Energy Commodities Trading Using a Phase Signal Derived from the Levy Index of Price and Volatility

Jonathan Blackledge  
*Technological University Dublin, jonathan.blackledge59@gmail.com*

Derek Kearney  
*Technological University Dublin, derek.kearney@tudublin.ie*

Claire Farrell  
*Technological University Dublin, claire.farrell@tudublin.ie*

Grace Kearney  
*Technological University Dublin, grace.kearney@tudublin.ie*

Follow this and additional works at: https://arrow.tudublin.ie/engscheleart2

Part of the Electrical and Computer Engineering Commons

Recommended Citation  
Energy Commodities Trading using a Phase Signal Derived from the Levy Index of Price and Volatility

J. M. Blackledge¹, D. Kearney², C. F. Farrell³ and G. Kearney⁴

¹Stokes Professor, Dublin Institute of Technology, Ireland
²School of Electrical Engineering, Dublin Institute of Technology, Ireland
³School of Manufacturing Engineering, Dublin Institute of Technology, Ireland
⁴School of Electrical Engineering, Dublin Institute of Technology, Ireland

Email: ¹jonathan.blackledge@dit.ie, ²derek.kearney@dit.ie, ³Claire.farrell@dit.ie, ⁴grace.kearney@dit.ie

Received 07/02/2013

ABSTRACT

Energy traders need to decide what markets and commodities to trade in, when to open and close trades and how to maximize profits. In this paper we consider an approach for analyzing energy commodity price data based on the Lévy index in order to develop a new short-term predictive trend indicator for the price. This is achieved by computing the unwrapped phase signal generated from the Lévy index of both the Stochastic Volatility and price and is evaluated using data from the Irish Energy Market, namely, time series for the price of Electricity, Gas and Oil. The initial results show the predictive hypothesis holds true and algorithms are developed for implementation on an open source trading platform (Alpari MetaTrader4) which includes a range of energy commodities. This is used to demonstrate the potential of the approach in support of energy commodities trading compounded in a set of prototype MetaQuotes Language 4 (MQL4) Apps which can be downloaded and evaluated further by interested readers.

Keywords: Energy Trading, Trend Analysis, Stochastic Volatility, Lévy index, Phase Signal.

1. Introduction

In the last decade, trading in energy commodities has become the world’s fastest growing market and is becoming an increasingly important source of global trading. This is because of the accelerated increase in the renewable energy industry, the emissions reduction schemes stemming from the Kyoto protocol and also the regulation of the commodities markets [1]. The purpose of analyzing commodity markets is to support the trading and investment decision-making processes in these markets. The approach used in analyzing markets can be either ‘fundamental’ or ‘technical’ but both cases are predicated on the ability to process signals and information, and, as stated in [1]: “Trading is a business... sometimes it takes money to make money. You can’t put a price on information.”

1.1 Financial Analysis

Financial analysis uses data such as import/export figures to determine an intrinsic value or ‘price’. If a price is trading for less than an expected value, then it is often assumed that it will rise at some future point in time and vice versa. This assumption is predicated on the existence of an ‘efficient market’, the so called ‘Efficient Market Hypothesis’ or EMH. It assumes that the commodity price reflects all the knowable information about an asset at any given time including the opinions of all market participants regarding the information and that investor’s incorporate the information as it emerges from a ‘linear system’. Thus, only the speculative or stochastic (random) component of a price change needs be modeled and the conventional distribution used for this (under the EMH) is a (zero mean) normal or Gaussian distribution for the price differences. The principal problem associated with the application of a ‘Gaussian model’ is that it fails to include rare, but extreme events that can occur in real world financial time series data [2], [3] and [4].

Financial time series analysis typically uses historical price and/or volume (demand) data and attempts to establish patterns that suggest a possible start, end or continuation of a trend. This may assume that the market is not efficient and that reoccurring price patterns provide indicators for future movement. It is the latter approach that is taken in
1.2 Financial Models

All financial models are based on a set of assumptions upon which is built a qualitative or a quantitative model. A qualitative financial model is composed of a single or, more usually, a set of proposed algorithms that may not have a unified theme but nevertheless provide a valuable contribution to financial analysis and asset management. A quantitative financial model is one that is underpinned by a unifying concept which yields a coherent and interconnected theoretical framework.

