UNIVERSITY OF BATH

Citation for published version:
Yang, X, Gu, C, Yan, X & Li, F 2020, 'Reliability-based Probabilistic Network Pricing with Demand Uncertainty', *IEEE Transactions on Power Systems*. https://doi.org/10.1109/TPWRS.2020.2976944

DOI:
10.1109/TPWRS.2020.2976944

Publication date:
2020

Document Version
Peer reviewed version

Reliability-based Probabilistic Network Pricing with Demand Uncertainty

Xinhe Yang, Chenghong Gu, *Member, IEEE*, Xiaohe Yan, Furong Li, *Senior Member, IEEE*

***Abstract*-- The future energy system embraces growing flexible demand and generation, which bring large-scale uncertainties and challenges to current deterministic network pricing methods.**

This paper proposes a novel reliability-based probabilistic network pricing method considering demand uncertainty. Network reliability performance, including probabilistic contingency power flow (PCPF) and tolerance loss of load (TLoL), are used to assess the impact of demand uncertainty on actual network investment cost, where PCPF is formulated by the combined cumulant and series expansion. The tail value at risk (TVaR) is used to generate analytical solutions to determine network reinforcement horizons. Then, final network charges are calculated based on the core of the Long-run incremental cost (LRIC) algorithm. A 15-bus system is employed to demonstrate the proposed method. Results indicate that the pricing signal is sensitive to both demand uncertainty and network reliability, incentivising demand to reduce uncertainties. This is the first-ever network pricing method that determines network investment costs considering both supply reliability and demand uncertainties. It can guide better sitting and sizing of future flexible demand in distribution systems to minimise investment costs and reduce network charges, thus enabling a more efficient system planning and cheaper integration.

***Index Terms*-- Network pricing, uncertainty, probabilistic, reliability, long-run incremental cost pricing.**

I. Introduction

THE future energy system with increasing distributed energy resources (DERs) bring significant challenges to planning and pricing schemes of distribution networks. In the UK, over 800,000 homes have installed PV panels, and 137,000 light-duty plug-in electric vehicles have been registered. The intermittent generation and flexible demand can cause unexpected peaks or valleys on networks and affect supply reliability. Meanwhile, the combination of variable DERs also results in uncertain network utilization.

The use-of-system charge is designed to recover network investment cost from network users and financially incentive economic sitting and sizing of potential demand and generation [1]-[2]. In the UK practice, the use-of-system charge needs to comply with principles of transparency, fairness and predictability set by the regulator. Current use-of-system charges for Extra High Voltage (EHV 132kV-22kV) and High Voltage (HV 22kV-1kV) distribution systems are derived by using deterministic power flows at system peak, where network utilization is traceable and predictable [3]. However, in the future scenario, due to the DER integration, the uncertainties will distort the effectiveness of traditional pricing methods, so that produce inaccurate cost-reflective signals and mislead demand and generation planning. This either leads to deficits of recovered cost for distribution network operators or leads to the end-users overpayments. Therefore it is urgent to develop new network pricing methods considering uncertainties of end customers, particularly those incurred by DERs.

Forward-looking charging methods are applied by UK DNOs on EHV and HV distribution systems. Long-run-incremental cost pricing (LRIC) and forward cost pricing (FCP) are the two commonly used deterministic-based network pricing schemes. LRIC pricing method is calculated by determining the present value change due to the incremental nodal demand injection or generation and discounts the future reinforcement cost into annual nodal network charge [4]. FCP divides the distribution network service area into isolated groups. FCP demand pricing is determined by calculating network reinforcement costs to accommodate a maximum 15% demand increment for each network group over next ten years and averaged at each voltage level within the network group [5]. Both methods consider load demand as deterministic, which are inefficient to evaluate network asset cost and allocate the cost fairly between users considering increasing uncertainties.

Limited literature has studied network pricing under uncertainties. Paper [6] considers long-term load growth to be uncertain and adopts the fuzzy set theory to generate deterministic network charges, using vertex expansion and the centre of gravity defuzzification. A reliability-based network pricing method is proposed in [7]. It calculates the charges based on network reliability performance under N-1 contingency, which requires the incurred contingency must align with the security requirements [8]. A sensitivity analysis is conducted to evaluate price signals under uncertain network reliability levels. However, those pricing methods for distribution networks still target at traditional load and generation. The latest improvement of pricing scheme for DERs simply applies F-factors to intermittent distributed generations (DGs) when calculating charge credits [9]. F factor is the proportion of the declared net capacity of a

Manuscript received September 28, 2018; revised December 24, 2018; accepted February 24, 2020. Date of current version February 13, 2020. Paper no. TPWRS-01423-2018.

X.Yang, C. Gu (corresponding author) and F. Li are with the Department of Electronic and Electrical Engineering, University of Bath, Bath BA2 7AY, U.K. (e-mail: xy511@bath.ac.uk; c.gu@bath.ac.uk; f.li@bath.ac.uk)

X. Yan is with the State Key Lab of Internet of Things for Smart City, University of Macau, Macau 999078, China. (e-mail: xiaohe_yan@yahoo.com)

generator that can be used to contribute to network security. It is only for DGs but cannot reflect demand uncertainties.

In terms of network utilization, power flows can be regarded as the most explicit performance index. Stochastic and probabilistic methods are two major classifications of power flow modelling under uncertainties. Traditionally, because of the implementation simplicity, stochastic methods including Monte-Carlo (MC) simulation [10] [11] [12], interval [13] and affine arithmetic (AA) [14] are typical methods to model uncertain power flows of a network with intermittent generation and load. Besides, probability theory is widely used to model uncertainties for generating analytical solutions for probabilistic power flows (PPFs). Papers [15] [16] apply the convolution technique with a Fast-Fourier transform method to formulate PPF but require a significant computational burden. Papers [17]-[19] propose cumulant and moment-based methods to construct PPF by combining various expansion approximations, which significantly improve the computation efficiency. The approximate method is another uncertain power flow modelling technique, providing statistical properties of uncertain objectives. Papers [20] [21] study the point estimate method to solve PPF and quantify the transfer capability of transmission networks. Although these methods well capture the uncertain features of power flows, they have not well studied how to incorporate them into design network pricing.

This paper proposes a novel reliability-based probabilistic Long-run incremental cost pricing method (PR-LRIC) for the distribution network, considering demand uncertainties. By assuming nodal peak demand to be a random variable following certain probability distribution, network power flows are directly obtained from nodal demand by using the combined Gram-Chalier and cumulant method. Network contingency is then analysed to 1) determine allowed overloading for network components to reflect the network reliability level, based on nodal tolerable loss of load (TLoL) curtailment under contingency events; 2) formulate the probability density functions (PDF) of contingency power flows (CPF) due to uncertain peak demand. Thereafter, the tail value at risk (TVaR) method is utilized to assess the probability and expected overloadings under probabilistic contingency power flows (PCPF). The calculated allowed overloading is applied as the trigger to reinforce the network. Combined it with PCPF in the risk model, network reinforcement horizons and asset costs can be determined. Finally, the core of the LRIC pricing is used as the basis to calculate the final nodal network charges. The proposed method is demonstrated in a practical UK 15-bus distribution system. The sensitivity of demand uncertainty and network reliability on pricing signals is also studied. It proves that according to network reliability levels, the proposed method captures demand uncertainty by producing diversified nodal network charges against varying uncertainty levels.

The main contributions of this paper are:

- Formulating network PCPF for charge calculation directly from uncertain demand peak and network reliability.
- Using risk to determine network reinforcement horizons and investment costs due to demand uncertainty.
- Designing a new network pricing method that distinguishes price signals based on network reliability and demand uncertainty levels, incentivising demand uncertainty reduction and connection to more robust networks.

