Expert Systems With Applications 243 (2024) 122892

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A dynamic price jump exit and re-entry strategy for intraday trading algorithms based on market volatility

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ARTICLE INFO

Keywords:
Price jump
Value-at-risk
Exit strategy
Re-entry strategy
Algorithmic trading
Intraday trading

ABSTRACT

Trading algorithms adopt automated risk management systems in order to mitigate against market risk and extreme market events. These systems are aimed at reducing potential losses due to unforeseen market events caused by a plethora of extraneous factors. One such unforeseen event is a price jump, a somewhat vaguely defined but abrupt change in asset price. In this paper, we propose a novel exit and re-entry strategy (suitable for intraday trading algorithms) capable of identifying market exit points, triggered by price jumps, and thereafter monitoring market stability conditions until an appropriate point of market re-entry has been identified. Validation results indicate that the proposed exit and re-entry strategy provides a new perspective on identifying points/intervals of price jump when compared with existing price jump identification methods and the opinion of a subject matter expert.

1. Introduction

As a result of the rapid growth in the volume of financial data available, the extrapolated extent of traditional manual financial market analyses has far exceeded the limits of feasibility. Since the conception of algorithmic trading during the early 1970s, financial markets have grown in popularity, drawing the attention of experts in the financial sector (Ravi & Kamaruddin, 2017). Large amounts of time and resources have been committed to the design and implementation of trading algorithms in the hope of creating competitive information advantages in an otherwise complex system. Factors influencing the complexity of financial markets include trends, cyclical variations, and inherent randomness, all affected by external factors such as diverse economic interrelations and unpredictable human behaviour (Dash & Dash, 2016). Many trading algorithms attempt to forecast financial market events, but as the market complexity escalates, so too does the difficulty associated with market forecasting. In such a milieu, it makes sense to divert attention away from predictive analyses and rather focus on prescriptive analyses with a view to identify and leverage hidden market information during knowledge-driven decisions.

As market trading activity takes place in a highly volatile environment, traders are faced with the problem of mitigating financial risk. Due to the importance of risk management, automated risk minimisation features are often embedded in trading algorithms and are continually evolving. The literature contains a plethora of methods for managing risk (see, for instance, Aven (2016) for a brief review). Such methods include risk management strategies in conjunction with volatility forecasting. In the area of volatility forecasting, the most common method employed is the *Generalised Auto-Regressive Conditional Heteroskedasticity* (GARCH) model (Donaldson & Kamstra, 1997; Echaust & Just, 2021; Franses & Van Dijk, 1996; Soltane et al., 2012; Yi et al., 2014). At a more fundamental level, many authors have attempted to understand the volatility of markets by conducting return distribution analyses such as mean–variance analyses and *value-at-risk* (VaR) analyses (Dowd, 2007; Linsmeier & Pearson, 2000). A drawback of these methods, however, is the underlying assumption that returns follow a fixed distribution which is indicative of future events (Singh et al., 2013).

The primary focus of this paper is on the algorithmic paradigm of *intraday trading*. Intraday traders utilise small trades and intraday price fluctuations to accumulate portfolio returns without keeping a position open overnight. Moreover, these traders employ trading strategies which identify buy or sell (long/short) signals once a trading opportunity presents itself (Sattarov et al., 2020). Since high market liquidity is a requirement for intraday trading, the *Foreign exchange* (Forex) market is often the asset of choice. In April 2019, an average of 6.59 trillion *United States* (U.S.) dollars were traded per day, confirming that the Forex market is the ideal playground for traders who typically buy and sell assets in quick succession (Lyócsa et al., 2020; Petropoulos et al., 2017).

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https://doi.org/10.1016/j.eswa.2023.122892
Received 22 February 2023; Received in revised form 28 August 2023; Accepted 7 December 2023
Available online 9 December 2023

A problem often experienced in intraday trading is that the accumulation of small returns may quickly be overshadowed by potential losses and unforeseen extreme market events. As observed during the 2007 and 2008 global financial crisis, the fixed distribution assumption of risk management strategies (often the assumption of normality) does not hold during extreme market events and may lead to considerable losses as a result of tail-risk (Broussard & Booth, 1998; Ozun et al., 2010; Yi et al., 2014). While such events may be few and far between, an increase in the resolution of market data from annual data to daily data results in a manifestation of market movement characteristics similar to extreme market events, known as *price jumps*, which occur significantly more frequently (Barndorff-Nielsen & Shephard, 2006; Eraker et al., 2003). The actual amount of loss forgone depends on the type of trade at the time of the price jump. For example, if a trader has an open long position and a downwards jump occurs in market price, the accumulated profit of the trade may be reversed and the total returns of the entire portfolio may even be reduced. One may argue that the price jump may well also be in the opposite direction, benefitting the trade, but for a risk-averse trader, the risk of this not happening may outweigh the potential return (Varian, 1989).