Both models are usually informed by subjective and then quantitative data analysis and often focus on a specific class of data, e.g. depending upon whether a macro- or micro-economic model is required. In both cases the assumptions which underpin the model, and, the computational procedure that are informed by the model, needs to be subjected to a range of computer-based ‘experiments’ known as back-tests. Back-testing uses historical financial data (taken to be consistent with the model assumptions) in order to compare the expected outcomes informed by the model(s) with the known outcomes in a historical, and, thereby fully deterministic sense.

1.3 Financial Indicators

While quantitative financial models are desirable because of the coherent concepts they attempt to convey, they are not always robust when applied to a variety of data types. For this reason, financial models often include hybrid forms that are based on a phenomenology associated with observed properties of the data to which the original (quantitative) model does not conform. All financial models try to balance the observed properties of the data with an intrinsic rationale on its temporal behaviour to design an algorithm which is computationally stable and whose performance is consistent within an acceptable tolerance. These properties are usually compounded in conventional time series analysis metrics such as the statistical moments, correlation and covariance coefficients, spectral and wavelet based metrics, and, specific to financial time series analysis, indicators such as the Bollinger Band, the Force and Momentum indices, Bear/Bull Power indices, Williams’ percentage range and so on, all of which can be computed on a moving window basis, and all requiring input ‘performance parameters’ that are either ‘hard-wired’ or user interactive.

With regard to financial models in general, it is arguable that the single most significant ‘known unknown’ is the Volatility. This is because a change in volatility has the most significant impact on an asset. Volatility measures variability or dispersion about a central tendency and is a measure of the degree of a price movement in a stock, a futures contract or any other market. The volatility is defined in terms of the standard deviation of the sample signal which is a measure of the dispersion of a signal whose variations in time are computed using a moving window. In order to compare volatilities for different interval lengths, it is common to express volatility in annual terms by scaling the estimate with an annualization factor (normalizing constant) which is the number of intervals per annum. Defining volatility in terms of variations in the standard deviation of asset returns from the mean implies that large values of volatility fluctuate over a wide range leading to high risk. This is why the Volatility is fundamental to all asset risk management.

In this context of the above, a quantitative model is one from which all indicators have the same common root. A qualitative model is based on an assembly of indicators that can be categorized as a ‘set’, that is, a collection of well defined distinct algorithms or ‘objects’ and can be considered as an object or ‘algorithm’ in its own right. The asset allocation model considered in this audit falls into this classification within the context of Modern Portfolio Theory. It includes a two-stage methodology that is well considered and cohesive predicated on the funds and the objectives considered.

1.4 Random Variables and Stochastic Processes

A random variable whose value evolves over time is known as a stochastic process. The pool price over a period of a week, for example, or, the electricity demand, over a month are examples of such processes [5]. A good stochastic model should not only describe the data, but also help explain and understand the system from which the data is derived. It should accurately predict what is observed in reality and be based on a well-defined rationale. The model should also take into consideration that the stochastic process, such as gas or electricity price over a one-day period, is non-stationary and, ideally, model rare but extreme events, which deviate significantly from the norm [2]. To this end financial model are increasingly based on the Fractal Market Hypothesis (FHM), which was originally proposed by Edgar Peters in 1996 [4]. The FHM explores the application of chaos theory and fractals to financial data. This is because of the statistically self-affine nature of financial signals in general.

The FHM considers the fact that investors may not directly react to information as it is received but instead react with a delay, displaying a non-linear delay time. Work conducted in [6] and [7] considers a financial time series (specifically the price differences) to be a stochastic function characterized by a symmetric Lévy distribution. The distribution is the by-product of an answer to the question: “under what
circumstances does the distribution associated with a random walk of a few steps look the same as the distribution after many steps” considered by Paul Lévy in the late 1930s. In [6] and [7] new algorithms for computing time variations in the Stochastic Volatility and Lévy index using a standard financial price model and a Green’s function solution to the Generalized Kolmogorov-Feller Equation (GKFE) are given. In particular, in [6], the methodology and derivation is applied to financial data, whilst in [7] it is applied to carbon price data.