The rest of the paper is organized as followed: Section II introduces the traditional deterministic LRIC and reliability-based LRIC network pricing methods. Section III presents the probabilistic power flow formulation. Section IV reports the main framework of the reliability-based probabilistic pricing model. Section V applies the proposed method to the test system for demonstration. Section VI makes further discussions. Section VII concludes this paper.

II. Traditional Deterministic Methods in Computing Network Reinforcement Horizon

This section introduces network reinforcement horizon determination under traditional LRIC pricing method and reliability-based LRIC network pricing (R-LRIC) method. Basically, LRIC network pricing is based on users' contributions on peak demand. It determines the present value whereof future network investment and calculates the network cost by taking the change of present value due to nodal injection or withdrawal. Therefore, the time horizon to reinforce the network is the key factor in the present value calculation.

A. Reinforcement Horizon in Traditional LRIC Pricing

In traditional LRIC network pricing, the time horizon n_j to reinforce the network component *j* is determined from the annual peak level of power flow (pf_j) and the rated capacity (C_j) of network component *j*, where the annual peak is assumed to be a deterministic value:

$$n_j = \frac{logC_j - logpf_j}{log(1+r)} \tag{1}$$

where r is the load growth rate.

Resulting from the incremental power withdraw or injection (ΔP_N) at node N, the new reinforcement horizon of the component *j* is：

$$n_{jnew} = \frac{logC_j - log(pf_j + \Delta pf_j)}{log(1+r)} \tag{2}$$

where Δpf_j is the power flow change along with component *j* resulting from nodal demand change (ΔP_N)

B. Reinforcement Horizon in Reliability-Based Pricing

The reliability-based network pricing uses a different approach to determine network reinforcement horizon. The method firstly defines the tolerant loss of load (TLOL), which converts the expected energy not supply (EENS) and network reliability parameters into extra capacity component *j*.

$$TLOL_j = \frac{\sum EENS}{MTTR_i \cdot FR_i} \tag{3}$$

where $\sum EENS$ is the sum of EENS from demand nodes supported by component *j*; $MTTR_i$ and FR_i are mean time to repair and failure rate of component *i* whose outage leads to the largest contingency power flow on network component *j*.

The TLoL then is taken as the allowed overloading under the reliability supply standard. The reinforcement horizon of component *j* is:

$$n_j = \frac{log(C_j + TLOL_j) - logpf_j}{log(1+r)} \quad (4)$$

where $pf_j$is the maximum contingency power flow of branch *j*.

The reinforcement horizon of component j due to the incremental nodal power change (ΔP_N) is determined by:

$$n_{jnew} = \frac{\log(C_j + TLOL_j) - log(pf_j + \Delta pf_j)}{log(1+r)} \quad (5)$$

where Δpf_j is the change of contingency power flow at component *j* due to the incremental nodal power change ΔP_N

In both methods, the critical variable pf, which represents either the maximum power flow or the maximum power flow under contingency, is assumed to be deterministic. Considering demand uncertainty, random variables should be used to represent the uncertain demand peak and consequently network utilization. In this way, it can be more practical to reflect customer impact on network investment and reinforcement horizon, producing cost-reflective use-of-system price signals.

III. Probabilistic Power Flow Considering Demand Uncertainty

In this section, the probabilistic contingency power flow (PCPF) formulation is proposed to support reliability-based probabilistic network pricing. The method refers to the probabilistic power flow (PPF) based on the cumulant and series expansion methods and provides analytical expressions of network PPFs directly from random nodal demand peaks.

A. Cumulant Method

The combined cumulant and Gram-Charlier expansion method are used to formulate the probabilistic power flow with uncertainties. Cumulants and moments are measures of a probability density function (PDF). For a random variable x with PDF $f_x(x)$, the moment generating function $\Phi_X(s)$ is:

$$\Phi_X(s) = E[e^{sx}] = \int_{-\infty}^{\infty} e^{sx} f_x(x)\, dx \quad (6)$$

The cumulant generating function $\Psi_X(s)$ is often written in terms of moment generating function as:

$$\Psi_X(s) = \ln \Phi_X(s) \quad (7)$$

The n^{th}-order raw moment m_n and cumulant λ_n are computed by taking the n^{th} derivative of each generating function with respect to s and evaluating at s=0.

Given a random variable z, which is the linear combination of independent variables $x_1,\ x_2 \dots\ x_m$

$$z = a_1x_1 + a_2x_2 + \cdots a_mx_m \quad (8)$$

The moment generating function $\Phi_Z(s)$ for the random variable z can be determined as:

$$\begin{aligned}\Phi_Z(s) &= E[e^{sz}] \\ &= E\left[e^{s(a_1x_1)s(a_2x_2)+\cdots s(a_mx_m)}\right]\end{aligned} \quad (9)$$

Because $x_1,\ x_2 \dots\ x_m$ are independent:

$$\begin{aligned}\Phi_Z(s) &= E\left[e^{s(a_1x_1)}e^{s(a_2x_2)} \dots e^{s(a_nx_m)}\right] \quad (10)\\ &= \Phi_{X1}(a_1s)\Phi_{X2}(a_2s) \dots \Phi_{Xm}(a_ms)\end{aligned}$$

The cumulant generating function $\Psi_Z(s)$ for random variable z can be calculated as:

$$\begin{aligned}\Psi_Z(s) &= \ln(\Phi_Z(s)) \\ &= \Psi_{X1}(a_1s) + \Psi_{X2}(a_2s) + \cdots \Psi_{Xm}(a_ms)\end{aligned} \quad (11)$$

The n^{th}-order cumulant of z can be computed by taking the *n*th derivative of $\Psi_Z(s)$ respect to s and evaluating it at $s = 0$

$$\begin{aligned}\lambda_n &= \Psi_Z^{(n)}(0) \\ &= a_1^n\Psi_{X_1}^{(n)}(0) + \cdots a_m^n\Psi_m^{(n)}(0)\end{aligned} \quad (12)$$

B. Gram-Charlier Expansion Method

The Gram-Charlier A series allows many PDFs to be expressed as a series, consisting of a standard normal distribution and derivatives. The series can be defined as:

$$f(x) = \sum_{i=0}^{\infty} c_i He_i(x)\alpha(x) \quad (13)$$

where $f(x)$ is the PDF of a random variable x, c_i is the *i*th series coefficient, $He_i(x)$ is *i*th Hermite polynomial and $\alpha(x)$ is the standard normal distribution function.

The Gram-Charlier form uses moments to compute series coefficients, while Edgeworth form uses cumulants due to the additive property of cumulants. Given the cumulants for distribution in the standard form, the exponential representation of the PDF can be expressed in its series representation:

$$f(x) = e^{(-\frac{\lambda_3}{3!}D^3 + \frac{\lambda_4}{4!}D^4 - \frac{\lambda_5}{5!}D^5 + \cdots)}\alpha(x) \quad (14)$$

where D^n is the operator of the *n*th order derivative of the unit normal distribution, λ_n is its cumulant, $\alpha(x)$ is the general normal distribution function with mean μ and variance δ^2

According to the cumulant concept, the 1st and 2nd order cumulants of a probability distribution equal to the mean and variance of the distribution. Equation (14) in Edgeworth form can be presented in the Maclaurin series in (15).

$$\begin{aligned}f(x) = \Bigg[1 &+ \frac{\left(-\frac{\lambda_3}{3!}D^3 + \frac{\lambda_4}{4!}D^4 - \frac{\lambda_5}{5!}D^5 + \cdots\right)}{1!} \\ &+ \frac{\left(-\frac{\lambda_3}{3!}D^3 + \frac{\lambda_4}{4!}D^4 - \frac{\lambda_5}{5!}D^5 + \cdots\right)^2}{2!} \\ &+ \frac{\left(-\frac{\lambda_3}{3!}D^3 + \frac{\lambda_4}{4!}D^4 - \frac{\lambda_5}{5!}D^5 + \cdots\right)^3}{3!} \\ &+ \cdots \Bigg] \alpha(x)\end{aligned} \quad (15)$$

By expanding each term and grouping them by the power of D, the PDF can be expressed as:

$$\begin{aligned}f(x) = \alpha(x) &- \frac{\lambda_3}{3!}D^3\alpha(x) + \frac{\lambda_4}{4!}D^4\alpha(x) - \frac{\lambda_5}{5!}D^5\alpha(x) \\ &+ \left(\frac{\lambda_6}{6!} + \frac{{\lambda_3}^2}{2!\,3!^2}\right)D^6\alpha(x) \\ &- \left(\frac{\lambda_7}{7!} + \frac{2\lambda_3\lambda_4}{2!\,3!\,4!}\right)D^7\alpha(x) + \cdots\end{aligned} \quad (16)$$

C. Probabilistic Contingency Power Flow (PCPF) Formulation

To investigate the reliability-based network charges for demand with uncertainties, network PCPF are formulated directly from demand peak, where the annual peak is modelled as a random variable following certain PDF acquired from historical data, denoted as $D_m \sim f_m(x)$.

