perform Pareto analysis to relate the replacement of the components to the effect on system reliability indices; finally, to determine the optimum scenario for replacement based on a comparison between the cost of unreliability due to deferring the replacement and the saving on reinvestment cost. The proposed approach is illustrated on a meshed test system modeled using U.K. transmission system parameters, a representative transformer age profile and regulatory energy not supplied values. The results demonstrate the feasibility of the framework for application in the area of power system reliability, and show its feasibility for informing replacement decisions.**

***Index Terms*—Ageing equipment, criticality measure, power system reliability, replacement plan, transmission network.**

I. Introduction

AGEING of power system equipment is one of the major issues facing power system utilities at present. Much of the installed equipment has exceeded its design life time and will, in time, potentially become less reliable. Consequently, having a considerable amount of aged equipment in a network will increase the risk of customer interruptions, which eventually could reach a level which is no longer acceptable. Additionally, the cost of replacing components in a transmission system is particularly high and the decisions regarding replacement should not be taken lightly. For example, the cost of replacing a power transformer can be around £4 million. Therefore, making correct asset management decisions is critical and careful analysis is required to find the balance between reliability and reinvestment costs. Additionally, electricity regulatory authorities commonly apply a reliability incentive scheme, as part of the price control scheme, under which the allowed level of return on reinvestment is determined.

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In recent years, there has been an increasing amount of literature on using quantitative risk approaches in replacement decision making [1]–[6]. One can classify those approaches into two classes, the risk matrix method [1]–[4], and the risk indices method [5], [6]. In the former, a risk matrix is constructed to define the replacement priority of components using their condition or age as the first axis and their criticality to the system, environment, and safety as the second axis. The risk matrix method is effective in prioritizing replacement priority into broad categories. The result, however, is sensitive to the characteristics of the matrix which may not be optimal for all cases and it does not directly link replacement with system reliability.

The risk indices method, which can also be referred to as the reliability indices method, allows integration of reliability optimization techniques. In the first application of the reliability indices method [5], the replacement decision is taken based on a comparison between the unreliability cost and the savings on capital expenditure when deferring the replacement action to the following years. However, the approach described makes a decision on the replacement of a single component and not the entire fleet. Reference [6] has implemented a similar approach on a fleet of underground cables. Nevertheless, the replacement volumes of cables were determined based on age only and did not consider the criticality of the cables to the system reliability. Hence, it can be argued that the currently applied quantitative risk methods in the area of power system component replacement planning have some shortfalls which need to be overcome.

This paper presents a replacement planning framework that for the first time combines the advantages of the risk matrix method and the reliability indices method. The framework uses the reliability importance measures for identifying the critical components for system reliability. Furthermore, by incorporating the end-of-life failure model into importance studies, This paper identifies the most critical components for system reliability in terms of ageing. This is a new application to the importance measure in reliability evaluation. Pareto analysis [7] is then performed to determine the effect of replacement scenarios on system reliability as power systems comprise many correlations between the components which are difficult to detect using only a reliability importance measure. After determining the effect of replacement scenarios on system reliability, a cost-benefit analysis is carried out to determine the optimum replacement plan. The cost of unreliability in this analysis is calculated using data from an incentive/penalty scheme which is typical of those commonly applied to regulate system reliability. It must however be recognized that the societal importance of a reliable transmission network could be significantly greater than the incentive mechanism would imply, particularly in the case of widespread and extended failures. The framework has been tested on a fleet of power transformers in a test system modeled using UK transmission system parameters.

II. Replacement Framework

A. Component Failure Model

The main purpose of power system reliability assessment is to provide probabilistic measures of the system adequacy that can be used in decision-making processes. The nature of the specific decision making process determines which models or methods have to be used. Failure models can be generally, classified as repairable failure and end-of-life failure. When discussing decision making of components replacement, the end-of-life failure model is the most essential input in reliability assessment. A lot of research has been done in the area of equipment lifetime modeling to overcome the lack of end-of-life failure data. Studies reported in [8]–[10] estimate the probability distribution functions of end-of-life failure using the data from failed and surviving components while [11] and [12] model end-of-life failure by combining expert judgment and condition monitoring data.

Life data analysis often represents end-of-life failure by probabilistic distribution functions [13]. However, probabilistic distribution functions cannot be directly integrated into the most common methods of bulk power system reliability evaluation: state enumeration and non-sequential Monte Carlo simulation. This is because those two methods use the unavailability as the reliability measure at the component modeling level. Unavailability due to end-of-life failure can be defined as the probability of finding the component being failed in a particular future time period given that it has survived to a specific age [14]. The definition involves two factors, the conditional probability of surviving to a specific age T and the future study period t. Reference [14] presents the state-of-the-art method for estimating the average unavailability due to end-of-life failure from probabilistic distribution functions. In power system literature, the commonly used probabilistic distributions for this purpose are normal and Weibull distributions [8], [15]–[17]. The method is based on dividing the study period t into N subintervals. Then, probability of end-of-life failure for each subinterval (P_i) is calculated using conditional probability theory. This is expressed by

