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Economic optimization of smart distribution networks considering real-time pricing

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Abstract With the development of smart meters, a real-time pricing (RTP) demand response is becoming possible for households in distribution networks. The power flow can be bidirectional in distribution networks which become smarter with distributed generators (DGs). It is expensive to import electricity from the generation far from load centers because of the cost of power loss and network use, so that it is more economical to use electricity generated by local distributed generators. Therefore, in order to curtail operating costs of distribution networks, this paper proposes a model of economic optimization conducted by distribution network operators. The electricity purchasing costs for distribution network operators are minimized by optimizing electric power from transmission systems and local distributed generators. Further, based on price elasticity, the formulations of load demand considering RTP are proposed with economic optimization of distribution networks. The economic optimization problems are resolved by an interior point method. The case study shows that peak load demand can be reduced about 3.5% because the household RTP and electricity purchasing costs of distribution network operators can save 28.86 £ every hour.

Keywords Distribution network, Economic operation, Electricity cost, Real-time pricing

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1 Introduction

With the development of smart meters, a real-time pricing (RTP) demand response is becoming possible and necessary for households to save their electricity expense. Household RTP also has significant potential for peak-shaving and load-shifting even though its price elasticity is smaller than industry RTP. Therefore, it is important for electric power system operators to make full use of household RTP. Recent studies mainly focused on how to increase proportion of using intermittent energy resources by RTP in electric markets [1–9]. Based on time-dependent and price-dependent characteristics of RTP, a RTP model used in day-ahead markets is built to minimize the expected total payment in [2]. A 24×24 price elasticity matrix is built to indicate the hourly varying rates to study the effects of demand reduction on system voltage [3]. RTP is modeled by adopting marginal pricing to justify the price function at a base price associated with base load level in a residential area [5]. In [6], the implementation of price based on demand response by an industrial consumer can increase the proportion of using wind power electricity. A game theoretical model accounting for the Stackelberg relationship between retailers and consumers in a dynamic price environment is proposed in [10]. These efforts are aimed at saving payment of wholesale markets or resolving problems in present electric power systems by RTP. Very limited efforts have been put into the following researches: (1) how to make full use of RTP from small household consumers; (2) what direct effects does household RTP make on the economy of both distribution networks and households; (3) how to include RTP into economic operation in distribution networks.

Furthermore, in recent years, with energy price increasing, the electricity price is to keep rising as well. In USA, average annual electricity price increased by 17% from

2003 to 2011. The average residential retail price also increased by 45%, from 8.72 cents per kilowatt-hour in 2003 to 12.61 cents per kilowatt-hour in July 2013 [11]. The rise of electricity prices leads to the rise of product costs, and then raises the consumer price index (CPI). As we know, rapid increasing of CPI shows that there is an inflation. Therefore, reducing electricity costs should be paid more attention. It is effective to reduce the operating cost of distribution networks by the distribution costs which account for about 16% of the electricity costs in UK. However, the structure of distribution networks currently is becoming more complex and cannot be modeled as a passive node because of the demand response and distributed generators (DGs) [12]. Furthermore, distribution networks transport electricity from DGs instead of transmission systems to end customers, which not only reduce distribution network usage cost but also potentially avoid congestion in transmission systems [13–22]. In [15], the optimal objectives are maximizing the power usage from DGs and the power usage costs of distribution networks. It is obvious that many research efforts have been done to overcome the intermittent of DGs which are included in distribution network optimal operation. However, reducing electricity costs of consumers with the consideration of DGs in distribution networks has not been tackled yet. Moreover, the concept of implementing economic optimization in distribution networks has not been investigated in depth in the literatures.

To this end, this paper develops an economic optimization in distribution networks with the consideration of demand response enabled by household RTP. It is based on two assumptions: (1) end consumers can receive hourly wholesale market electricity prices one day ahead; (2) distribution network operators have the right to buy electric power from both transmission systems and local DGs without considering suppliers or retailers in. The small household RTP is modeled with demand price elasticity. The optimal objective is to minimize the operation cost for distribution network operators. In addition, the impact of price elasticity on electric power purchasing cost of distribution network operators is investigated in this paper as well. The classic optimal algorithm—interior point method is used to resolve the optimization model. The proposed methods are demonstrated in IEEE 33-busbar system.

