Citation for published version:
Zhang, Z, Li, F & Shi, H 2019, 'A Pricing Strategy Reflecting the Cost of Power Volatility to Facilitate Decentralized Demand Response', *IEEE Access*, vol. 7, pp. 105863-105871.
https://doi.org/10.1109/ACCESS.2019.2932499

DOI:
10.1109/ACCESS.2019.2932499

Publication date:
2019

Document Version
Peer reviewed version

Link to publication

A Pricing Strategy Reflecting the Cost of Power Volatility to Facilitate Decentralized Demand Response

Zhong Zhang [1], Furong Li [1], Senior Member, IEEE, Heng Shi [1]
[1] Department of Electronic & Electrical Engineering University of Bath, Bath, BA2 7AY, U.K.

Corresponding author: Zhong Zhang (e-mail: z.zhang3@bath.ac.uk).

ABSTRACT Previous pricing strategies including time-of-use price and dynamic price reflect system marginal cost and calculate consumers' bills according to the quantity of their electricity usage. Little effort is made to understand the impact of power volatility on total production costs. This paper thus proposes a novel pricing strategy reflecting the cost arising from power volatility. Firstly, the impact of volatility on the production cost is investigated to quantify volatility cost. Secondly, a novel pricing model is proposed to allocate the volatility cost to consumers and renewable energy generations (REGs). It can reveal the coupling relationship between an individual load/REG curve and the system load curve. Thirdly, under the proposed pricing strategy, customers/REGs help to flatten the system load curve and reduce the production cost in a decentralized manner, which is certificated theoretically based on the Haar wavelet transforms. Validation on residential level loads shows that the volatility and peak-to-valley difference of aggregated load curve is reduced by 34.07% and 19.81%, respectively. The problem of synchronous response among customers faced by hourly price strategies is addressed by the proposed strategy. A test on megawatt-level loads shows a 61.95% reduction in system load volatility and a 2.21% reduction in production cost. It also reduces the peak-to-valley difference by 6.52%.

INDEX TERMS Pricing strategy, volatility cost, correlation coefficient, decentralized demand response, wavelet transforms.

I. INTRODUCTION

To utilize flexible resources in the demand side to reduce the production and operational cost, various pricing strategies and demand response (DR) programs have been proposed. These pricing strategies and DR programs aim to reduce system load peak, decrease the production cost, and postpone network investment [1]-[10]. Increasing penetration of renewable energy generations (REGs) makes DR more important.

Pricing strategies adopted in practice and proposed in the literature include time-of-use (TOU) price [1], [2], day-ahead dynamic price [3], [4] and real-time price [5]-[7], which could reflect system marginal cost to some extent. Consumers' bills are computed according to the quantity of their electricity usage. However, these strategies and DR programs seldom explore the impact of load/REG volatility on the production cost, thus failing to reflect the cost caused by the volatility. This issue will be addressed in this paper. A novel pricing strategy reflecting the cost of volatility is proposed to motivate consumers to contribute to flattening the system load curve and reducing the total production cost in a decentralized manner.

A proper price strategy or a market mechanism in power systems should be cost-reflective, reduce system operational cost, and ensure fairness for all market participants. TOU price schemes divide a day into several segments and set different prices for them. These price schemes reflect the difference in marginal costs between peak and off-peak load periods and aim to reduce the load volume in the defined peak period. However, as the shiftable loads increase in power systems, TOU price schemes may create a new peak in the defined off-peak period due to the herding effect [11]. Similar schemes to TOU price involve critical peak pricing (CPP) [12] and peak load pricing (PLP) [13], [14].

Dynamic price (DP) and real-time price (RTP) schemes could reflect the system hourly marginal cost. Unlike TOU schemes defining a fixed price curve, DP schemes [3], [4] broadcast variable price signals to consumers. Sometimes, iteration processes are needed to update the prices until reaching to a convergent state. For example, in [5], [15] market models based on Stackelberg games are proposed for the electricity trading between an upstream supplier and multiple downstream consumers. Iteration and bi-directional communication are required to reach a stable price. Consumers need to submit their load curves in each iteration, which limits the participation of small residential consumers who are not smart enough to bid or compete in the market.

Under RTP schemes, prices are determined before the gate closure of each real-time trading period. Prices can reflect the real-time electricity supply and demand conditions [5]-[7]. However, continuous decision-making process and bi-directional communication are necessary, which makes DP and RTP schemes applicable to intelligent participants, such as consumer agents and aggregators [16], [17] rather than some small residential consumers, who are restricted by the ability of bi-directional online interaction.

With the increasing penetration of renewable energy resources, the power system will witness a problem of insufficient ramping capacity which is caused by the increasing volatility of system net load (load minus the power of REGs). This problem has been pointed out in [18]. Markets for flexible ramping products are investigated in [19], [20]. In these markets, controllable generators are economically compensated for their providing flexible ramping products. However, to our best knowledge, how to allocate the ramping cost among consumers and renewable energy sources has not yet been well addressed.

To investigate the cost related to the volatility and allocate cost among those who cause the volatility, i.e. consumers and renewable energy generators (REGs), we propose a novel pricing strategy considering the cost of volatility. Our pricing strategy satisfies three market axioms: **1)** The pricing model should follow the cost causation as much as possible. Market players causing cost should pay for it and those mitigating cost should be rewarded for it [21], [22]; **2)** In the short term, the pricing and allocation model should enable to reduce the production cost; **3)** In the long term, it should ensure the effective operation for the market. Contributions of this paper include:

i) The impact of load volatility on the production and operational cost is analyzed. Electricity production costs can be divided into electricity quantity cost and volatility cost. The quantity cost depends on the volume of electricity usage. The volatility cost is related to the volatility of the system net load curve. It is allocated among consumers and REGs.

ii) A novel apportionment factor for allocating the volatility cost among consumers/REGs is proposed. It reveals the correlation between an individual load/power curve and the system net load curve. This would establish an effective mechanism that penalizes consumers/REGs whose volatility has great alignment with that of the system net load curve, while reduces the bill of consumers who have little impact on the volatility of the system net load curve. The proposed apportionment factor has properties of normalization and additivity, which ensures market fairness and scalability.

iii) The pricing model motivates consumers to contribute to reducing the volatility and peak-to-valley ratio of system net load in a decentralized manner, which is certificated theoretically through Haar wavelet transforms and Cauchy Inequality Criterion. The DR scheme is achieved in a decentralized manner with no need for online interaction. It enables large consumers, such as industrial and commercial users, and small consumers, such as residential users participating in the market equally. From the long-term perspective, the proposed pricing strategy will not cause new peaks even in case of high penetration of flexible resources in the demand side. More meaningful, the proposed pricing model is applicable to the scenarios of consumers coexisting with REGs.