In this paper, a new ‘phase signal’ is considered obtained by computing the Lévy index of the Stochastic Volatility and of the price with the aim of devising a short-term indicator which combines the underlying information from both indices in order predict more accurately the short-term trend of the price. In this case, the analysis is applied to energy commodities data relating to the Irish energy sector - Electricity Spot price (System Marginal Price – SMP), Oil (Brent Oil) and Gas (National Balancing Point – NBP) data. In this context and because the focus of this work is on predicting trend behavior of energy commodities, useful when applied to energy trading buy/sell decisions, a brief introduction to energy trading platforms is presented in Section 2. The method of computing the Stochastic Volatility and Lévy index of the energy price data is given in Section 3 and Section 4 focuses on the derivation and computation of the phase signal using MATLAB programming environment. Finally, a presentation of some example results is given of the output from applying the algorithm(s) to the Alpari MetaTrader4 trading platform as discussed in Section 5.

2. Energy Trading Platforms
As the commodity markets are highly volatile it is imperative that traders receive accurate information regarding their trading accounts and ample market access [1]. Energy trading and risk management platforms provide energy market participants with a means of optimizing the physical and financial positions of multiple commodities [9]. Energy trading is broken up into two types, non-regulated bilateral trading and regulated financial Over-the-Counter (OTC) trading. In the regulated OTC markets, broker feedback (SweetFutures) is that the top platform used by clients is the WebICE followed by Trading Technology International’s (TT’s) X-Trader and then CQG’s Integrated Client. Non-OTC energy futures markets, for example, crude oil and Reformulated Blendstock for Oxygenate Blending (RBOB), can be traded using a multitude of platforms. The most popular are X-Trader, CQG, NinjaTrader and JTrader. Demonstration versions of all the platforms (the majority of which are free) can be requested via the SweetFutures website at http://www.sweetfutures.com

A full analysis of the leading platforms for energy trading was conducted in [9] and paid access to this analysis can be obtained via the research company directly. As a result of improved technology and increased competition, most retail commodity traders, find that their needs are sufficiently met with their brokers’ free trading platforms and have the ability to deliver timely price data and efficient trade execution [1].

3. The Stochastic Volatility and Lévy Index
In this section, we introduce the principal indices used to compute the phase signal, i.e. the unwrapped phase obtained from computing the Lévy index of the price and the volatility.

3.1 Computation of the Stochastic Volatility
As outlined in [6] and [7], the standard price model is based on the idea that prices are composed of the previous price plus some random independent change that includes a stochastic function \( \sigma(t) \) and \( u(t) \). The price of a stock as a function of time \( s(t) \) is given by

\[
s'(t) = \mu s(t) + \sigma s(t) u(t)
\] (1)

where \( s' \) is the price derivative, \( \mu \) is the ‘Drift’ and \( \sigma \) is the ‘Volatility’. The second term on the right hand side of equation (1) arises from the fact that price fluctuations depend not only on the price - the first term on the right hand side of equation (1) - but also on a random and time varying change determined by \( u(t) \) whose amplitude is determined by \( \sigma \). However, in general, both \( \mu \) and \( \sigma \) can vary with time, and in the context of equation (1), \( \sigma(t) \) is referred to as the Stochastic Volatility. The drift function \( \mu(t) \) tends to vary over long time scales reflecting the long term trends associated with a price index. In principle, \( u(t) \) can be any stochastic function with statistical behavior conforming to a range of Probability Density Functions (PDFs). The conventional EMH model is to assume that the log price changes are Gaussian distributed so that \( u(t) \) is taken to be a zero-mean Gaussian distributed function. If this function is taken to have a fixed standard deviation of one, then
the volatility becomes a measure of the standard deviation, at least, for a (zero-mean) Gaussian PDF. The stock price model given by Equation (1) then provides a method for estimating the Stochastic Volatility $\sigma$ in terms of a lower bound. Equation (2) gives a numerical estimation of the Stochastic Volatility for a time series $s_n$ of length $N$ under the ‘phase only condition’ [6]

$$\sigma = \sqrt{\frac{1}{N-1} \left[ \sum_n \left| \ln(s_{n+1}/s_n) \right|^2 \right]}$$  \hspace{1cm} (2)

Computing the Stochastic Volatility for a sampling window of arbitrary size which is taken to be moved over a time series one element at a time (a ‘moving window’) the stochastic volatility signal or ‘indicator’ can be obtained based on Equation (2).

