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Energy Procedia 125 (2017) 389–397

Energy Procedia

www.elsevier.com/locate/procedia

European Geosciences Union General Assembly 2017, EGU
Division Energy, Resources & Environment, ERE

Energy, variability and weather finance engineering

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Abstract

Weather derivatives comprise efficient financial tools for managing hydrometeorological *uncertainties* in various markets. With ~46% utilization by the energy industry, weather derivatives are projected to constitute a critical element for dealing with risks of low and medium impacts –contrary to standard insurance contracts that deal with extreme events. In this context, we design and *engineer* -via *Monte Carlo* pricing- a weather derivative for a *remote island* in Greece -powered by an autonomous diesel-fuelled generator- resembling to a standard *call option* contract to test the benefits for both the island's *public administration* and a *bank* -as the transaction's counterparty.

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Keywords: Weather derivatives; uncertainty; financial engineering; Monte Carlo; remote island; call option; public administration; bank

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1. Introduction

A major challenge for many *energy systems* in the globe -irrespective of size or composition- is the management of *energy supply uncertainties* that have their grounds on *hydrometeorological* conditions (eg. temperature, rainfall, wind) at the *monetary* level, as most energy units are not sufficiently flexible to adapt to weather condition changes (eg. *wind* turbines are dependent on wind variability with no direct storage capacity; *hydropower* units are primarily dependent on precipitation, with dry periods limiting their output potential continuity; while many types of *thermal*

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Peer-review under responsibility of the scientific committee of the European Geosciences Union (EGU) General Assembly 2017 – Division Energy, Resources and the Environment (ERE).
10.1016/j.egypro.2017.08.073

plants cannot change rapidly their output in order to meet the real-time demand, etc.). For that reason, *financial risk management* products -called *weather derivatives*- that allow power supply units to protect both their capital and the continuity of their revenues against unpredictable weather conditions -via a mechanism of *financial compensations*- have been developed. In our work we design a *call option* type weather derivative for a simple autonomous energy system in the remote -and non-connected to the continental grid- island of Astypalaia (36°33 N; 26°21 E) in Greece to identify the municipality's benefits across changes in *temperature* and *population* (due to touristic seasonality).

Nomenclature

T_i	*Mean temperature* of day *i*
HDD_i	*Heating Degree Days*; total degrees within a day *i* where the average temperature is *below 18.3 °C*
CDD_i	*Cooling Degree Days*; total degrees within a day *i* where the average temperature is *above 18.3 °C*
NAD_i	*Net Accumulated Degrees*; after the abstraction of the degree index with the lower value, starting at day *i*
Tick	Monetary value (constant) per NAD_i, expressed in $
OCC	*Option Contract Cost*; the *fee* to buy the option contract, irrespective of whether it yields profit or not
SP	*Strike Price*; the value in units of the weather index (degree days) for which the contract is *triggered*
$Payoff_i$	Difference between NAD_i and the *SP* (in degree days), multiplied with the *Tick*
BE	*Break Even*; the payoff level where the profits cover exactly the *OCC* so that the total position is zero
$Margin_i$	Deviation between the *local* and the *international* oil price due to tourism and temperature, per day *i*
TM_i	*Total Margin*; $Margin_i$ multiplied with the *total number of barrels* of oil equivalent (boe), per day *i*
$Dummy_i$	Component of the $Margin_i$ that concerns population increase due to tourism seasonality
$Actual_i$	*Actual payoff* of a contract on day *i*, based on historical data of *NAD*
$Simulated_i$	*Simulated payoff* of a contract on day *i*, based on the *Monte Carlo* pricing method
TDD_i	*Total Daily Demand* on day *i*; the aggregate daily energy use (in MWh), according to the historical data
PP_i	*Profit Percentage* on day *i*; fraction of monthly TM_i covered by the difference of $Actual_i$ and $Simulated_i$
UAPE	*Unbiased Absolute Percentage Error*; measure for assessing forecast error, *unbiased* with respect to scale
PD_i	*Positive Difference* on day *i*; the difference between $Actual_i$ and $Simulated_i$, only when $Actual_i > Simulated_i$
CDPD	*Contract Days with Positive Difference*; total number of days where $Actual_i > Simulated_i$
TCD	*Total Contract Days*; total number of days for *HDD* or *CDD* contracts (either $Simulated_i \neq 0$ or $Actual_i \neq 0$)
RP	*Risk Probability*; probability of the occurrence of an underpriced contract, i.e. $Actual_i > Simulated_i$
RE	*Risk Exposure*; quantified *loss potential* for the financial institution, expressed in $