$$P_i = \frac{\int_T^{T+i\Delta t} f(t)dt - \int_T^{T+(i-1)\Delta t} f(t)dt}{\int_T^{\infty} f(t)dt} \tag{1}$$

where T is the age of the component, $f(t)$ is the probabilistic density function, and Δt is the length of the subintervals. Assuming that the component fails at any point within the subinterval i, the average unavailable duration UD_i is given by

$$UD_i = t - \frac{(2i-1)\Delta t}{2}. \tag{2}$$

Having calculated the probability of end-of-life failure and the average unavailable duration for each subinterval in the study period t, the average unavailability due to end-of-life failure U_a can be approximated by the sum given by (3). The details of the derivation can be found in [14]. This method has been adopted here to incorporate end-of-life failure into the reliability assessment:

$$U_a = \frac{1}{t}\sum_{1}^{N} P_i \cdot \left[t - \frac{(2i-1)\Delta t}{2}\right]. \tag{3}$$

(Note: It should be mentioned that the actual data on reliability obtained from condition monitoring can be used in this method instead of chronological age of the component. This data could be incorporated, for example by using an equivalent age of the component adjusted according to its individual condition [14]. Additionally, sensitivity and uncertainty analysis can be performed using end-of-life failure models formulated from available data to assess the effect of end-of-life data shortage on system reliability and its application in power system, e.g., replacement decision.)

B. Reliability Importance Measure

Measuring the reliability importance of power system components has been extensively discussed in power system reliability literature [18]–[20]. According to [18], importance measures can be classified into structural importance (IS) and criticality importance measures (IC). Structural importance (IS) is calculated using the partial derivative of the system reliability to the component reliability, which can be substituted by simple sensitivity analysis. The IS assesses the structural importance of the component because it presents the difference between the system reliability when the component has an outage model and the system reliability when the component is ideal. IS can be defined as

$$IS = \frac{\Delta S_{\mathrm{r}}}{\Delta C_{\mathrm{r}}} \tag{4}$$

where $\Delta \mathrm{S_r}$ is the incremental change in system reliability and $\Delta \mathrm{C_r}$ is the incremental change in component reliability.

Criticality importance (IC) is calculated using the IS as given by (5). IC measures the criticality importance by considering the reliability of the component in addition to its structural importance. Thus, when using IC measure, the less reliable component of the two having equaled structural importance will be considered as more influential:

$$IC = IS \times \frac{C_{\mathrm{r}}}{S_{\mathrm{r}}} \tag{5}$$

where $\mathrm{C_r}$ and $\mathrm{S_r}$ are the base case component reliability and system reliability, respectively.

For this study, the criticality importance measure was chosen because the reliability of a component is essential in replacement decision making. In order to calculate IC, the energy not supplied (ENS) index was chosen as the system reliability measure whereas the average unavailability was defined as the component reliability measure. IS in (5) is calculated using a simple sensitivity analysis of the ENS index to the change in the component unavailability.

By including an end-of-life failure model into importance studies, this paper has identified the most critical components affecting system reliability taking into account both the aged state and their location in the system. This is a new application to the importance measure in reliability evaluation.

C. Pareto Analysis

Ranking of power system components provides only part of the important information for replacement decision making. It brings the attention to specific critical equipment but does not reflect the effect on the system reliability if they are replaced or left in service.

Power system reliability is inherently a nonlinear function of component reliability, involving many hidden correlations and interactions between the components. Increased reliability is usually obtained using redundant parallel operation creating one of the most important correlations. When calculating criticality measures using traditional sensitivity analysis, parallel operation may cause misleading results. For example, two components may have the same effect on system reliability with one way sensitivity analysis, but replacing one of them can eliminate the effect of the other. Conversely, in some cases replacing one of them may not improve the reliability at all so both have to be replaced. Most transmission systems have designs based on the $\mathrm{N}-1$ criterion or better, which prevents a load shedding event with one component out of service. Therefore, most load shedding events are caused by having more than one component out of service and further analysis is needed to distinguish between individual component effects on reliability.

Pareto Analysis or the 80/20 principle has been applied in many different disciplines since it was introduced in the 1950s [7]. The 80/20 principle states that "approximately 20–30 per cent of any resource accounted for 70–80 per cent of the activity related to that resource" [7]. This means that a large number of achievements can be completed by fewer inputs. It has been found that this principle can be applied to any kind of resource, and that the linear conception that 50 per cent of the causes will lead to 50 per cent of the results is not true for the vast majority of cases [7]. In this paper, this principle has been applied to determine the contribution of individual components to system unreliability. This has been completed by replacing the components one after another starting from the top of a ranking of components based on the criticality measure IC. By performing this analysis, the relationship between increase in system reliability and resulting replacement scenario can be determined.