In deriving Equations (2) the ‘phase only condition’ is the same as modeling a stochastic function $u(t)$ in terms of a random walk in the (complex) Fourier domain where the amplitude of each step is the same. Example m-code for computing the Stochastic Volatility is captured in Appendix B of [6].

### 3.2 Computation of the Lévy Index

The use of Gaussian statistical models relates to the concept of the Efficient Market Hypothesis (EMH), with models for asset pricing which are concerned with the arrival of new information. This type of model is the basis for the Black-Scholes equation, which assumes that the underlying statistics associated with the price difference (or log price differences) of an economic signal are Gaussian.

The Black-Scholes equation is intimately connected with the assumption of the stochastic function $u$ being characterized by a Gaussian PDF [7]. This yields a deterministic model that is based on the classical diffusion equation. However, as stated previously, the principal problem with such a model is that it fails to include rare but extreme events that can occur in real-world financial time-series data. Therefore, the work in [7] considers the stochastic function to be characterized by a Lévy distribution which, in turn, can be viewed as a generalization of the classical diffusion equation. The Characteristic Function (i.e. the Fourier Transform) $P(k)$, of a Lévy PDF $p(x)$ is given by

$$P(k) = \exp(-\alpha |k|^\gamma), \quad 0 < \gamma \leq 2$$

where $\alpha$ is a constant and $\gamma$ is the Lévy index. For values of the Lévy index between 0 and 2, this function corresponds to a PDF of the form

$$p(x) = \frac{1}{|x|^\gamma}, \quad x \to \infty$$

Lévy processes are consistent with a fractional diffusion equation for the stochastic function $u(x,t)$ which can be derived from Einstein’s evolution equation

$$u(x,t+\tau) = u(x,t) \otimes p(x)$$

where $\otimes$ denotes the non-causal convolution integral over $x$. The approach to deriving both the Black-Scholes equation and fractional diffusion equation is based on applying a condition to the Characteristic Function as shown in [7]. Einstein’s evolution equation can also be used to derive the Kolmogorov-Feller Equation (KFE), which provides a model for the stochastic function $u(x,t)$ that is independent of a specific PDF [6]. It can also be used to derive The Generalized KFE (GKFE) whose solution depends on the choice of memory function $m(t)$ used [6]. The ‘choice’ is based on the ‘best characteristic’ of the stochastic system in terms of the influence of its time history. In [6], the Mittag-Leffler function is selected which yields a time series model where

$$u(t) = \frac{\alpha}{t^\beta}, \quad \beta > 0$$

where $\alpha$ is a scaling constant and $\beta = 1/\gamma$. The model represents the Impulse Response Function (IRF) for a random scaling fractal signal. For the discrete case when $u_n = u(t_n)$ for $n = 1, 2, \ldots, N$ is taken to be a window of data from an input price series, we can write

$$u_n = u_n^\alpha, \quad t_n > 0$$

where $\alpha = \beta - 1$. In general, $\alpha$ may be greater than or less than zero therefore providing a measure of any ascending or descending trends in the data $u_n$, respectively. An estimate of the parameter $\alpha$ for the time series $s_n$ is chosen which minimizes the least squares error function for $u_n$ and $s_n$ to give [6], [7]
The evaluation of this parameter - the modified Lévy index which we refer to here on as the ‘Lévy index’ - is then repeated on a moving window basis for an entire range of price values and the Stochastic Volatility of the same price values. This requires two look-back windows to be specified. The first window is required to compute the Stochastic Volatility using Equation (2) and the second window to compute the Lévy index given by Equation (3). The size of these windows with regard to the length of the data stream and their size relative to each other affects the output in terms of the localized behavior of the Stochastic Volatility relative to the price value and the Lévy index relative to both price and volatility. The windows used to compute the Stochastic Volatility should be relatively small compared to those used to compute the Lévy index, which uses a least squares fit requiring relatively large samples of data in order to obtain a statistically significant estimate of the alpha index.

4. Computation of the Phase Signal

In signal analysis, a real-valued signal can be represented in terms of an analytic signal from which the amplitude, frequency and phase modulations of the original signal can be determined [3]. The instantaneous phase $\theta(t)$ is given by

$$
\theta(t) = \tan^{-1}\left[\frac{q(t)}{f(t)}\right]
$$

where $q$ is the Hilbert transform of $f$. In our analysis, $f$ is taken to be the Lévy index of the spot price (real part, independent variable) and $q$ is the Lévy index of its corresponding Stochastic Volatility (imaginary part, dependent variable).

