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Impact of fuel-dependent electricity retail charges on the value of net-metered PV applications in vertically integrated systems

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HIGHLIGHTS

- A top-down approach of developing traditional electricity charges is provided.
- The combined effect of pricing strategies, rate structures and fuels is examined.
- Fossil fuel prices can substantially affect the net metering compensation.
- A financial risk assessment for net-metered PV systems is performed.

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ABSTRACT

Retail electricity charges inevitably influence the financial rationale of using net-metered photovoltaic (PV) applications since their structure as well as their level may vary significantly over the life-cycle of a customer-sited PV generation system. This subsequently introduces a further uncertainty for a ratepayer considering a net-metered PV investment. To thoroughly comprehend this uncertainty, the paper employs a top-down approach – in vertically integrated environments – to model the volatility of partially hedged electricity charges and its subsequent impact on the value of bill savings from net-metered PV systems. Besides the utility's pricing strategy and rate structures, particular emphasis is given in modeling the fossil fuel mix component that introduces a significant source of uncertainty on electricity charges and thus on the value of bill savings of net-metered, customer-sited, PV applications.

1. Introduction

Net metering (NEM) is an electricity policy that allows utility customers to offset some or all of their electricity consumption by using their own generating system, mainly rooftop photovoltaic (PV) systems. NEM is an alternative to feed-in-tariff (Fi) schemes that have been widely adopted as a cost-effective measure to promote the installation of distributed generation (DG) systems. A FiT scheme is a form of subsidy that guarantees a predetermined price to the PV electricity producers by enforcing the grid operators to purchase their electricity output under long-term contracts. On the other hand, NEM schemes work by offsetting households' energy consumption, while any excess energy may be credited back to consumers, at retail price or at an avoided cost rate. Alternatively, the excess energy may be transferred to a subsequent billing period to be used as energy credit against future electricity usage.

Thus, as the market for distributed PV generation is growing and as the associated capital costs continue to decline, NEM policies are becoming increasingly attractive to homeowners of all incomes. However, the return on investment in such schemes is highly related to the volatility of electricity retail prices as these are the dominating factors that affect the value of the net-metered applications. The picture becomes more complex, bearing in mind that the retail tariff charges are subject to change over the life-cycle of a distributed PV system. This introduces a further uncertainty for a ratepayer considering a long-term net-metered PV investment.

To this end, NEM policies have induced a skepticism on a range of stakeholders due to: (a) uncertainties arising from the major shifts in the way consumers are using and, subsequently, paying for their energy (Hatami et al., 2011), (b) the financial impact of such policies on ratepayers that do not participate to NEM schemes (Beach and McGuire, 2013), and (c) the sustainability of the existing retail energy market structures to accommodate such policies (Borenstein., 2007). Thus, utilities and regulatory authorities are actively searching for NEM schemes that can: (a)

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promote distributed PV energy penetration and (b) exhibit minimal distortions to utilities' revenue requirements.

It is, however, clear that electricity retail rate designs influence the customer-side financial rationale of using net-metered PV generation both for residential and commercial customers. In particular, a number of recent studies have examined the influence of specific rate structures (flat, tiered or time differentiated) on the annual bill savings of net-metered PV customers (Black, 2004; Mills et al., 2008; Darghouth et al., 2011; Poullikkas, 2013).

Some further studies (Borenstein, 2005; Suna et al., 2006) have discussed the impact of wholesale electricity market characteristics (e.g., renewable energy penetration, capacity, energy and loss savings) on the value of distributed PV systems. Within those studies, it is acknowledged that the wholesale electricity market profile can subsequently influence the cost of retail electricity supply and thus, the value of NEM compensation mechanisms. A primary step to address the influence of the retail price change on the value of NEM compensation mechanisms is found in Darghouth et al. (2013). The study in Darghouth et al. (2013) has considered retail rate designs and NEM in parallel with potential changes under future electricity market scenarios for California, US. It has particularly examined: (a) the influence of both high future PV and wind energy penetration, (b) the influence of high and low natural gas prices and (c) the influence of carbon emission pricing on the value of bill savings under a range of rate options and PV compensation mechanisms.

Our paper, in particular, focuses on the customer-side financial rationale of using solar technology and investigates the impact of a key source of uncertainty in the future value of bill savings from residential net-metered PV systems, particularly in vertically integrated systems. The source of uncertainty rests with changes in retail electricity charges, mainly affected from volatile fossil fuel prices. To isolate the effect of fossil fuel varying prices in a vertically integrated environment, on the value of annual bill savings from PV net-metered systems, a top-down approach ranging from residential electricity tariff formulation to fossil fuel price forecasting and net metering compensation mechanisms is presented. Therefore, the scoping study responds to the ongoing efforts of developing risk and cost-based decision making processes for net-metered PV applications and investments in vertically integrated systems. The latter suggests that the generation, transmission and distribution facilities are owned either by private regulated utilities or by public companies/government agencies which operate as a natural monopoly for the supply of electricity in a given geographical area (Stoft, 2002). This type of electricity market organization has been predominant in the past century before the deregulation and the introduction of competition in the electricity sector (mainly at the supply side) (Kirschen and Strbac, 2004), however it is still applicable in many occasions and for various reasons (T. E. Parliament and the Council of the European Union, 2009). In such vertically-integrated systems, tariff structures aim to reflect on the fixed and variable costs incurred by utilities to produce and transmit each kWh of energy to all electricity end-users that receive services in their jurisdiction. Conversely, under liberalized electricity markets, customer tariffs reflect on the competitively determined electricity prices derived from the continuous interaction of multiple generating and load-serving entities (Kirschen and Strbac, 2004).

2. Methods

2.1. Retail electricity charges and net metering compensation mechanisms

Under net metering, retail customers can offset their electricity purchases from the grid with energy generated from their own rooftop PV systems. Thus, net metering values the energy produced by these PV systems at the rated value of retail electricity. The retail electricity rate includes the cost of producing electrical energy, the costs associated with investment in and operation of transmission and distribution facilities as well as any other costs incurred to ensure the reliability of the system.

Thus, this section provides a generic top-down approach that includes a sample of retail electricity tariff formulations as well as their interface with net metering compensation mechanisms.

2.1.1. Total revenue requirements – vertically integrated systems

The total revenues collected from the sale of electricity should recover the utilities' total costs of providing the service plus a fair rate of return. Under the traditional regulation of vertically integrated utilities, this revenue requirement is determined by inclusion of both fixed and variable costs. A generic illustration of the Total Revenue Requirements (*TRR*) is given in the following equation.

$$TRR = FiC + VrC \tag{1}$$

With reference to (1), *FiC* refers to the fixed cost component and comprises all the fixed related expenditure of the utility's total costs (e.g. levelized fixed costs from generation down to distribution, fixed price contracts, etc.). *VrC* refers to the variable cost component and represents the total variable costs (e.g., fossil fuels, CO_2 emissions, operation and maintenance, etc.) that are a function of the energy units produced.

The fixed cost component (*FiC*) is usually a function of the overnight costs of the generation, transmission and distribution facilities owned by the utility plus any other associated fixed price contracts and financial obligations (Stoft, 2002; Kirschen and Strbac, 2004). A general mathematical formulation of the annual fixed cost component is shown in the following equation.

$$FiC = \sum_{g=1}^{G} [(LC_g + FOM_g) \times P_g^{\max}] + LC_{TD} + FO \tag{2}$$

With reference to (2), *G* refers to the total number of generating units in a system, LC_g refers to the annual levelized capital cost of each generating unit *g*, FOM_g is the fixed operation and maintenance cost and $P_g^{\max}$ is the rated capacity of each unit *g*. Moreover, LC_{TD} refers to the annual levelized capital costs of transmission and distribution facilities. Finally, *FO* refers to the associated costs of any other annual financial obligation of the utility.