1.1. Weather Derivatives: General issues

Weather derivatives are financial tools used by organizations or individuals as part of a risk management strategy to reduce risks associated to a wide range of adverse or unexpected weather conditions. Financial agreements based on the rationale of weather derivatives can be traced in ancient Greece; specifically they are reported to have been profitably used by *Thales of Miletus* (624 – 546 BC) [1]. These financial products are *index-based* instruments that usually utilize observed weather data at a specific weather station to create an index on which an agreed payoff can be based. The main distinction of weather derivatives from *standard insurance contracts* is that the former contracts cover events of low risk, high (occurrence) probability and low financial impact, whereas the latter cover events of high risk, low (occurrence) probability and high financial impact. The *option* is a weather derivative contract, which gives the holder -upon paying an *OCC*- the *right* -however not the *obligation*- to *buy* or *sell* an *underlying* asset at a specific *strike price* by a specific date. The seller has the corresponding obligation to fulfill the transaction -to sell or buy- if the buyer (owner) *exercises* the option. The option is exercised at least at the *BE*, covering exactly the OCC.

1.2. Weather Derivatives: Financial notations

The weather derivative of our analysis is a typical *call option* based on *temperature* –as the underlying index. We use the *HDD* and *CDD* metrics as a measure of our underlying index. Both metrics calculate the difference between the mean temperature of any day *i* and the temperature of *optimal thermal comfort*, which we consider to be equal to 18.3°C. In our case, the designed option contract has the following main characteristics:

- The engineered contract is a *call option* of *one-month* duration. Its *payoff* has no *upper limit* (uncapped) and is calculated at *maturity*, assuming constant interest rates.
- The *tick size* of the contract is assumed to have a *constant value* of 10$ per NAD.
- The *strike prices* are set for different *standard deviations* from historical means of accumulated HDD and CDD (see Fig. 2 (b)).
- There are *no-arbitrage* conditions assumed for a *fair-pricing* by the bank (financial institution). The fair price is defined as the discounted expected payoff of the contract (see Eq. (6)).

The following notations concern the fundamental concepts used for the design of the option contract:

$$CDD_i = \max(T_i - 18.3; 0) \tag{1}$$

$$HDD_i = \max(18.3 - T_i; 0) \tag{2}$$

$$H_{month} = \sum_{i=1}^{30} HDD_i \tag{3}$$

$$C_{month} = \sum_{i=1}^{30} CDD_i \tag{4}$$

$$NAD_i = \max(H_{month} - C_{month}; C_{month} - H_{month}) \tag{5}$$

$$Payoff_i = Tick \cdot \max(NAD_i - SP; 0) \tag{6}$$

In order to calculate the weather derivative's payoff at the end of the one-month period, we calculate the NAD; starting at day *i* and then subtracting the degree index with the lower value. For the different strike prices set, based on the statistical properties of the historical data, we calculate the payoffs for each starting day of the contract.