Detailed work is carried out in the following parts. The impact of the volatility on production cost is investigated in Section II. Cost-reflective pricing strategy and allocation model are presented in Section III. Consumers' DR model and how the decentralized DR is realized are illustrated in Section IV. In Section V, numerical simulation studies are implemented. Finally, Section VI concludes this paper.

II. ANALYSIS OF VOLATILITY COST

In the future power system with great penetration of renewable energy generations, the volatility of the system net load will have a great impact on the system operational cost. On the one hand, the volatility will cause the ramping, start-up, and shut-down of fossil fuel generators. On the other hand, volatility will increase the production cost from fossil fuel generators, which is analyzed in the following.

In power systems, the marginal cost depends on the fossil fuel generators and increases with the amount of net load [23], [24]. The marginal generation costs can be approximated as a linear function against the net load:

$$U = aP + b \tag{1}$$

where, U refers to the marginal generation cost; P refers to the net load power; a and b are two constants and a is positive.

The impact of load volatility on the production cost is investigated considering a fluctuating net load curve $\mathbf{P_1}$ and a flat load curve $\mathbf{P_2}$ as shown in FIGURE 1, where, $\mathbf{P_1} = \{P_{1,t}, t = 1, 2, \dots, \mathrm{N}\}$ and $\mathbf{P_2} = \{P_{2,t}, t = 1, 2, \dots, \mathrm{N}\}$.

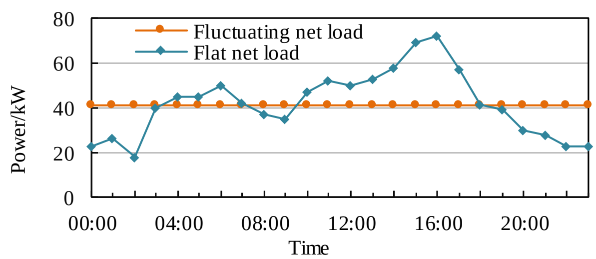


FIGURE 1. A flat load curve and a fluctuating load curve

To analyze the impact of volatility on the production cost, the total electricity consumption of the two load curves are assumed to be equal, namely:

$$\sum_{t=1}^{\mathrm{N}} P_{1,t}\,\mathrm{T} = \sum_{t=1}^{\mathrm{N}} P_{2,t}\,\mathrm{T} = E \tag{2}$$

$$P_{2,t} = P_m = \frac{E}{\mathrm{NT}} \qquad t = 1, 2, \dots, \mathrm{N} \tag{3}$$

where, E refers to the total electricity over a specific period, e.g. a day; P_m is the average power of each net load curve; T refers to the length of a time slot. N refers to the number of time slots.

Based on the function of marginal generation cost in Eq. 1, total production costs of the two net load curves are:

$$\begin{aligned} \mathrm{C}_1 &= \mathrm{T}\sum_{t=1}^{\mathrm{N}} P_{1,t}\left(aP_{1,t}+b\right) \\ &= \mathrm{T}\sum_{t=1}^{\mathrm{N}} (aP_{1,t}{}^2 + bP_{1,t}) = a\mathrm{T}\sum_{t=1}^{\mathrm{N}} P_{1,t}{}^2 + bE \end{aligned} \tag{4}$$

$$\begin{aligned} \mathrm{C}_2 &= \mathrm{T}\sum_{t=1}^{\mathrm{N}} P_{2,t}\left(aP_{2,t}+b\right) \\ &= a\mathrm{T}\sum_{t=1}^{\mathrm{N}} P_{2,t}{}^2 + bE = \frac{aE^2}{\mathrm{NT}} + bE \end{aligned} \tag{5}$$

where, C_1, C_2 refer to the electricity cost of load curve $\mathbf{P_1}$ and $\mathbf{P_2}$, respectively.

Based on the Cauchy Inequality Criterion: $k_1{}^2 + k_2{}^2 \geq (k_1+k_2)^2/2$, there is:

$$\sum_{t=1}^{\mathrm{N}} P_{1,t}{}^2 \geq \mathrm{N}P_m{}^2 \tag{6}$$

Substitute Eq. 6 into Eq. 4, and replace P_m by $/\mathrm{NT}$. It can be derived that:

$$C_1 \geq C_2 \tag{7}$$

Only if $P_{1,1} = P_{1,2} = \cdots = P_{1,\mathrm{N}}$, there is $\mathrm{C}_1 = \mathrm{C}_2$, otherwise $\mathrm{C}_1 > \mathrm{C}_2$.

Eq. 7 indicates that the production cost of a fluctuating net load curve is higher than a flat load curve. The difference between C_1 and C_2 is caused by the volatility of the fluctuating net load.

$$\begin{aligned} \mathrm{C_v} = \mathrm{C}_1 - \mathrm{C}_2 &= a\mathrm{T}\sum_{t=1}^{\mathrm{N}} (P_{1,t}{}^2 - P_{2,t}{}^2) \\ &= a\mathrm{T}\sum_{t=1}^{\mathrm{N}} [(P_{1,t}-P_{2,t})^2 + 2P_{1,t}P_{2,t} - 2P_{2,t}{}^2] \\ &= a\mathrm{T}[\sum_{t=1}^{\mathrm{N}} \left(P_{1,t}-P_m\right)^2 + \sum_{t=1}^{\mathrm{N}} 2(P_{1,t}-P_{2,t})P_{2,t}] \\ &= a\mathrm{T}\sum_{t=1}^{\mathrm{N}} (P_{1,t}-P_m)^2 = a\mathrm{TN}S_1{}^2 \end{aligned} \tag{8}$$

where, $\mathrm{S}_1{}^2$ is the variance of fluctuating net load curve, $\mathrm{C_v}$ is the volatility cost.