Unlike fixed costs, the variable costs (*VrC*) are a function of the energy units produced. These comprise fossil fuel costs, CO_2 emission costs as well as operation and maintenance expenditures (Stoft, 2002; Kirschen and Strbac, 2004). The mathematical formulation of *VrC* is shown in the following equation.

$$VrC = \sum_{g=1}^{G} ER_g \times (FC_g + EMC_g + VOM_g) \tag{3}$$

With reference to (3), FC_g is the fuel cost (in \$/MWh), EMC_g refers to the associated CO_2 emissions costs (in \$/MWh), whilst VOM_g refers to the variable operation and maintenance costs (in \$/MWh). Finally, ER_g refers to the total energy (in MWh) produced by each generating unit *g*.

2.1.2. Formulation of retail electricity charges from first principles

Vertically integrated utilities aim to allocate their total revenue requirements to all of their customers' classes (e.g. residential, commercial, industrial, rural, etc.) that receive service in their jurisdiction. To this aim, appropriate tariffs are designed to establish a revenue collection mechanism. Within each tariff, the

fixed and variable costs are reflected in various ways in accordance to the cost allocating decisions of utilities and regulatory authorities. Tariff appropriateness is evaluated using criteria that include: effectiveness of revenue collection, fairness, economic efficiency, promotion of energy efficiency and conservation, customers' interpretation (Lazar, 2011; Robinson et al., 2011).

Short-term (e.g., hourly, daily, etc.) electricity price variations are not usually reflected in tariffs of medium or small scale customers (Robinson et al., 2011). However, a fuel adjustment cap may be present in their monthly bill charges, reflecting the volatile fossil fuel price variation that inevitably affects the cost that must be recovered (Robinson et al., 2011). Such adjustment caps are sometimes referred to as rate riders (Alberta Government: Utilities Consumer Advocate). They are used by utilities as a mechanism that allows the charges to vary (without the need for a new rate case) in order to recover unpredictable cost variations (e.g., fuels prices) over which the utility presumably has no control. A representative example of fuel adjustment clauses embedded in residential tariffs can be found in Electricity Authority of Cyprus residential tariffs. This kind of electricity tariffs are considered partially hedged (Robinson et al., 2011) and these are the main focus of this paper.

To this end, residential electricity rates typically consist of a monthly fixed customer charge plus an energy charge ($/kWh) based on the amount of kWh consumption. These are generally known as two-part retail rates, which are mainly expressed through volumetric flat charge rates, or volumetric block charge rates with increasing or decreasing block rates. The latter suggests that the energy charge ($/kWh) for each block of energy units (kWh) may increase or decrease with the number of units (kWh) consumed. The generic procedure used to determine volumetric charge rates is illustrated in Fig. 1. To this extent, we wish to emphasize that, within this paper, all tariff formulations and structures are assumed generic in the sense that they are developed using fundamental principles that emulate how real-life tariff structures are designed.

2.1.2.1. Volumetric flat charge rates. Flat-rate pricing refers to a strategy where electricity is charged at the same rate ($/kWh), independent from the time each customer places his burden (i.e. demand) on the system. Thus, flat charge rates are merely a function of the customer's energy consumption volume within a billing period. Customer total billing charges, under flat-rate pricing, typically consist of a fixed customer charge (*CC*) plus an amount determined by a Flat Charge Rate (FCR^m) and the total amount of kWh energy consumption. These billing charges may take the form given in the following equation.

$$TB^m = CC + FCR^m \times UG^m \tag{4}$$

where TB^m refers to the total customer bill charges and UG^m to the customer's energy consumption (in kWh) within a billing period m (e.g., month).

2.1.2.2. Volumetric block charge rates. The volumetric block charge rate is a variation of the flat charge rate. To this extent, volumetric block tariffs may have inclining or declining block charges. Thus, the energy charge (in $/kWh) for each block of energy units (kWh) may increase or decrease with the number of energy units consumed. The structure (i.e. inclining or declining) of the blocks, their number, the energy level of each block and their associated energy charges depend on utilities' preferred pricing strategies. A typical formulation for calculating the total customer bill charges under a volumetric block charge rate scheme is shown in the following equation.

$$\begin{aligned} TB^m &= CC + \sum_{k=1}^{NB} B_k^m \times [\min\{A_k, C_k\}] \\ A_k &= \max\{UG^m - X_{k-1}, 0\} \\ C_k &= X_k - X_{k-1} \\ X_0 &= 0 \\ X_k &= m_k \times AMC \\ X_{NB} &= +\infty \end{aligned} \tag{5}$$

where TB^m refers to the total customer bill for a billing period m, *CC* to the fixed customer charge (in $/billing period), *NB* refers to the number of blocks, B_k^m to the energy charge (in $/kWh) of each block k, *AMC* to the Average Monthly Consumption of a typical residential customer and X_k to the cut-off or boundary point (in kWh) of each block. Moreover, A_k, C_k and m_k serve as auxiliary variables to facilitate the calculation process. In particular, m_k takes the form of constant factors (%) that define the relationship of X_k with respect to *AMC*, thus enabling the modeling of the cut-off point (boundary) of each block k in (5). To clarify the process, Table 1 shows two indicative numerical examples of the total monthly bill calculation (TB^m) reflecting on the case of a two-tiered block rate.

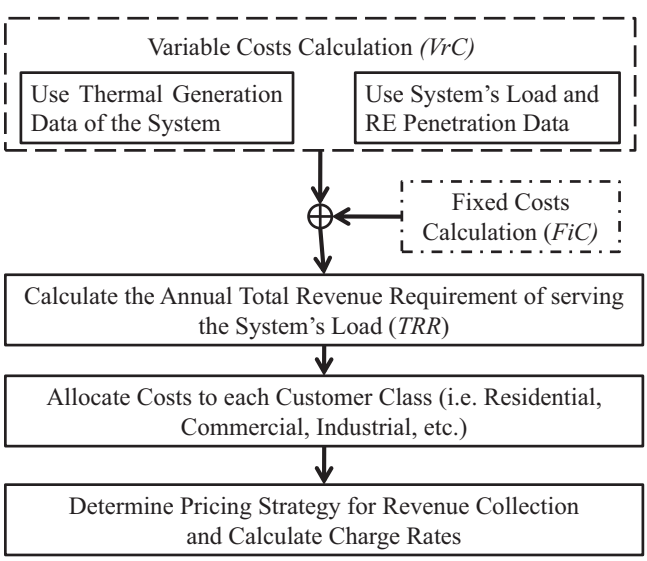

Fig. 1. Procedure followed to provide generic volumetric charge rates.

Table 1
Indicative examples of calculating the total monthly bill of a block rate with two tiers.