2. Methodology: Market structure and options valuation

2.1. Marginal value model

We assume a *margin*, to be a deviation between the *international* and the *local* fuel price, due to socioeconomic and meteorological particularities of the study area, incorporated in a simple model, presented in Eq. (7). In addition, we adopt this assumption for reasons of methodological simplification; as the factors influencing the international price are quite complex -and outside the scope of our study- we consider it to be a benchmark, upon which the rest of the island's energy costs are built. Hence, the local oil price is modelled with the following assumptions:

- The fuel necessary for the island's energy output *cannot be supplied directly from the international market* to the municipality due to the island's small size and -hence- its inability to influence the price via the purchase of large quantities. In a few words, *the island does not impact the international price at all via means of demand change*.
- From the municipality's part, there is *zero adaptability* of the fuel supply; actually suggesting that we assume *no past stocks* of fuel in order to avoid buying on the (local) *spot* price, especially in cases of price boosts. The only way assumed to manage the spot price variability is the weather derivative.

- The *local fuel supplier is neutral* towards any weather derivates' transaction; meaning that he only supplies diesel to the municipality at the spot price -on which his revenues depend exclusively- and does not participate in any other way (eg. via a *put option* towards the bank or the municipality or even a *mixed strategy*) in the market. We acknowledge that in a more realistic market structure, all transaction combinations would be feasible between all counterparties (municipality, bank and oil supplier) and with any kind of options' strategy. However, this would add significant complexity in our model and would be outside the scope of our work.
- The *mean daily temperature* and the *increase in population due to tourism seasonality* are supposed to be the two largest contributing factors of the energy demand; hence of the local price as well. Therefore, the marginal value time series will -more or less- reflect a composition between the international price pattern (as benchmark) and the island's energy demand pattern, according to Eq. (7) (see also Fig. 2 (a) for a clear depiction of the result).

The effect of the mean daily temperature on energy demand is commonly analyzed through taking into account the difference between the mean daily temperature and the *base* temperature used to calculate the HDD and CDD. This base (optimal thermal comfort) temperature, namely, 18.3°C is a point of *minimum energy use* in the U-shaped relationship between temperature and energy use (see Fig. 1 (b)). In the literature this base temperature may vary; however we follow the approach of Fazeli et al. [2], who find 18.3°C to be used in the majority of related studies.

The effect of the increase in population due to tourism on energy demand is considered to be a *dummy variable* for different 10-day periods -throughout the *high season* (June 1st to September 28th)- by contrasting *different mean daily energy demands for same temperatures*. Although, we have insufficient data to identify accurately seasonality patterns of tourist arrivals in the island of Astypalaia, we can fairly conclude that tourists exceed approximately six (6) times the local population, which -according to our approach- would mean six (6) times higher energy demand. We use the following simple linear model to reproduce the above assumptions:

$$\mathrm{Margin}_i = abs(18.3 - T_i) + 6 \cdot (Dummy_i - 1) \tag{7}$$

In Table 1, we provide a list of the dummy variable values for each 10-day period, as well as their effect on the margin. Although touristic arrivals do not relate directly with the weather derivative, they influence at a second level (after the international oil price) the local spot price as *seasonal benchmark*; especially from the municipality's point of view, which seeks to save money from its budget by choosing the optimal periods to buy a contract. Hence, after isolating this effect we can deal exclusively with the effect of temperature on the option's payoff simulation.

Table 1. Margin due to population increase, based on the seasonality of tourism.

Time period of the year	Dummy Variable	Margin due to tourism
29th September - 31th May	1.00	0
1st June - 10th June	1.05	0.30
11th June - 20th June	1.10	0.60
21st June - 30th June	1.20	1.20
1st July - 10th July	1.35	2.10
11th July - 20th July	1.70	4.20
21st July - 30th July	2.10	6.60
31st July - 9th August	2.35	8.10
10th August - 19th August	2.65	9.90
20th August -29th August	2.60	9.60
30th August - 8th September	2.00	6.00
9th September - 18th September	1.60	3.60
19th September - 28th September	1.35	2.10