The purpose of computing the instantaneous phase of the Lévy indices of both the price and Stochastic Volatility is to combine the two signals into one in order to investigate its predictive trending strategy. The interpretation of the phase signal with regard to this is that if the phase crosses zero and is positive then the price starts to trend upward and if the phase crosses zero and is negative then the price starts to trend downward. However, this phase (the wrapped phase when the value is confined to a fixed period) can exhibit high-frequency oscillations which makes it difficult to examine the correlation describes above.

To minimize the oscillation a novel approach to unwrapping the phase is applied following [3] which develops an alternative definition of the phase that replaces the arctangent approach. This definition relies on taking the logarithm of the analytic signal and developing an equation for the instantaneous frequency, which measures the instantaneous rate of change of the phase. The unwrapped phase is then given by integrating the result. Using this alternative definition, the phase can be computed and plotted against time to provide a predictive interpretation of the price signal. MATLAB itself has a built-in ‘unwrap’ function, which aligns closely with the results obtained using the algorithm given in [3] algorithm for the arctangent function details of which are given in [8]. However, it is necessary to conduct an additional processing step to this unwrapped phase signal which, in effect, removes the constant of integration so that the signal oscillates monotonically thereby aiding interpretation. This involves generating a best-fit linear line of the unwrapped phase signal obtained by applying the MATLAB function polyfit of degree one (thereby applying a linear best fit) and calculating a model for the unwrapped phase using the polyval MATLAB function. The model values are then subtracted from the original unwrapped phase signal. Thus results in the adjusted signal oscillating about the axis where, once again, the interpretive rule can be applied. The m-code used to compute the adjusted unwrapped phase signal is given in Appendix G of [8].

5. Results

We an overview of example results based on the computation of the Stochastic Volatility and the modified unwrapped phase signal based on computing the Lévy indices of the price and volatility combined. We start with a study of the Irish Electricity Spot Prices.

5.1 The Stochastic Volatility of Irish Electricity Spot Prices

Reference [10] defines price volatility as a measure of the changes in price observed over a period of time albeit, hourly; daily; weekly or yearly. Electricity markets experience pronounced short-term volatility due to the uncertainty associated with the fundamental characteristics such as its non-storability. This leads to volatility in
price because any fluctuation in demand must be balanced by power generation. Other characteristics include the oligoplastic generation side, uncertainties in load and generation and the inelastic nature of demand over short time periods [11], [12] and [13]. The output from the computation of the normalized Stochastic Volatility of the daily Irish System Marginal Price (SMP) is represented in Figure 1. The output is computed on a moving window basis using Equation (2), with a look back window of 100 elements. The results are informative upon inspection of the correlated upward and downward trends of the SMP data and the Stochastic Volatility. For example, between 250 and 500 days the signal shows a high-level of fluctuations with a corresponding increase in trend of the Stochastic Volatility. It clearly shows the continuous high volatility experienced in the Irish electricity market since the launch of the Single Electricity Market in 2007 with no overall change in trend as shown by a virtually horizontal blue ‘SV Trendline’ given in Figure 1.

As a liberalized market, price is governed by the interaction between supply and demand. Consequently the drivers for volatility are the factors that influence supply availability and the intensity of the dynamics in the system demand. From the plot of the Stochastic Volatility there is evidence of the impact of weather and seasonality. For example, the two high peaks encircled in green in Figure 1, correspond approximately to the severe winter weather conditions of 2009 and 2010, respectively, when supply was critical to meet the extra demand causing a shock in price and volatility. Also evident is the cyclical pattern in volatility demonstrating the seasonality based on the demand – lower volatility in summer months. Other factors also compound the high level of volatility such as the global recession having a knock-on effect on energy demand and also the temporary shocks such as political unrest causing increased volatility.