As a solution to this complication, price jump identification methods have been proposed in the literature (for pinpointing price jumps either in real time or retrospectively). These methods, however, lack the capability of

1. providing *a priori* monetary estimates of the total loss as a result of a price jump,
2. providing robustness against strong market trends over short time frames which have the same impact as price jumps and which are often missed by these methods, and
3. providing an analysis of post-price jump market correction activities.

In this paper, we address each of these problems by proposing a novel automated exit and re-entry strategy (suitable for intraday trading algorithms) with the primary aim of anticipating price jumps in a timely manner and then analysing market volatility until a suitable point of market re-entry has been identified. We acknowledge that market volatility (induced by price jumps) should not necessarily be excluded from trading decisions, but that these decisions depend on the type of trading strategy employed. In its most basic form, our strategy may be viewed as an indicator of intervals of extreme market volatility (induced by price jumps) during which an appropriate trading decision is made, depending on whether a range-based (volatility-avoiding) or trend-based (volatility-seeking) trading strategy is utilised. As per the previous discussion and the title of this paper, however, we argue the relevance of our strategy from the perspective of range-based trading strategies.

Exit strategies are already implemented at scale in financial markets and are known as circuit breakers, which temporarily halt trading activity during extreme recordings of volatility (Kim & Yang, 2004). The existence of these circuit breakers supports the argument for a need of exit strategies for trading algorithms.

The remainder of the paper is organised as follows: A brief review of the literature on risk analyses and their relevance to the problem at hand, as well as automated price jump exit strategies, is provided in Section 2. The proposed design and implementation of our automated exit and re-entry strategy is then described in some detail in Section 3. Thereafter, this strategy is applied in Section 4 to two case studies for verification purposes, aimed at proving its utility in the Forex market. This is followed by a detailed discussion of the case study results. The paper finally closes in Section 5 with an appraisal of the proposed strategy and suggestions for future work.

2. Literature review

This section contains a brief review of the literature pertaining to price jump identification. The review opens with a discussion on existing price jump exit strategies in Section 2.1. Here an emphasis is placed on price jump identification methods. Thereafter, the discussion continues with an exposition of methods that have been harnessed in attempts to create suitable exit and re-entry strategies in Sections 2.2 and 2.3.

2.1. Price jump methods

Price jump detection methods have become a popular topic of interest for researchers in the fields of financial risk management and market volatility analysis. There is no formal definition for the notion of a price jump, but such a jump is commonly referred to as an abrupt change or discontinuity in the market price (Boudt & Petitjean, 2014). We extend this definition by also considering extreme price trends which occur over short time frames.

There is no consensus in the literature on the magnitude and time frame associated with a price jump; these descriptors would seem to depend on subjective opinion. Au Yeung et al. (2020) vaguely defined data jumps as spikes in time series data at points in time which are unknown *a priori*, thereby omitting any specification of the required magnitude of the spike in order to be classified as a jump. We believe that this vague definition was intentional so as to ensure that the definition remains independent of any underlying process (Hanousek et al., 2014). The vagueness of the definition, however, increases the difficulty associated with applying methods from the realm of statistical inference and/or testing. As a result, the general consensus in the literature is to model a log-price return series in continuous time as a semi-martingale process with dynamics defined by the stochastic differential equation

$$\mathrm{d}\log x(t) = \mu(t)\mathrm{d}t + \sigma(t)\mathrm{d}W(t) + Y(t)\mathrm{d}J(t), \tag{1}$$

where $x(t)$ is the asset price at time t, $\mu(t)$ is a drift variable, $\sigma(t)$ is the process volatility, $W(t)$ is a standard Brownian motion, $J(t)$ is a counting process independent of $W(t)$, and $Y(t)$ is a price jump size (Boudt & Petitjean, 2014; Hanousek et al., 2014; Lee & Mykland, 2008).