Eq. 6 indicates that the production cost of a flat net load curve only depends on the quantity of the total electricity usage. This part of the cost is referred to as the quantity cost in this work. Eq. 8 indicates that the volatility cost of a net load curve is proportional to the variance of the load curve, namely $a\mathrm{TN}S_1$, which is referred to as the volatility cost in this work.

Without loss of generality, for any form of marginal cost function, the total product cost of a flat net load curve is defined as the quantity cost. The difference between the costs of a fluctuating net load curve and the corresponding flat load curve is defined as the volatility cost. Costs related to the ramping, start-up and shut-down of fossil fuel generators also belong to the volatility cost, which is allocated to consumers and REGs through the proposed pricing strategy in the next Section.

III. PRICING AND ALLOCATION MODEL

Unlike most existing electricity markets that allocating the total cost to consumers just according to the quantity of their electricity usage, the proposed pricing strategy considers both the quantity and the volatility of consumers' electricity usage, as well as the volatility of REGs.

For the two parts of the total cost, i.e. quantity cost and volatility cost, the quantity cost is allocated to consumers according to the quantity of their electricity usage and the volatility cost is allocated to consumers/REGs according to the impact of their volatility on the net load volatility. Unlike the electricity quantity, the volatility does has the feature of additivity. For example, the algebraic sum of all load/REG's variances is not equal to the variance of the net load curve, as given by Eq. 9. A reasonable apportionment factor needs to be defined.

$$\sum_{i=1}^{\mathrm{M}} S_i{}^2/S_{\mathrm{n}}{}^2 \neq 1 \tag{9}$$

where, $S_i{}^2$ is the variance of a load/REG curve i; S_{n} is the variance of the net load curve; M is the number of consumers and REGs.

A. DEFINITION OF APPORTIONMENT FACTOR FOR VOLATILITY COST

The apportionment factor for volatility cost is defined to satisfy the first axiom that consumers causing costs should pay for it and those mitigating costs should be rewarded for it [22]. A load/REG curve that is positively correlative to the net load curve will aggravate net load volatility and give rise to the increase of the total volatility cost, and vice versa.

The impact of an individual load/REG's volatility on the net load volatility depends on two factors: scale factor and correlation factor. In detail, the scale factor refers to the volatility degree of a load/REG curve. The correlation factor refers to its correlation with the net load curve. Accordingly, the product of the two factors is defined as the apportionment factor to allocate the volatility cost, as given by:

$$v_i = \frac{S_i}{S_{\mathrm{n}}} R_i \tag{10}$$

where, v_i refers to the apportionment factor. At the right side of Eq. 10, the first term S_i/S_{n} represents the scale factor and the second term R_i refers to the correlation coefficient between a load/REG curve and the net load curve. It reflects the synchronization degree between a load/REG curve and the net load curve.

The apportionment factor defined by Eq. 10 can properly allocate system volatility cost to customers because it has two inherent properties: normalization and additivity.

B. PROPERTIES OF THE PROPOSED APPORTIONMENT FACTOR

i) Normalization

The proposed apportionment factor has the property of normalization, i.e. the sum of apportionment factors of all loads/REGs is equal to 1 as described by Eq. 11. It ensures that total volatility cost can be exactly apportioned to loads/REGs.

$$\sum_{i=1}^{\mathrm{M}} v_i = 1 \tag{11}$$

The proof of Eq. 11 is given by Eq. 26 presented in the Appendix.

ii) Additivity

Additivity means that the sum of apportionment factors of curve i and j and equal to the apportionment factor of their combined curve, namely:

$$v_i + v_j = v_k \tag{12}$$

where v_k is the apportionment factor of the combined curve $\boldsymbol{P}_k$ ($\boldsymbol{P}_k = \boldsymbol{P}_i + \boldsymbol{P}_j$, namely $P_{k,t} = P_{i,t} + P_{j,t} \ \ \forall t$).

The proof of Eq. 12 is given by Eq. 27 presented in the Appendix. The proof of additivity can be easily extended to scenarios of more than two curves. The property of additivity makes the pricing strategy generalized and scalable. It will not cause confusion when two or more consumers/REGs collaborate to use one meter. In addition, the cost of small consumers will not be influenced by large consumers or consumer alliances.

In summary, the volatility cost is apportioned to consumers/REGs according to the proposed apportionment factor as given by:

$$C_{i,\mathrm{v}} = C_{\mathrm{n,v}} v_i \tag{13}$$

where, $C_{n,v}$ is the volatility cost of net load curve; $C_{i,\mathrm{v}}$ is the volatility cost allocated to consumer/RES i; v_i is apportionment factor for allocating volatility cost defined in Eq. 10.

A consumer can cut down his electricity bills through reducing his electricity usage, load volatility or the correlation with the net load curve. A REG installed with energy storage can also reduce its volatility cost by reducing its volatility or correlation with the net load curve.

IV. DECENTRALIZED DEMAND RESPONSE (DR)

The proposed pricing strategy can reduce the net load volatility and peak-to-valley ratio. The transmission system operator (TSO) or distribution system operator (DSO) broadcast a forecast net load curve based on the day-ahead forecast of system load and REGs. Consumers can manage their electricity usage into an opposite trend against the net load curve to reduce their correlation with the net load curve. However, as the flexible resources increase in power systems. A high DR ratio may result in a reverse load fluctuation and even peak-to-valley inversion under TOU price [25]. To tackle this problem, the proposed pricing strategy can realize a decentralized DR, i.e. no forecast net load curve is broadcasted centrally in advance. The proposed pricing strategy can encourage consumers/REGs to reduce the volatility of their own load/output curve. Then, the volatility and the peak-to-valley ratio of the net load can be also reduced. The DR strategy for consumers/REGs is provided in Section IV-A. The decentralized DR effect is verified based on the Haar wavelet transforms in Section IV-B.