To determine the PCPF of a certain network component *j*, contingency analysis is first applied to find the contingency component (CC) of *j*, which is defined as that if the unavailability of network component *i* leads to the maximum contingency power flow (CPF) along component *j*, *i* is assigned to the CC of *j*. The CPF analysis is conducted by assuming that each branch is out of service in turn. Then, the sensitivity factor (SF_{j,D_m}) is required to represent the nodal demand *m* contribution to the CPF along network component *j*. Once the CC of *j* is determined, the SF_{j,D_m} for *j* regarding each node is calculated by taking the difference of CPFs with and without demand increment under its CC outage condition.

$$SF_{j,D_m} = \frac{\Delta CPF_j}{\Delta P_{Dm}} \tag{17}$$

where ΔCPF_j is the change of CPF along with component *j* due to the incremental nodal demand ΔP_{Dm} at *m*.

By assuming $D_1 \ldots D_m$ are independent random variables and utilizing the cumulant method in (7), cumulant generating function and each order cumulant of D_m can be determined. As the maximum CPF_j can be represented as the sum of nodal demand contribution to component *j*, the SF_{j,D_m} is taken as the weight of each demand node in formulating the cumulant generating function of CPF_j in (8)-(11). Therefore, the *n*th-order cumulant $\lambda_{j,n}$ of the CPF at network component *j* can be reformulated by using (12):

$$\lambda_{j,n} = SF_{j,D_1}^{n} \Psi_{D_1}^{(n)}(0) + \cdots + SF_{j,D_m}^{n} \Psi_{D_m}^{(n)}(0) \tag{18}$$

where Ψ_{D_m} and $\Psi_{D_m}^{(n)}(0)$ denote the cumulant generating function and the *n*th-order cumulant D_m.

Combined with Gram-Charlier expansion, the PDF of CPF for component *j* can be expressed by (16) and converted into the standard PDF form [22] so that the integral of PDF remains 1, denoted as $f_{pf_j}(x)$.

IV. Reliability-Based Probabilistic Network Pricing

In this section, the network reinforcement horizon determination based on the PCPF acquired from the previous section and TVaR method is introduced. The enhanced reliability-based probabilistic Long-run incremental cost (PR-LRIC) network pricing method is proposed to generate the final deterministic charge signals to network users.

A. Reinforcement Horizon Using Tail Value at Risk (TVaR)

Figure 1 illustrates the calculation of TVaR for probabilistic contingency power flow (PCPF). Once the PDF of PCPF $f_{pf_j}(x)$ is formulated, the projection of $f_{pf_j}(x)$ after n_j years of load growth can be represented as an increasing function of $f_{pf_j}(x)$:

$$g_j(x) = f_{pf_j}\left(\frac{x}{(1+r)^{n_j}}\right) \tag{19}$$

where *r* is the load growth rate.

The tail value at risk (TVaR) is used to calculate the expected overloading level of a network component under contingency after n_j year load growth. The expected loading level in contingency is:

$$TVaR_{g_j(x)} = \frac{\int_C^{\infty} x \cdot g_j(x)\, dx}{1 - G_j(C)} = \frac{\int_C^{\infty} x \cdot f_{pf_j}\left(\frac{x}{(1+r)^{n_j}}\right) dx}{1 - F_{pf_j}\left(\frac{C}{(1+r)^{n_j}}\right)} \tag{20}$$

where $G_j(x)$ and $F_{pf_j}(x)$ are the cumulative distribution functions (CDFs) of $g_j(x)$ and $f_{pf_j}(x)$ respectively, *C* is the rated capacity of the network component, 1-$G_j(C)$ denotes the probability of overloading.

With the incremental nodal demand ΔP_N, the maximum CPF under $f_{pf_j}(x)$ increases by Δpf and the PDF of maximum CPF can be formulated as $f_{pf_j}(x - \Delta pf)$. The projected PDF $g_{incre_j}(x)$ of maximum CPF and expected loading level $TVaR_{g_{incre_j}(x)}$ after $n_{j\,new}$ years of load growth can be represented as:

$$g_{incre_j}(x) = f_{pf_j}\left(\frac{x - \Delta pf}{(1+r)^{n_{j\,new}}}\right) \tag{21}$$

$$TVaR_{g_{incre_j}(x)} = \frac{\int_C^{\infty} x \cdot g_{incre_j}(x)\, dx}{1 - G_{incre_j}(C)} \tag{22}$$

where $G_{incre_j}(x)$ is the cumulative distribution functions of $g_{incre_j}(x)$, $1 - G_{incre_j}(C)$ is the probability of overloading.

The TLoL from (3) is defined as the maximum expected overloading level under network contingency. The network component reinforcement is required when TVaR exceeds the sum of rated capacity and TLoL. Then by setting the TLoL as the threshold of the overloading level and assuming after n_j and $n_{j\,new}$ years the overload of component *j* reaches the

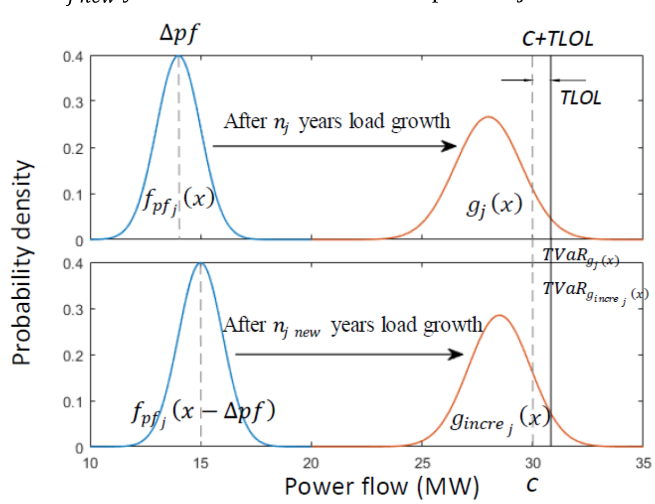


Fig. 1. Tail value at risk of contingency power flow PDF after years load growth that triggers the reinforcement

threshold, two implicit functions are formulated to represent the trigger of the reinforcement:

$$R(n_j, x) = TVaR_{g_j(x)} - (C + TLoL) = 0 \tag{23}$$

$$R(n_{j\,new}, x) = TVaR_{g_{incre_j}(x)} - (C + TLoL) = 0 \tag{24}$$

Equation (23) and (24) can be solved by using the Newton–Raphson method, and the solved n_j and $n_{j\,new}$ are reinforcement horizons of component j without and with the incremental nodal demand.