The importance of price jump identification dates back to research conducted by Merton (1976), who believed that price jump analyses form a pivotal subsidiary of volatility analyses. Since then, tests have been developed for identifying abrupt changes in market price — research papers on this topic include those by Carr and Wu (2003), Huang and Tauchen (2005), and Woerner (2011). One of the earliest contributions was the Barndorff-Nielsen Shepherd test (Barndorff-Nielsen & Shephard, 2006), which is aimed at determining whether asset prices follow a continuous sample path. Notably, the test adopts a realised bi-power variation process and quadratic variation, along with a non-parametric test by which to classify price jumps. Based on analyses of selected assets, the conclusion was drawn that most price jumps were due to governmental macroeconomic announcements.

Lee and Mykland (2008) proposed a price jump identification test focused on high-frequency data which is applicable to a wide variety of financial markets (*i.e.* the stock market, interest rates, and the Forex market). The authors highlighted the importance of method robustness by adopting a non-parametric approach. The proposed test is capable of quantifying the direction and magnitude of a price jump. The validation results indicated its superior performance over the tests of Jiang and Oomen (2005) and Barndorff-Nielsen and Shephard (2006). Aït-Sahalia and Jacod (2009) proposed an alternative test that diverts attention away from quantifying the effect of jumps on the market and focuses on determining whether or not price jumps are present in a price time series, irrespective of the price data structure.

Asgharian and Nossman (2011) analysed the amount of spillover between stock market volatility changes between U.S. stocks and European stocks. Their results indicated that a significant number of market fluctuations traced back to U.S. stock market events which, at the time (2011), had become more prominent during the previous two decades. Furthermore, the market spillover effect may be used to signal appropriate points of portfolio reallocation.

It is clear that there has been an abundance of research related to price jump detection (applicable to intraday algorithmic trading). A prevalent problem in these methods, however, is a general lack of research conducted on the re-stabilisation/correction of market volatility after a price jump has occurred with a view to identify a suitable and risk-averse point of market re-entry.

2.2. Value-at-risk analyses

VaR analyses are a form of risk management in which it is assumed that the assets' values depend purely on their prices and are not influenced by the relevant trade volumes or trade types (buys or sells) (Gourieroux & Jasiak, 2010). The notion of VaR was proposed to answer the following simple question: Over the next M trading days, what is the expected maximum loss of a portfolio at a specified confidence level (Christoffersen, 2012; Soltane et al., 2012)? To answer this question, time series volatility analyses are employed.

Consider an asset/portfolio return series denoted by $y_t = \eta_t + \sigma_{t-1}\gamma_t$, where η_t is the expected return at time t, σ_{t-1} is the standard deviation of historical returns, and γ_t is a shock variable with a mean of zero and a standard deviation of one. The VaR of the return series at time step t associated with a risk level probability p is calculated as

$$\mathrm{P}(y_t \leq v_t) = p, \tag{2}$$

where v_t is a specified value, from which the distributions and variance of returns are utilised to calculate VaR v in the generic form

$$v_t = \mu_t - K\sigma_t, \tag{3}$$

where μ_t denotes the mean value of the distribution and K is a positive constant (Yoshida, 2009).

Risk managers have a diverse array of volatility measures at their disposal for calculating the VaR of an asset or portfolio. These measures include simple auto-regressive models, GARCH models, and Morgan's RiskMetric (a universally accepted benchmark measure) (Christoffersen et al., 2001).

The notion of normality is the most common assumption of return series volatility (Dowd, 2007). In this case, the parameters in (3) are simply determined as the mean and variance of the return distribution and K is assigned the value ϕ^{-1}, the inverse function value of the cumulative standard normal distribution associated with a certain level of probability, as illustrated graphically in Fig. 1. With these simple modifications, the expression in (3) is adjusted to

$$v_t(p) = \mu_t + \phi^{-1}(p)\sigma_t. \tag{4}$$

Furthermore, the variance of a return series is calculated as

$$\sigma_t^2 = (1-\lambda)\epsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 \tag{5}$$

according to Morgan's RiskMetric, where the variance is considered as an exponential filter, the conditional mean is fixed, and $\lambda \in [0,1]$ is a decay factor (Christoffersen et al., 2001). Assuming that the distribution of the data set is normal, the VaR is calculated as in (4).