A. DR STRATEGY

When the total electricity demand/generation is fixed, a consumer/DEG can reduce its volatility cost by reducing the variance of its load/output curve under the proposed pricing model given by Eq. 10 and 13. The electricity usage strategy can be modeled as:

$$\min \sum_{t=1}^{\mathrm{N}} (p_{i,t} - P_{i,m})^2 \tag{14}$$

$$\mathrm{s.t.} \sum_{t=1}^{\mathrm{N}} p_{i,t} \mathrm{T} = E_i \tag{15}$$

where, $p_{i,t}$ refers to the load/output value after self DR measures; $P_{i,m}$ refers to the mean value of a load/output curve $\mathbf{P}_{\mathrm{i}}$. Eq. 15 indicates that the total electricity demand/generation is equal to E_i, which is constant. The objective function Eq. 14 is to minimize the variance of the load/output curve, which is equivalent to minimize the sum of squares of all load/output values because of:

$$\sum_{t=1}^{\mathrm{N}} (p_{i,t} - P_{i,m})^2 = \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - {E_i}^2/\mathrm{NT}^2 \tag{16}$$

The deduction of Eq. 16 is given Eq. 28 presented in the Appendix. ${E_i}^2/\mathrm{NT}^2$ is constant, so it has no impact on the optimization solution. The objective function (Eq. 14) of the DR model can be rewritten as:

$$\min \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 \tag{17}$$

B. THEORETICAL PROOF OF THE DECENTRALIZED DR FUNCTIONALITY

The proposed pricing strategy that charges consumers/REGs of their volatility can help to reduce the peak-to-valley ratio and the volatility of the net load curve. The theoretical proof based on Haar wavelet transforms and Cauchy Inequality Criterion is provided in this section.

Due to factors of living habit, production cycle, temperature and weather conditions, the correlation coefficient between consumer load profiles is generally positive [26], [27], which results in high volatility and peak-to-valley ratio in the aggregated system load curve. From the perspective of the frequency domain, the load curve can be decomposed into constant component and fluctuating components. The synchronization of fluctuating components in consumer load curves is the dominating factor causing the peak-to-valley difference in the system load curve. Hence, reducing fluctuating components in each load is in favor of reducing total volatility and peak-to-valley difference at the system level. The proposed pricing strategy that charges consumers of their load variance could promote consumers to reduce fluctuating components in their own load curves.

Wavelet Transforms (WT) is a popular technique in time-frequency transformations [28]. For an original function $f(t), t = 1, 2, \dots, \mathrm{N}$, it can be expanded in the basis of a set of wavelet functions:

$$f(t) = \sum_{j}\sum_{k} a_{j,k}\psi_{j,k}(t) \tag{18}$$

where, $\psi_{j,k}(x)$ refers to a wavelet function, $a_{j,k}$ refers to a wavelet coefficient, j refers to a scale factor, k refers to a time shift factor, N refers to the length of the time window.

Considering the Haar WT, its mother wavelet is defined as:

$$\psi_{0,0}(\mathrm{t}) = \begin{cases} 1, & 0 \le t \le \mathrm{N}/2 \\ -1, & \mathrm{N}/2 < t \le \mathrm{N} \\ 0 & otherwise \end{cases} \tag{19}$$

It can be translated and dilated by scale factor j and time shift factor k:

$$\psi_{j,k}(\mathrm{t}) = 2^{j/2}\psi_{0,0}(2^{j}t - k\mathrm{N}),\ \ j = 1,2 \dots, k = 0,1, \dots 2^{j} - 1 \tag{20}$$

The $a_{j,k}$ represents the "amount" of $f(t)$ presenting in wavelet $\psi_{j,k}$, and is calculated by:

$$a_{j,k} = \frac{1}{2^{j/2}}\sum_{t=1}^{N} f(t)\,\psi_{j,k}(\mathrm{t}) \tag{21}$$

Three levels of Haar wavelet functions are depicted in FIGURE 2.

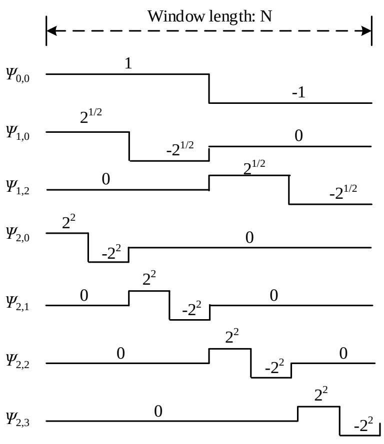


FIGURE 2. Three levels of Haar wavelet functions

The total "amount" of $f(t)$ presenting in level j of wavelet functions, namely the sum of $a_{k,j}$, $k = 0,1, \dots 2^{j} - 1$, is equal to:

$$A_j = \sum_{k=0}^{2^{j}-1} a_{j,k} = \sum_{t=1}^{\mathrm{N}} f(t)\,\phi \tag{22}$$

$$\phi = \begin{cases} 1, & 0 \le mod(2^{j}t, \mathrm{N}/2^{j}) \le \mathrm{N}/2 \\ -1, & \mathrm{N}/2 < mod(2^{j}t, \mathrm{N}/2^{j}) \le \mathrm{N} \end{cases} \tag{23}$$

A_j refers to the amount of fluctuating component in $f(t)$ on level j. According to the Cauchy Inequality Criterion: $(k_1 + k_2)^2 \le 2({k_1}^2 + {k_2}^2)$, there is:

$$A_j{}^2 = (\sum_{t=1}^{N} f(t)\,\phi)^2 \le \mathrm{N}\sum_{t=1}^{\mathrm{N}} f(t)^2 \tag{24}$$

Eq. 24 indicates the sum of squares of all values of $f(t)$ multiplied by N provides an upper bound to the square of A_j. Consequently, minimizing the variance of load curve through Eq. 17 could lower the upper bound of the amount of the fluctuating component in a load curve. It further reduces the aggregated load peak and volatility at the system level. And the relevant production cost will be reduced, which satisfied the second axiom: in the short term, the pricing and allocation model will encourage to reduce the production cost.

