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Network Pricing with Investment Waiting Cost based on Real Options under Uncertainties

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***Abstract*—Existing capacity-based network pricing uses discounted cash flows to calculate network costs, unable to reflect the uncertainties and flexibilities of the network users. Such shortcoming could distort the cost-reflectivity of pricing signals, particularly those for renewables and flexible technologies, causing more constraints and curtailment issues in networks. Corresponding to these issues, this paper designs a new pricing method, Incremental Cost Network Pricing based on Real Options (ICOC), which can reflect network user uncertainties on network investment by using real options theory. Under this concept, network operators can delay investment for a certain period by paying waiting cost based on options' value until more information is available, thus avoiding non-reversible investment due to uncertainties. The options' cost will be levied on network users as i) rewards if they provide flexibilities to the system, or ii) waiting costs if they present uncertainties to the system. The reward or cost to the network users is determined by a binomial tree pricing under a risk-neutral condition, which is added onto asset present value as the total cost to be recovered. Such cost is allocated to network users based on their nodal incremental costs. The proposed method is demonstrated on a practical network with different users, i) uncertain, ii) flexible; iii) certain and nonflexible. The new ICOC pricing scheme can capture the impact of network user uncertainty on network investment and thus set cost-reflective price signals to influence their behaviours.**

***Index Terms*—Network investment, Network Charges, Uncertainty, Real Options, Long-run Incremental Cost**

I. Introduction

To reduce CO_2 emission, renewables, electric vehicles (EVs) and energy storage are increasing [1]. Energy storage can change their energy utilisation behaviour by shifting load and thus provide flexibility [2] to the power system. For example, controllable storage can discharge during system peak and provide alternative ways to meet network capacity requirements, deferring network reinforcement. By contrast, in some cases, these technologies can introduce severe uncertainties, reducing the available capacity of the system and bringing close investment. For example, uncontrollable energy storage and EVs might charge at the peak power flow period, bringing along uncertainties to systems [3] and thus, the system unused capacity is reduced during peak time.

These new grid-connected technologies pose severe challenges on current network pricing schemes, which requests a new pricing scheme to recover investment costs and guide network users to use existing networks efficiently. The current network pricing schemes have two key steps: 1) evaluating asset costs and 2) allocating asset costs to network users. Since uncertainty or flexibility will directly increase or reduce system peak, they will add or reduce costs in evaluating network investment. Currently, long-run incremental cost (LRIC) pricing [4] and Forward Cost Pricing (FCP) [5]are investment-oriented and they are widely used in UK distribution networks. LRIC is designed based on unused capacity and FCP evaluates asset investment cost on a 10-year horizon. Although LRIC is more efficient than FCP to reflect the locational information of network users [4], they both are not fit for the new environment.

Current schemes assume that the network must be invested after a certain year, normally determined by the Net Present Value (NPV) approach [6]. The NPV approach, based on the discount cash flow method has the following defects. It does not consider uncertainty or flexibility in timing an investment. On the contrary, the reinforcement horizon should become dynamic. The impact of flexibilities and uncertainties should be considered and evaluated. Uncertainty suggests that there is a potential cost of forwarding investment. By contrast, flexibility provides potential benefits by deferring system investment. It is longer if load growth is small due to those flexibilities can reduce peak demand, vice versa. Thus, the future investment of networks should 'wait and see' to acquire more information before making investment decisions [7]. In addition, the current network pricing schemes cannot reflect the ability of future demand management of network users. Thus, the traditional pricing scheme overestimates the use-of-system charge of flexible loads and underestimates that for uncertain loads. The network users should get incentives by providing flexibility and be penalised by posing uncertainties.

One key challenge in incorporating uncertainties into network pricing is to model them while evaluating investment costs. Generally, there are two methods, the weighted average cost of capital (WACC) [8] and real options [9]. WACC calculates the cost of capital, where each category of capital is proportionately weighted. It assumes that the risk is constant and new projects will not impact the risk level, which is

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unrealistic in network pricing [10]. The real options method uses values associated with net present value and augments this with the cost of uncertainty [11, 12]. It addresses decision-making issues in sunk investments, based on giving up waiting cost resulting from future uncertainties. By paying the waiting cost, network operators could wait, i.e. defer investment, to receive more information and thus could reduce the impact of uncertainties on investment. Thus, it is normally used as a decision-making tool for future investment [13-15]. The real option pricing method can be divided into three main classes: 1) binomial tree model [16, 17]; 2) Monte Carlo simulation method [18-20] and 3) Black-Scholes model [14, 15]. All these approaches have some flaws when applied to real options valuation. Although the binomial tree model is less accurate than the Monte Carlo simulation method and the Black-Scholes model, it is a straightforward model and provides an analytical technique to calculate options costs in network investment. It offers more flexibility by altering the inputs in each step to include the differences in the ability to exercise an option. The optimal risk-averse investment policies also can be analysed via the real options method [16]. It provides an opportunity to access more information regarding users' behaviours in the future to reduce the impact of uncertainties. Paper [17] uses the real options method to convert the impact of uncertainties on future network investment into the waiting costs to reduce the risk of investment decision making under uncertainty, which avoids non-reversible investment. Although some studies [21] evaluate the uncertainty of load by setting a high load growth rate, it is not accurate to capture the behaviour of network users on investment.