2.3. Entropy

The notion of entropy can be traced back to the 1860s when Rudolf Clausius, a German physicist, attempted to assign a term to irreversible heat loss within the field of thermodynamics (Cropper, 1986). Since its conception, entropy has been pivotal in the Second

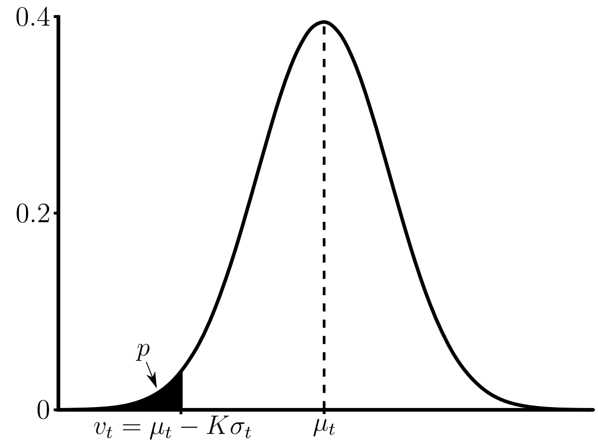


Fig. 1. Value-at-risk calculation for a normally distributed return series. *Source:* Adapted from Yoshida (2009).

Law of Thermodynamics. Loosely defined, entropy is an indication of system disorder or chaos. Its precise definition, however, depends on the field of application. In the theory of dynamics, for example, entropy is defined as the average flow of information per unit of time. In probability theory, entropy is a measure of uncertainty (Liu et al., 2011). According to Brissaud (2005), the notion of entropy comprises three facets:

Information. Entropy provides an indication of an outsider's perspective on the loss of information in physical systems.

Freedom. Entropy provides a quantifiable level of the degree of freedom in a system.

Disorder. Entropy is equivalent to the degree of disorder of a system.

Entropy has become an important source of information for analysts and has enjoyed a diverse array of implementations, as identified in a review by Zhou et al. (2013). The authors' findings are summarised in the remainder of this section.

In the context of finance theory, entropy is often associated with probability theory and is a measure of system uncertainty. Broadly speaking, entropy is applied to portfolio selection (a subfield of risk management) and asset selection. Philippatos and Wilson (1972) were the first to apply entropy to portfolio selection. The authors proposed a mean-entropy approach during the selection of assets based on information provided by the closing prices of fifty assets over a 14-year period. They found that the selection processes were in agreement with Markowitz's portfolio theory and Sharpe's single-index models. Also pertaining to portfolio selection, Xu et al. (2011) utilised entropy to analyse the effects of randomness on portfolio risks. Notable other contributions involving portfolio selection and entropy analyses include studies by Jana et al. (2009), Rödder et al. (2010), and Zhang et al. (2012).

Gulko (1997) furthered the implementation of entropy in the financial sector by introducing the notion of *Entropy Pricing Theory* (EPT) for options pricing. According to Gulko, the proposed EPT model provided similar results to those obtained by the Sharpe–Lintner and the Black–Scholes formulae. Further developments related to entropy asset pricing were made by Buchen and Kelly (1996) who implemented the *Principle of Maximum Entropy* (MEP) to determine asset distribution through the examination of asset prices. In view of the *Minimum Cross-Entropy Principle* (MCEP), Buchen and Kelly (1996) refined their findings by showing that MCEP implementations provided similar results to those returned by their previous MEP model.

In a more general sense, the notion of entropy is amenable to many mathematical theories. These include the popular Shannon entropy and Tsallis entropy, to name but two.

2.3.1. Shannon entropy

Shannon entropy (Shannon, 1948) is a measure of uncertainty implied by stochastic systems or processes and is of primary consideration in this paper. Consider a discrete random variable x taking values in a set X and which is distributed according to a probability mass function $P : X \mapsto [0,1]$. The expected level of information or uncertainty inherent in the possible outcomes of x is

$$\mathrm{H}(P) = E[-\log P(X)] = -\sum_{x\in X} P(x)\log(P(x)) \tag{6}$$

according to Shannon's measure of entropy. In the case of a continuous random variable x, the measure is adapted to

$$\mathrm{H}(P) = -\int_{-\infty}^{\infty} P(x)\log P(x)\,\mathrm{d}x, \tag{7}$$

where P is the probability density function of x. Since the Shannon entropy associated with a collection of random events is a decreasing function, the entropy reaches a maximum value when all possible events are equally plausible. The flexibility of this measure has resulted in a situation where Shannon entropy can be applied to global data sets as well as local data sets if only a subset of data points are of importance (Maszczyk & Duch, 2008). Shannon entropy assists in understanding stochastic processes and has seen a wide range of applications in the field of information science (Wu et al., 2013).