In summary, under the proposed pricing strategy, the DR scheme is achieved in a decentralized manner. There is no need of online communication between the upstream operator and downstream consumers/REGs. To reduce their volatility cost, consumers/REGs are encouraged to flatten their own load/output curves in a decentralized manner.

V. CASE STUDIES AND ANALYSIS

Case studies are conducted on several cases including consumers on the residential level (based real smart metering data [29]) in Section V-A to D, consumers on the residential level coexisting with PV generation in Section V-E, and large consumers on the megawatt level (based on real data from a UK project [30]) in Section V-F.

A. COST-REFLECTION AND RATIONALITY OF THE PRICING STRATEGY

In the first case, 10 real residential load curves and the aggregated curve are presented in FIGURE 3. Their variances, correlation coefficients, and volatility apportionment factors are given in FIGURE 4.

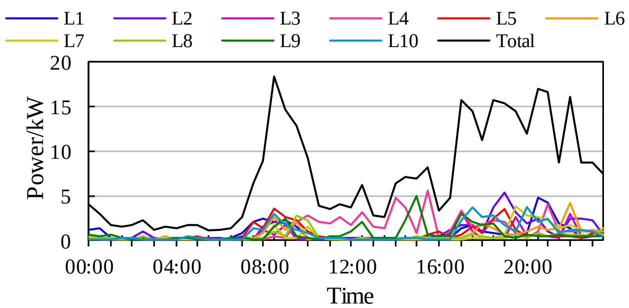


FIGURE 3. 10 consumer load curves and the aggregated load curve

The volatility apportionment factors of all consumers are positive, indicating that they have positive impacts in aggravating the volatility of the total load curve. The volatility apportionment factors have a similar trend as the correlation coefficients. Generally, if a consumer load is more strongly correlated to the total load, it will undertake more volatility cost. Although load No. 4 has a relatively high variance, its apportionment factor is relatively small because of its weak correlation with the total load curve.

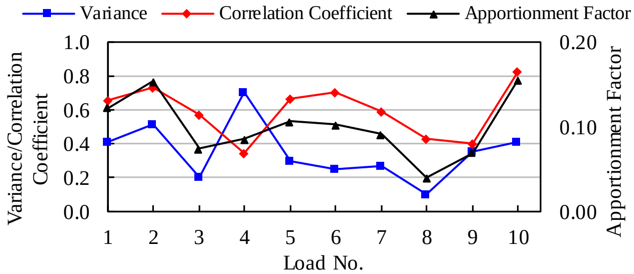


FIGURE 4. Relevant indicators of 10 consumer load curves

A consumer's bill is relevant to the quantity of his electricity usage, variance, and correlation with the system load curve. The pricing model can be easily applied to a large number of small consumers without increasing the operational or computational complexity, which means that the pricing strategy has good scalability.

B. EFFECT OF DECENTRALIZED DR

Each consumer reduces its bill by minimizing its load variation. Assuming that each consumer has 10% of shiftable load at each time slot, after self-management/DR, the wavelet components in all load curves at each level have been reduced as shown in FIGURE 5. Those relatively high fluctuating components are reduced significantly after DR.

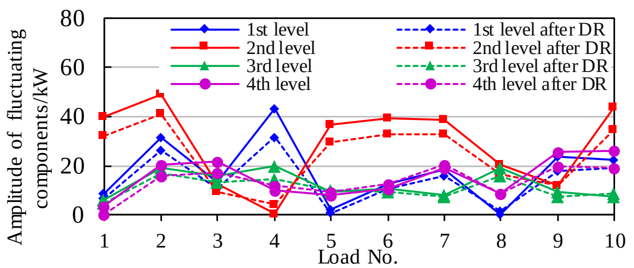


FIGURE 5. Amount of fluctuation components before and after DR

The aggregated load curves before and after DR are given in FIGURE 6. The peak-to-valley difference and variance of the aggregated load curve are reduced by 19.81% and 34.07%, respectively.

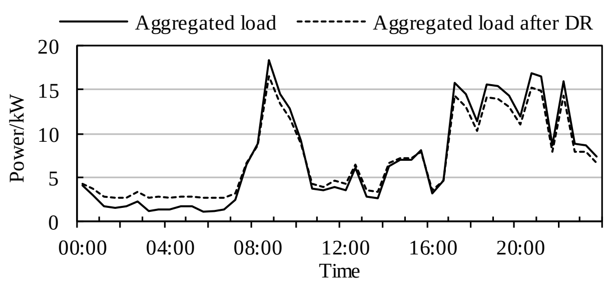


FIGURE 6. Aggregated load curves before and after DR

C. FAIRNESS OF THE COST ALLOCATION MODEL

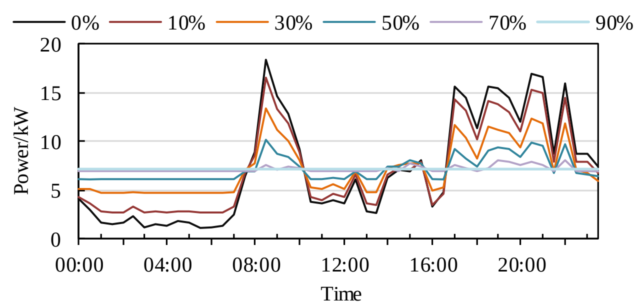
Market fairness is ensured by the additivity of the proposed model. It means that even if a number of consumers cooperate and connect to the system using one meter, they cannot reduce their total bills and have no impact on other consumers. Supposing that 5 consumers numbered 6 to 10 cooperate to use one meter and is denoted by L6', the recalculated volatility apportionment factor of the alliance L6' is 0.47, equal to the sum of their respective apportionment factors as shown in TABLE I. It indicates that a larger consumer or a consumer alliance will not undermine the benefit of other small dispersed consumers, verifying the fairness of the proposed pricing strategy.