The cost allocation method can be classified into two main groups, which are 1) levied averagely over the network users (such as postage stamp [22], DRM [23]and FCP [5]) and 2) levied based on the cost causation principle [24] (such as LRIC and LMP [25]). LRIC and LMP allocate the cost based on the incremental or marginal effect of load change considering the location differences, which have significant advantages to give cost-reflective incentives to the load and generations.

This paper proposes a novel Incremental Cost Network Pricing based on the Real Options (ICOC) approach, which can reflect the uncertainties of the network users. Firstly, the original reinforcement horizon of networks is calculated based on the present value and peak flows of branches. Then, the waiting cost or rewards of network assets/branches to be invested is quantified to reflect uncertainties based on the risk-neutral theory. The uncertainty level is classified into different scenarios to show their contributions to peak branch flows. Thus, the investment cost is determined by asset present value and augmented with waiting cost or rewards. After evaluating the cost to be levied from uncertain and flexible loads, it is allocated to network users based on their contribution to peak power flows along branches. Network users providing flexibility can receive negative waiting cost, i.e. rewards, resulting from investment deferral. The waiting cost or reward is allocated to the network users according to the impact of uncertainty on peak branch flow the binomial option pricing model. The proposed method is compared with the LRIC pricing method by demonstrating on a UK GSP network.

This paper has the following key contributions.

- It designs a new network pricing method with a dynamic network investment horizon, which can capture the impact of customer uncertainties on network investment, thus making investment more flexible and efficient;
- It defines the costs of uncertainty and rewards for flexibilities via real options method based on customer's impact on future network investment, in which way the price signals are more cost-reflective to influence customer behaviours;
- enhances the fairness of the pricing scheme. It means flexible users receive more incentives and uncertain users pay higher charges.

The rest of the paper is organised as follows: Section II designs the ICOC pricing method based on real options for different types of users under uncertainty or flexibility. Section III gives an outline of the whole process. Sections IV demonstrate the model in a practical distribution network. Section V draws the conclusion.

II. Network Pricing Method Based on Real Options

Network pricing scheme design contains two key steps, 1) investment cost evaluation and 2) cost allocation. The impact of uncertainty on network investment decision making is evaluated as waiting cost based on the real options method in previous work [17]. This work focuses on cost allocation based on the uncertain and flexible features of different users. It shows that the waiting cost can be captured by the real options method, which could evaluate the additional cost resulting from network investment deferral. Paying the waiting cost provides an alternative way for network owners under uncertainties, reducing risks and costs simultaneously. [17] provides a theoretic method for this work to evaluate network costs under uncertainty and flexibility. In traditional LRIC, the allocated cost is asset cost over its whole life span with a certain reinforcement horizon. The ICOC is designed to reflect the impact of uncertainty on network prices by combining the LRIC and the real options method.

A. Cost in Traditional Network Pricing

Traditional network pricing scheme uses discount cash flow. The present value of assets is determined in (1). The time to reinforcement horizon is calculated in (2) to show the time horizon when the power flow reaches branch capacity [4].

$$PV_0 = \frac{Asset_l}{(1+dr)^{n_l}} \tag{1}$$

$$n_l = \frac{\log C_l - \log P_l}{\log(1+r_l)} \tag{2}$$

where power flow P_l can grow to capacity C_l after year n_l with the load growth rate r_l, dr is the discount rate, and $Asset_l$ is the asset cost of this branch.

Normally, the mean value of predicted peak demand is used in the calculation, which means the actual demand peak may be higher than the predicted value under the worst-case. Thus, with

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the same predicted mean value, uncertain load contributes more to the system peak, reducing network unused capacity. For example, uncontrolled electric vehicle charging might increase system peak. Flexible load has the capability to reduce peak load and increase spare capacity for the system by offering flexibility. For example, energy storage can discharge during the system peak period when the energy price is high, providing flexibility to the system. The flexibility level is evaluated in terms of peak reduction.

B. Options Pricing Method for Uncertainty

The real options method provides an opportunity for network owners to defer system investment by paying the waiting cost based on the real options method. This allows network investors waiting for more information about systems in the future to make investment decisions, which reduces the impact of uncertainties on system planning. To reflect the impact resulting from uncertainties, asset cost evaluation should be reformed by adding waiting cost with asset present value.

To evaluate the options cost resulted from uncertainty, the binomial options pricing method [9] is applied, which is a numerical method. The binomial pricing model uses binomial lattice (tree) to determine the present value in a number of time steps from now to the end. Each node in the tree represents a possible present value of the asset in a particular time step, called the term and it is assumed to be one year in this paper. The binomial options method performs recursively, starting from each final node (the step at right side treetop) and then calculating backwards through the tree towards the first node (the left side root of the tree), as shown in Fig.1. There are three key steps in determining the option's value: 1) creating a binomial tree; 2) calculating the waiting cost at the final node; 3) calculating the waiting cost back to the start node.