We can generally expect a positive correlation between the island's total energy demand and the marginal value (that is added to the international price to form the local spot price). Indeed, according to Fig. 1 (a) we observe such a relation. In addition, we observe a *U-shaped* relationship (that could be modelled by a second order polynomial) between temperature and energy demand (see Fig. 1 (b)), suggesting that for any deviation from the thermal comfort optimum, inhabitants will attempt to compensate their surroundings' temperature via increased energy use, either for cooling or heating. At this point we have to denote that this relationship cannot be generalised for any climate zone; as closer to its ideal shape it is mostly observed in Mediterranean climate zones [3] and generally climate zones with significant seasonal temperature variability. More specifically, it is also notable that for Astypalaia, the relationship is asymmetric towards the curve's right part; suggesting that at the island's geographical position, high temperatures are more frequent than low temperatures; therefore *increased energy use is more likely to occur for cooling than for heating*. Indeed, according to Fig. 2 (a), our model on the margin provides the most significant deviations between the local and the international (historical) diesel price per barrel [4] for 2014-15 during the summer. In addition, the rough indication that CDD are much more likely to accumulate than HDD -according to Fig. 1 (b)- is verified in Fig. 2 (b). As analyzed below, this affects the municipality's general preference for positions on CDD rather than HDD.

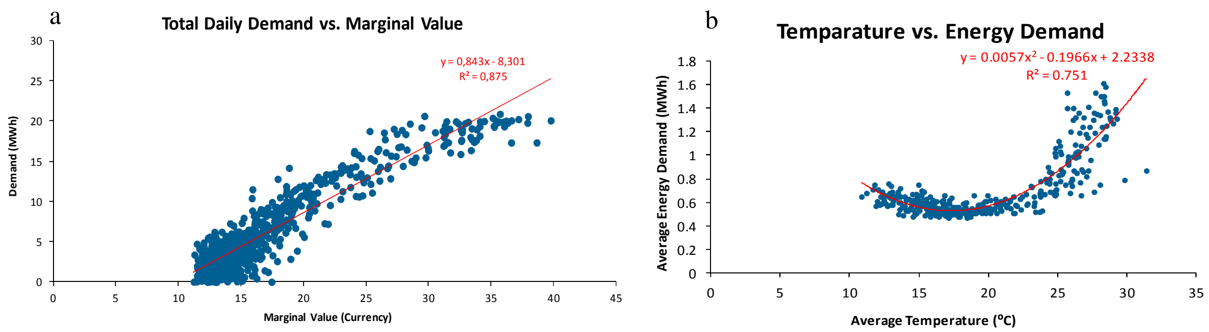

Fig. 1. (a) Relationship between total daily energy demand and the modelled marginal value, suggesting that under our assumption of inflexible supply, increased demand increases the local price; (b) Relationship between mean daily temperature and energy demand, generally following a *U-shape* -here asymmetrical towards the right- suggesting higher energy use across temperature deviations from the thermal comfort optimum.

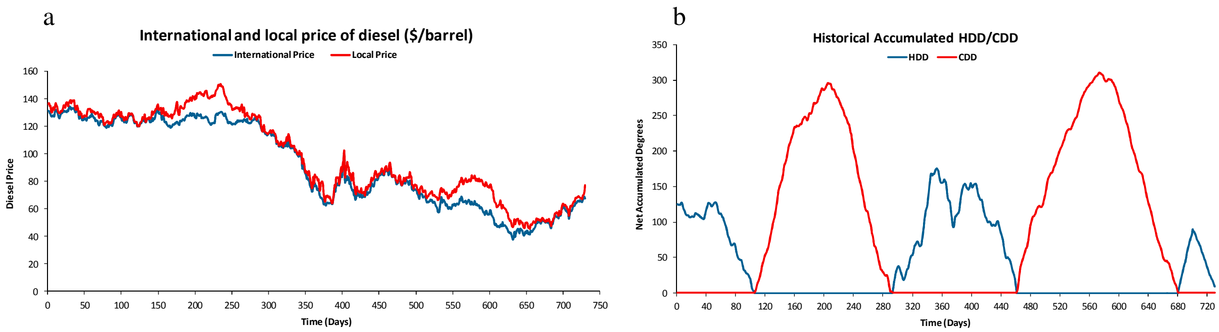

Fig. 2. (a) International and local price of diesel oil based on [4] and Eq. (7) respectively; (b) Historical accumulated HDD/CDD for 2014-15.