B. Network Component Pricing

As long as the reinforcement horizons of components are acquired, the present value (PV_j) of future reinforcement of component j can be calculated via its asset cost and reinforcement horizon:

$$PV_j = \frac{Asset_j}{(1+d)^{n_j}} \tag{25}$$

where d is the discount rate, n_j is the calculated reinforcement horizon from (23)

The present value of component j with additional nodal power withdrawn or injection ΔP_N can be calculated as:

$$PV_{j\,new} = \frac{Asset_j}{(1+d)^{n_{j\,new}}} \tag{26}$$

where $n_{j\,new}$ is the calculated reinforcement horizon from (24)

The change in the present value as a result of the nodal injection or withdrawal is given by:

$$\Delta PV_j = PV_{j\,new} - PV_j \tag{27}$$

The annualized incremental cost (IC) of network component j is the difference in the present value of the future investment as a result of ΔP_{Dm} at demand node m multiplied by an annuity factor:

$$IC_j = \Delta PV_j \times annuity\ factor \tag{28}$$

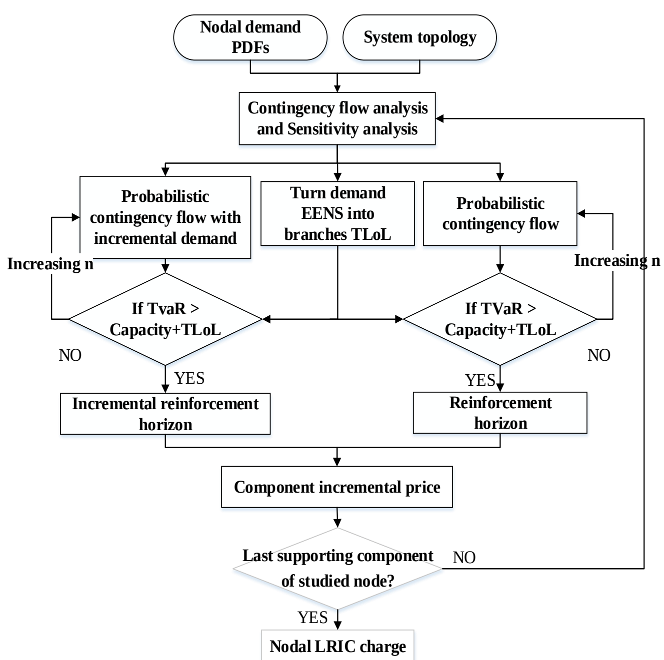


Fig. 2. Flowchart of reliability-based probabilistic pricing method

Therefore, the final LRIC to support node m is determined by the sum of the incremental costs of all its supporting components:

$$LRIC_m = \frac{\sum_j IC_j}{\Delta P_{Dm}} \tag{29}$$

C. Flowchart

The implementation of the proposed pricing method is shown in Figure 2. For pricing a certain node, the sampled historical demands and forecast demand at system peak time are required to formulate the PDF of nodal demand. Combined with the system topology information, it is then to conduct contingency flow analysis and sensitivity analysis to calculate the TLoLs and formulate PCPFs of supporting components. It is followed by using TVaR to determine network reinforcement horizons under demand uncertainties and nodal injection. Component incremental prices are calculated and summed up to form final nodal network charges. The proposed method can be easily applied to calculating network charges on demand in a distribution system.

V. Demonstration

A. System Description

A 15-bus distribution network shown in Figure 3 is used for demonstration. The probability density functions of nodal peak demand at bus 1001, 1003, 1006, 1007, 1009 and 1013 are assumed to follow the probability distributions of Normal (20.5,0.8), Normal(25,2), Uniform(6,9), Normal(12,0.5), Normal(23,1) and Gamma(7.5,0.5), respectively. Before the load flow modelling, all nodal demands are scaled by their coincidence factors. For simplicity, all coincidence factors are assumed to be 1. The discount rate and annuity factors of network assets are assumed to be 7.4% and 7.8%. The load growth rate is 2%.

Table I presents the TLoL of each network branch and its corresponding CC. For reliability indexes, mean time to repair for branches connected of 66KV-66KV busbars are 7.5 hr/time and the mean time to repair of the rest branches are 4 hr/time. Failure rates of all components are assumed to be identical as 0.5 time/yr.

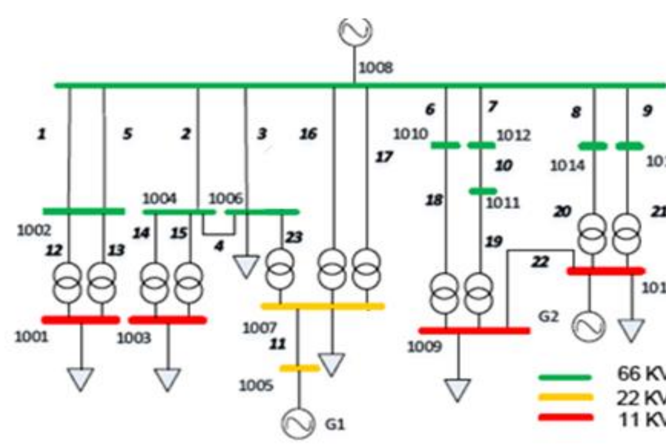


Fig. 3. System topology of the test system

B. Probabilistic Contingency Power Flow (PCPF)

The 8th order expansion is used to formulate the PDFs of CPFs because of the better performance in fitting the tail part of probability density distributions and smaller overall variance. The PDF curves of the example branches are shown in Figure 4 and compared with simulated results from the Monte-Carlo method of 3000 iterations.

It can be observed that the PDF curves of CPF generated from analytical expressions highly coincide with the simulated CPF probability density distributions, especially in the tail part. It indicates the effectiveness of the proposed method to approximate PCPFs with analytical expressions.

C. Pricing Result

Table II gives the breakdown of reinforcement horizons of branches with (n_{new}) and without (n) the incremental demand at example nodes under the proposed PR-LRIC method. It also compares results with those from P-LRIC and LRIC methods.

At bus 1003, the incremental demand contributes positively to the utilization levels of all supporting branches. Expect L4, the reinforcement horizons (n) of those positive branches under PR-LRIC method are earlier than the horizons calculated from R-LRIC method while having deferrals compared with horizons from the LRIC method. For L4, although the reinforcement horizon (n) from PR-LRIC is 23.27yr which is smaller than the horizons computed by using LRIC (23.73yr) and R-LRIC (26.28yr), the incremental demand has the least impact on bringing forward the reinforcement of L4. Incremental demand at 1003 forces 1.68yr, 1.98yr and 4.15yr earlier reinforcement of L4 when using PR-LRIC method R-LRIC and LRIC method respectively. For bus 1006, although it is supported by L4, it does not contribute to the contingency power flow at L4 so that the reinforcement horizon (n) and the horizon due to incremental demand (n_{new}) remain the same under reliability-based methods (PR-LRIC and R-LRIC). By contrast, under the original LRIC method, the incremental demand defers the reinforcement of L4 by 4.03yr due to the negative contribution of peak power flow, creating a negative branch incremental charge. The reinforcement horizons (n and n_{new}) of the rest supporting branches for bus 1006 follow the similar rule as bus 1003, i.e. the results from PR-LRIC method are located between those acquired from R-LRIC and LRIC.