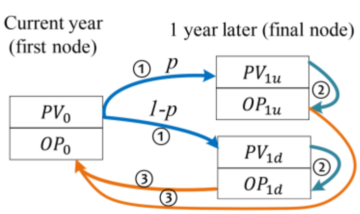

Fig.1. The tree method for one term.

Under an uncertain environment, by assuming the time step to be one year, the asset present value is PV_0 in the current year. The asset present value is shown in (3). With a probability of p, the asset present value will grow u times to PV_{1u}. By contrast, with a probability of $1-p$, it will decrease d times to PV_{1d} one year later.

$$PV_1 = PV_{1u} \times p + PV_{1d} \times (1-p) \tag{3}$$

$$u = \frac{PV_{1u}}{PV_0} \tag{4}$$

$$d = \frac{PV_{1d}}{PV_0} \tag{5}$$

OP_{1u} and OP_{1d} are the waiting cost for asset present value change resulting from the possibility of present value increase or decrease one year later, shown in (6-7).

$$OP_{1u} = max(0, PV_{1u} - PV_1) \tag{6}$$

$$OP_{1d} = max(0, PV_{1d} - PV_1) \tag{7}$$

Based on the risk-neutral method, the difference between the probability present value and the options' value equals the risk-free portfolio (the present value one year later PV_1) in (8).

$$PV_{1u} - OP_{1u} = PV_{1d} - OP_{1d} = PV_1 \tag{8}$$

Based on the discount cash flow model, the present value of the investment one year later is determined by riskless interest rate r_r in (9). Thus, in the current year, the waiting cost (OP_0) can be evaluated in (10) based on the [9]. Combining (8) with (9), the present value change probability over time is derived in (11).

$$PV_0 = e^{-r_r t} \times (PV_{1u} - OP_{1u}) \tag{9}$$

$$\begin{aligned} OP_0 &= e^{-r_r t} \times [OP_{1u} \times p + OP_{1d} \times (1-p)] \\ &= e^{-r_r t} \times [\tfrac{e^{r_r t}-d}{u-d} \times OP_{1u} + \tfrac{u-e^{r_r t}}{u_0-d} \times OP_{1d}] \end{aligned} \tag{10}$$

$$p = \frac{e^{r_r t}-d}{u-d} \tag{11}$$

where, specific factors u and d describe the present value change from the current year to the next year, and t is the length of the period.

C. Multi-Terms Binomial Options Pricing Model

If an investment horizon is n_l years, the binomial pricing method should be extrapolated to n_l years, which is the concatenation of the single term trees introduced in (3-11).

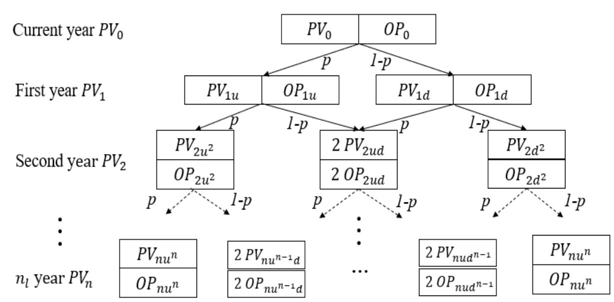

Fig.2. Multi-Terms of the option.

Thus, the waiting cost calculates the value from the final node in the year n_l to the current year. Based on the binomial tree method, the waiting cost in year $n_l - 1$ can be calculated based on the waiting cost in the year n_l. Therefore, the waiting cost for users with uncertainties can be iterated to the current year with n_l times recursivation, shown in (12). This procedure is shown in Fig.2.

$$OP_0 = e^{-r_r t} \times \left[\sum_{i=0}^{n} \frac{n_l!}{i! \times (n_l - i)!} \times p^i \times (1-p)^{n_l - i} \times \Delta PV\right] \tag{12}$$

$$\Delta PV = \max(0, u^i \times d^{n_l - i} \times PV_0 - PV_n) \tag{13}$$

where ΔPV is the present value difference between the starting node and the final node, i is the index of the year ($i \leq n_l$).

D. Incremental Cost Allocation

The current pricing schemes assume that networks should be invested after a certain year when the capacity is fully loaded

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and asset cost is allocated to network users based on their contribution to system peak power change.

The peak power flow change due to nodal power changes is determined by the linearised DistFlow model [26, 27]. An index matrix, inspired by the power transfer distribution factor, is built by the sensitivity of the injected nodal power on branch power flow changes in (14). The power flow change on branch l is ΔP_l due to the additional power change (ΔP_N) on node N. Index $M_{n,l}$ is used to measure the impact of load or generation located at node N on branch l's flow.

$$M_{n,l} = \frac{\Delta P_l}{\Delta P_N} \tag{14}$$

The reinforcement horizon will change to n_{l_new} with the nodal injection or withdrawal, expressed as [4]:

$$n_{l\_new} = \frac{\log C_l - log(P_l + \Delta P_l)}{log(1 + r_l)} \tag{15}$$

In the incremental cost pricing, the change of the present value and the waiting cost resulting from the nodal energy change are calculated respectively in (17-18) [4] :

$$PV_{l\_new} = \frac{Asset_l}{(1+dr)^{n_{l\_new}}} \tag{16}$$

$$OP_{0\_new} = e^{-r_r t} \times \left[\sum_{i=0}^{n} \frac{n_{l\_new}!}{i! \times (n_{l\_new} - i)!} \times p^i \times (1-p)^{n_{l\_new} - i} \times \Delta PV_{new}\right] \tag{17}$$

$$\Delta PV_{new} = \max(0, u^i \times d^{n_{l\_new} - i} \times PV_{0\_new} - PV_{new}) \tag{18}$$