2.2. Expected payoffs from the Monte-Carlo simulations

There is plethora of derivatives' valuation methods; the most common of them being the *Black-Scholes* method. However, as highlighted by Mircea and Cristina [5] this is not a suitable method for derivatives with an underlying weather index. Due to limited data availability and based on the assumption that the NAD for the contract period -as well as the daily increments in the accumulated degrees- are *normally distributed* [6;7], we applied *Monte Carlo* simulations as a technique to calculate *potential payoffs* via *repeats* of a statistically derived model. The features of the model are described by Kung [8], cross-referenced with other studies [9] and adjusted as following:

1. Starting at each day, *sampled a random trajectory of daily temperature in discrete form*, via an *AR(1)* stochastic process over the one-month period of the contract.
2. Calculated the *NAD* (see Eq. (5)) from the *simulated temperature*.

3. Calculated the *payoff* (see Eq. (6)) for each option for a set SP.
4. Repeated steps 1, 2 and 3 to get many *potential paths* for the daily temperature and -therefore- potential payoffs.
5. Calculated the *expected payoff* (the Simulated_i) for each day *as the mean payoff of all samples*.
6. Repeated the process for *various SPs* deriving from the change in *variability* (here expressed by the *Standard Deviation*) of historical/observed accumulated HDD (μ=38.99; σ=53.11) and CDD (μ=96.68; σ=111.83).

Higher order autoregressive models, *Autoregressive Moving Average* (ARMA), as well as *Fractional Gaussian Noise* (FGN) models can reproduce more complex autocorrelation structures, with the latter being able to reproduce even the *long term persistence* (i.e. Hurst-Kolmogorov dynamics) of parental time series. However, frameworks like these are mostly beneficial in the context of studying the long term behaviour of temperature and its large-scale characteristics, rather than examining short future time intervals -as in our case. Consequently, in order to sample the random temperature trajectories, we decided to use a first order autoregressive model, *AR(1)*.

The simulation framework includes the generation of 10,000 synthetic 30 day-long time series, starting at each day of the historical time series. For every cluster of *synthetic* time series produced, the accumulated HDD and CDD were calculated and used as input for determining the payoffs. The *mean payoff* was calculated as the mean of all clusters for a given day *i*. In order to compare the difference in the outcomes for *alternative strike prices*, we tested the model for various standard deviations away from the mean of the historical accumulated HDD and CDD.

Temperature, as every hydrometeorological variable, is subject to the Earth's motion; thus periodicity comprises an essential characteristic of its temporal evolution. In order to stochastically reproduce temperature, via the *AR(1)* model, we *normalized* the historical time series (by removing periodicity). In particular, *double periodicity* appears in temperature; one in the *monthly* scale and one in the *hourly* scale. In addition, alternative models using dynamic processes and volatility functions can tackle the problem as well [10].

3. Results of the market model

We assume that the municipality purchases a contract at day *i* at the price of the *simulated payoff* and benefits if the *actual payoff* at *maturity* is higher ($Actual_i > Simulated_i$). The actual payoff derives from the historical time series of accumulated HDD and CDD. We selected four (4) different sets of strike prices for HDD and CDD [11], as listed in Table 2 and 3; in particular, we test for *0.5*, *1.0*, *1.5* and *1.75* standard deviations from the mean of accumulated HDD and CDD. Furthermore, we transform energy demand in *barrels of oil equivalent* (boe) by dividing the TDD_i (in MWh) by a factor of *~1.7*, as in Eq. (8). Thus, we evaluate the *sum of the* TM_i imposed by the local supplier for the period of the contract; the *percentage* of profit or loss (see Eq. (9) and Fig. 3) for the municipality is that sum in relation to the difference between the two payoffs (see Fig. 4). We have excluded the last 30 days from the results of the PP_i as there was no data available for the complete time periods in question. However, this did not impact on the accuracy of our results, as it is evident that the municipality shows repeated preferences towards CDD contracts.

$$TM_i = \text{Margin}_i \cdot \frac{TDD_i}{1.7} \tag{8}$$

$$PP_i = \frac{Actual_i - Simulated_i}{\sum_{i}^{i+29} TM_i} \tag{9}$$

Table 2. Average profit percentages of the municipality for alternative call option strike prices.