UG^m=1000 kWh, NB=2, m_1=50%, AMC=860 kWh, X_0=0, X_1=430 kWh, X_2=+∞, CC=20$/month, B_1=0.10 $/kWh, B_2=0.20 $/kWh			
k	A_k	C_k	min{A_k,C_k}
1	A_1=max{UG^m–X_0,0}=max{1000,0}=1000	C_1=X_1–X_0=430–0=430	min{1000,430}=430
2	A_2=max{UG^m–X_1,0}=max{570,0}=570	C_2=X_2–X_1=+∞–430=+∞	min{570, +∞}=570
TB^m=CC+430×B_1+570×B_2=20+430×0.10+570×0.2=177$			
UG^m=400 kWh, NB=2, m_1=50%, AMC=860 kWh, X_0=0, X_1=430 kWh, X_2=+∞, CC=20 $/month, B_1=0.10 $/kWh, B_2=0.20 $/kWh			
k	A_k	C_k	min {A_k,C_k}
1	A_1=max{UG^m–X_0,0}=max{400,0}=400	C_1=X_1–X_0=430–0=430	min{400,430}=400
2	A_2=max{UG^m–X_1,0}=max{−30,0}=0	C_2=X_2–X_1=+∞–430=+∞	min{0, +∞}=0
TB^m=CC+400×B_1+0×B_2=20+400×0.10=60$			

2.1.3. Net metering formulation

The net metering formulation realized in this paper permits customers to offset their volumetric charges within each monthly billing period. Therefore, the PV generation is credited based on the bill period in which it occurs. The aggregation between residential energy demand and PV generation is simply the subtraction of the total per month (m) energy consumption of a residential customer (UG^m) and the cumulative photovoltaic energy yield (PV^m) of each month as given in (6). This aggregation is hereinafter referred to as Net Customer Demand (NCD^m).

$$NCD^m = UG^m - PV^m \tag{6}$$

Moreover, in this paper, it is assumed that bill energy credits (CR^m) will occur whenever the Net Customer Units (NCU^m) per month is negative. The associated formulation, shown in (7), suggests that the bill credits at the end of each month are transferred to the next month's bill. It is noted that under the formulation considered, any explicit fixed customer charge (CC) per month is not being offset.

$$NCU^m = NCD^m - CR^{m-1} \tag{7}$$

Therefore, the total customer bill (TB^m_{NEM}) per month (m) under net metering compensation can be formulated separately for volumetric flat charge rates and for volumetric block rates. These formulations are shown in (8) and (9) respectively, by using the variables defined in (4)–(7).

$$\begin{aligned} TB^m_{NEM} &= CC + FCR^m \times [\max\{NCU^m, 0\}] \\ CR^m &= \max\{-NCU^m, 0\} \end{aligned} \tag{8}$$

$$\begin{aligned} TB^m_{NEM} &= CC + \sum_{k=1}^{NB} B^m_k \times [\min\{A_k, C_k\}] \\ A_k &= \max\{NCU^m - X_k, 0\} \\ C_k &= X_k - X_{k-1} \\ X_0 &= 0 \\ X_k &= m_k \times AMC \\ X_{NB} &= +\infty \\ CR^m &= \max\{-NCU^m, 0\} \end{aligned} \tag{9}$$

2.2. Description of test system and data assumptions

To facilitate a numerical evaluation of the formulation process described in Section 2.1, a test system based on the vertically integrated system of Cyprus (Electricity Authority of Cyprus) is used as an example test system. The test system is electrically isolated and relies predominantly on oil products (i.e. heavy fuel oil and Diesel) for the generation of electricity.

2.2.1. Vertically integrated utility description

The thermal capacity of the test system embraces 11 conventional units (Table 2). Specifically, three steam turbines burning heavy fuel oil are used as base-load units whilst two combined-cycle gas turbines (CCGTs) and six open-cycle gas turbines (OCGTs) burning Diesel Oil are used as intermediate and peaking units respectively. Based on the data specifics given in Table 2, the utility's fixed (FiC) and variable (VrC) cost components are calculated through the formulations presented in (2) and (3). To this aim, the combined fixed costs of transmission, distribution and any other financial obligations of the utility are assumed to be equal to 30% of the total fixed cost of generation facilities.

The system's expected peak load is 1000 MW whilst its annual load factor is equal to LF=56.7%. This entails an annual energy consumption of 4.97 TWh. For simplicity, it is assumed that all energy is consumed by a single class of residential customers. The number of residential customers served by the system is assumed to be 482,000 and the Average Monthly Consumption (AMC) of a typical residential customer is 860 kWh.

Moreover, the test system benefits from Renewable Energy (RE) penetration, predominantly by wind and solar technologies, which could cover approximately 13.2% of the total annual energy needs. The further particulars of this assumption are shown in Table 3.

Table 2
Conventional generation fleet assumptions.

Unit type	–	ST	CCGT	OCGT
Unit category	–	Base	Intermediate	Peak
Rated capacity (MW)	P_g^{max}	130	220	40
No. of units	G	3	2	6
Efficiency (%)	η_g	35%	46%	30%
Fuel type	–	Heavy fuel oil	Diesel	Diesel
Reference fuel price ($/MT)	$FFP_{g,REF}$	550	892.7	892.7
Net calorific value (MJ/MT)	NCV_g	40800	42800	42800
Fuel cost ($/MWh)	$FC_{g,REF}$	138.66	163.23	250.29
Availability (%)	–	98%	97%	99%
Overnight costs ($/kW)	–	1800	1200	600
Priority order	–	1–3	4–5	6–11
Fixed O&M cost ($/kWy)	FOM_g	18	12	6
Variable O&M cost ($/MWh)	VOM_g	3	2	1
CO_2 emissions cost ($/MWh)	EMC_g	20	15	23
Annual discount rate (%)	–	10%	10%	10%
Expected lifetime (yr)	–	35	30	25
Capital recovery factor (–)	–	0.1037	0.1061	0.1101
Levelized fixed generation cost ($/kWy)	LC_g	186.64	127.3	66.1

2.2.2. Customer load and PV generation

The monthly load profile of a typical residential customer is obtained from load data averaged over a sample of 100 residential customers, located throughout the service territories of the vertically integrated utility (Electricity Authority of Cyprus) described in Table 2. The load data were captured at a thirty-minute interval and span through a 12-month period. Fig. 2 illustrates an average customer's consumption pattern normalized over the assumed AMC value (860 kWh).

The rooftop PV energy generation is also monitored (University of Cyprus Photovoltaic Technology) at a thirty-minute interval, spanning through the same 12-month period as the customer load data quoted above and is shown in Fig. 3.

The data pertain to a 1 kW_p mono-crystalline PV system with an effective area of 7.03 m^2 located in region of annual solar potential of approximately 2000 kWh/m^2. The overall PV system efficiency is at 11.9%, including inverter efficiency and relevant system losses (e.g. cabling, etc.). The above assumptions result in an annual PV energy yield of approximately 1700 kWh/kW_p.

Table 3
RE penetration assumptions.

Unit type	Wind	Solar
Rated capacity (MW)	200	200
Capacity factor (%)	18%	19.4%
Overnight costs ($/kW)	1800	2300
Expected lifetime (yr)	20	20
Annual discount rate (%)	10%	10%
Capital recovery factor (–)	0.1175	0.1175
Annual levelized cost ($/kWy)	211.5	270.25

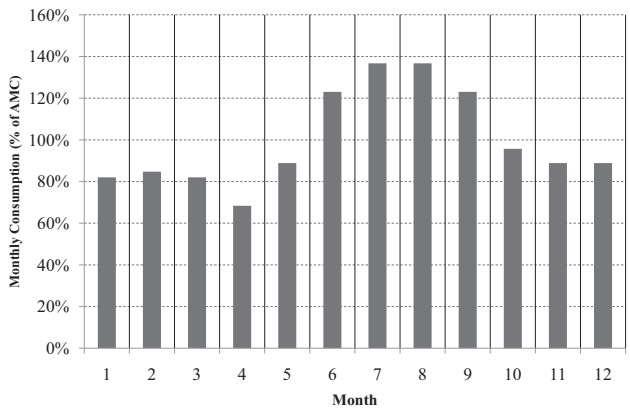

Fig. 2. Monthly consumption pattern shown as percentage of the *AMC*.