5.2 Lévy Index and Phase Signal Analysis of the Irish Electricity Spot Prices

The Lévy index is computed to provide a short-term trend prediction of the price index from Equation (3) using a moving window of 200. Figure 2 illustrates the output from this computation for the electricity price and it’s Stochastic Volatility. The interpretation of this indicator is that when the Lévy index cuts above or below zero there is an upward trend or downward trend respectively. By examining Figure 2, it can be seen that the Lévy index predictive hypothesis holds true. For example, a downward trend is observed between 0 and 250 days in both the SMP price index and Stochastic Volatility when the Lévy index becomes negative. Likewise the upwards trend evident from 250 to 500 days in the Stochastic Volatility corresponding to when the Lévy index becomes positive, or between 1250 and 1500 days for similar evidence in the SMP price data. Also, on closer inspection, the polarity of the respective Lévy indices is clearly observed, albeit with a lag that is determined by the size of the look-back window – see between 500 and 750 days and around 1000 to 1250 days in Figure 2.

Figure 1. Irish Electricity Spot Price and corresponding computed Stochastic Volatility using a daily base average from November 2007 to July 2012.

Figure 2. Lévy index Analysis of the Irish Electricity Spot Price and of the corresponding Stochastic Volatility from November 2007 to July 2012.

For ease of trend analysis and to possibly reveal further underlying trends in the price index, a phase signal of the Lévy index of the price and Stochastic Volatility signals is computed as discussed in Section 4. The results are presented in Figure 3. The blue line shows the wrapped instantaneous phase signal. Areas of excessive oscillation (around the 500 mark) can be removed by applying the method of calculating an unwrapped instantaneous phase. The oscillations are removed, however, it is clear
that the trend is compounding. This feature is removed using a least squares best-fit model and subtracting it from the value computed as discussed in Section 4. Therefore the overall trend can be more easily analyzed as it oscillates about the time-axis and the interpretation rule can be applied as before.

**Figure 3. Instantaneous Phase signal of the Irish Electricity Spot price (daily base average from 1 November 2007 to 26 July 2012) - wrapped and unwrapped**

This is shown in **Figure 4** where it is seen that the hypothesis holds true for the phase signal with the price signal trending upward when the adjusted phase signal cuts above zero as illustrated around the 1250 day mark. The overall conclusion from inspecting the adjusted unwrapped phase signal is that it indicates the SMP trend should remain on an upward trend as the phase remains positive from approximately 1100 days.

**Figure 4. The Adjusted unwrapped Phase Signal of the Irish Electricity Spot Price (daily average SMP) from 1st November 2007 to 26th July 2012**

5.3 Results for Oil and Gas Commodities in the Irish Energy Market

Analysis of the Stochastic Volatility of the gas prices and the correlation with oil prices in the Irish energy market is considered in [17]. The results from applying the adjusted unwrapped phase signal analysis to the gas and oil data is presented in **Figure 5** and **Figure 6** respectively. It is clear from these results that the hypothesis holds predominantly true.

**Figure 5. Instantaneous phase signal adjusted (red line) of NBP Gas data from Oct 2005 to June 2012.**

**Figure 6. Instantaneous phase signal adjusted (red line) of Brent Oil data from Oct 2005 to June 2012.**

5.4 A Comparative Analysis using the Lyapunov Exponent

The Lyapunov exponent can help quantify the characteristics of algorithms that are based on physical models that exhibit chaos, i.e. a measure of the systems’ ’chaotic’. For iterative processes where stable convergent behavior is expected, an output that is characterized by exponential growth can, for example, be taken to be due to unacceptable numerical instability. However, physical models that exhibit chaos are intrinsically unstable and do not converge to a specific value. Thus determining a systems’ Lyapunov exponent can help to quantify the characteristics of such models [3].

Copyright © 2012 Sces .
There are numerous Lyapunov exponents for a dynamical system; however, the most commonly used is the maximum Lyapunov exponent, which gives an estimation of the degree of chaos in the underlying dynamical system. The sign of the Lyapunov exponents indicates the existence of chaos and their value gives a measure of how chaotic a system is [14]. Reference [15] provides the criteria for maximum Lyapunov exponent such that stochasticity exists if the maximum Lyapunov exponent is less than zero, chaos exists if it is greater than zero and noise chaos is present if it is near zero. In deriving a method of calculating the Lyapunov exponent, [3] considered the equation for an iterative process. By considering the error associated with a time series \( S_n \) for each iteration \( n \), it can be shown that the Lyapunov exponent \( L \) is given by

\[
L = \frac{1}{N} \sum_{n} \ln\left(\frac{x_{n+1}}{x_n}\right)
\]  

(4)

Where \( N \) is the data length. Interestingly, [14] state in their conclusion that an alternative method to measure stability is to employ an Impulse Response Function which is the method applied in this paper using Mittag-Leffler function as part of a Green’s solution to the GKFE.