Strike Price	HDD SP (DD)	CDD SP (DD)	Highest profit (%)	HDD average profit (%)	CDD average profit (%)
μ + 0.5σ	66	153	46.36	0.07	0.60
μ + σ	92	209	40.29	-0.22	0.45
μ + 1.5σ	119	264	27.75	-0.70	0.18
μ + 1.75σ	132	292	21.73	-0.58	-0.03

In order to test our model's accuracy, we follow Oetomo and Stevenson [12], employing the *Unbiased Absolute Percentage Error* (UAPE), which provides an unbiased measurement with respect to the scale of the error, based on actual and simulated payoffs for each contract day. The PD_i in Eq. (11) is the difference between the actual and the simulated payoffs *only for underpriced contracts*. The *CDPD* is defined as the number of contract days with $PD_i>0$. The *TCD* is the total number of contract days that have a meaningful $UAPE_i$ (meaning that either the $Actual_i$ or the $Simulated_i$ is different than zero). The *RP* is the probability of the occurrence of an underpriced contract, while the *RE* is a quantified measure of the *loss potential* for the financial institution (bank), equal to the probability to sell an underpriced contract multiplied by the total potential losses.

$$UAPE_i = \left| \frac{Actual_i - Simulated_i}{\left(\frac{Actual_i + Simulated_i}{2} \right)} \right| \tag{10}$$

$$PD_i = \max(Actual_i - Simulated_i; 0) \tag{11}$$

$$RP = \frac{CDPD}{TCD} \tag{12}$$

$$RE = RP \cdot \sum_{i=1}^{CDPD} PD_i \tag{13}$$

Table 3. UAPE, RP and RE of the financial institution for alternative call option strike prices.

Strike Price	Contract Type	Strike Price (DD)	Mean UAPE (%)	Mean PD ($)	RP (%)	Risk Exposure ($)
μ + 0.5σ	HDD	66	53.05	221.14	30.92	7589.51
	CDD	153	40.49	180.10	55.24	19400.26
μ + σ	HDD	92	59.66	216.76	26.79	5225.39
	CDD	209	39.48	167.61	54.48	14427.96
μ + 1.5σ	HDD	119	64.83	192.73	20.42	2321.47
	CDD	264	47.77	156.42	36.84	4840.86
μ + 1.75σ	HDD	132	66.68	160.25	16.91	1246.63
	CDD	292	46.75	73.43	21.08	603.74

Below, we present the major points ascertained from Tables 2 and 3 on the assumption that both parties share *common information* (eg. they use the same model for pricing the option contracts):

- In contrast to CDD contracts, HDD contracts typically demonstrate *higher average percentages of UAPE*, as well as *lower risk probabilities*; meaning that there is lower chance for a contract to have higher actual payoff than its price. This actually signifies that *a less accurate forecast on a HDD than on a CDD contract favors the financial institution* considerably. Furthermore, the latter is also less exposed for HDD contracts, except in the case of an extremely high strike price (=292) for CDD contracts; which was reached at only few days.
- An increased strike price obviously means less risk adopted by the financial institution; however it is doubtful if the island's public administration would accept a strike price higher than 66 (=μ+0.5σ) for HDD contracts and 264 (=μ+1.5σ) for CDD contracts. Therefore, the financial institution should carefully consider the *risk level* (risk appetite) it is prepared to accept so as to make contracts attractive to its counterparty.