D. Replacement Justification

For transmission system asset managers there is a choice between replacing the equipment now and delaying the replacement to the following years. The typical decision for the asset manager would be to postpone the replacement of assets to the following year in order to achieve maximum utilization of assets and savings in the reinvestment cost. Postponement of the replacement, however, increases the risk of having an end-of-life failure, and hence, customer supply interruptions. The replacement decision should be justified by performing cost-benefit analysis to compare the cost of unreliability when the replacement is deferred and the benefit gained by saving on reinvestment cost.

Since the year 2000, European national regulatory authorities have started to impose a reliability regulation scheme in order to ensure that the budget constraints on transmission system investment do not affect the continuity of supply to the end users [21]. The reliability regulation schemes are based on incentives/penalties calculated using some of the reliability indices,

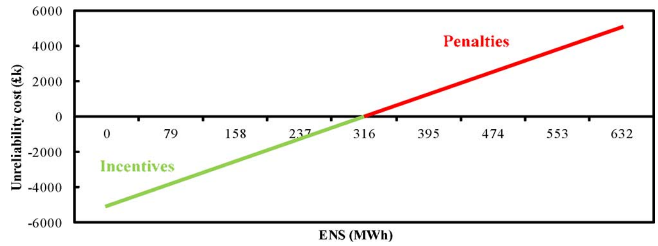

Fig. 1. Cost of system unreliability as a function of ENS based on Ofgem's incentives/penalties scheme.

commonly energy not supplied (ENS). For example in Great Britain, the regulator has applied an incentive scheme to National Grid Electricity Transmission plc (NGET) [22]–[24]. The proposal has set a target of ENS equal to 316 MWh. Achieving an ENS less than this target will be rewarded at a rate of £16 000 per MWh. Comparably, any values of ENS more than the target will incur penalties with the same rate. This paper uses the scheme as a measure of the cost of unreliability, but it is recognized that this may not represent the full societal or reputational costs of extended or widespread power failure, and these factors also need to be taken into account in replacement planning. This incentive scheme is illustrated in Fig. 1.

In order to calculate the saving on reinvestment cost ($\Delta \mathrm{C}_{\mathrm{saving}}$), the time value of replacement cost in the current year and time value of replacement cost in the following year have to be calculated. The time value of the replacement cost in the current year (referred to as *present value PV* in economics terminology) equals the current cost of replacement. The reinvestment is usually carried out as a series of equal installments at equal time intervals, i.e., uniform annual payments (annual value). The present value (PV) can be calculated from annual values (AV) adjusted for time value of money. The time value of money depends on the type (simple or compound) of interest rate considered [25], [26]. For simple interest rate, PV can be calculated using (6):

$$PV = AV\left(\frac{1-(1+ir)^{-n}}{ir}\right) \tag{6}$$

where ir is the interest rate and n is number of installments. The time value of replacement cost in the following year (*future value FV*) can be calculated using the present value. For simple interest rate, FV can be calculated from PV by (7):

$$FV = PV(1+n*ir) \tag{7}$$

where ir is the interest rate and n is number of future years. The saving on reinvestment equals the difference between the future value of the replacement cost and the present value. Then, saving on reinvestment cost ($\Delta \mathrm{C}_{\mathrm{saving}}$) can be obtained by

$$\Delta C_{\mathrm{saving}} = PV*n*ir. \tag{8}$$

Equation (8) shows the interest earned on the money when it is not spent on replacement.

In order to economically justify the postponement of reinvestment decision, i.e., the replacement decision, the cost of unreliability and the saving in reinvestment cost are calculated for all the replacement scenarios obtained from Pareto analysis. These

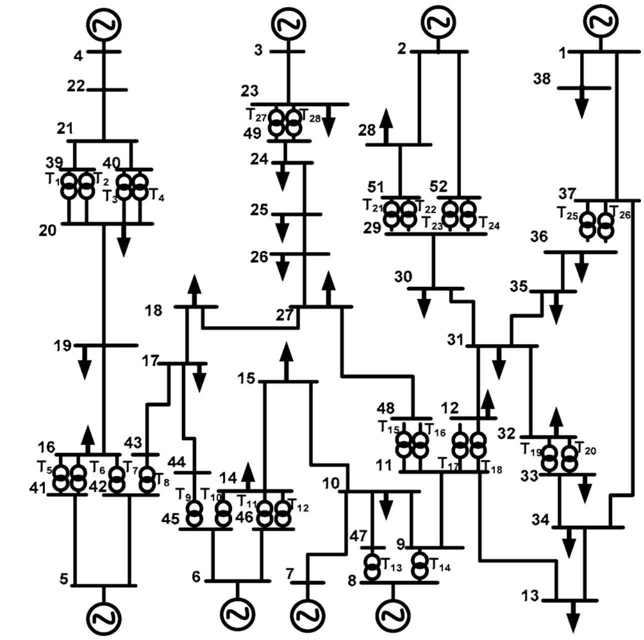

Fig. 2. Test network single line diagram.

scenarios are then compared to determine the maximum number of components whose replacement can be deferred to the following year without compromising the system reliability. The optimum replacement decision is the scenario for which the cost of unreliability is less than the saving in reinvestment cost and has the maximum number of components that can be left in service for an additional year.