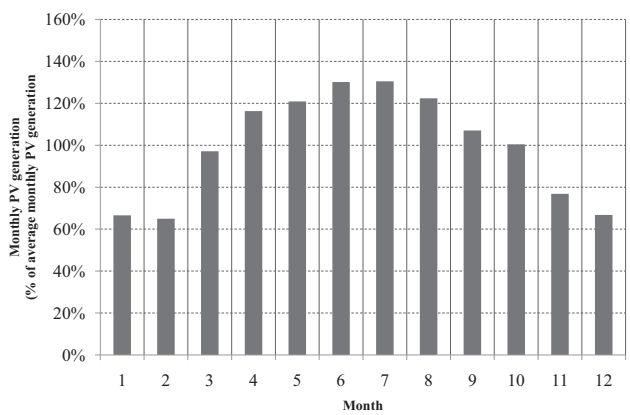

Fig. 3. Measured monthly PV generation shown as percentage of the average monthly PV generation.

2.3. Fossil fuel prices forecasting

The use of Heavy Fuel Oil and Diesel is assumed in the generation mix of the example utility (Table 2). Oil prices may be driven by statistical trends; however, they are also affected by economic supply and demand which are also affected by complicated political decisions. At a glance, historical crude oil prices from January 1978–October 2013 (US Energy Information Agency (EIA)), can be quite informative. First, from the early 1980s until about year 2000, oil prices were quite stable with occasional spikes and quite similar volatility across the years. After year 2000, an increasing trend is noted, in the level of prices and maybe also in the volatility of prices. This period includes the record prices in mid-2008 and then the record drop in the following few months.

To model the uncertainty of crude oil prices, a method based on Markov-regime switching models (Hamilton, 1989) is used. Regime-switching models can be used as they are among the state of the art models that are currently being used in econometrics and especially in forecasting energy prices (Janczura and Weron, 2010; Wu et al., 2013). These models are detailed enough to capture changes in the mean and volatility of energy/fuel prices,[1] but at the same time they are intuitive and transparent enough for the reader to be able to understand the processes by which the forecasts are obtained. As part of our previous work, a thorough description of a complete model for Brent oil price forecasting is given in (Charalambous et al., 2013a, 2013b). Brent is a benchmarked trading classification of crude oil, in oil spot markets (Bhattacharyya, 2011). Therefore, in the context of this work, it is assumed that the prices of other oil products will be dominated by the relative future price movement of Brent. Thus, our model is hereby used to statistically assess and project price trajectories for Brent ($FFP_{BRENT,m}$) beyond the reference fuel prices of December 2013 (US Energy Information Agency (EIA)).

In particular, our previous modeling effort is based on a simple and a more advanced model; the Geometric Brownian Motion (GBM) and the Regime switching between 2 Geometric Brownian Motions (RSGBM2). The RSGBM2 is a generalization of the GBM model as it uses a hidden Markov chain to allow logarithmic changes in price to alternate between two GBMs based on a transition probability matrix (resulting from historical monthly Brent price data). Thus, two regimes are considered (in contrast with GBM which considers one regime); the "low-volatility" and the "high-volatility" regime. Hence, the historical logarithmic-returns of Brent prices are grouped into two regimes – the ones experiencing lower volatility (relative to the entire distribution) and the ones experiencing higher volatility (relative to the entire distribution). These two groups are modeled by two separate normal distributions with parameters μ_1, μ_2 and σ_1, σ_2 respectively. This division of historical data into two distributions (instead of a single distribution as in the case of GBM) allows a more detailed representation of the Brent price movements.

Within this paper, the parameters of each model are estimated over four times period to show how the parameters change as more data are added to the estimation. Specifically, the first estimation uses monthly data from 1978 to 2000, the second from 1978 to 2005, the third from 1978 to 2010 and the fourth from 1978 to 2013. Table 4 shows the parameter estimates using the two competing models.

Focusing on GBM over the four different periods we notice two trends. As mentioned above, we firstly estimate the logarithmic return of oil prices and then model the distribution of the logarithmic returns. The mean parameter (μ) increases significantly from first to the second period (goes from 0.169% to 0.458%). In the next two time periods additional, but smaller, increases are observed as they progress to 0.478% and 0.479% in the third and fourth period respectively. The volatility parameter (σ) seems to remain constant and varies from 10.112% to 10.384%.

In the case of RSGBM2, a more detailed representation of the trends is observed underlying the evolution of the logarithmic return of Brent prices. Most of the variation seems to be picked up

Table 4
Estimation of GBM and RSGBM2 models using monthly oil price data from 1978 to 2013.

GBM	1978–2000	1978–2005	1978–2010	1978–2013
μ	0.169%	0.458%	0.478%	0.479%
σ	10.384%	10.173%	10.381%	10.112%
Number of parameters	2	2	2	2
Number of observations	275	335	395	429
Negative log-likelihood	232.64	291.14	334.26	374.29
RSGBM2	**1978–2000**	**1978–2005**	**1978–2010**	**1978–2013**
μ_1	−0.203%	−0.026%	0.550%	0.533%
μ_2	0.587%	0.955%	0.219%	0.269%
σ_1	3.877%	4.785%	6.823%	6.751%
σ_2	14.544%	14.053%	18.109%	18.004%
$p1,2$	13.224%	10.176%	3.505%	3.066%
$p2,1$	14.768%	12.026%	12.971%	12.350%
Number of parameters	6	6	6	6
Number of observations	275	335	395	429
Negative log-likelihood	283.58	334.59	384.73	429.90

[1] Even though we refer to prices, when regime switching models are estimated, the underlying time series is the logarithmic return of energy prices. Hence, mean and volatility estimates are those of the logarithmic return of prices.

Table 5
Goodness of fit tests of GBM and RSGBM2 models using monthly oil price data from 1978 to 2013.

	1978–2000	1978–2005	1978–2010	1978–2013
Panel A: Akaike IC				
GBM	230.64	289.14	332.26	372.29
RSGBM2	277.58	328.59	378.73	423.90
Best Model:	**RSGBM2**	**RSGBM2**	**RSGBM2**	**RSGBM2**
Panel B: Schwartz Bayes IC				
GBM	227.03	285.33	328.28	368.22
RSGBM2	266.73	317.15	366.79	411.72
Best Model:	**RSGBM2**	**RSGBM2**	**RSGBM2**	**RSGBM2**
Panel C: log-likelihood test				
GBM	232.64	291.14	334.26	374.29
RSGBM2	283.58	334.59	384.73	429.90
Test Stat	101.58	86.89	100.93	111.24
Best Model:	**RSGBM2**	**RSGBM2**	**RSGBM2**	**RSGBM2**

by the volatility parameters. Specifically, the RSGBM2 model assigns logarithmic returns into a "high volatility" regime (regime 2) and a "low-volatility" regime (regime 1). The classification of returns into one of these two regimes is done by maximizing the likelihood function of the RSGBM2 model. The lowest volatility across low-volatility regimes is observed in the first period (3.88%) and the highest in the third period (6.83%), which includes the big spike and its reversal in 2008. In the last period the volatility appears to decrease in the low-volatility regimes. In the "high-volatility" regime, we observe the lowest volatility to appear in the second period (14.05%) and the highest in the third period (18.11%).The following can also be noted. Both the mean and volatility parameters for the RSGBM2 model, behave as the upper and lower bounds for the mean and volatility parameters of the GBM model. The underlying question is which model is better and which one should be used? Table 5 reports three goodness-of-fit tests (Akaike information criterion, Schwartz–Bayes information criterion and the likelihood test) between the two models (GBM and RSGBM2) over the four time periods. A consensus in favor of the RSGBM2 model is observed.