- The public administration of Astypalaia is more inclined to purchase CDD contracts and *is better off speculating on a hotter summer than a colder winter*. Our analysis demonstrated that there are some HDD contracts (notably in February 2013, December 2014 and February 2014) that would have achieved sizable profits if they had been bought. However, considering the municipality's public role and activity, the optimal strategy would probably be to both *hedge* its weather risks via option contracts and *schedule* its significant events -that are expected to attract visitors and bring income to the island's business units- mainly during summer periods.

Below, in Fig. 3 and 4, we present the aggregate results of our analysis for both counterparties (the municipality and the bank) *across the change in the variability (in terms of standard deviation) of the strike prices*:

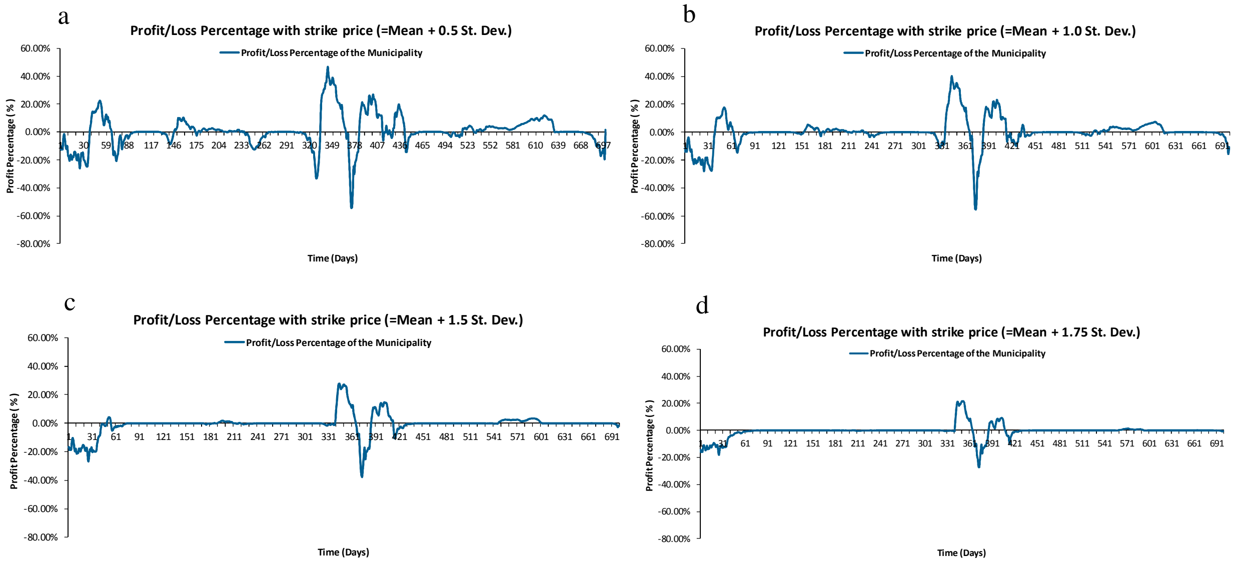

Fig. 3. Profit/Loss percentage for the municipality of Astypalaia for different strike prices: (a) Mean + 0.5 Standard Deviations; (b) Mean + 1.0 Standard Deviations; (c) Mean + 1.5 Standard Deviations; (d) Mean + 1.75 Standard Deviations.