III. Test System and Data

A. Test System Description

The proposed framework has been applied to a fleet of power transformers in a model meshed test system. The test system broadly represents the transmission network of a large metropolitan city. The single line diagram of the network is shown in Fig. 2. The transmission voltage levels are 400 and 275 kV. The network has 8 equivalent generation buses/in-feed points and 24 load buses at different voltage levels (132, 66, and 33 kV). It has 28 interbus transmission transformers (400/275 kV tagged in the single line diagram as T1–T28) and 42 transmission lines and cables. Each load bus represents a substation that contains step down transformers, substation cables, circuit breakers and disconnectors. The total number of step down transformers is 126 (not shown in the single line diagram). Though the test network does not represent any existing real network, all of its components are modeled using the typical parameters of the U.K. transmission network.

B. Transformers' End-of-Life Failure Data

The age of the transformers in the test system has been assigned in accordance with the age distribution of transformers in the England and Wales transmission system. The age distribution is shown in Fig. 3. The system contains a considerable number of transformers that have exceeded the original design life time (25 or 40 years).

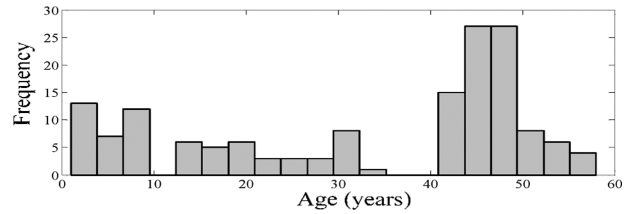

Fig. 3. Age distribution of the test system's transformers.

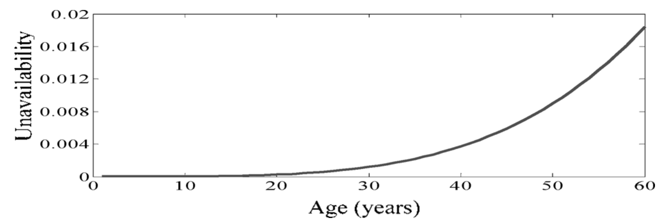

Fig. 4. Unavailability due to end-of-life failure using normal distribution ($\mu = 65$, $\sigma = 16$) for a range of ages (0–57).

The end-of-life failure of power transformers in the test system is characterised by a normal distribution with a mean value (μ) equal to 65 years, and a standard deviation (σ) equal to 16 years. In order to calculate the unavailability due to end-of-life failure using a normal distribution function, probability of end-of-life failure (1) is approximated by (9) which is adopted from [14]:

$$P_i = \frac{Q\left(\frac{T+(i-1)\Delta t-\mu}{\sigma}\right) - Q\left(\frac{T+i\Delta t-\mu}{\sigma}\right)}{Q\left(\frac{T-\mu}{\sigma}\right)} \tag{9}$$

where Q is calculated by

$$Q(x) = \begin{cases} w(x) & \text{if } x \geq 0 \\ 1 - w(-x) & \text{if } x < 0 \end{cases}$$

$$w(x) = z(x)(b_1 s + b_2 s^2 + b_3 s^3 + b_4 s^4 + b_5 s^5)$$

$$z(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right), \quad s(x) = \frac{1}{1+rx}$$

$$\text{r} = 0.2316419 \quad \text{b1} = 0.31938153 \quad \text{b2} = -0.356563782$$

$$\text{b3} = 1.781477937 \quad \text{b4} = -1.821255978$$

$$\text{b5} = 1.330274429.$$

Fig. 4 shows the unavailability calculated using the mentioned normal distribution for the age range of the test system transformers (0–57 years) for a one-year study period. From Fig. 4, it can be seen that there is a nonlinear relationship between age and unavailability. It is apparent that the youngest transformers (0–18 years) have small values of unavailability that does not increase rapidly with age, whereas the unavailability of older transformers (30–60 years) increases rapidly with age. This shows that a one-year age difference can make the unavailability vary significantly when the transformer is old.

C. Load and Network Model

Since the integration of annual load curve into bulk power system reliability assessment by enumerating the demand at each hour requires excessive computation time and effort, it is commonly presented by multi-step load level model [27]. The

TABLE I
SIX-STEP LOAD LEVEL MODEL OF THE TEST SYSTEM

Step No.	Load level (%)	Covered time period (weeks)	Annual Probability
1	98.9	9	0.173
2	92.3	12	0.230
3	88.1	7	0.135
4	80.4	6	0.115
5	74.5	5	0.0962
6	71.4	13	0.250
		$\sum = 52$	$\sum = 1$

accuracy of the results is proportional to the number of the steps, and hence, proportional to the computation time. The selection of the number of the steps is a trade-off between the required level of accuracy and the computational time of the evaluation. Different transmission networks have different sensitivities to the load levels, and hence to the number of the steps in the load model. For the test system considered in this study, the annual demand variation is presented by an optimum 6-step load level model. The model is constructed from historical operating points of the England and Wales network system. They are chosen to accurately represent assumed periods of time that they cover during the year. Table I shows the loading levels as a percentage of the peak demand, the time period covered and corresponding probabilities of occurrence of the time period. Moreover, for each loading level there are different power injections from generation and in-feed buses in order to present the seasonal variation of power flow in the network. In addition, the variation of the thermal capability of equipment (higher or lower than the nameplate thermal rating) with different seasons of the year is also modeled. This is considered because it effects the reliability calculation as it will be explained in the next section.