TABLE I.
Volatility apportionment factor before and after cooperation

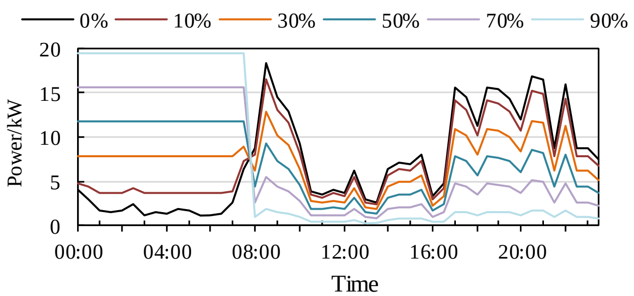
	L6	L7	L8	L9	L10	Sum	L6'
Apportionment Factor	0.12	0.10	0.04	0.05	0.18	0.47	0.47

D. COMPARISON OF PROPOSED PRICING MODEL TO TOU MODEL

The proposed pricing model will not cause peak-to-valley inversion even if a large proportion of loads transforms into flexible loads. The proposed pricing model is compared with TOU price model considering several flexibility levels (10%, 30%, 50%, 70%, 90%) of the load. DR results are shown in FIGURE 7. It shows that when the flexibility degree reaches to 50%, the aggregated system load is approaching a flat curve under the proposed pricing strategy, while peak-to-valley inversion appears under the TOU strategy. Results verify that the proposed pricing strategy can ensure the effective operation of the electricity market in the long run, which follows the third axiom presented in Section 1.



a) Total load curve after DR under the proposed pricing strategy



b) Total load curve after DR under TOU strategy

FIGURE 7. DR results considering different percentages of shiftable loads

E. ADAPTABILITY TO RENEWABLE ENERGY RESOURCES

The proposed model can be extended to scenarios with REGs, such as PV. Its revenue is calculated based on the electricity quantity that it supplies. Meanwhile, it is required to undertake the volatility cost.

A scenario considering 10 residential consumers (L1 to L10) and 2 PVs (PV1 and PV2) are tested. PVs are taken as negative loads. Results of apportionment factors before and after DR are listed in TABLE II.

TABLE II.
Apportionment factors (**AF**) considering PV integration

Factors	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**
AF before DR	0.118	0.150	0.071	0.044	0.096	0.099
AF after DR	0.116	0.149	0.069	0.027	0.092	0.097
Factors	**L7**	**L8**	**L9**	**L10**	**PV1**	**PV2**
AF before DR	0.089	0.036	0.050	0.147	0.037	0.064
AF after DR	0.086	0.032	0.043	0.146	0.049	0.086

In this case, the apportionment factors for the two PVs are 0.037 and 0.064, respectively, indicating that they need to pay the volatility cost. The reason is that the load peak appears in the morning and late afternoon. PVs, as negative loads, increase the peak-to-valley difference and volatility of the net load curve.

After the decentralized DR, the variance of the net load curve is reduced from 33.55 kW^2 to 23.20 kW^2. The apportionment factors of consumers decrease and that of PVs increase because consumers flatten their load curves and PV curves do not change. This case verifies that the proposed pricing strategy can allocate the volatility cost among consumers and REGs.

F. VALIDATION OF COST REDUCTION CONSIDERING LARGE CONSUMERS ON THE MEGAWATT LEVEL

In the second case, the proposed pricing strategy is tested on megawatt level consumers. Each consumer has a 10% shiftable load. The original load curves are given in FIGURE 8. Parameters of a and b in Eq. 1 are set as 15 £/MW^2 and 30 £/MW, respectively.

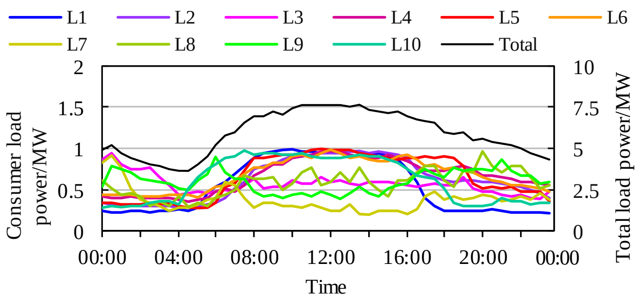


FIGURE 8. 10 consumer load curves and the aggregated load curve

Aggregated load curves before and after consumer self-management are shown in FIGURE 9. The variance of the aggregated curve is reduced from 1.75 MW^2 to 0.67 MW^2, reduced by 61.95%. The total production cost is decreased by 2.21%. This large test case shows that the decentralized DR promoted by the proposed pricing strategy can also effectively reduce the volatility and peak-to-valley difference of the aggregated load.

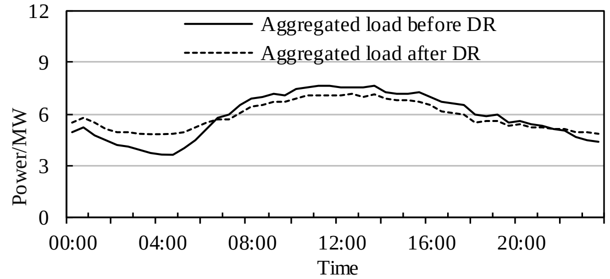


FIGURE 9. Aggregated load curves before and after DR

VI. CONCLUSIONS

Increasing penetration of renewable energy generation into the future power system will increase the net load volatility which will further increase the production cost. The impact of volatility on total production costs is investigated in this paper. A novel pricing strategy is proposed to allocate the volatility cost among consumers. A volatility apportionment factor with the inherent merits of normalization and additivity is proposed. It can reflect the coupling relationship between an individual load/REG curve and the aggregated net load curve.