2 Characteristics and formulation of RTP

2.1 Definition

Real-time pricing programs in which customers are charged at hourly fluctuating prices reflect the real costs of electricity in the wholesale market [9]. Compared with other kinds of demand response, RTP is fully flexible for the following reasons: (1) it does not need baseline price; (2) it changes based on wholesale real-time prices. Economists believe that RTP programs are the most efficient and direct for enabling demand response programs in competitive markets [9].

The prices are informed to RTP customers according to hourly electricity price in the wholesale electric market one day ahead. Therefore, customers have enough time to plan their responses, such as shifting use (often by shifting load to off-peak hours or by using onsite generation) or hedging day-ahead prices with other products if they cannot curtail their demand [10]. Hence, the day-ahead RTP is more suitable for day-ahead optimization of distribution networks.

2.2 Formulations

Price elasticity of demand is a measurement of the relationship between the changes in the quantity demanded of a particular good and its price. It can reflect the price sensitivity of demand to energy price. The price elasticity of demand can be written as:

$$\varepsilon = \frac{(Q_{\text{new}} - Q_{\text{old}})/Q_{\text{old}}}{(P_{\text{rnew}} - P_{\text{rold}})/P_{\text{rold}}} \tag{1}$$

where ε is price elasticity rate of demand, $\varepsilon \leq 0$; P_{rnew} and P_{rold} are prices after changing and before changing, respectively; Q_{new} and Q_{old} are the quantity demand corresponding to P_{rnew} and P_{rold}, respectively. When the price increases, the demand always decreases, leading to price elasticity being negative. The larger the value of $|\varepsilon|$, the more sensitive quantity demand is to price changes.

The price elasticity rate of RTP can be written as:

$$\varepsilon = \frac{P_{\text{RTP}}(t)/P_{\text{initial}}(t)}{E_{\text{var}}(t)/E_{\text{initial}}(t)} \quad (\varepsilon \leq 0) \tag{2}$$

From (2), P_{RTP} is derived as:

$$P_{\text{RTP}}(t) = \varepsilon \frac{E_{\text{var}}(t)}{E_{\text{initial}}(t)} P_{\text{initial}}(t) \tag{3}$$

Then, the updated load demand considering RTP is written as:

$$\begin{aligned} P_{\text{Lopt}}(t) &= P_{\text{initial}}(t) + P_{\text{RTP}}(t) = \left(1 + \varepsilon \frac{E_{\text{var}}(t)}{E_{\text{initial}}(t)}\right) P_{\text{initial}}(t) \\ &= \Delta \bullet P_{\text{initial}}(t) \end{aligned} \tag{4}$$

$$\Delta = \left(1 + \varepsilon \frac{E_{\text{var}}(t)}{E_{\text{initial}}(t)}\right) \tag{5}$$

where $P_{\text{RTP}}(t)$ is the variation power supplied by RTP demand response at time t; $E_{\text{inital}}(t)$ is the initial wholesale market price at time t; $E_{\text{var}}(t)$ is the wholesale market price variation at time t corresponding to $E_{\text{inital}}(t)$; $P_{\text{Lopt}}(t)$ is the updated load demand at time t; $P_{\text{initial}}(t)$ is the initial load demand at time t before considering RTP; Δ is the updated coefficient.

3 Economic optimization of smart distribution networks

3.1 Assumptions

Based on practical situations, following assumptions have been made for accomplishing economic optimization in distribution networks.

1) The electricity prices and the capacity of DGs are known to distribution network operators.
2) Distribution network operators know the prices and the capacity of electricity supplied by utilities. Hence, the electric optimization is implemented by distribution network operators after the wholesale market closes one day ahead.
3) The prices of electricity bought from utilities by distribution networks are the same as the wholesale market price in each hour.

3.2 Structure of economic optimization in distribution networks

The economic optimization of smart distribution networks is conducted by distribution network operators. The system structure of economic optimization in smart distribution networks is shown in Fig. 1. There are two steps to accomplish the optimization. Firstly, updating load profile by RTP using Eqs. (2)–(4). Secondly, optimizing power output from transmission system (also called the utility in this paper) and DGs to meet the optimized load with the least power purchasing cost, meanwhile recognizing operational limits of distribution networks.

At the first step, the initial load is forecasted by daily load of distribution networks, composed of urban residential load only. The hourly fluctuating electricity price of wholesale markets is informed to domestic consumers a day ahead. The domestic consumers decide how much RTP they will supply according to the fluctuating prices and feedback the data to distribution network operators. Then, the distribution network operator updates the initial load and calculates the updated load demand according to RTP.