IV. RELIABILITY ASSESSMENT PROCEDURE

The test system is modeled in DIgSILENT's PowerFactory software package. DIgSILENT Programming Language (DPL) is used to develop a dedicated reliability assessment programme based on the non-sequential Monte Carlo (MC) simulation. The four-step system reliability assessment procedure includes: 1) load level selection, 2) component state selection, 3) failure effect analysis and remedial actions by system operator; and 4) calculation of reliability indices. Each of the steps is discussed in the following sections.

It should be mentioned that the main purpose of the developed research grade software was to facilitate studies of the influence of ageing components on power system reliability within the computational environment of DIgSILENT's PowerFactory software package as one of currently most widely used and trusted commercial software packages by power system utilities. It was not aimed to introduce more advanced technique for power system reliability evaluation. There are other advanced and computationally more efficient techniques for assessing composite power system reliability, e.g., [28]–[31], however, they are either not commercially available or they have been developed and demonstrated as "stand alone" applications by different researchers.

A. Load Level Selection

The load levels are enumerated one by one from the 6-step load level model. For each level, 20 000 iterations of Monte Carlo (MC) simulation are executed and the system reliability indices are calculated.

B. Component State Selection

The function selects the state of each component by generating a random number between 0 and 1. Then, it compares the component's unavailability due to random failure and unavailability due to end-of-life failure to the random number. If the random number is less than one of the two unavailability values, the components will be considered as unavailable. In this case study the unavailability due to random failure is assumed to be zero as it is much smaller than the unavailability due to end-of-life failure, which is of primary importance in this study. (*Note*: It is a fact that the system reliability indices will be affected by this assumption. However, the assumption is justified by the fact that the average unavailability due to random failure of power transformers is very small, i.e., 0.001 [32](equivalent to the unavailability of 30 years old transformer), and the test system considered in this study has 93 transformers older than 30 years. Furthermore the assumption will affect the results, i.e., different amount of energy not supplied, only when both end-of-life failure and random failure occur simultaneously, which is not likely to happen due to much smaller transformer unavailability due to random failure.)

C. Failure Effect Analysis and Remedial Actions by System Operator

The function utilizes DC load flow to examine potential violations of loading limits in the network. Therefore, the reactive power constraints are not addressed. This is appropriate since for the long term reliability assessment the active power constraints are the crucial aspect. When a violation of the limits (different thermal limits for individual load levels) is detected, an overload relief procedure, based on system generation re-dispatch and load shedding, is performed. The procedure is based on the sensitivity of the system overload to bus injections [33]–[35], which is presented by a sensitivity factor S_n calculated by

$$S_n = \sum D_{nl}(-1)^k \tag{10}$$

where

S_n	sensitivity factor of bus n;
k	0 if $F_l > 0$ or $= 1$ if $F_l < 0$;
F_l	power flow through the overloaded line l;
D_{nl}	distribution factor of bus n for line l.

Buses with a negative sensitivity factor have an inverse relationship between their injection and the system overload. The opposite is true for buses with a positive sensitivity factor. Generation and load buses are sorted according to the value and the sign of the sensitivity factor S_n. The generation re-dispatch and load shedding are performed by choosing a pair of buses that have different signs and enough increase/decrease reserve and exchanging a specific amount of power between them. The amount of power exchanged is determined by selecting the minimum of 1) the increase reserve available in the increasing bus, 2) the decrease reserve available in the reducing bus, and 3) the exchange power that will relieve the overload of a line. The generation re-dispatch is attempted first to alleviate the overload, then, if necessary, load is shed at the most sensitive buses. This will ensure optimum load shedding. The process is repeated until the overload is completely eliminated. For this case study, it has been assumed that the generation and the in-feed injections are 100% reliable. This will not affect the analysis because for this study only the influence of the transmission equipment on system reliability is of interest [5].

D. Calculation of Reliability Indices

The indices for the annual loading curve are calculated by using corresponding indices of each loading level and their associated probabilities. For each loading level the indices are obtained by averaging the results from the iterations of the Monte Carlo simulation.