Finally, the subplots *a–d* in Fig. 4 show the entire time series of oil prices (solid line) superimposed by the monthly conditional probability of being classified in the low-volatility regime. This conditional probability takes values from 0% to 100%, where 0% (100%) implies that the process on the specific month is classified as being in the high-volatility (low-volatility) regime. The four subplots show that in the period of either spikes or increases in volatility, the model classifies the process further away from the low-volatility regime; that is, the monthly conditional probability changes from 100% towards 0%.

Thus, to forecast Brent prices ($FFP_{BRENT,m}$) over a 60-month period, the RSGBM2 model, re-estimated over the period 1978–2013, is used. Our 60-month forecasts for $FFP_{BRENT,m}$ are shown in Fig. 5. For clarity, the 10th to the 90th percentile of the forecasts are displayed. For example, the 50th percentile $FFP_{BRENT,m}$ shows that 50% of all future forecasts are less than or equal to the values displayed. Fig. 5 also illustrates the reference $FFP_{BRENT,REF}$ which is basically the tabulated Brent price for December 2013.

Having modeled future price movements of Brent (which is traded as a commodity on a daily basis) through RSGBM2, it is assumed that the various oil classifications (e.g. Heavy Fuel Oil and

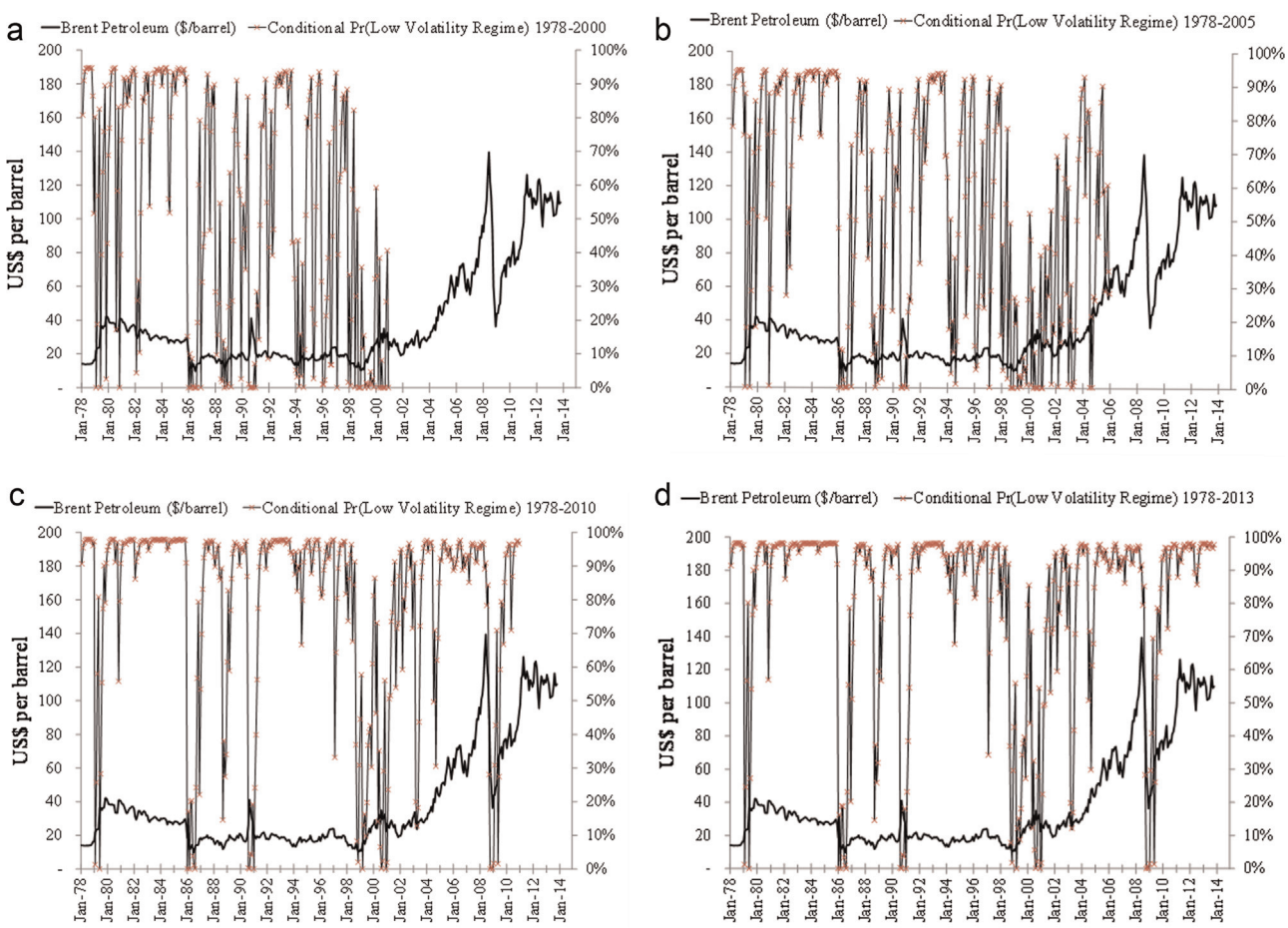

Fig. 4. Time series of oil prices superimposed by monthly conditional probability of being classified in the low-volatility regime.

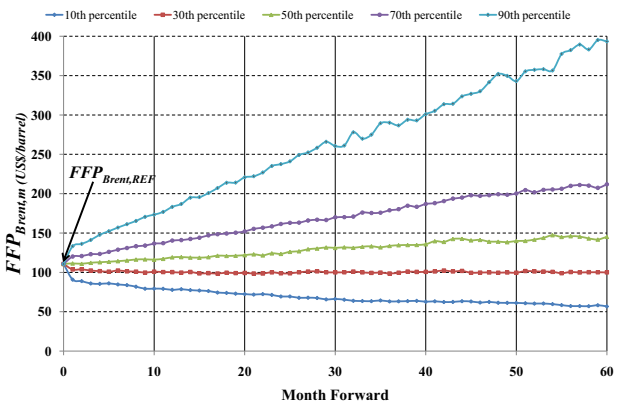

Fig. 5. Statistical Forecasting of Brent prices (i.e. $FFP_{BRENT,m}$) over 60 months starting on January 2014 to December 2018.

Table 6
Regression analysis

	HFO	Diesel
R^2	0.975	0.983
Intercept (κ_1, κ_2)	−14.34	58.44
Brent coefficient (λ_1, λ_2)	0.797	1.113

Diesel) are dominated by Brent's price volatility. Therefore, a simple approach is adopted for illustration purposes, that relies on linear regressions between Brent and Heavy Fuel Oil (HFO) historical monthly prices from 1990 to 2013 and between Brent and Diesel historical monthly prices from 1996 to 2013 in order to obtain the prices for the particular fuel mix of the test system (as per (10) and Table 2). The regression results are shown in Table 6, where, κ is the intercept, λ is the coefficient for Brent prices and ε refers the zero-mean error term.

$$\begin{aligned} FFP_{HFO,m} &= \kappa_1 + \lambda_1 \times FFP_{BRENT,m} + \varepsilon_{HFO,\ m} \\ FFP_{DIESEL,m} &= \kappa_2 + \lambda_2 \times FFP_{BRENT,m} + \varepsilon_{DIESEL,\ m} \end{aligned} \tag{10}$$

3. Results

3.1. Impact of fuel price volatility on energy charges

Two key pricing strategies are considered in this paper. The main difference in the two rests with how the revenue requirement (*TRR*) is recovered through the fixed and energy customer charges. Both strategies (I and II), consider three residential sample tariff structures, namely: (a) a volumetric flat charge rate (*FCR*), (b) a two-tiered volumetric block tariff with increasing energy charge rates (*IBR*) and (c) a two-tiered volumetric block tariff with decreasing energy charge rates (*DBR*).