At the second step, DGs are owned by domestic consumers. Their electricity prices and the capacity that can supply to distribution networks are clarified in contracts between domestic consumers and the distribution network operators. The utility is the transform system that supplies

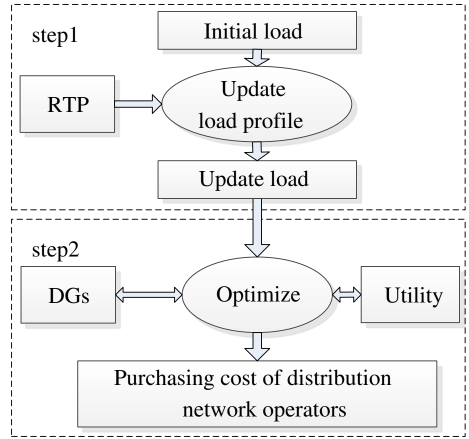

Fig. 1 System structure of economic optimization at distribution networks

electricity to the distribution network, and it is supposed that there is only one utility connecting to the distribution network. The distribution network operator optimizes the electricity bought from DGs and the utility each hour one day ahead to meet the updated load demands.

3.3 Formulations of economic optimization of distribution network operators

The economic optimal objective of distribution network operators is to minimize electricity purchasing costs for distribution network operators.

$$\min C(t) = C_{\text{trans}}(t)P_{\text{trans}}(t) + C_{\text{DG}}(t)P_{\text{DG}}(t) \tag{6}$$

where $C(t)$ is electricity purchasing cost of a distribution network operator at time t; $C_{\text{trans}}(t)$ is the price of electricity bought from transmission system at time t; $C_{\text{DG}}(t)$ is the price of electricity bought from DG; $P_{\text{trans}}(t)$ is electricity bought from transmission system at time t; $P_{\text{DG}}(t)$ is electricity bought from DG at time t.

The main constraints of economic optimization of distribution network operators are as follows:

1) *Power Balance*: The sum of the power purchased from transmission grid and the total power generated by the different DG sources must be balanced by the optimal local demand and the power loss in the transmission lines.

$$P_{\text{trans}}(t) + P_{\text{DG},i}(t) = P_{\text{Loss}}(t) + P_{\text{Lopt}}(t) \tag{7}$$

2) *Price elasticity equation*:

$$\varepsilon = \frac{P_{\text{RTP}}(t)/P_{\text{initial}}(t)}{E_{\text{Var}}(t)/E_{\text{initial}}(t)} \tag{8}$$

3) *Load curtailment*: The RTP supplied by resident c must be less than the maximum variation permitted power.

$$0 \le P_{\mathrm{RTP,c}}(t) \le \max P_{\mathrm{RTP,c}}(t) \tag{9}$$

where $P_{\mathrm{Loss}}(t)$ is power loss in all circuits in a distribution network; max $P_{\mathrm{RTP,c}}(t)$ is the maximum variation permitted in power for resident c.

3.4 Models of DGs

DGs can be classified into dispatchable DGs and inflexible DGs. The former dispatchable DGs include small thermal generators, micro combined heat and power unit (CHP), etc. Inflexible DGs include wind generators, photovoltaic generators, etc. To be typical, DGs consist of wind and CHP in this paper.

1) *Wind turbine*: wind speed profile is modeled as Weibull density function. Then, the expected value of wind power output is described as [23]:

$$\begin{aligned} P_{\mathrm{W},i,\mathrm{ex}}&(t+1) \\ &= \int_0^{P_{\mathrm{w},i,\mathrm{r}}} P_{\mathrm{W},i}(t+1) f_\omega\big(P_{\mathrm{W},i}(t+1), t+1\big) dP_{\mathrm{W},i}(t+1) \\ &\quad + P_{\mathrm{w},i,\mathrm{r}} f_\omega\big(P_{\mathrm{W},i}(t+1), t+1\big) \end{aligned} \tag{10}$$

where $P_{\mathrm{w},i,\mathrm{ex}}(t)$ is the expected output of wind turbine i; $P_{\mathrm{w},i,\mathrm{r}}$ is the rate of wind turbine; $P_{\mathrm{w},i}\ (t)$ is the power output of wind turbine i; f_ω is the wind power probability density function.

The wind power is seen as the negative load, which is adopted by distribution network operators.