V. Case Study

A. Criticality Measure

In calculations of the importance measures IS and IC, the seed of the random number generator for the MC simulation is kept constant to ensure consistent results of reliability indices for different loading levels. Sensitivity analysis of system reliability (measured by ENS) to transformers reliability (measured by unavailability due to end-of-life failure) is performed. The steps for calculating the importance measures are:

1) Assess the base case system reliability and estimate base case ENS.
2) Perform sensitivity analysis by considering that the transformers are ideal ($\mathrm{unavailability} = 0$), one by one, and estimate ENS at each case. [Note: Referring to (4), more accurate sensitivity results of ENS would be obtained by using a small incremental change in component unavailability values. In standard reliability assessment simulations, as in this case, however, the unavailability values of the components are not directly integrated into the reliability indices. At each iteration of Monte Carlo simulation, a component is considered unavailable when its unavailability is greater than or equal to a generated random number. If a very small incremental change in the unavailability value is used it may not affect the results of reliability assessment in some cases as the generated random number may still be smaller than the component unavailability $\pm$ the incremental change. For example, if a component, whose unavailability is 0.02, is considered to be failed because the generated random number is 0.01, it will be also considered to be failed if an incremental change of ± 0.002 is applied to its unavailability since the unavailability will still be greater than 0.01. In order to comprehensively assess the effect of changing in component unavailability, the sensitivity analysis is performed by assuming ideal transformer (unavailability$= 0$) This assumption, however, does not affect the accuracy of the results as the purpose of the performed sensitivity analysis is to assess the effect of the replacement of components (age$= 0$, hence, unavailability$= 0$) on system reliability and to compare it with decision to postpone the replacement].
3) Repeat steps 1 and 2 for individual loading levels.
4) Calculate annual base case ENS and annual ENS for individual cases in step 2 using loading level probabilities.
5) Calculate IS for each transformer using (4).
6) Calculate IC for each transformer using (5).

TABLE II
Base Case ENS for Different Annual Load Levels (MWh/Year)

Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
1538.5	260.6	558.2	0	0	0

TABLE III
Transformers With IC $\neq 0$ Ranked From Largest to Smallest Based on IC

Tx	Age (years)	IC	Tx	Age (years)	IC
L20-T3	53	0.20228	L12-T2	47	0.03053
L20-T1	53	0.17957	L20-T6	48	0.02551
L19-T1	47	0.17718	L18-T2	47	0.01963
L19-T3	43	0.15458	L12-T4	45	0.01445
L20-T5	48	0.10204	L12-T5	45	0.01359
L26-T1	45	0.08172	L18-T3	47	0.01216
L20-T4	48	0.07653	L19-T4	51	0.01213
L26-T4	45	0.07078	L17-T3	48	0.01100
L26-T2	47	0.06877	L28-T1	45	0.01040
L16-T3	54	0.05845	L28-T2	45	0.01040
L16-T6	43	0.04903	L16-T5	43	0.00941
L17-T1	46	0.04401	L27-T1	45	0.00503
L26-T3	45	0.03996	L27-T3	45	0.00336
L18-T1	47	0.03990	L27-T5	44	0.00168
L19-T2	50	0.03474	L53-T3	47	0.00166
L17-T4	49	0.03301	L53-T1	49	0.00111

All calculations are performed using a 2.83-GHz quad core CPU PC with 3.5 GB of RAM. The calculation of the IC for the test system was completed in two weeks. The computation time for large power network, e.g., England and Wales transmission network, which is approximately 5 times larger than the test system, would take approximately 11 weeks using the same PC. For the assessment of large power networks the computation time can be reduced by using multiple PCs as in the case study reported in [36].

Table II shows the base case ENS for individual load levels of the 6-step annual load model. It can be seen that the system is 100% reliable if a constant load level equal to one of the low demand levels is used. If a constant load level equal to one of high demand levels is used, then the system becomes unreliable and there are different values of ENS. The overall annual ENS is 401.6 MWh/year.

The IC calculation results show that only 32 out of 154 transformers in the test system have an influence on system reliability. For the remaining 118 transformers, the ENS value does not change if they have been considered ideal. Table III shows the transformers that have IC $\neq 0$, their IC values, and their age. All the transformers that appear in the table are step down transformers. They are not shown in the single line diagram due to the complexity of the network; therefore, they are named by the load point index. From this, one can conclude that the reliability problems, which are linked with transformer failure, originate

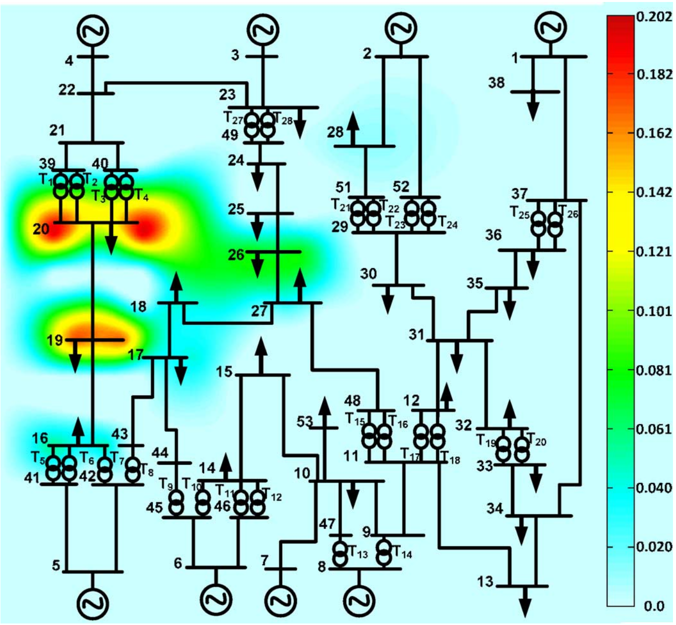

Fig. 5. Reliability importance measure (IC) for power transformers.