Taking the Stochastic Volatility of the SMP, both the Lévy index and Lyapunov exponent are determined. The resulting Lyapunov exponent returns a noisy result; therefore, it is necessary to apply a moving average filter to enable a fair comparison between the two approaches with a window size based on recommendations from [16]. The results show the profile of the two predictive indices are quite similar. Examining the timing of when the indices cross zero show that for 50% of the time one index cuts the axis before the other. Consequently, it suggests that neither approach gives a faster and therefore superior response. Notwithstanding this fact, however, the Lévy index approach is rooted in the FMH as shown through in [3], [6] and [7] unlike that of the Lyapunov exponent.

6. Implementation on MetaTrader4

Research into the available platforms that support commercializing the methodology presented in this paper revealed that the well renowned MetaTrader4 (a FOREX trading platform) is now being applied to energy trading. InterTrader, Alpari and Forexyard all apply it to energy exchange markets. For the purpose of implementing the algorithms presented the Alpari MetaTrader4 system is used. Information on downloading and operating the platform is available from the Alpari website at http://www.alpari.com. This includes limited use of a free demonstration system. The platform allows the user to create customized trading indicators using the MetaQuotes Language (MQL4), a version of C++ adapted for financial software engineering and includes a live feed of data from the Internet. An example of implementing the algorithms considered is given in Figure 7. This shows a screen shot of the platform for hourly ‘G-Gas Oil’ commodity prices. The charts show the custom indicators created for the Stochastic Volatility, Lévy index, Lyapunov index and, at the bottom, the phase signal analysis. From Figure 7, we see that for the period from the 16th December until the 28th December, the price is on an increasing trend as predicted by the phase signal (bottom red trend line in Figure 7). It then predicts a decrease in price.

The Lyapunov chart shows an alternative index used by [14] in investigating the volatility of the Nord Pool market and is shown here for comparative purposes. Further understanding and application of the Lyapunov exponent are considered in [14] and [15]. For readers interested in evaluating the software developed and advancing it further, the MQ4 function used to generate the example given in Figure 7 can be downloaded from

http://eleceng.dit.ie/jblackledge/Indicators.zip
7. Discussion and Conclusion

The Lévy index predictive hypothesis has been tested on the Irish Electricity Spot price (base average daily SMP), gas prices from the NBP market and Brent Oil data. As part of this study, a Hurst exponent simulator was used to generate a large number of data sets from a small number of real data in order to verify and to test the hypothesis further. This gives confidence in the robust nature of the predictive ability of the Lévy index.

The instantaneous phase signal is computed using the Lévy indices of the price index and the Stochastic Volatility and applying an alternative method to the arctangent function for generating an unwrapped phase so as to remove the high frequency oscillations. The resulting output is adjusted to remove the monotonically increasing compounding term and realign such that the interpretative rules can be applied i.e. if the phase signal is greater than zero an upward trend of the price index is predicted and vice versa. Applying this rule to sample data shows that the hypothesis holds true in the majority of instances.

To understand the commercial value of this type of analysis an instantaneous unwrapped phase signal application (App) has been developed for the AlpariMetaTrader4. Using real-time Gas-Oil data, the predicative ability of this application has been tested and some example results illustrated in Figure 7.

Overall, a key value of this type of methodology is in its application as an indicative index for energy commodities trading as demonstrated by the output from AlpariMetaTrader4 platform. It could also be useful for electricity generating companies in developing their bidding strategies.

Acknowledgements

J M Blackledge is supported through the Science Foundation Ireland Stokes Professorship Programme. The authors word like to acknowledge the support of Professor Eugene Coyle and Dr Marek Rebow of the Dublin Energy Laboratory. A special word of thanks go to Mr. E Farrell (BSc Physics and Mathematics, Loughborough University) who developed the MQ4 script to generate the modified unwrapped phase signal application on the Metatrader4 trading platform as a proof of concept.
REFERENCES