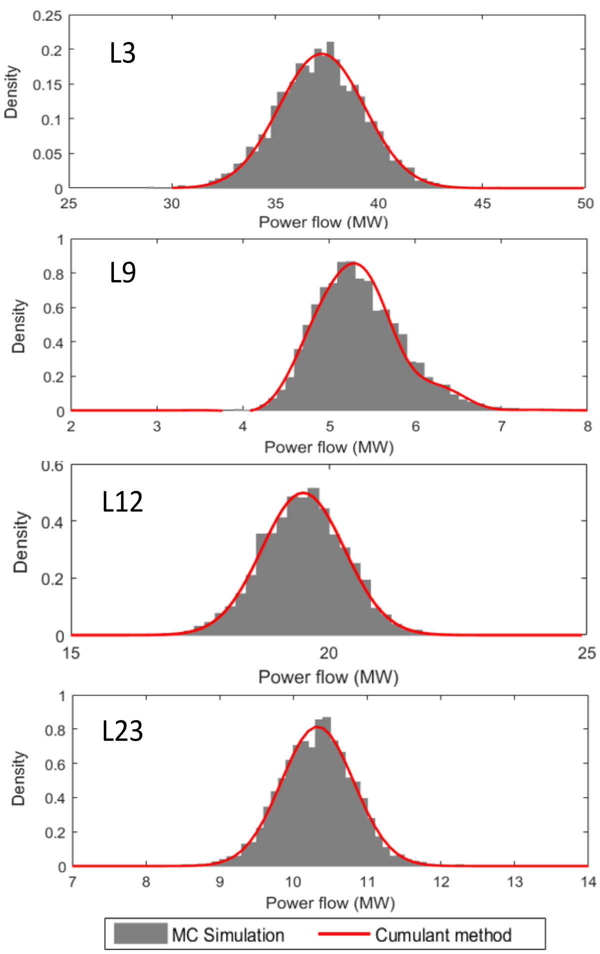


Fig. 4. PDFs of probabilistic contingency power under combined cumulant and expansion method (Red) and Monte-Carlo method (Gray)

TABLE I
CONTINGENCY COMPONENT (CC) AND TOLERANCE LOSS OF LOAD (TLOL) OF NETWORK BRANCHES

Branch	CC	TLoL (MW)	Branch	CC	TLoL (MW)
L1	L5	2.40	L13	L12	4.50
L2	L3	3.69	L14	L15	4.50
L3	L2	3.71	L15	L14	4.50
L4	L2	2.40	L16	L17	2.57
L5	L1	2.40	L17	L16	2.47
L6	L22	0.75	L18	L22	0.75
L7	L22	0.75	L19	L22	0.75
L8	L21	1.02	L20	L21	1.02
L9	L20	1.02	L21	L20	1.02
L10	L22	0.75	L22	L18	0.52
L11	L17	0.00	L23	L16	2.03
L12	L13	4.50			

TABLE II
BREAKDOWN OF REINFORCEMENT HORIZONS UNDER PR-LRIC R-LRIC AND LRIC METHOD

Bus	Branch	PR-LRIC (yr)		R-LRIC (yr)		LRIC (yr)	
		n	n_{new}	n	n_{new}	n	n_{new}
1003	L2	17.86	16.68	18.70	17.45	15.10	13.83
	L3	17.67	16.49	18.50	17.25	14.88	13.66
	L4	23.27	21.59	26.68	24.70	23.73	19.58
	L14	27.98	26.15	29.12	27.14	23.73	21.75
	L15	27.98	26.15	29.12	27.14	23.73	21.75
	L16	45.52	45.42	45.67	45.57	41.52	41.42
	L17	47.33	47.23	47.51	47.40	43.51	43.41
	L23	38.10	38.22	38.27	38.39	33.38	33.68
1006	L2	17.86	16.69	18.70	17.45	15.10	13.90
	L3	17.67	16.49	18.50	17.25	14.88	13.59
	L4	23.27	23.27	26.68	26.68	23.73	27.76
	L16	45.52	45.42	45.67	45.56	41.52	41.41
	L17	47.33	47.23	47.51	47.40	43.51	43.40
	L23	38.10	38.23	38.27	38.40	33.38	33.69

TABLE III
PRICING RESULTS UNDER PROPOSED PR-LRIC METHOD AND COMPARISON WITH R-LRIC AND LRIC

Bus	PR-LRIC(£)	R-LRIC(£)	LRIC(£)
1001	13589.5	13613.1	23607.8
1003	23240.4	23077.7	36951.3
1006	11122.3	11156.1	5104.6
1007	6854.1	6883.6	6124.1
1009	6438.4	6809.6	6916.3
1013	1256.6	1418.1	5291.4

Aforementioned results illustrate that the proposed method preserves the ability to convert demand reliability requirement and network reliability indices into extra capacities of network components and lead to reinforcement deferrals. It meanwhile uses probabilistic contingency peak power flows rather than deterministic values to refine reinforcement horizons without incremental demand and indicates that demand uncertainty limits reinforcement deferrals.

The numerical final pricing results (unit charges) of the PR-LRIC method are shown in Table III and compared with the results from deterministic reliability-based LRIC pricing (R-LRIC) and traditional LRIC pricing (LRIC).

From Table III, it can be observed that buses 1001, 1003 and 1009, charges from PR-LRIC are 42.4%, 37% and 7% lower than charges from LRIC. Those buses pay for using the same group of branches, however, in the PR-LRIC the reliability tolerance allows reinforcement deferrals of branches so that buses have lower charges under PR-LRIC compared to charges from LRIC. For buses 1006 and 1007, the charges from PR-LRIC are 11122.3 £/MW/yr and 6854.1 £/MW/yr while the charges from LRIC for the two buses are reduced by 54% and 10.7%. It is because that under LRIC method buses 1006 and 1007 obtain the reward (negative charge) for using L4, however, under PR-LRIC method, they do not contribute to CPF of L4, so that they do not have such a reward or charge. For bus 1013, the charge from PR-LRIC (1256.6 £/MW/yr) is about four times smaller than that from LRIC (5291.4 £/MW/yr). This is due to that bus 1007 is not responsible for CPFs of branch L6, L7, L10, L18 and L19 under PR-LRIC. On the contrary, it positively contributes to power flows on those branches under LRIC and get charged for using them. Compared to results from the R-LRIC method, the proposed method does not produce big charge difference on buses 1001, 1003, 1006 and 1007. This is due to that the assumed variances of nodal demand peaks in the test system are considerably small, demands with uncertainty in the probabilistic method can be regarded as deterministic values in R-LRIC method, and therefore the results from two methods are approximate.

D. Pricing Sensitivity to Nodal Uncertainty

This section investigates the impact of changing demand uncertainty on network reinforcement horizons and charges under the proposed method. Figure 5 presents the

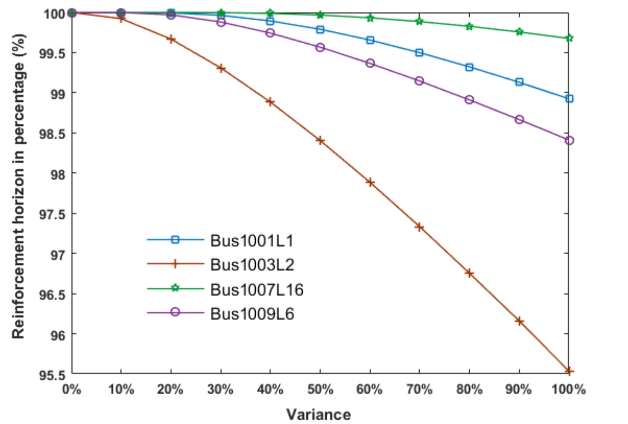


Fig. 5. Reinforcement horizon (in percentage) compared to R-LRIC method result under different uncertainty scales

reinforcement horizons of example branches with specified nodal demand peak variance reductions. The original demand peak variances stated in test system are assigned as the 100% variance scenario, and the calculated results from the R-LRIC method is denoted as 0% variance scenario where the deterministic value is on used and variances equal to 0. The reinforcement horizons under different variance scenarios are represented in percentages compared to the result of 0 variance scenario.

It can be observed that with the variances of demand peak at buses 1001, 1003, 1007 and 1009 increase from 0% to 100%, the reinforcement horizons of branches L1, L2, L16 and L6 drop by 1.1%, 4.5%, 0.3% and 1.6% respectively, indicating that the lager demand uncertainty the sooner the reinforcement is. The reinforcement horizon of branch L2 is brought forward significantly when demand variance at bus 1003 increases from 0 to base variance scenario. It is mainly due to that the scale of base variance at bus 1003 is considerably large compared to the variance of rest nodal demands. In addition, the demand at bus 1003 contributes a large proportion to the power flow at branch L2. Theoretically, the reinforcement horizon from the proposed method equals that from the R-LRIC method at 0 variance scenario. With the growing scale of demand peak uncertainty, earlier network reinforcement is required.