2) CHP: the production cost of CHP is defined as [24]:

$$\begin{aligned} C_i\big(P_i^{\mathrm{c}}, H_i^{\mathrm{c}}\big) = a_i\big(P_i^{\mathrm{c}}\big)^2 + b_i P_i^{\mathrm{c}} + c_i + d_i\big(H_i^{\mathrm{c}}\big)^2 + e_i H_i^{\mathrm{c}} \\ + f_i H_i^{\mathrm{c}} P_i^{\mathrm{c}} \end{aligned} \tag{11}$$

where $C_i(P_i^{\mathrm{c}}, H_i^{\mathrm{c}})$ is the cost of the CHP in unit i; a_i, b_i, c_i, d_i, e_i and f_i are coefficients.

CHP can be dispatched by distribution network operators freely and be paid as their contracts.

4 Demonstration

The IEEE 33-node test system with 33 nodes and 37 branches, is taken as an application example to demonstrate the proposed concept. The reference voltage at slack bus is 12.66 kV. The initial active power load for the whole system per hour is shown in Table 1. The slack bus voltage and the angle are assumed to be 1 and 0, respectively. It is supposed that households at all nodes but slack bus node can access to RTP and their price elasticity rate is the same. There are 10 CHP generators of 50 kW placing on nodes 15, 22, 24 and 20 CHP generators of 50 kW connecting to node 30. 10 wind generators of 10 kW are on node 7 and node 32, and 20 wind generators of 10 kW are connected to nodes 24 and 25, as shown in Fig. 2. In this distribution network, electricity prices of CHP and the wind generator are set as 60 and 128.8 £/MWh, respectively. The hourly wholesale market electricity prices are shown in Table 1 [25].

Table 1 Initial load and wholesale market electricity price

Time	Initial load (MW)	Electricity price (£/MWh)	Time	Initial load (MW)	Electricity price (£/MWh)
0:00	2.65	67.71	12:00	3.18	90.25
1:00	2.63	67.40	13:00	3.15	86.03
2:00	2.66	63.25	14:00	3.20	79.18
3:00	2.75	62.96	15:00	3.38	74.31
4:00	2.98	62.08	16:00	3.67	91.76
5:00	3.33	61.61	17:00	3.73	123.69
6:00	3.46	71.05	18:00	3.72	122.64
7:00	3.41	82.35	19:00	3.66	92.99
8:00	2.94	87.44	20:00	3.48	87.55
9:00	3.26	91.45	21:00	3.23	79.56
10:00	3.19	95.91	22:00	3.00	75.64
11:00	3.21	95.08	23:00	2.71	67.83

4.1 Electric optimal results when ε is -0.1

The first step is to update daily load profile with RTP according to Eqs. (3) and (4). Because the initial load demand and the initial electricity price of wholesale market at each hour are constant, the RTP at time t which households can supply is decided by ε. When ε is −0.1, the updated load demand profile is shown in Fig. 3. The more quickly wholesale market electricity prices change, the more RTP responses are. RTP can shave peak load effectively. Take 6:00 as an example, the wholesale market electricity price goes up to 71 from 61 £/MWh at 5:00, then RTP is -0.059 MW, that is the initial load demand is reduced from 3.82 to 3.76 MW. The highest wholesale market electricity price and the initial peak load demand are at 17:00. However, because of RTP, the load demand at 17:00 is curtailed about 3.5%. The peak load demand considering RTP happens at 19:00 when the wholesale market electricity price is 92.99 £/MWh, much lower than 123.69 £/MWh at 17:00.

The second step is to optimize the active power output of utility, CHPs and wind generators based on the optimal load demand. Without implementing economic optimization, distribution network operator needs to buy electricity of 3.51 MWh on average from the utility (transmission system) to meet the load demands every hour, which costs