Since the waiting cost allows network investors to obtain more information before making an investment decision, it is reasonable to add the waiting cost in evaluating the cost to be recovered under uncertainties. Therefore, the waiting cost is added to the present value ($PV + OP$), forming the recovery cost (Rct). The incremental cost for network users with uncertainties is:

$$ICOC_N = \frac{\Delta(Rct)}{\Delta P_N} = \frac{\sum_l [(PV_{l_{new}} + OP_{0_{new}}) - (PV_l + OP_0)]}{\Delta P_N} \times af \tag{19}$$

where, the annuity incremental cost of the branch is calculated based on the difference between the sum of asset present value in terms of ΔP_N. af is the annuity factor. The incremental cost to support node N is the summation of the incremental cost overall branches it uses.

E. Reward Method for Flexibility

Since uncertainties reduce the available capacity of the system, the load with flexibility addresses this challenge by moving away the demand from peak time. Because peak power flow can be reduced due to flexibility, the present value at the final node is smaller than that at the start node. Thus, the waiting cost for customers, setting as a reward i.e. negative cost, can be calculated based on the risk-neutral theory for customers providing flexibility. At the final point, the incentives of the probability value for the users providing flexibility, OPf_{1u} and OPf_{1d}, are derived in (20-21) from (6-7). The reward for users providing flexibility at the current point is in (22).

$$OPf_{1u} = max(0, PV_1 - PV_{1u}) \tag{20}$$

$$OPf_{1d} = max(0, PV_1 - PV_{1d}) \tag{21}$$

$$Rd = -OP_1 = -e^{-r_r t} \times [\frac{e^{r_r t} - d}{u-d} \times OPf_{1u} + \frac{u - e^{r_r t}}{u-d} \times OPf_{1d}] \tag{22}$$

The reward is added to the present value ($PV + Rd$) as the cost recovery (Rct). Therefore, if uncertainty load evolves into flexible load, they can get incentives instead of the punishment by reducing system peak and consequently total investment.

III. Implementation Process

There are two main stages in setting pricing signals to network users, which are cost evaluation and cost allocation. These two steps are depicted in Fig.3 to show the whole implementation procedure.

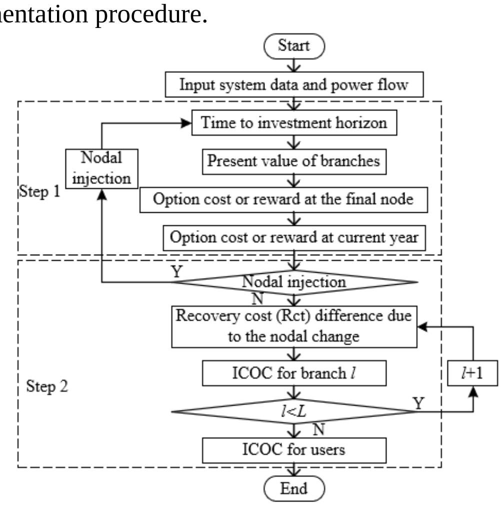

Fig. 3. Flowchart of the whole implementation process

A. Stage 1: Recovered Cost Evaluation

Two parts of the cost, asset present value and addition cost (waiting cost or reward), should be recovered from network users. The cost to be recovered is recalculated by considering the uncertainty of network users through the real options method. In this stage, the reinforcement horizon of network assets and the recovered cost are determined. Firstly, with system data, system peak power flow can be determined and accordingly the reinforcement horizon for each branch can be calculated. Because the present value converts the asset cost from the future year back to the current year, the final node of the waiting cost or reward should be calculated at the year when investment occurs. The number of terms of the binomial tree in options calculation equals the reinforcement horizon. The waiting cost or reward is directly determined by network users' uncertainty or flexibility level. With reinforcement horizon (n_l) and waiting cost or reward at the final node in the year n_l, it is easy to calculate waiting cost or reward in the current year backwards from n_l.

B. Stage 2: Cost Allocation

To allocate the cost to be recovered to network users, the incremental cost pricing method is implemented. The

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incremental cost is derived by a nodal power injection at each node. Then, the difference of the recovery cost as a result of the nodal injection can be calculated for each branch. For network users at node *N*, the recovery cost difference due to the nodal injection is summarised from all the branches that support them. The steps will terminate to calculate ICOC for different network users.

IV. PRACTICAL NETWORK DEMONSTRATION

A practical UK Grid Supply Point area distribution network is selected to demonstrate the proposed models in Fig.4 [28]. The slack bus is modelled as a generation (G1008). To simplify the demonstration, the peak demand, normally evaluated via worst case, is assumed as 3-sigma higher than the predicted mean value. It assumes that the peak power flow occurs at the peak load period assessed by the coincidence factor.