3.1.1. Calculation of reference electricity charges

The numerical evaluation of the two pricing strategies is based on the fixed cost component (2) and the variable cost component (3) formulations of the total revenue requirements (1). The evaluation is based on the data given in Table 2 and Table 3 and on the use of a set of reference fuel prices, which pertain to the actual market prices of Heavy Fuel Oil and Diesel for December 2013 (US Energy Information Agency (EIA)).

Using these reference fuel prices, the variable cost component is evaluated as follows. Based on the system's type of units and on their commitment priority order, each generating unit (g) shown in Table 2, will deliver an expected annual energy amount (ER_g in MWh). The cost of ER_g will be inevitably dependent on the fossil fuel type, each unit is using. Thus, based on the type of fuel of each generator, we set the reference fossil fuel price $FFP_{g,REF}$ (in \$/MT) to be equal to the actual market prices in December 2013 (see Table 2). The reference fuel prices are concurrently used to calculate a reference total cost of fuels per MWh for each generator ($FC_{g,REF}$ in \$/MWh) as shown in (11). Within (11), NCV_g refers to Net Calorific Value (in MJ/MT) of each unit's fuel type, η_g to the efficiency of each generating unit and $FFP_{g,REF}$ to the reference fuel prices associated to each generating unit.

$$FC_{g,REF} = \frac{FFP_{g,REF} \times 3600}{\eta_g \times NCV_g} \tag{11}$$

Therefore, the formulation shown in (3) can be modified as in (12), to explicitly define a reference variable cost component (VrC^{REF}) based on a reference fuel cost ($FC_{g,REF}$) per MWh for each generator g.

$$VrC^{REF} = \sum_{g=1}^{G} ER_g \times (FC_{g,REF} + EMC_g + VOM_g) \tag{12}$$

Within (12), ER_g refers to the expected annual energy generation (in MWh) from each generating unit g. All other terms of (12) are defined in Table 2.

Therefore, the fixed cost component (*FiC*) and the reference variable cost component (VrC^{REF}) are used to calculate a reference total revenue requirement (TRR_{REF}) which results in some reference electricity charges as per (13).

$$CC = \frac{a \times TRR_{REF}}{NoC \times 12} FCR^{REF} = \frac{b \times TRR_{REF}}{ES} a + b = 1 \tag{13}$$

Within (13), TRR_{REF} is the reference annual total revenue requirement, *NoC* refers to the total number of customers, *CC* refers to the fixed monthly customer charge, FCR^{REF} is the flat energy charge rate and *ES* is the total annual electricity sales of the utility. Parameters a and b define the ratio of TRR_{REF} that will be recovered through the monthly customer charges and energy charges respectively. Therefore, the average customer monthly bill (ATB^{REF}) can be calculated as a function of the monthly customer charge (*CC*), the flat energy charge rate (FCR^{REF}) and the Average Monthly Consumption (*AMC*) of a typical residential customer as in (14).

$$ATB^{REF} = CC + FCR^{REF} \times AMC \tag{14}$$

Both strategies shown in Table 7, although different in their structure, result in collecting the same amount of revenue from

Table 7
Reference energy charges for two pricing strategies.

Pricing Strategy I				
Fixed Customer Charge (CC_I)	***FCR I*** (\$/kWh)	***IBR I***[a] (\$/kWh)	***DBR I***[a] (\$/kWh)	***Cut-off point***[a] $X_1 = 430kWh$
61.19 \$/month	0.1544	0.1372	0.1684	B_1^{REF}
		0.1716	0.1404	B_2^{REF}
Pricing Strategy II				
Fixed Customer Charge (CC_{II})	***FCR II*** (\$/kWh)	***IBR II***[a] (\$/kWh)	***DBR II***[a] (\$/kWh)	***Cut-off point***[a] $X_1 = 430$ kWh
0 \$/month	0.2256	0.2005	0.2461	B_1^{REF}
		0.2507	0.2051	B_2^{REF}

[a] It is noted that for the block rates, the cut-off (boundary) point between the two blocks is assumed to be 430 kWh, which decodes into 50% of the assumed *AMC*. The relationship between the energy charge rates of the two blocks is set to $B_1^{REF} = 0.8 \times B_2^{REF}$ and $B_1^{REF} = 1.2 \times B_2^{REF}$ for the *IBR* (I&II) and *DBR* (I&II) cases respectively.

customers. However, these two particular pricing strategies are deliberately selected due to the fact that they show extremities (lower and upper bounds) of the retail rates that consumers may be offered by utilities. Specifically, if a net-metered customer is offered the rate structure of pricing strategy I, then he actually receives compensation only for the fuel, CO_2 and variable operation and maintenance costs that the utility avoids; thus ignoring the fact that his distributed system may contribute to the overall system generation, transmission and distribution adequacy. On the other hand, if he is offered the rate structure of pricing strategy II, then he receives full retail rate compensation; thus largely affecting the utility's revenue and/or the rate that non-participating (to NEM) customers have to pay.

3.1.2. Adjusting reference energy charges to account for fossil fuel price variation

To model the effect of fossil fuel varying prices, on the variable cost component, the formulation shown in (12) is modified as shown in (15). The latter is used to calculate the deviation of the monthly variable cost component (VrC^m) from the reference variable cost component (VrC^{REF}) defined in (12). This is achieved through the use of a weight factor in the form of $\frac{FFP_{g,m}}{FFP_{g,REF}}$. This weight factor is able to adjust the variable costs as per the estimated fuel prices of a future month (m). Hence, the forecasts obtained through the RSGBM2 model ($FFP_{g,m}$), shown in Fig. 5, and their regressions (Table 6) are integrated into the modeling process. Therefore, an updated variable cost formulation (VrC^m) – and a consequent updated total revenue requirement ($TRR^m = FiC + VrC^m$) – is deduced according to the monthly variation of fuel prices.

$$VrC^m = \sum_{g=1}^{G}\left[ER_g\left(FC_{g,REF} \times \frac{FFP_{g,m}}{FFP_{g,REF}} + EMC_g + VOM_g\right)\right] \tag{15}$$

By means of (13)–(15) and based on the RSGBM2 model results and regressions, the energy charges of our five-year evaluation period are calculated for each monthly billing period (m) for all rate structures and pricing strategies. As an example, the flat charge rates (FCR^m) per billing period of the first year, for both pricing strategies (I and II), are shown in Table 8, based on the RSGBM2 50th percentile forecasting results. It should be noted that block charges (B_k^m) are modeled based on the reference design principles (i.e. number of blocks, cut-off points, relationship between the block energy charges, etc.) discussed in Subsection 3.1.1.