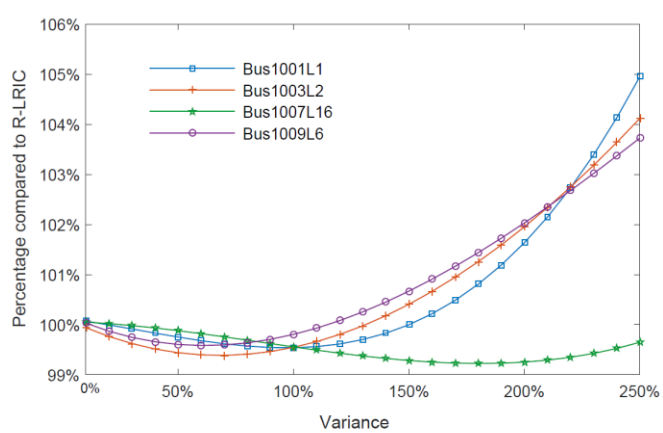


Fig. 6. Incremental charges (in percentage) compared to R-LRIC method under different demand uncertainty scales

Figure 6 presents the trends of incremental charges of branches L1, L2, L16 and L6 paid by demand nodes 1001, 1003, 1007 and 1009 respectively, against variances of nodal demand peaks expanding from 0% scenario to 100% scenario and beyond.

At 0% variance scenario, the incremental charges equal to the charges from R-LRIC method and decrease to the lowest charges at 90%, 50%, 170% and 60% variance scenario for L1, L2, L16 and L6 respectively. The lowest charges are not lower than 99% of incremental charges at 0 variance scenario. Beyond the lowest point, the incremental charges increase at a different scale with growing variances of corresponding nodal demands. The PCPFs of branches L1 and L6 are resulted from solely supporting demand at bus 1001 and bus 1009, the uncertainty of those demands directly affects the PCPFs, so the increasing rates of branches incremental costs are much higher. Compared to the charge on bus 1009 for using branch L6, a larger base variance of the demand at bus 1001 leads to a higher growth rate of the incremental charge of branch L1. For branches L2 and L16, the probabilistic contingency power flows are formed by joint nodal demand, which means the PDFs of L2 and L6 CPF are formulated as the combination of weighted demand peak levels and uncertainty scales. The variance of demand at bus 1003 has a significant effect on the PDF of L2 CPF, while demand variance at bus 1007 is tiny and makes a small contribution to L6 CPF. Thus, with increasing uncertainty scale, the growth rate of incremental charge on bus 1003 at L2 is apparently greater than the charge on bus 1007 at L6.

E. *Pricing Sensitivity to Network Reliability*

This section studies the impact of network reliability under the proposed method. Based on different failure rates, the incremental charges of example connection lines under different nodal uncertainty scenarios are presented in Figure 7.

For failure rate at 0.1 time/yr to 0.4 time/yr, the incremental charges of branch L1 are insignificantly diverse with the uncertainty of demand 1001 increasing from 25% δ^2 to 200%δ^2. While as the failure rate increases to 1 time/yr, the incremental charge of L1 is £3057.2 at 25%δ^2 scenario and £3291.5 at 200% δ^2 scenario. The diversification of the incremental charge reaches 7.7%. For the incremental charges of L2 on bus 1003, L16 on 1007 and L6 on 1009, the charges under different demand uncertainty scenarios highly coincide unless failure rates of branches L2, L16 and L6 exceed 0.4 time/yr, 0.8 time/yr and 0.3 time/yr respectively. When the failure rate rises to 1 time/yr, the incremental charge of branch L2 on bus 1003 at large uncertainty scenario (150% δ^2) increases by 9% compared to small uncertainty scenario (12.5%δ^2). The incremental charge of branch L16 for bus 1007 has a small difference (4%) between small uncertainty scenario (25%δ^2) and large uncertainty scenario (200%δ^2). The incremental charge of L16 for bus 1009 at large uncertainty scenario (400%δ^2) is 26% greater than that in the small uncertainty scenario (50%δ^2).

Under the proposed method, for a more robust network, the network charge is less when connecting with identical

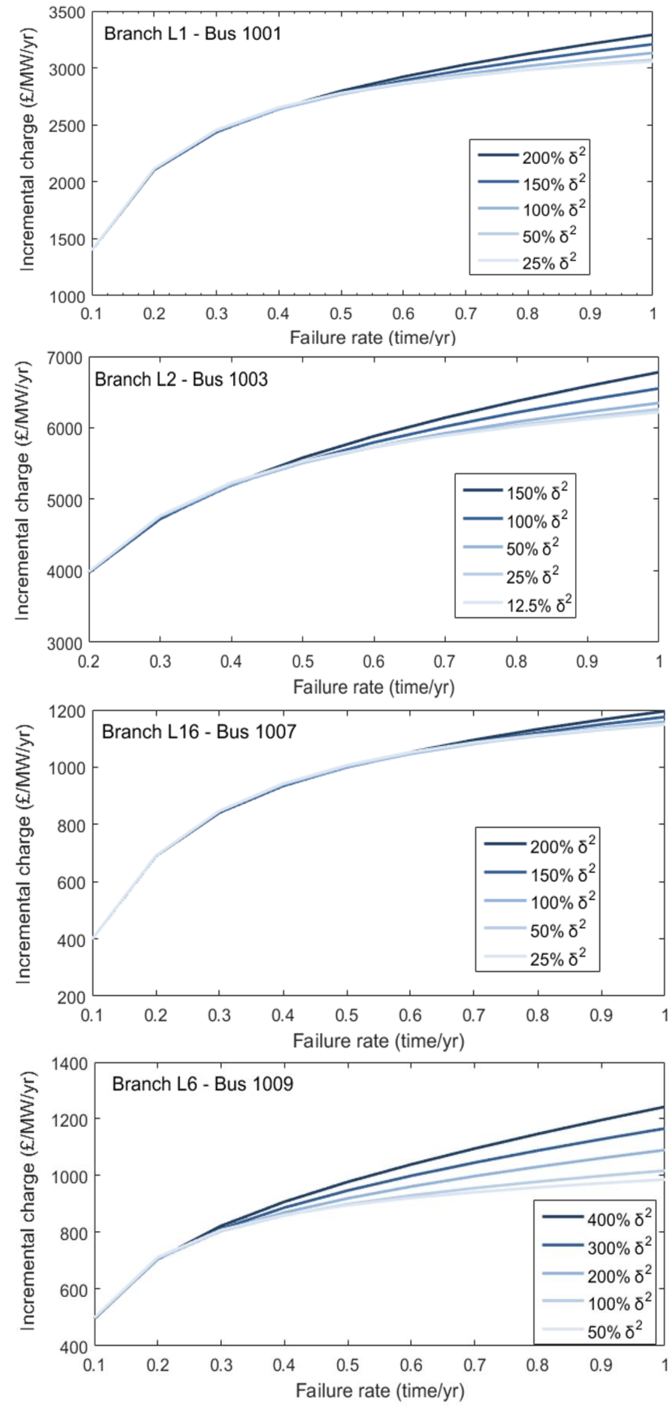


Fig. 7. Incremental charges with varying failure rate under different uncertainty scenarios

uncertain demand. Moreover, the charge signals vary insignificantly with demand uncertainty change, indicating that the robustness can offset the uncertainty effect on the network charge. Vice versa, a less reliable network generates higher charges, and the network charges are more sensitive to the uncertainty variance.