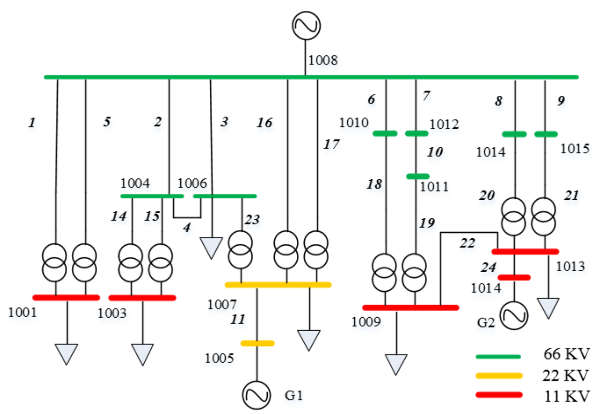

Fig.4. A Grid Supply Point area test system.

There are three scenarios are set to analyse the performance of the proposed pricing scheme: 1) The load at bus 1003 has EVs. On the one hand, it may contribute 5MW more than the predicted mean value to the peak demand due to its uncertain charging. On the other hand, it may offer 5MW flexibility if it is well regulated. 2) The network users at bus 1006 with controllable energy storage can provide 3MW flexibility to the system. 3) An auxiliary generation (G1) is located at bus 1005 with a peak predicted output of 5MW (mean value), which may generate less 1MW and contribute to peak power flow due to the uncertainty. Assuming the branches asset lifespan is 40 years with an annuity factor 0.0831 [4]. Typical load growth is 2% and the discount rate is 5.6% and network losses are neglected in this work.

The capacity of branches No.2 and No.3 is 24MW. The interconnector (branch No.23) between two voltage levels has a capacity 6.5MW. The highest asset cost is £1.85 billion from branch No.2, which has a significant impact on network charges for load and generation. Although the transformers have different capacities, the asset costs are assumed as £0.44 million.

A. *Pricing Signal for Non-regulated EVs*

The non-regulated EVs, as uncertain load, at busbar 1003 reduces the unused capacity of the system due to its uncertainty and the waiting cost and network charges from the branches that support this load are analysed.

Since the uncertainty of network users increases the peak demand, the branches that support this node will have positive waiting costs with their power flow increases. The predicted mean value of the demand peak for the users at busbar 1003 is 28.4MW, which may increase to 33.4MW due to its uncertain charging. As shown in Table I, the waiting cost for branch No.2 is £122.8k and the waiting cost for branch No.15 is only £21.8k. This is because of the asset cost difference and the contribution difference of the load at busbar 1003 to these branches.

TABLE I
The waiting cost of each branch (MW)

Branch	No.2	No.3	No.14	No.15	No.16	No.17	No.23
Cost(£k)	122.8	114.5	22.6	21.8	53.3	42.5	33.4

With the determined waiting cost of each branch, the network cost can be calculated and compared with the existing LRIC pricing method, which is shown in Fig.5. The blue bars represent the branch charges from the LRIC pricing method and the red bars are determined from the ICOC pricing method. The network charge from branch No.2 increases £442.8/MW from £7555.9/MW to £7998.7/MW due to the reduced unused capacity from the uncertainty. It increases £165/MW from branches No.14&15. However, this uncertainty also makes the branches network charges decrease from -£71.8/MW to -£96.4/MW from No.4 and decrease from -£319.8/MW to -£329.6MW from branch No.23.

In total, the network charge for the non-regulated EVs at bus 1003 is £20876.1/MW, considering the waiting cost of uncertainty. Although the demand peak only increases 5MW resulting from uncertainty, the use of system charge is £1106.3/MW higher than that calculated from LRIC, which is £19769.8/MW.

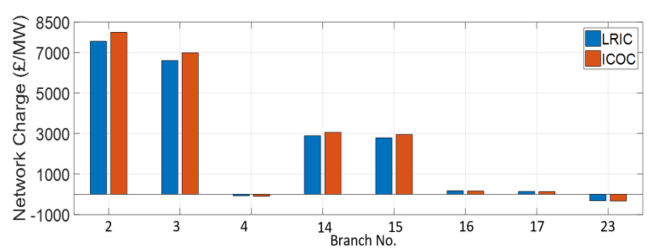

Fig.5. The network charges for non-regulated EVs from different branches.

B. *Pricing Signal for Energy Storage Offering Flexibility*

The pricing for energy storage, as flexible load, at bus 1006 offering system flexibility is demonstrated. It can offer 3MW branch flow decreases at the peak power flow time, which can reduce its demand peak from 20.2MW to 17.2MW.

Based on the risk-neutral theory, the reward of different branches, listed as negative cost, are shown in Table II. The branches that support this node will have a reward if their branch flows are decreased. Branches No.2 & No.3 have the lowest reward, £118.1k & £110.2k, due to the high asset cost and the flexibility contribution from the network user at bus 1006. The flexibility offered by the customers significantly defers future investment, giving more incentives to promote flexibility.