3.2. Value of bill savings under net metering

The value of bill savings under net metering is achieved through the *Value of Bill Savings* (i.e. *VBS*) index shown in (16). This index expresses the bill savings on a $/kWh basis, by considering the annual reduction in the customer's bill per kWh generated by a PV system (Darghouth et al., 2013). As noted in (Darghouth et al., 2013), this is a valuable index, since it allows for a direct comparison of customers' bills with different loads as well as a comparison under different PV to Load ratios. The PV to Load ratio refers to the ratio of the annual PV energy yield over the annual energy consumption of a customer.

$$VBS = \frac{\sum_{m=1}^{M}\left(TB^m(VrC^m) - TB_{NEM}^m(VrC^m, PV^m)\right)}{\sum_{m=1}^{M} PV^m} \tag{16}$$

As evident in (16), the *VBS* calculation embraces the total customer bill, without a net-metered PV system ($TB^m(VrC^m)$) and the total customer bill, with a net-metered PV system ($TB_{NEM}^m(VrC^m, PV^m)$). The total customer bills, TB^m and TB_{NEM}^m, can be obtained as given in (4)–(5) and in (8)–(9) respectively when using the fuel-adjusted energy charges, FCR^m (Table 8) and B_k^m. M refers to the number of billing periods (in months) of the evaluation.

Table 8
Fuel-adjusted energy charges for two pricing strategies. *RSGBM2* 50th *Percentile Forecasting Results*.

Billing period (m)	FCR_I^m	FCR_{II}^m
REF	0.1544	0.2256
1	0.1552	0.2263
2	0.1547	0.2259
3	0.1563	0.2272
4	0.1571	0.2278
5	0.1578	0.2285
6	0.1588	0.2292
7	0.1598	0.2301
8	0.1613	0.2314
9	0.1616	0.2316
10	0.1611	0.2312
11	0.1624	0.2323
12	0.1648	0.2343

4. Discussion

The subsequent *VBS* analysis utilizes the 1 kW_p PV generation data shown in Fig. 3. The 1 kW_p PV size is able to offset 16.7% of the customer's annual energy consumption shown in Fig. 2(i.e. 16.7% PV to Load ratio). Moreover, a 100% PV to Load ratio scenario under a 6 kW_p PV size is also examined. Therefore, for these two PV to Load ratios, the *VBS* is evaluated under the two pricing strategies (I and II) and their associated rate structures (*FCR, IBR, DBR*). The results are shown in Figs. 6 and 7.

The impact of the different fuel prices percentiles (Fig. 5) is also marked in Figs. 6 and 7. In particular, the impact of the 5th, 50th and 95th percentiles of the Brent and Diesel fuels' forecasts is illustrated. These percentiles are used to capture the extremity of the fuel prices impact on the *VBS* evaluation. Moreover, the *VBS* under these percentiles is also benchmarked against a reference scenario that assumes that fuel prices remain constant throughout the evaluation period (i.e. five years).

Both Figs. 6 and 7 reveal that pricing strategies moderate the expected *VBS*. Specifically, it is apparent that pricing strategy II offers a larger incentive (i.e. higher *VBS*) than strategy I to customers considering a net-metered PV investment. This is because, for pricing strategy II, the energy (per kWh) charge offered includes not only the variable but also the fixed cost component of the total revenue requirements. Thereby, a NEM customer avoids a larger consumption cost and benefits from this indirect subsidy

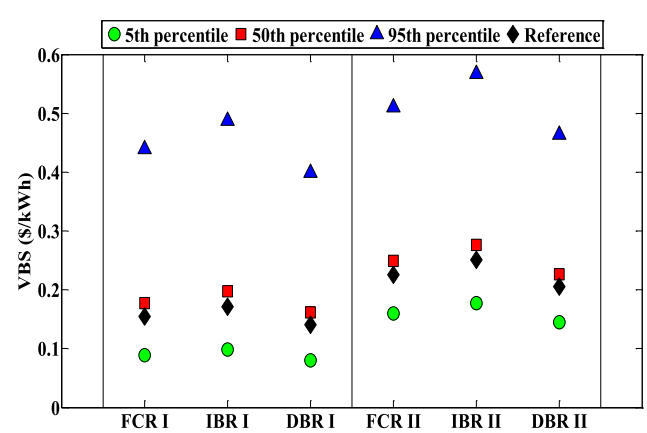

Fig. 6. *VBS* results based on the fuel price forecasts' 5th, 50th and 95th percentile values and benchmarked against the reference scenario for a 16.7% PV to Load ratio.

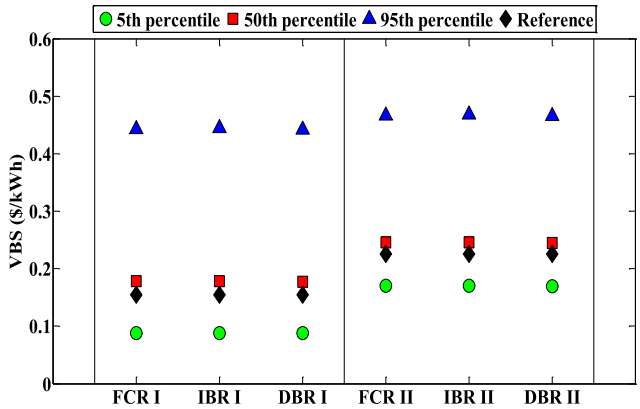

Fig. 7. *VBS* results based on the fuel price forecasts' 5th, 50th and 95th percentile values and benchmarked against the reference scenario for a 100% PV to Load ratio.

(Raskin, 2013). However, it should be borne in mind that allowing NEM customers to offset all fixed utility costs may lead to revenue inadequacies (for utilities) and perhaps increased costs for other customers that do not participate in NEM.

In addition, the tariff structure under which the customer is charged has a considerable effect on *VBS*. In particular, under the 16.7% PV to Load ratio examined, the *IBR* structure would enable a NEM customer to offset a higher consumption cost compared to *FCR* and *DBR* structures, thus significantly increasing the value of investment. Conversely, a customer charged under a *DBR* structure would accrue a lower benefit for the same investment due to the fact that *DBR* structures offer a lower charge rate as energy consumption increases. As shown in Fig. 6, under both pricing strategies I and II, the profitability of the investment (*VBS*) for a *DBR* customer is eroded. However, the rate structure impact on the value of bill savings gradually diminishes as the PV to Load ratio reaches higher levels. To this end, Fig. 7 shows that for the 100% PV-to-Load ratio all rate structures yield equal bill savings. Moreover, Figs. 6 and 7 show that fuel price variation is a prevailing factor that also controls the respective *VBS* of residential customers. The results clearly suggest that the competitiveness of net-metered PV systems is counteracted by diminishing fossil fuel prices.

4.1. Financial risk assessment for net-metered PV applications

To assess the financial risk of *VBS* under the calculated range of fossil fuel prices forecasts the following formulation is considered. A *VBS* probability distribution is extracted through utilizing all fuel price forecasts deduced in Section 2.3. Specifically, a cumulative probability distribution $F(x)$ of *VBS* values is calculated through the formulation shown in (16). The *VBS* distribution is extracted from each of the fuels' price percentiles (1st–99th) obtained by the RSGBM2 model. Table 9 illustrates the process of calculating the distribution of *VBS* values for the *FCR* case of pricing strategy I (FCR_I). Similarly, cumulative probability distributions can be calculated for all tariff structures shown in Table 7. To this end, Figs. 8

Table 9
VBS distribution calculation process.