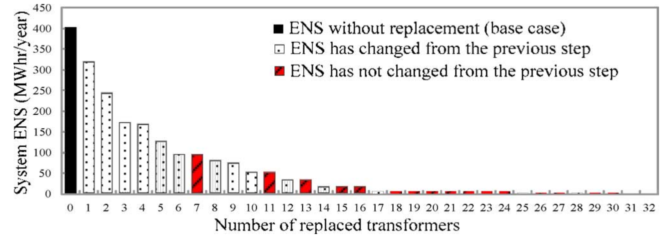

Fig. 6. ENS for replacement scenarios of transformers.

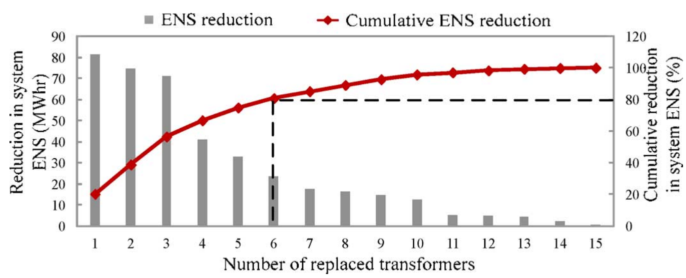

Fig. 7. Reduction in system ENS and cumulative reduction in system ENS against replacement scenarios.

from load supply points. It is also apparent from Table III that all the critical transformers are in the age range 43–54 years. Compared with the age histogram of the test system's transformers (see Fig. 3), this age range has the highest frequency of occurrence in the test system. Interestingly, the highest aged transformers (54–57 years old) did not appear in the table. This can be explained by the fact that the reliability importance measures depend on both the age (represented by the unavailability) and the location of the transformer in the network.

The alternative representation of the IC measure is given by a "heat" map showing areas in the system most affected by ageing of the components. This representation is particularly useful when the network contains areas of particular strategic importance. Fig. 5 shows the heat map of the test system. As seen in the figure, the most critical transformers are located in a limited area. The strategic impact of unreliability in this area in terms of societal, reputational and environmental impacts can be considered in further studies if required.

B. Pareto Analysis

In order to relate the replacement scenarios to the reliability benefit, transformers shown in Table III were replaced one at a time starting with the top ranked one. That is to say, the first scenario is replacing 1 transformer (L20-T3), the second scenario is replacing 2 transformers (L20-T3 and L20-T1), and so on until all 32 transformers are replaced. Fig. 6 presents the calculated ENS against the number of replaced transformers following the previously explained procedure. As it appears from Fig. 6, the reduction in ENS has an inverse exponential relationship with the number of replaced transformers which illustrates the suitability of 80/20 principle for replacement planning. Fig. 6 also shows that there are 17 transformers whose replacement will not achieve a further reduction in ENS. In other words, in the model a 0 ENS, or a 100% reliable system, can be achieved by replacing a smaller number of transformers than might be expected from the importance measure results shown in Table III. Those 17 transformers are highlighted in Table III in grey. When looking at those transformers, it is apparent that they are located on different buses. However, there are transformers, which belong to the same buses and have been replaced earlier. This replacement has resulted in eliminating the effect of those 17 transformers on system reliability. For example, replacing transformer L20-T4 does not have an impact on system reliability because L20-T3, L20-T1, and L20-T5 were replaced at previous steps.

Fig. 7 shows the reduction in ENS and the cumulative reduction for the replacement scenario excluding 17 transformers which have no effect on the system reliability. It can be seen from the figure that there are 15 transformers which have noticeable effect on ENS reduction. It is apparent that 80% reduction in the ENS can be achieved by replacing 6 transformers (18.8% of the most critical transformers) in confirmation of the applicability of Pareto analysis to power system reliability and component replacement. Fig. 7 directly links the reduction in ENS to the number of replaced transformers.