2.3.2. Tsallis entropy

Tsallis entropy (Tsallis, 1988) is a generalisation of Shannon entropy and includes additional parameters aimed at sensitising the entropy measure to different probability density function shapes. In principle, however, there is little difference between Shannon entropy and Tsallis entropy. In the case of a discrete random variable x assuming values in X according to a probability mass function $P : X \mapsto [0,1]$, the Tsallis entropy measure is

$$\mathrm{T}_\alpha(P) = 1/(\alpha-1)\left(1-\sum_{x\in X}(P(x))^\alpha\right), \tag{8}$$

where $\alpha > 0$ and $\alpha \neq 1$. As $\alpha \to 1$, the definition in (8) reduces to that in (6). In the case of a non-negative continuous random variable with probability density function $P(x)$, the measure becomes

$$\mathrm{T}_\alpha(P) = 1/(\alpha-1)\left(1-\int_0^{\infty}(P(x))^\alpha\,\mathrm{d}x\right), \tag{9}$$

where $\alpha > 0$ and $\alpha \neq 1$. As $\alpha \to 1$, the definition in (9) reduces to that in (7).

3. Methodology

In this section, we present our design of an automated price jump exit and re-entry strategy, consisting of two sequential phases. During the first phase, price jumps are identified in real time. Once a price jump has been identified, the second phase is triggered during which market conditions are monitored until a safe point of re-entry has been determined. Both phases are first discussed in some detail in Sections 3.1 and 3.2, respectively, after which a high-level discussion follows in Section 3.3 on combining the phases during real-time implementation.

3.1. Phase 1: The exit phase

During the exit phase, the objective is to identify price jumps according to a method of identification adapted from Munkhdalai et al. (2000), called extended Min-Max normalisation. Consider a Forex market price time series $F = f_0, \ldots, f_n$. The price time series is transformed to a return time series

$$r_t = \ln f_t/f_{t-1}, \qquad t = 1,\ldots,n, \tag{10}$$

which transforms the non-stationary price series into a stationary return series. By utilising the distribution of the return series r_t and the formulations of Morgan's RiskMetric, as discussed in Section 2.2, the variance σ_t^2 of the return series is calculated as in (5) and VaR v_t is calculated as in (4) under the assumption of normality, where p is the probability density function of the standard normal distribution. Instead of utilising the entire historical return series to calculate v_t, only a subset of near historical entries (over a limited look-back window) is utilised.

Once VaR v_t has been calculated for one time step ahead, the VaR for an analysis horizon g is

$$v_{t+g} = v_t\sqrt{g}. \tag{11}$$

Due to the symmetry of the standard normal distribution, a confidence interval

$$CI_{t+g} = f_t(1 \pm v_{t+g}) \tag{12}$$

for the price series is easily obtained, based on the calculated value v_{t+g}, where the confidence interval lower bound is truncated to be non-negative. The confidence interval represents the range in which the gth recorded price value is expected to fall. If the price series exits the confidence interval, a notable change in market volatility has been identified in the context of historical events, thereby, signalling a possible price jump. If the gth price value is reached without the time series exiting the interval CI_{t+g}, the process is repeated, now shifting the look-back window forward by g entries so as to consider the latest price entries during the analysis, while the oldest g entries are discarded.

The main benefits of adopting a confidence interval, as opposed to the traditional methods discussed in Section 2.1, are twofold. First, the trading algorithm is able to adapt continuously to the confidence interval range corresponding to the most recent market volatility measures in accordance with the algorithm's risk-utility. Secondly, by utilising a confidence interval, the market is allowed to react randomly, given that it remains within the confines of the confidence interval. The approach brings with it three additional benefits. These benefits are:

1. The confidence interval threshold values are known before the market propagates into the future. A trading algorithm will, therefore, always have knowledge of a realistic profit/loss estimate over the next analysis horizon. In contrast with existing methods, the profit/loss estimate can be assigned a monetary value instead of the intensity impact measure commonly used.
2. Small price jumps, which may be flagged by traditional measures, are acceptable and non-exit triggering, as long as they remain within the confidence interval. The confidence interval provides some degree of robustness against rapid market corrections and market overreactions (resulting in negligible effects of market jumps) — capabilities that are not included in existing models.
3. The confidence interval approach is not only capable of identifying large market jumps, but also quick, strong trends not caused by a single price jump but by multiple consecutive jumps which may not be identifiable by existing models. During these quick, strong trends the market risk increases and, depending on the risk-utility of the trading algorithm, may require trade activities to be halted.