TABLE II
The reward of each branch (MW)

Branch	No.2	No.3	No.14	No.15	No.16	No.17	No.23
Cost(£k)	-118.1	-110.2	-22.4	-21.6	-52.9	-42.2	-32.3

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Based on the reward for the flexibility from energy storage at bus 1006, the network charges are determined in Fig.6. The blue bars are network charges from LRIC and the red ones are from the proposed ICOC method. The flexibility of energy storage reduces network charges. The network charge at branch No.2 decreases by £354.1/MW from £6274.2/MW in LRIC to £5920.1/MW in ICOC. The charge at branch No.3 is £6187.0/MW from the LRIC pricing method, which drops to £5838.0/MW by the proposed ICOC. The network charges at branch No.23 increases from -£338.8/MW to £-319.6/MW, but this impact is very small compared to the reduction of the other two branches.

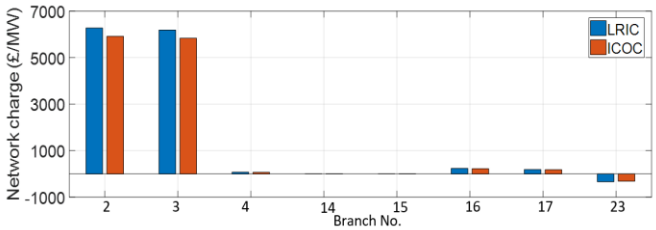

Fig.6. Network charges for energy storage at bus 1006 from different branches.

In summary, the network charge for the user with energy storage at busbar 1006 is the summation from the supported branches. The LRIC for this user is £12616.6/MW and it decreases by £735.6/MW in ICOC by £11881.0/MW when considering flexibility in the pricing method.

C. Pricing Signal for Renewable Generation with Uncertainty

For renewable generation at bus 1005, the uncertainty increases network charges from positive waiting cost, shown in Table III. The waiting cost of branch No.2 is £11.7k and for branches No.16 & No.17, the waiting costs are £4.4k and £3.5k.

TABLE III
The waiting cost of each branch (MW)

Branch	No.2	No.3	No.14	No.15	No.16	No.17	No.23
Cost(£k)	11.7	10.9	2.4	2.3	4.4	3.5	2.6

Branch No.23 is taken as an example for analysis in Fig.7. This binominal tree shows the present value and options value change on branch No.23. In the current year, the peak power flow is 5.85MW and the present value is £60.6k with renewable generation at bus 1005 (peak predicted output of 5MW). With the load growth rate, the power flow peak will increase to 5.97MW according to the Power Transmission Distribution Factor (PTDF) matrix based on the DC power flow, with 5MW renewable output at busbar 1005. However, because of the uncertainty from the renewable generation, its peak output is assumed to be 4MW, which will reduce less peak power flows on branch 23. The peak power flow on this branch will be 6.06MW according to the PTDF matrix based on the DC power flow with a possibility of 97%.

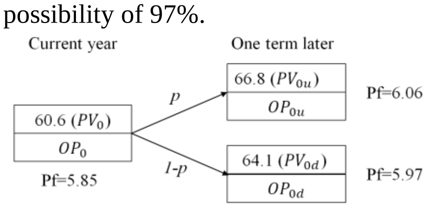

Fig.7 The binomial tree for branch No.23 under renewable uncertainty

The network charges for the renewable generation are negative from both LRIC and ICOC pricing methods, which is because generation gains benefit from the network by reducing peak branch flows shown in Table IV. However, due to the uncertainty of renewables, this benefit reduces resulting from the positive waiting cost, shown in Table IV. The network charges increase from -£37.1k to -£35.1k for branch No.16 and from -£29.6k to -£28.0k for branch No.17.

Therefore, the network charges for the generation at busbar 1005 increase 22.5% from -£1307k/MW produced LRIC model to -£1067k/MW generated from the proposed ICOC model due to the uncertainty.

TABLE IV
The network charges for renewables at bus 1005 from different branches

Branch	No.16	No.17	No.23
LRIC (£k)	-37.1	-29.6	-23.1
ICOC (£k)	-35.1	-28.0	-21.9

D. Pricing Signal Change for Regulated EVs

The EVs can provide flexibility if they are well regulated by the network operators. This section compares the pricing signal difference for regulated and non-regulated EVs. Sensitivity analysis is conducted to show the waiting cost or reward and network charge change with different loading levels from 10MW to 40MW. It assumes that the network users with EVs at busbar 1003 contribute 10% of the peak demand due to the uncertainty. However, if these EVs are properly controlled, the uncertainty can be transferred as the flexibility to the system, which is assumed to offer to 10% decrease of the peak demand. This case analyses the network charges change for EVs with uncertain and flexible features.

Fig.8 shows the waiting cost or reward change resulting from the EVs providing uncertainty with increasing the demand level. With behaviour change, the EVs are regulated and thus uncertainty changes to flexibility. The blue line represents the ICOC pricing signal change and the red one is the ICOC change with flexibility. When the loading level is low, the waiting cost or reward for different users is low. At loading level 10MW, the waiting cost is £2710 for the uncertain EVs operation and the reward is £4070 for the regulated EVs for their flexibility. The reward for flexibility increases more dramatically with increasing load level. This is because the slope of the present value is steeper at a higher loading level, which means the present value change for the flexibility is more significant, which is reflected directly in the waiting cost or reward calculation. At loading level 40MW, the waiting cost for the uncertainty resulting from EVs is £122.9k and the reward is £184.7k for EVs if it provides flexibility. This means the network users with EVs can obtain more benefits if they are well regulated and offer flexibility under less unused capacity.