C. Justification of Replacement

In order to match the regulatory incentive/penalty scheme to the test system, the ratio of the test system demand to the total demand of the England and Wales network was calculated. The ENS baseline target of the test system was calculated by multiplying the ratio by 316 MWh (the baseline target for NGET). The calculation determined 70 MWh as the baseline target for the test system. The same incentives/penalties rate (£16 000) was used to determine the cost of unreliability. Table IV shows the cost of unreliability results starting from no replacement (0 transformers to be replaced) to replacing all 15 transformers which have a negative effect on system reliability. As can be seen from the table, the cost of applying the unreliability incentive changes sign after replacing 6 transformers. This is due to achieving the baseline target ENS by replacing 6 transformers

TABLE IV
COST OF UNRELIABILITY FOR REPLACEMENT PLANS

Number of replaced transformer	ENS (MWh)	Difference from target (MWh)	Cost of unreliability (k£)
0	401.6	331.6	5304.8
1	320.3	250.3	4005.2
2	245.7	175.7	2811.7
3	174.6	104.6	1673.3
4	133.6	63.6	1017.7
5	100.8	30.8	492.7
6	77.3	7.3	117.2
7	59.7	-10.3	-165.5
8	43.6	-26.4	-421.9
9	29.2	-40.8	-652.6
10	17.0	-53.0	-848.7
11	11.7	-58.3	-932.2
12	6.9	-63.1	-1010.1
13	2.7	-67.3	-1077.0
14	0.7	-69.3	-1109.3
15	0.0	-70.0	-1120.0

TABLE V
SAVING ON REINVESTMENT COST FOR THE REPLACEMENT SCENARIOS.

Number of replaced transformers	Present value (PV) of deferring the replacement (k£)	Future value (FV) – non spent money with interest (k£)	Saving on reinvestment (k£)
0	60000	63240	3240
1	56000	59024	3024
2	52000	54808	2808
3	48000	50592	2592
4	44000	46376	2376
5	40000	42160	2160
6	36000	37944	1944
7	32000	33728	1728
8	28000	29512	1512
9	24000	25296	1296
10	20000	21080	1080
11	16000	16864	864
12	12000	12648	648
13	8000	8432	432
14	4000	4216	216
15	0	0	0

only. In addition, the maximum incentive for achieving 0 MWh of ENS is £1.12 million.

In order to calculate the future value of reinvestment cost for the replacement plans, a simple annual interest rate of 5.4% is used [37].

The saving on reinvestment cost is calculated using (8) for one-year postponement. The cost of replacing a power transformer, which is the present value of reinvestment, is taken as £4 million. Considering the first replacement scenario as example, replacing 0 transformers, i.e., deferring the replacement of 15 transformers to the next year, results in savings of £3240 K. (This would be the amount of interest earned for a year by postponing replacement of 15 transformers for one year, i.e., the saving on reinvestment cost. Table V shows the results of the ΔC_{saving} calculations.

Fig. 8 shows an economic comparison between the cost of unreliability and saving on reinvestment cost for different replacement plans. The figure, also, shows the actual cost of replace-

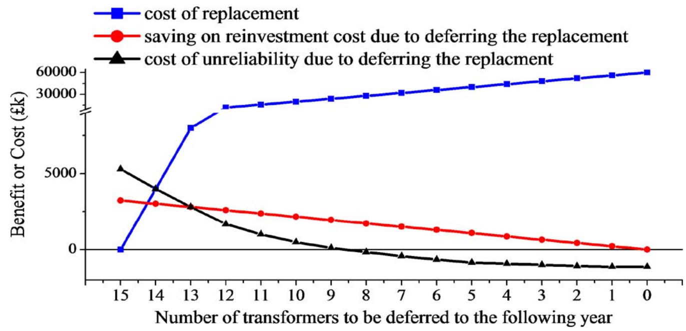

Fig. 8. Economic comparison of replacement plans.

ment. The aim of this comparison is to estimate the maximum number of transformers whose replacement can be postponed without jeopardizing system reliability. This number is determined when the saving on reinvestment cost due to deferring the replacement of transformers becomes greater than the cost of unreliability caused by leaving them in service. It can be seen from Fig. 8 that the cost of unreliability when deferring replacement of 15 or 14 transformer to the following year is greater than the saving on reinvestment cost. Moreover, the cost of unreliability is greater than the cost of replacing one transformer, i.e., deferring the replacement of 14 transformers. After replacing 2 transformers, the saving on reinvestment cost becomes larger than the unreliability cost. Therefore, the maximum number of transformers to be replaced in the following years, i.e., not to be replaced this year, without compromising the system reliability is 13. Hence, the optimum number of transformers to be replaced is 2.

VI. CONCLUSIONS

This paper introduced a framework for making decisions about the replacement of power system equipment. The framework is based on mapping the criticality of the component to system reliability and determining the impact of its replacement on system reliability. An economical comparison between the cost of unreliability based on regulatory incentives and the saving on reinvestment cost by deferring replacement is performed to determine an optimum replacement plan for a model system.

The first contribution of this paper is that the framework combines the merits of the two commonly-used quantitative risk approaches, risk matrix and risk indices. By applying this merger, this paper introduces a more comprehensive decision-making framework for component replacement.

The second contribution is bringing out the use of Pareto analysis in this area of power system studies. The use of Pareto analysis provides an insight into the effect of equipment replacement volume on system reliability.

Finally, This paper provides an example of using reliability regulation scheme in decision making.

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