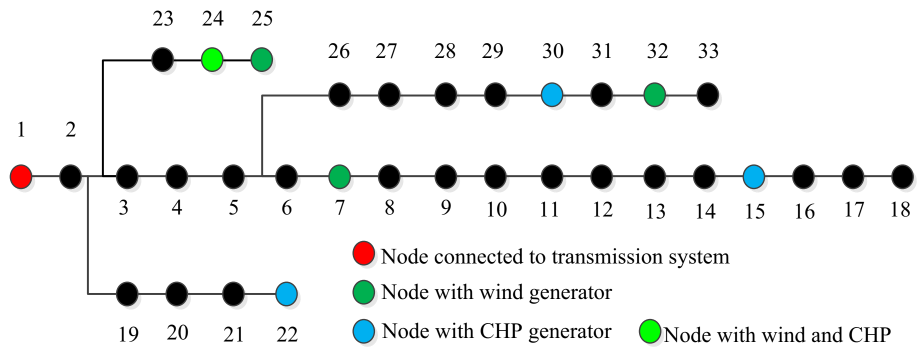

Fig. 2 IEEE 33-node test system

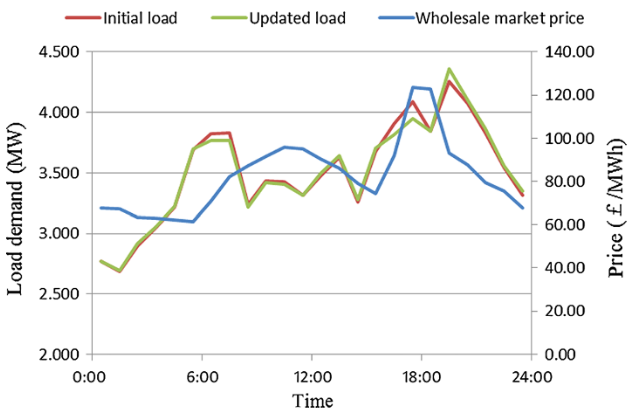

Fig. 3 Updated load demand considering RTP

289.54 £/h. Supposing that the purchasing cost of distribution networks account for 50% of consumer electricity cost, the average household electricity cost without economic optimization of distribution network is 164.98 £/MWh. When there is economic optimization in distribution network considering DGs, distribution network operators can buy electricity from DGs close to the end consumers.

The economic optimal results are shown in Table 2. In one day, the average electric power generated by wind generators every hour is 0.32 MW, the maximum is 0.6 MW from 19:00 to 21:00, and the minimum is 0.06 MW at 14:00. Although the electricity price of wind generators is higher than that of CHP and the utility, all electric power generated by micro wind generators is bought by distribution network considering the environment in this case. Electric power from CHP is dispatchable and cheaper than wind, so CHP plays an important role in economic optimization of distribution network. Electricity generated from CHP is much more than that from wind generators and is about twice as much as the utility. The average electric power from CHP each hour is 2.06 MW.

Correspondingly, electricity distribution network operators bought from the utility is 27.36 MW on one day after economic optimization considering DGs, reducing by 67.6%

Table 2 Electric optimization of distribution networks

Time	Wind (MW)	CHP (MW)	Utility (MW)	Purchasing cost	
				With optimization (£/h)	Without optimization (£/h)
0:00	0.12	1.77	0.88	181.24	187.55
1:00	0.06	1.76	0.88	172.64	181.98
2:00	0.24	1.78	0.90	194.64	184.69
3:00	0.30	1.82	0.94	207.02	192.66
4:00	0.24	1.94	1.05	212.50	200.52
5:00	0.36	2.13	1.22	249.33	228.57
6:00	0.36	2.18	1.24	265.27	268.57
7:00	0.42	2.15	1.21	282.74	311.28
8:00	0.30	1.93	1.01	242.75	283.31
9:00	0.18	2.10	1.15	254.35	313.67
10:00	0.24	2.06	1.12	261.93	328.01
11:00	0.10	2.08	1.15	247.02	316.62
12:00	0.30	2.06	1.14	265.13	315.88
13:00	0.48	2.05	1.12	281.18	314.01
14:00	0.06	2.09	1.17	225.77	262.88
15:00	0.30	2.17	1.24	260.98	275.69
16:00	0.24	2.26	1.33	288.55	351.44
17:00	0.36	2.28	1.34	348.91	492.29
18:00	0.12	2.33	1.41	328.18	473.39
19:00	0.60	2.35	1.41	349.40	405.44
20:00	0.60	2.22	1.29	323.42	359.83
21:00	0.60	2.10	1.17	296.37	307.90
22:00	0.54	1.96	1.06	267.33	269.28
23:00	0.60	1.82	0.93	249.56	227.23

of active power bought from the utility without economic optimization considering DGs, as shown in Fig. 4.