The proposed pricing strategy reflecting the cost of volatility can encourage consumers/REGs to reduce the volatility of their load/output curve. It also contributes to flattening the net load curve in a decentralized manner, which is theoretically certificated based on the Haar wavelet transforms. Validation on a case of residential-level loads shows that the peak-to-valley difference and the variance of the aggregated load curve are reduced by 19.81% and 34.07%, respectively. On a large case considering megawatt-level consumers, the aggregated load variance and the total production cost are reduced by 61.95% and 2.21%, respectively. Moreover, the pricing model will not cause a new load peak or peak-to-valley inversion even in conditions of high levels of flexible loads. This is an important advantage of the proposed pricing strategy over TOU prices.

The proposed pricing strategy is applicable to consumers and producers. As the proposed model is has the merit of additivity and the volatility cost is calculated based on the net load curve of a player, it is applicable to prosumers in the future power system. The pricing model can prevent consumers from colluding to make a profit. It makes it possible for small consumers and large consumers to participate in DR programs equally. The demand response is carried out by encouraging players to reduce the volatility of their load/REG curves in a decentralized manner. Even if the information is asymmetric for large and small electricity players, the method is still applicable.

APPENDIX

A: CORRELATION COEFFICIENT

Let $\boldsymbol{P}_i$, $i = 1, \mathbf{2}, \dots, \mathrm{M}$ denotes a load/REG curve, and $\boldsymbol{P}_s$ denotes system load curve. The correlation coefficient is formulated as:

$$R_i = \frac{\mathrm{Cov}(\boldsymbol{P}_i, \boldsymbol{P}_\mathrm{n})}{S_i S_\mathrm{n}} = \frac{\sum_{t=1}^{\mathrm{N}}(P_{i,t} - P_{i,m})(P_{\mathrm{n},t} - P_{\mathrm{n},m})}{\sqrt{\sum_{t=1}^{\mathrm{N}}(P_{i,t} - P_{i,m})^2}\sqrt{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n},m})^2}} \tag{25}$$

where S_i and S_n refer to standard deviations (SDs) of a load/RED curve and the net load curve, respectively; $P_{i,t}$ and $P_{\mathrm{n},t}$ refer to load values of $\boldsymbol{P}_i$ and $\boldsymbol{P}_\mathrm{n}$ at time slot t, respectively; $P_{i,m}$ and $P_{\mathrm{n},m}$ refer to mean values of $\boldsymbol{P}_i$ and $\boldsymbol{P}_\mathrm{n}$, respectively.

B: PROOF OF NORMALIZATION

$$\begin{aligned}
\sum_{i=1}^{\mathrm{M}} v_i &= \sum_{i=1}^{\mathrm{M}} \frac{S_i}{S_\mathrm{n}} R_i = \sum_{i=1}^{\mathrm{M}} \frac{\mathrm{Cov}(\boldsymbol{P}_i, \boldsymbol{P}_\mathrm{n})}{(S_\mathrm{n})^2} \\
&= \frac{\sum_{i=1}^{\mathrm{M}}[\sum_{t=1}^{\mathrm{N}}(P_{i,t} - P_{i,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})]}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}[\sum_{i=1}^{\mathrm{M}}(P_{i,t} - P_{i,m})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})]}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}[(\sum_{i=1}^{\mathrm{M}} P_{i,t} - \sum_{i=1}^{\mathrm{M}} P_{i,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})]}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}[(\sum_{i=1}^{\mathrm{M}} P_{i,t} - \sum_{i=1}^{\mathrm{M}} P_{i,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})]}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}[(P_{\mathrm{n},t} - P_{\mathrm{n,m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})]}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} = 1
\end{aligned} \tag{26}$$

C: PROOF OF ADDITIVITY

$$\begin{aligned}
v_k &= R_k \frac{S_k}{S_\mathrm{n}} = \frac{\sum_{t=1}^{\mathrm{N}}(P_{k,t} - P_{k,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}(P_{i,t} + P_{j,t} - P_{i,m} - P_{j,m})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= \frac{\sum_{t=1}^{\mathrm{N}}(P_{i,t} - P_{i,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&\quad + \frac{\sum_{t=1}^{\mathrm{N}}(P_{j,t} - P_{j,\mathrm{m}})(P_{\mathrm{n},t} - P_{\mathrm{n,m}})}{\sum_{t=1}^{\mathrm{N}}(P_{\mathrm{n},t} - P_{\mathrm{n,m}})^2} \\
&= R_i \frac{S_i}{S_\mathrm{n}} + R_j \frac{S_j}{S_\mathrm{n}} = v_i + v_j
\end{aligned} \tag{27}$$

where v_k is the apportionment factor of the combined curve $\boldsymbol{P}_k$ ($\boldsymbol{P}_k = \boldsymbol{P}_i + \boldsymbol{P}_j$, namely $P_{k,t} = P_{i,t} + P_{j,t}$ $\forall t$).

D: Deduction of Eq. 16.

$$\begin{aligned}
&\sum_{t=1}^{\mathrm{N}}(p_{i,t} - P_{i,m})^2 = \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - 2P_{i,m}\sum_{t=1}^{\mathrm{N}} p_{i,t} + \mathrm{N}{P_{i,m}}^2 \\
&= \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - 2\mathrm{N}{P_{i,m}}^2 + \mathrm{N}{P_{i,m}}^2 = \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - \mathrm{N}{P_{i,m}}^2 \\
&\sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - \mathrm{N}(E_i/\mathrm{NT})^2 = \sum_{t=1}^{\mathrm{N}} {p_{i,t}}^2 - {E_i}^2/\mathrm{NT}^2
\end{aligned} \tag{28}$$