F. *Revenue Reconciliation*

It should be noted that pricing results in this paper are not the final tariffs applied to users but the incremental charge. Generally, the incremental charge cannot recover the revenue

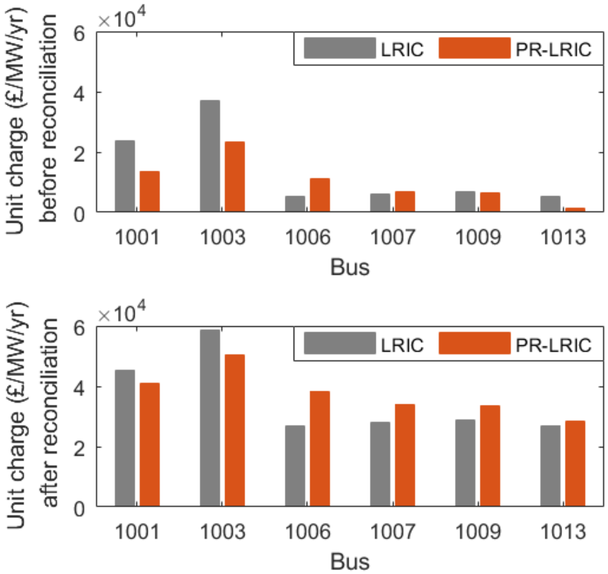


Fig. 8. Unit charge before and after revenue reconciliation

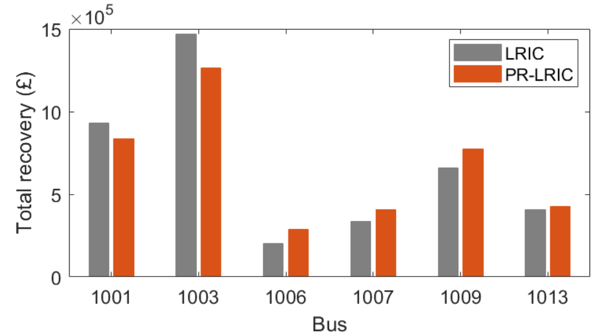


Fig. 9. Total revenue recoveries from demands

targets for distribution network operators (DNOs). DNOs are allowed by the regulator to recover their network cost and earn a fixed rate of return through revenue reconciliation. The revenue reconciliation 1) calculates the users' incremental charge; 2) allocates direct/indirect operating cost to users; 3) scales up charges by a fixed adder or fixed multiplier method so that the total revenue collected from network charges can meet the revenue target for DNOs [24] [25].

By using the fixed adder method, figure 8 compares unit charges before and after revenue reconciliation, and figure 9 compares the revenue recovery from the traditional LRIC method and the proposed PR-LRIC method. The allowed revenue is assumed to be £4 million. The fixed adders are 21767.6 £/MW/yr and 27260.3 £/MW/yr for LRIC and PR-LRIC respectively. The unit charges after reconciliation follow the same pattern as results before reconciliation. However, considering the demand size, the total revenue recovery has a different pattern. For example, the unit charge of bus 1006 is the third highest in PR-LRIC, but the total recovery is the lowest due to its smallest demand capacity.

The results in figure 9 are the total annual charges after revenue reconciliation, calculated by using unit charges, demand and scaling. With the LRIC method, the revenues recovered from demand at bus 1001 and 1003 are the highest (£0.93m and £1.47m respectively), which is due to their large demand size and big contributions on the peak demand of their supporting circuits. Under the PR-LRIC method, revenue recoveries from demands at bus 1001 and 1003 reduced by 2% and 5.1% to £0.84m and £1.26m. The reduction is mainly compensated by the increasing recovery proportion of bus 1006, 1007 and 1009, with increases of 2.2%, 1.9%, and 2.9%, respectively. The recovery from demand at bus 1013 has a small increment from £0.41m to £0.43m. The reason of those reductions and increments are due to the difference between the pricing principles of LRIC and PR-LRIC. PR-LRIC considers demand uncertainty and network reliability but original LRIC does not. Uncertainty produces unexpected network cost element, as the maximum of the uncertain demand should be accommodated by network capacity. By contrast, network reliability allows the certain load to be curtailed while reliability standards are met, which can in turn release some network capacity and thus reduce network costs. For example, in PR-LRIC, uncertainties of 1001 and 1003 lead to earlier network reinforcements and increase network cost compared to LRIC. By contrast, circuits supporting buses 1001 and 1003 have large TLOLs (shown in Table I) to tolerate demand uncertainties, therefore, time to reinforce those circuits is deferred compared to results in LRIC. Thus, the nodal charges for 1001 and 1003 are reduced. The calculated final network charges for buses 1001 and 1003 is reduced compared to results from the original LRIC because both uncertainty and reliability are considered. They also cause reductions in total revenue recovery from the two buses.

To justify the effectiveness of the proposed pricing method in incentivizing customers to reduce uncertainties, results in figure 7 are provided. It depicts that charges are all positive relative to the scale of demand uncertainties. For buses 1001, 1003, 1007 and 1009, reducing uncertainty from maximum scenario to minimum scenario leads to 234 £/MW/yr, 559 £/MW/yr, 46 £/MW/yr and 256 £/MW/yr unit charge reductions respectively. The designed network charge is effective to reflect this price change due to the uncertain variation so that incentivize customers to reduce uncertainties.

VI. Discussion

This paper designs a novel network pricing method for the incremental charge, considering the users' uncertainties in the pricing signal for the first time. The revenue collected from the incremental charge takes a large proportion of total revenue. Meanwhile, among all charge elements, the incremental charge is the most indicative cost signal to network users reflecting the users' energy usage behaviours.

In UK practice, demand uncertainty is not considered in any pricing methods and only treated in price control. The network charge is set at the upfront of each price control period. During a price control period, if the difference between incurred network cost and forecast network cost exceeds a threshold, the electricity distribution companies are allowed by the regulator to revise their network charges [25]. However, the ex-post charge revision and lack of uncertainty signal disable users' abilities to respond to the pricing signal. Whereas, the proposed pricing method provides users ex-ante network charges consisting of clear uncertainty signal.

The proposed method requests users to submit their forecast demands during peak periods and combines with historical peak demands of users to formulate probabilistic demands pattern. As a monopoly industry, network charge should comply with many principles set by regulators and 'transparency' is one of them. The pricing methodology must be publicly available and DNOs are compulsory to provide users with their forecast network charges if requested. Users thus can obtain informative network charges by submitting different forecast peak demands. If the forecast demand is not accurate, the DNO would treat this user with large uncertainty in next year and increase network charges produced by the proposed method to indicate that. Thus, the proposed pricing method can incentivize users to: 1) reduce peak demand, which can reduce the overall network utilisation and 2) reduce peak demand volatility, which can reduce uncertain network utilisation that triggers earlier network investment. In this way, DNOs can avoid or defer unnecessary reinforcement while still connecting users to existing networks. The overall benefits are: i) lower network investment cost for DNOs, ii) and reduced network charges for network users.

The proposed pricing method emphasises the impact of short-term uncertainty on network cost allocation. However, the long-term uncertainty (e.g. load growth rate) is considered to have a broader impact on the superstructure of the network charge paradigm including network regulatory framework and DNO investment planning. Paper [6] has modelled uncertain load growth by using fuzzy set theory, while other methods such as stochastic modelling and ambiguity sets via Robust Optimisation could be also used. Dynamic Programming could be used to evaluate the impact of long growth uncertainty on network investment planning. A comprehensive network pricing method considering load growth uncertainty will be studied in future work.