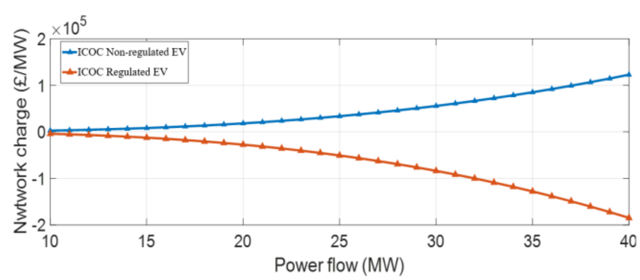

Fig.8. The waiting cost or reward change with demand increase

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Fig.9 shows network charge differences for EVs providing uncertainty, flexibility, and without both uncertainty and flexibility resulting from the status of its operation. If EVs are without any uncertainty or flexibility, the network charges for them are the same as LRIC pricing, which is represented in the blue bars. At a low loading level of 10MW, these three types of network charges for EVs are similar, around £1200/MW. This is because the unused capacity of the branches is sufficient to accommodate the load uncertainty. For network charges with uncertainty, represented by the orange bars, it increases higher than LRIC, which means the uncertainty makes EVs pay more network charges. It is £13930/MW, which is 5% higher than that from the LRIC pricing signal (£13230/MW) at loading level 40MW. The charges for regulated EVs that can offer flexibility to the system are depicted in the yellow bar. It increases slower than those in LRIC and ICOC. This means EVs providing flexibility will obtain more savings at high loading levels. At 40MW, the ICOC for flexible EVs is £12180/MW, which is 8.6% less than the LRIC pricing signal and 14.3% less than ICOC for the EVs with uncertainty at the same loading level.

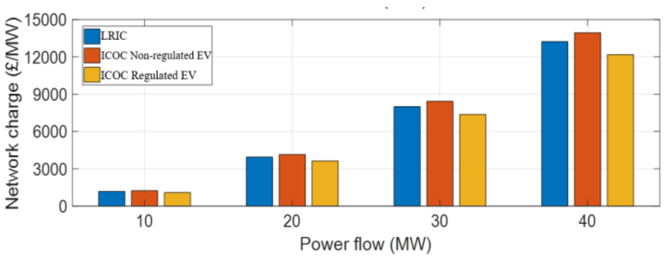

Fig.9. Network charges comparison with load increase

E. Sensitivity Analysis for the Uncertainty Level Change

The sensitivity analysis is applied to the load on busbar 1001. The transmission capacity is 45 MW between busbar 1008 and 1001, and the peak demand on bus 1001 is 30MW in the current year. The load with certainty will grow under load growth rate r_l. Thus, the waiting cost or reward is zero and network charges for these customers are the same as the charges calculated by the original LRIC.

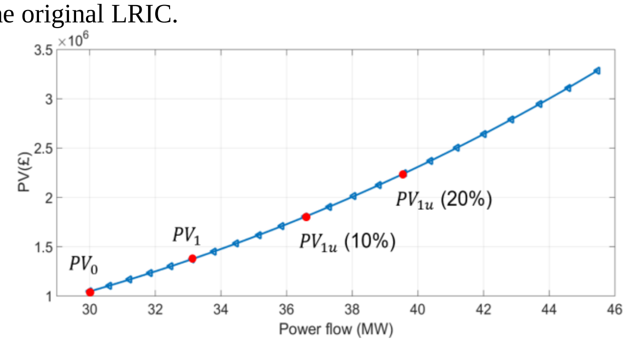

Fig. 10. The present value change for different uncertainties

Assuming that the load grows to 36.43MW under small uncertainty (10%) and grows to 39.74MW with big uncertainty (20%). In the current year, the power flow is 30MW with the present value of £1046.5k (PV_0) for the branch. The peak will grow to 33.12MW with no uncertainty (the present value PV_1 of the branch is £1373.9k) after one term. Under small uncertainty, the present value of the branch will grow to £1785.6k (PV_{1u} 10%) and grow to £2268.4k (PV_{1u} 20%) under big uncertainty, which is given in Fig. 10.

To determine the waiting cost of network users under small uncertainty (10%), the binomial tree is built in Fig.11. Based on (1-7), the possibility (p) is determined to be 9.91% and the waiting cost at the current year is £38.1k. It also assumed that it has $(1-p)$ possibility to keep the same loading level, which with the waiting cost zero. Similarly, the waiting cost for the network users with big uncertainty is £50.1k. Thus, the cost to be recovered (Rct) is £1084.6k and £1096.6k for the branch under small and big uncertainty respectively.