Cumulative probability $F(x)$ (%)	Fossil fuel price percentile values (RGBM2)	*VBS* percentile values (in $/kWh)
1	FFP_{HFO_1st}, FFP_{DIESEL_1st}	0.1006
2	FFP_{HFO_2nd}, FFP_{DIESEL_2nd}	0.1094
⋮	⋮	⋮
99	FFP_{HFO_99th}, FFP_{DIESEL_99th}	0.2395

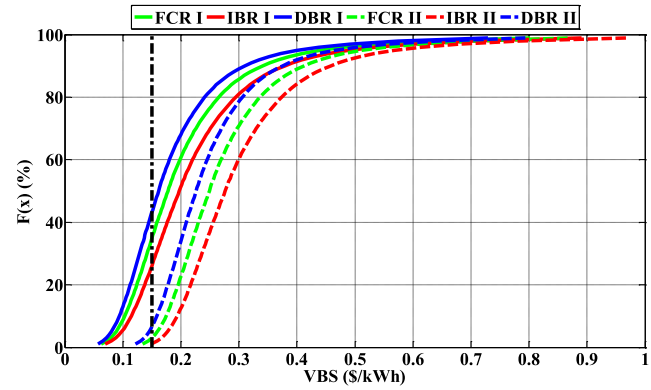

Fig. 8. Cumulative *VBS* distributions $F(x)$ of a 16.7% PV to Load ratio for the two utility pricing strategies in comparison to the *LCOE* target value (marked by the vertical line).

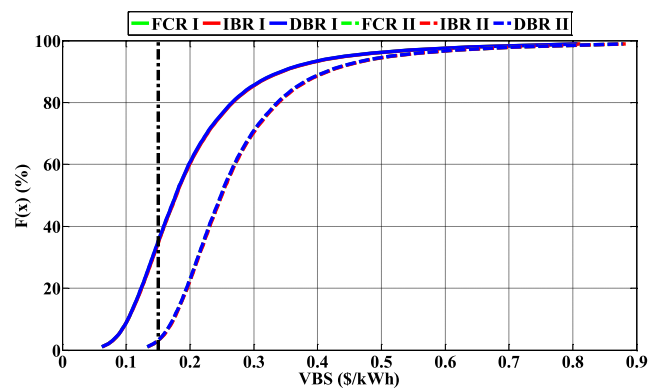

Fig. 9. Cumulative *VBS* distributions $F(x)$ of a 100% PV to Load ratio for the two utility pricing strategies in comparison to the *LCOE* target value (marked by the vertical line).

and 9 show all cumulative distributions $F(x)$ of *VBS* under the 16.7% and 100% PV to Load ratios considered in this paper.

Once the *VBS* distributions have been calculated, their values are directly compared to a target *VBS* level. By means of an example, a *VBS* target value equal to $0.15/kWh is assumed. This target pertains to an estimation of the Levelized Cost of Energy (*LCOE*) of PV generation. *LCOE* can be perceived as a stream of equal payments, normalized over the expected energy production, which would allow a stakeholder to recover all costs over a determined financial lifetime (Darghouth et al., 2013). Thus, the financial risk of the PV investment in its first five years of operation may be examined through Figs. 8 and 9 for the 16.7% and 100% PV to Load ratio respectively. To this end, Table 10 tabulates the probability of *VBS* being less than the *LCOE* target value set.

The tabulated results confirm that pricing strategies fundamentally control *VBS*. In fact for pricing strategy II, the probability of the *VBS* being less than the *LCOE* target value, significantly decreases. Moreover, it is clear that the rate structures (in both pricing strategies) substantially influence the *VBS*. In particular, under the large array of fuel forecasting prices, the *DBR* structure (in both pricing strategies) exhibits the larger probability of not being able to meet the target value of providing a *VBS* in the order of the *LCOE*

Table 10
Probability of *VBS* being less than the *LCOE* target value.

	Strategy I			Strategy II		
PV to Load ratio	FCR_I	IBR_I	DBR_I	FCR_{II}	IBR_{II}	DBR_{II}
16.7%	$P=34\%$	$P=26\%$	$P=43\%$	$P=2\%$	$P=1\%$	$P=6\%$
100%	$P=34\%$	$P=34\%$	$P=34\%$	$P=3\%$	$P=3\%$	$P=3\%$

for PV generation. Nevertheless, this effect gradually decreases as the PV to Load ratio increases.

It is, nevertheless, obvious that retail charges, due to fuel prices volatility, introduce a significant uncertainty to the *VBS* of a net-metered PV application. This is clearly reflected on the five-year evaluation period examined in this paper, thus enabling interested stakeholders to further evaluate the financial risk of their investments.

5. Conclusions and policy implications

Net metering provisions are increasingly attracting interest as low-cost, easily implementable schemes that play an integral role in the growth of rooftop photovoltaic installations. The relatively simple as well as fundamental logic of their entailing policies constitute them appealing to retail electricity customers. To this, end a number of studies have been conducted in recent years to identify public perceptions and attitudes towards net metering actions and policies. These studies (e.g., Raskin, 2013 and Poullikkas et al., 2013) have provided some important findings. In general, these studies imply that people may hold inaccurate perceptions about their energy consumption and savings under PV net-metering applications, mainly due to large knowledge gaps regarding electricity costs structures and underlying business economics of utilities that are associated with investment in and operation of transmission and distribution facilities and other costs incurred to ensure reliability and fund public policy initiatives endorsed by utility regulators (Raskin, 2013). It is, however, important for potential net metering customers to understand that net metering is an investment and as such, there may be a possibility that the actual return will be different than expected. To this extent, the literacy lack identified in the general group of retail energy customers constitutes a “noisy communication channel” that fails to link the intrinsic characteristics of NEM to the underlying revenue collection practices of utilities. This inevitably entails inaccurate financial assessments of profitability and returns on investment, for NEM customers.

Therefore, this paper has attempted to firstly reiterate the impact of the inherent uncertainty embedded in electricity charges and retail tariffs on the return of investment expected from net-metered residential PV systems. In particular, the retail rates' volatility and its subsequent impact on net-metered PV applications were approached in a threefold manner; volatility resulting from: (i) the pricing strategy of the utility, (ii) the rate structure under which the customer is charged, and (iii) rate rider clauses through fuel prices adjustment caps depending on volatile fuel prices.

Specifically, the extremities of the utility's pricing strategy were examined in order to capture the upper and lower bound of a net metering compensation mechanism. These bounds aim to highlight that the true avoided cost of the utility would lie within these values. Thus, net metering schemes could be more suitably tailored to the specifics of each utility through alternative pricing strategies thus minimizing cross-subsidies between NEM and regular customers. In addition, the traditional volumetric tariff structures were thoroughly examined in order to evaluate their effect on net-metered applications. It is clear that rate structures can potentially have a significant effect on the bill savings generated by a net-metered PV system due to the difference in the marginal rates offered to customers as per their energy consumption levels.

It is also acknowledged, that the uncertainty in fuel prices changes heavily depends on the electricity fuel mix. For example, in a country with mostly nuclear and hydro, fuel prices are relatively stable and hence do not constitute a source of uncertainty in retail electricity rates. In addition, renewable energy can serve to hedge fuel prices related risks. Nevertheless, the uncertainty is highest in regions where the main fuel for electricity generation has high price volatility, such as oil. This is particularly evident in small and isolated systems such as the one simulated in the paper by means of an example.

To this extent, it should also be highlighted that regulatory uncertainties could be more significant than that due to fuel prices. Other sources of uncertainties include elements such as PV output, degradation and failures, feedback from PV uptake to future rate changes (see Cai et al., 2013), and change in mix of generation in the long run. While a thorough analysis is not within the scope of this work, the authors would like to highlight that the influence of these other sources of uncertainties on the return of NEM investments is equally important.

In conclusion, through adopting a flexible forecasting model – RSGBM2 – and generic retail rate formulations, this paper has presented a top-down transparent method that quantifies the financial risk of net metering (from the customer's perspective) in a vertically integrated system by accounting for the combined effect of utility pricing strategies, rate structures and fuel price volatility.

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