VII. Conclusion

This paper proposes a reliability-based probabilistic network pricing method which computes nodal network charges considering the uncertainty of demand, providing pricing signals to demand under different uncertainty levels and network reliability conditions. Extensive demonstration on a practical 15-bus system produces the following findings:

- Reinforcement deferrals of network components can be obtained by considering tolerance loss of load as extra capacity during contingencies. However, demand uncertainties offset the deferral, which expand potential network overloading under contingency. Reducing demand uncertainty can thus further defer network reinforcement.
- For a specific network component, its reinforcement horizon is sensitive to demand uncertainty that contributes to the largest proportion of its contingency power flow. The overall uncertainty of a specific network component depends on the joint effect of sensitivity factors and uncertainty scales of all connected demands.
- The proposed method produces nodal network charge signals to incentive demand to reduce their uncertainties by lowering their use-of-system costs. The pricing signals also indicate that networks with high reliable performance have smaller investment cost under demand uncertainty, thus producing low charges.

This paper designs a new network pricing that reflects the actual cost of the distribution network to supply uncertain demand considering network reliability levels. It can generate pricing signals to guide better siting and sizing of future demand and incentivize networks users to improve their behaviour predictability. This can further promote the utilisation of existing systems, minimizing investment costs for network operators and reducing charges for network users.

References

[1] Ofgem, ''EHV Distribution Charging Methodology (EDCM)'', April 2011.

[2] Ofgem, ''Report on the Draft Common Distribution Charging Methodology'', September 2009.

[3] Ofgem, ''Electricity distribution charging boundary between higher (EDCM) and lower (CDCM) voltages - Impact Assessment'', Jun 2010.

[4] F. Li and D. L. Tolley, "Long-Run Incremental Cost Pricing Based on Unused Capacity," in IEEE Transactions on Power Systems, vol. 22, no. 4, pp. 1683-1689, Nov. 2007.

[5] FCP Methodology Implementation and Guidance Notes, Worksrteam A.

[6] C. Gu, W. Yang, Y. Song and F. Li, "Distribution Network Pricing for Uncertain Load Growth Using Fuzzy Set Theory," in IEEE Transactions on Smart Grid, vol. 7, no. 4, pp. 1932-1940, July 2016.

[7] C. Gu, J. Wu and F. Li, "Reliability-Based Distribution Network Pricing," in IEEE Transactions on Power Systems, vol. 27, no. 3, pp. 1646-1655, Aug. 2012.

[8] ENA, ''Engineering Recommendation'', 2006, pp. 2-6

[9] ENA, ''EHV Distribution Charging Methodology (EDCM) Export (generation) charges'', Report to Ofgem, June 2012

[10] H. Zhang and P. Li, "Probabilistic analysis for optimal power flow under uncertainty," in IET Generation, Transmission & Distribution, vol. 4, no. 5, pp. 553-561, May 2010.

[11] F. H. Tavakoli, M. Hojjat and M. H. Javidi, "Determining optimal location and capacity of DG units based on system uncertainties and optimal congestion management in transmission network," 2017 Iranian Conference on Electrical Engineering (ICEE), Tehran, 2017, pp. 1260-1265.

[12] V. Vai, E. Gladkikh, M. C. Alvarez-Herault, B. Raison and L. Bun, "Planning of low-voltage distribution systems with uncertainty on load demand in urban areas," 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Milan, 2017, pp. 1-6. S

[13] V. Mohan, R. Suresh, J. G. Singh, W. Ongsakul and N. Madhu, "Microgrid Energy Management Combining Sensitivities, Interval and Probabilistic Uncertainties of Renewable Generation and Loads," in IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 7, no. 2, pp. 262-270, June 2017.

[14] V. Mohan, J. G. Singh, and W. Ongsakul, "An efficient two stage stochastic optimal energy and reserve management in a microgrid," Appl. Energy, vol. 160, pp. 28–38, Dec. 2015.

[15] R. N. Allan, B. Borkowska, and C. H. Grigg, "Probabilistic analysis of power flows," the Institution of Electrical Engineers, vol. 121, pp. 1551-1556, 1974.

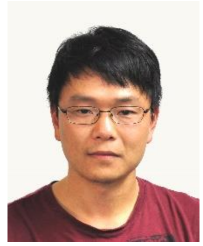
[16] A. M. Leite da Silva, V. L. Arienti, and R. N. Allan, "Probabilistic Load Flow Considering Dependence Between Input Nodal Powers," IEEE Transactions on Power Apparatus and Systems, vol. PAS-103, pp. 1524-1530, 1984.

[17] Pei Zhang and S. T. Lee, "Probabilistic load flow computation using the method of combined cumulants and Gram-Charlier expansion," in IEEE Transactions on Power Systems, vol. 19, no. 1, pp. 676-682, Feb. 2004xssd

[18] A. Schellenberg, W. Rosehart and J. Aguado, "Cumulant-based probabilistic optimal power flow (P-OPF) with Gaussian and gamma

distributions," in IEEE Transactions on Power Systems, vol. 20, no. 2, pp. 773-781, May 2005.
[19] M. Fan, V. Vittal, G. T. Heydt and R. Ayyanar, "Probabilistic Power Flow Studies for Transmission Systems With Photovoltaic Generation Using Cumulants," in IEEE Transactions on Power Systems, vol. 27, no. 4, pp. 2251-2261, Nov. 2012.
[20] Chun-Lien Su and Chan-Nan Lu, "Two-point estimate method for quantifying transfer capability uncertainty," in IEEE Transactions on Power Systems, vol. 20, no. 2, pp. 573-579, May 2005.
[21] J. M. Morales and J. Perez-Ruiz, "Point Estimate Schemes to Solve the Probabilistic Power Flow," in IEEE Transactions on Power Systems, vol. 22, no. 4, pp. 1594-1601, Nov. 2007.
[22] Munkhammar J, Mattsson L, Ryde´n J (2017) Polynomial probability distribution estimation using the method of moments. PLoS ONE 12(4): e0174573
[23] B. H. Kim, M. L. Baughman, "The economic efficiency impacts of alternatives for revenue reconciliation", IEEE Trans. Power Syst., vol. 12, no. 3, pp. 1129-1135, Aug. 1997.
[24] C. Gu and F. Li, "New development in distribution network pricing for revenue recovery in the Great Britain," 2011 IEEE Power and Energy Society General Meeting, San Diego, CA, 2011, pp. 1-5.
[25] Ofgem, "Strategy decision for the RIIO-ED1 electricity distribution price control-Uncertainty mechanisms", March 2013.

Xinhe Yang was born in Fujian, China. He received the B.Eng. degree in electrical and electronic engineering from the University of Bath, Bath, U.K., and the B.Eng. degree in electrical power engineering from North China Electric Power University, Baoding, China, both in 2016. He is currently pursuing the Ph.D. degree in electronic and electrical engineering with the University of Bath. His main research interests include power system planning and power systems economics.



Chenghong Gu (M'14) was born in Anhui, China. He received the bachelor's degree in electrical engineering from Shanghai University of Electric Power, Shanghai, China, in 2003, the master's degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2007, and the Ph.D. degree from the University of Bath, Bath, U.K, in 2010. He is currently a Lecturer with the Department of Electronic and Electrical Engineering, University of Bath. His major research interests include multi-vector energy system, smart grids, and power economics.

Xiaohe Yan (S'16) was born in Shaanxi, China. He received the Bachelor's degree in electrical engineering from the Xi'an University of Technology, Xi'an, China, in 2013, and the Master's degree in electrical power system and Ph.D. degree in power system from the University of Bath, Bath, U.K., in 2015 and 2019, respectively. He is currently a Research Associate with the University of Macau. His major research interest interests include the area of power system planning, analysis, and power system economics.

Furong Li (SM'09) received the B.Eng. degree in electrical engineering from Hohai University, Nanjing, China, in 1990, and the Ph.D. degree in electrical engineering from Liverpool John Moores University, Liverpool, U.K., in 1997, with a dissertation on applications of genetic algorithms in optimal operation of electrical power systems. She is currently a Professor and the Director of the Center for Sustainable Power Distribution, University of Bath, Bath, U.K. Her major research interests include the area of power system planning, analysis, and power system economics.