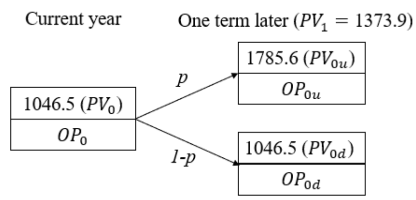

Fig.11. The binomial tree under small uncertainty

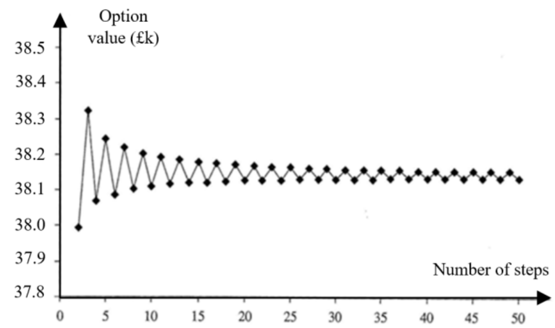

Fig.12 The convergence of the cost of the options

If the term (yearly) can be divided into shorter iteration terms (in months), the waiting cost at the final node is more accurate. Fig.12 shows the convergence of the waiting cost for network users with small uncertainties. Dividing the original annual term into shorter terms, although the waiting cost of the first iteration term is £38.0k not equal to the convergence value, the difference is less than 0.3% and is neglectable.

For the customers who can provide flexibility to the system, it is assumed that those with big flexibility can offer 20% branch peak reduction and 10% peak reduction with small flexibility. Based on the binomial pricing method, the reward is determined through the binomial tree. It assumes that the loading level will have a possibility of (1-p) to keep the same for network users with flexibility. The PV_{1u} will change to £783.1k and £566.3k for the users with small and big flexibility respectively. Therefore, for network users with small flexibility, the reward is £54.3k. It is £61.0k for network users with big flexibility. These are the investment savings due to the flexibility of the customers, which will give them lower use-of-system charges. This special change is mainly because 1) the negative cost means that the cost to recover from network users is lower than that in the original asset present value in NPV or LRIC model due to the investment deferral; 2) the reward for users can offer large flexibility is smaller, but its absolute value is high, which means they can enjoy more reduced revenue recovery. Thus, it makes the new present values £992.2k and £985.5k for the branches under small and big flexibility.

Considering the uncertainty and flexibility of network users, the cost to be recovered is changed by adding the waiting cost or reward to the asset present value. The present value, waiting cost or reward and incremental pricing signal for users under different levels of uncertainty or flexibility are shown in Fig.13. The area in blue shadow represents the original present value (£1046.5k) in the current year without considering any uncertainty or flexibility of network users. The grey bar above the present value in the figure represents the waiting cost, which means the total cost to be recovered from customers (Rct in the red) becomes larger due to its uncertainty. The green bar is the reward, which means the total cost to be recovered from customers becomes lower due to the flexibility it provided.

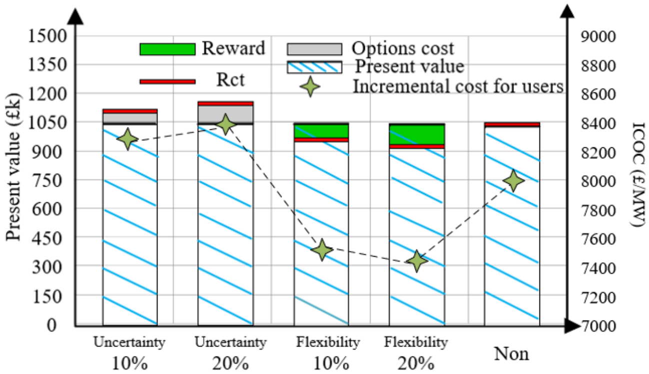

Fig.13. Pricing signal for users under different uncertainty or flexibility

The pricing signals can be calculated from the difference of asset value change based on the incremental cost with nodal injections. The original network price is £7999.3/MW in LRIC, which is the same for network users without uncertainty or flexibility. It increases to £8283.6/MW and £8374.0/MW for users with small and big uncertainty respectively based on ICOC. For network users that can provide small or big flexibility to the system, the network cost will reduce to £7585.4/MW and £7533.8/MW respectively. This implicates that network users with more flexibility will have lower network charges and network users with more uncertainty will have higher charges.

V. Conclusions

This paper designs a novel pricing scheme for network users to capture their uncertainty and flexibility, and consequently the impact on network investment. It can help network operators to reward or penalise network users according to their contribution to network investment deferral. Through extensive demonstration, the following key findings are obtained:

- The flexibility or uncertainty of network users can be captured by the risk-neutral theory and reflected in the network cost evaluation.
- The proposed ICOC pricing scheme efficiently incentivises flexible load and penalises uncertain load;
- The load with high flexibility enjoys low network charges, which allows the existing network to accommodate more load and generations without reinforcing the branches.

This work is beneficial to further the capability increase of distribution networks to accommodate increasing renewable penetration. In addition, it provides a powerful tool for network operators to evaluate users' behaviour and it can affect the use of system behaviour of network users to increase the efficiency of network utilisation. Since the key innovation of this work is to design the new pricing scheme for uncertain and flexible load, the evaluation of uncertainty and flexibility levels are not considered but will be conducted in future work.

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