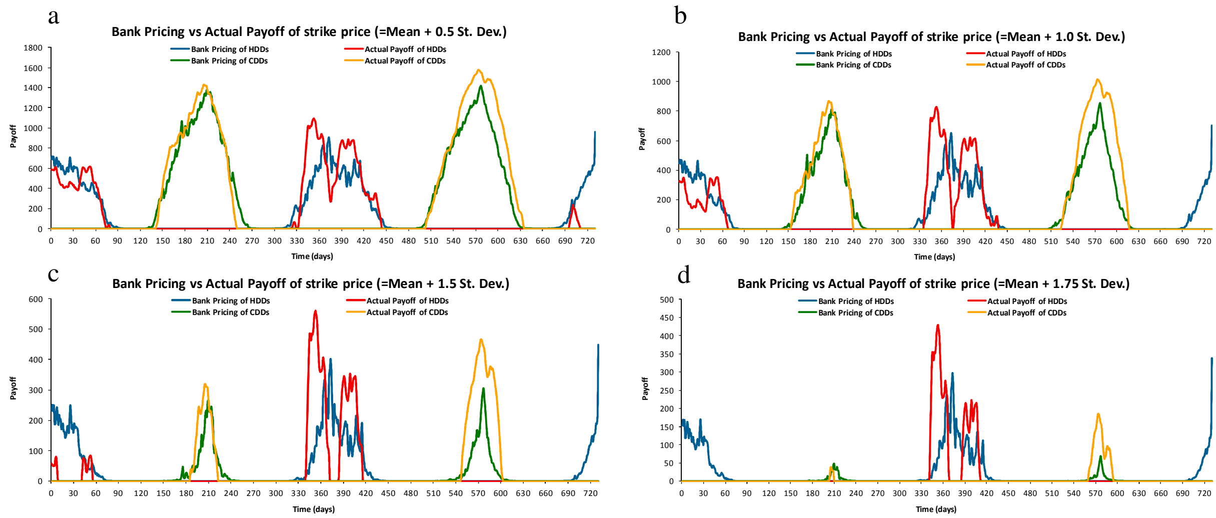

Fig. 4. Simulated payoffs -used as contract prices by the financial institution- and actual payoffs for different strike prices: (a) Mean + 0.5 Standard Deviations; (b) Mean + 1.0 Standard Deviations; (c) Mean + 1.5 Standard Deviations; (d) Mean + 1.75 Standard Deviations.

4. Conclusions

In our work we engineered a call option weather derivative contract in order to investigate the potential of the non-connected remote island of Astypalaia in Greece -powered by a diesel fuel generator- to manage successfully its energy supply, under specific assumptions on the oil market structure, the fuel spot price and the financial scheme. It is considered that these elements are crucial prerequisites in order to identify the (economic) potential of operating such financial instruments at energy markets of small-scale. Moreover, we identified the main features of the area's climatology; especially those concerning temperature -as the underlying index of the engineered contract- further relating them to the island's energy use patterns. These features prove to be very important for the preference of the counterparty that wishes to use weather derivative contracts as a means of insurance against high spot prices (which was also verified by our quantitative analysis). Based on Monte Carlo simulations we designed a model for pricing the option contract. Our results may comprise a guide for both the municipality and the financial institution in order to assess their possible preferences on contract types (HDD or CDD) and changing variability (in terms of standard deviation) of the strike price. The concept of *common information* might be considered a limitation; nevertheless it can be utilized as a starting point for elaborating existing weather derivatives' models.

Stochastic models comprise one of the most reliable solutions in cases of limited data; however reanalysis data of temperatures and other weather variables is a quite viable solution [13]. In the search for a more accurate stochastic generation scheme for our study, we also tested the *Best Linear Unbiased Estimator* (BLUE) model, developed by Koutsoyiannis and Langousis [14]. However, stochastic forecasting models are proven reliable only for predicting the values of a variable for a time-lag equal to no more than two time steps ahead and are under no circumstances reliable for longer predictions. Even *ensemble-based* forecasting methods -which show a significant potential [15]- provide reliable forecasts for a window limited to 5-7 days [16]. Nevertheless, forecasting models only have value in weather finance engineering if they result in improved decision making; thus, the challenge would be how to *merge* the information derived from the simulation and the information which becomes available from weather forecasts as we approach the initiation of the contract.

Although in our case we used a framework based on simplifying assumptions, we designed a starting point for a more complete, thorough and accurate analysis of specific scenarios in which weather derivatives can find potential use. The model is easy to implement and associates costs and benefits of weather derivatives' use in order to buffer the weather variation risks in remote islands based on autonomous energy units, as well as to diversify the portfolio of the financial institutions involved and -thus- reduce their exposure.

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