And then the average electricity purchasing cost of the distribution network operator is 260.68 £/h, saving 28.86 £/h than the case without economic optimization of distribution network considering RTP, as shown in Fig. 5. From 10:00 am to 19:00 pm, the electricity purchasing costs of

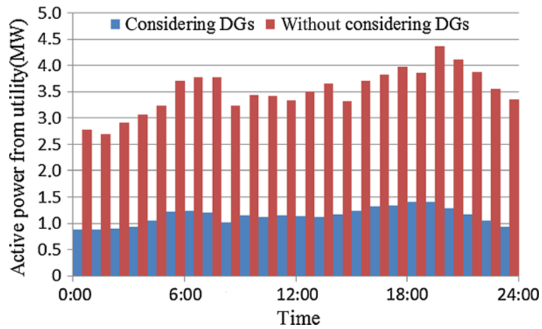

Fig. 4 Active power from uitility comparison

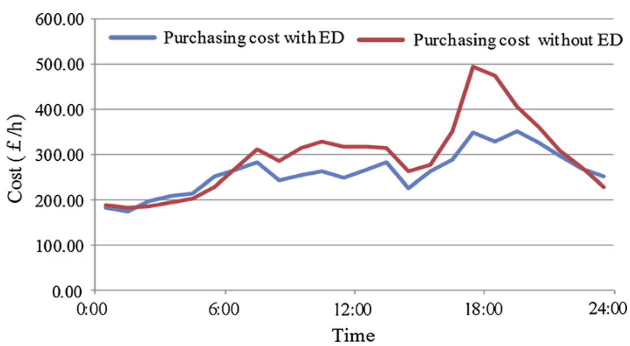

Fig. 5 Electricity purchasing cost curtailment in distribution networks

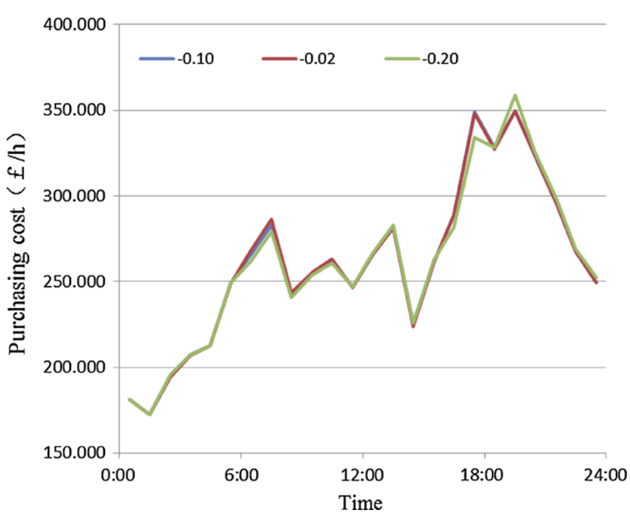

Fig. 6 Influence of price elasticity rate of RTP on economic optimization

distribution network operator with economic optimization are much smaller than that without economic optimization. Especially at 17:00 the electricity purchasing costs of distribution network operator are reduced from 492.29 to 348.91 £/h. This is because households on RTP shift their load when the wholesale market electricity prices increase, and distribution network operators buy a part of electricity from DGs instead of the utility by economic optimization. Therefore, the economic optimization of distribution networks considering RTP can save electricity procurement costs in distribution networks effectively.

4.2 Influence of price elasticity rate on economic optimization

The economic optimization results are shown in Fig. 6. When price elasticity rate of RTP are set as -0.02, -0.1 and -0.2, the amount of purchasing cost of distribution network operator on one day are 6,259.94 £, 6,256.21 £, 6,245.87 £, respectively. The larger the absolute value of price elasticity rate of RTP is, the more sensitive RTP is on the electricity price, and then the more money saved on the active power purchasing cost of distribution network operator. However, the difference of purchasing cost with each other on one day is very small. Therefore, although price elasticity of household RTP is smaller than that of industrial RTP, its benefits for electric power systems and end consumers cannot be neglected.

5 Conclusion

This paper proposes formulations of the updated load demand considering household RTP and builds the economic optimization model of distribution networks, considering DGs. The objective of the economic optimization for distribution network operators is to minimize the electricity purchasing costs of distribution network operators. As demonstrated by the case study, the generation cost for distribution networks can be reduced by 28.86 £/h. The economic optimization of distribution network operators considering RTP can use the active characteristics of present distribution networks and builds a direct economic relationship between distribution networks and domestic consumers. It is an effective way to update load demands and reduce household electricity costs. And by comparing the economic optimal results with different price elasticities, it is certified that household RTP can drive considerable benefits to networks and consumers although their price elasticity is smaller than that of the industrial RTP.

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