REFERENCES

[1] M. Muratori, and G. Rizzoni. "Residential demand response: Dynamic energy management and time-varying electricity pricing," *IEEE Trans. Power Syst*, vol. 31, no. 2, pp. 1108-1117, Mar, 2016.
[2] J. Yang, J. Zhao, F. Wen, and Z.Y. Dong. "A framework of customizing electricity retail prices," *IEEE Trans. Power Syst*, vol. 33, no. 3, pp. 2415-2428, May, 2018.
[3] R. Lu, S. H. Hong, and X. Zhang. "A dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach," *Appl. Energy*, vol. 220, pp. 220-230, Jun, 2018.
[4] K. Vanthournout, B. Dupont, W. Foubert, and C. Stuckens, and S. Claessens. "An automated residential demand response pilot experiment, based on day-ahead dynamic pricing," *Appl. Energy*, vol. 155, pp. 195-203. Oct, 2015.
[5] M. Yu, and S. H. Hong. "A real-time demand-response algorithm for smart grids: a stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 879-88, Mar, 2016.
[6] S. J. Kim, and G. B. Giannakis. "An online convex optimization approach to real-time energy pricing for demand response". *IEEE Trans. Smart Grid*, vol. 8, no.6, pp. 2784-2793, Nov, 2017.
[7] D. Srinivasan, S. Rajgarhia, B. M. Radhakrishnan, A. Sharma, and H.P. Khincha. "Game-theory based dynamic pricing strategies for demand side management in smart grids," *Energy*, vol. 126, pp. 132-143, May, 2017.
[8] X. Huang, S. H. Hong, M. Yu, Y. Ding, J. Jiang. "Demand Response Management for Industrial Facilities, A Deep Reinforcement Learning Approach," *IEEE Access*, 2019. (early access)
[9] Z. Jiang, Q. Ai, R. Hao. "Integrated demand response mechanism for industrial energy system based on multi-energy interaction," *IEEE Access*, vol. 7, Jun, pp. 66336-66346, 2019.
[10] H. Han, S. Gao, Q. Shi, et al. "Security-based active demand response strategy considering uncertainties in power systems," *IEEE Access*, vol. 5, pp. 16953-16962, Aug. 2017.
[11] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings. "Putting the "smarts" into the smart grid: A grand challenge for artificial intelligence," Com- munications of the ACM, vol. 55, no. 4, pp. 86–97, Apr, 2012.
[12] J. Aghaei, and M. I. Alizadeh. "Critical peak pricing with load control demand response program in unit commitment problem". *IET Gener Transm & Dis*, vol. 7, no. 7, pp. 681-690, Jul, 2013.
[13] P. Samadi, H. Mohsenian-Rad, R. Schober, and V. W. Wong. "Advanced demand side management for the future smart grid using mechanism design," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1170-1180. Sep, 2012.
[14] Y. Liang, L. He, X. Cao, and Z. J Shen. "Stochastic control for smart grid users with flexible demand," *IEEE Trans. Smart Grid,* vol. 4, no. 4, pp. 2296-2308, 2013.
[15] E. Nekouei, T. Alpcan, D. Chattopadhyay. "Game-theoretic frameworks for demand response in electricity markets," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 748-58, Mar, 2015.
[16] A. Dorri, S. S. Kanhere, and R. Jurdak. "Multi-agent systems: A survey," *IEEE Access*, vol, 6, pp. 28573-28593, Jun, 2018.
[17] R. Khatami, M. Heidarifar, M. Parvania, M and P. Khargonekar. Scheduling and pricing of load flexibility in power systems. *IEEE Journal of Selected Topics in Signal Processing,* vol.12, no. 4, pp. 645-656, Aug, 2018.
[18] Q. Wang, B.M. Hodge. "Enhancing power system operational flexibility with flexible ramping products: A review," *IEEE Trans. on Ind. Inform.*, vol. 13, no. 4, pp. 1652-1664, Aug, 2016.

[19] B. Zhang, and M. Kezunovic. "Impact on power system flexibility by electric vehicle participation in ramp market," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1285-1294, May, 2016.
[20] M. Khoshjahan, M. Moeini-Aghtaie, M. "Fotuhi-Firuzabad. "Developing new participation model of thermal generating units in flexible ramping market," *IET Gener. Transm. Distrib*, vol. 13, no. 11, pp. 2290-2298, May, 2019.
[21] J. Mays. "Cost allocation and net load variability," *IEEE Trans. Power Syst,* vol. 33, no. 2, pp. 2030-2039, Mar, 2018.
[22] P. Chakraborty, E. Baeyens, and P. P. Khargonekar. "Cost Causation Based Allocations of Costs for Market Integration of Renewable Energy," *IEEE Trans. Power Syst,* vol. 33, no. 1, pp. 70-83, Jan, 2018.
[23] J. D. Weber, and T. J. Overbye. "A two-level optimization problem for analysis of market bidding strategies," *IEEE Power Engineering Society Summer Meeting*, Vol. 2. 1999.
[24] L. Mitridati, and P. Pinson. "A Bayesian inference approach to unveil supply curves in electricity markets," *IEEE Trans Power Syst*, vol. 33, no. 3, pp. 2610-2620, May, 2018.
[25] M. Charwand, and M. Gitizadeh. "Optimal TOU tariff design using robust intuitionistic fuzzy divergence based thresholding". *Energy*, vol. 147, pp. 655-662, Mar, 2018.
[26] T. Räsänen, D. Voukantsis, H. Niska, K. Karatzas, and M. Kolehmainen. "Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data," *Appl. Energy*, vol. 87, no. 11, pp. 3538-354, Nov, 2010.
[27] G. Chicco. "Overview and performance assessment of the clustering methods for electrical load pattern grouping," *Energy*, vol. 42, no. 1, pp. 68-80, Jun, 2012.
[28] C. S. Burrus, R. A. Gopinath, and H. Guo, "Introduction to wavelets and wavelet transforms: a primer," *New Jersey: Prentice hall*, vol. 1, 1998.
[29] C. f. E. Regulations, 16 May 2011, "Electricity Smart Metering Customer Behaviour Trails (CBT) Findings Report".
[30] https://www.westernpower.co.uk/projects/sola-bristol