3.2. Phase 2: The monitoring phase

As a result of implementing the VaR analysis discussed in the previous section, a price series can propagate in three directions into the future: (1) The series can remain within the confidence interval, indicating that market conditions are perceived to be evolving as expected, thereby exhibiting a low level of market uncertainty. Once the market exits the confidence interval, either (2) upwards or (3) downwards, an

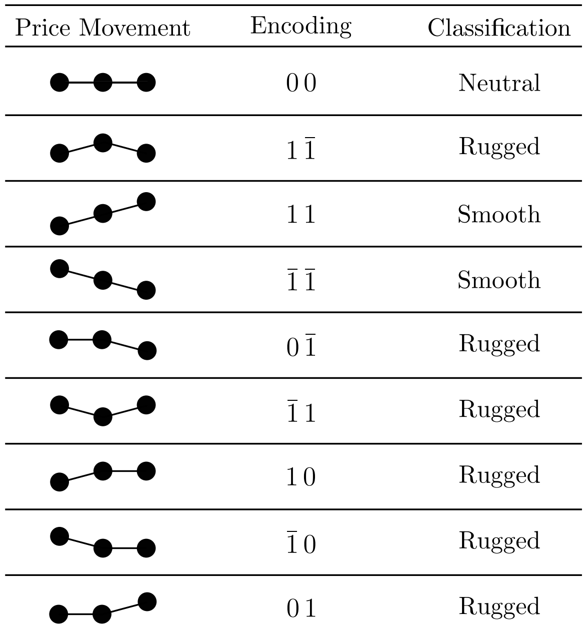


Fig. 2. All nine combinations of price series movements and the corresponding price series "landscape" classification thereof.
Source: Adapted from Malan and Engelbrecht (2009).

unexpected event may be considered to have occurred, indicating that market uncertainty has increased and, therefore, justifying a halt in trading. This type of market condition analysis conforms to the type of scenario often encountered during entropy analyses based on the measures discussed in Section 2.3. As a result, the second phase of the strategy involves an entropy analysis aimed at determining market re-entry points by considering the fluctuation of market uncertainty levels during price jumps.

The method of entropy analysis employed during the second phase of our strategy lends itself to the incorporation of entropic information characteristics indicative of neutrality, smoothness, and ruggedness typically utilised in fitness landscape analysis within the field of (meta-heuristic) optimisation (Miller, Forgarty et al., 2000; Miller, Job et al., 2000). Inspired by these characteristics, we consider the "landscape" of a time series over fixed intervals of length three obtained from a random walk. The perceived level of neutrality, smoothness, or ruggedness of the market can provide an indication of market uncertainty when a price sub-series is examined.

A sequence of symbols $S(\beta) = s_1, \ldots, s_n$ corresponding to a price time series $F = f_0, \ldots, f_n$ is generated, representing the market direction, where

$$s_t = \begin{cases} \bar{1}, & \text{if } f_t - f_{t-1} < -\beta \\ 0, & \text{if } |f_t - f_{t-1}| \leq \beta \\ 1, & \text{if } f_t - f_{t-1} > \beta \end{cases} \tag{13}$$

and where $\beta \geq 0$ is a fixed threshold value governing the sensitivity of identifying upward or downward market movements. The value of β is selected based on the perceived market volatility and may differ from one asset to the next. If $\beta = 0$, for example, the entropic information analysis is at maximum sensitivity due to landscape neutrality (*i.e.* the value $s_t = 0$) being removed from consideration.

By combining two consecutive entries s_t and s_{t+1} of the sequence $S(\beta)$, the direction of change of three consecutive market price entries can be classified as either neutral, smooth, or rugged, as illustrated graphically in Fig. 2.

Based on the encoded price movements, an adaption of Shannon entropy is applied to measure the characteristics of the price series landscape. For ruggedness, the expression

$$\mathrm{H}(\beta) = -\sum_{p \neq q} P_{[pq]} \log_6 P_{[pq]} \tag{14}$$

is considered, while for smoothness, the formulation

$$\mathrm{h}(\beta) = -\sum_{p = q} P_{[pq]} \log_3 P_{[pq]} \tag{15}$$

is considered, where the symbols pq are selected as elements from $S(\beta)$ and where $P_{[pq]}$ denotes the probability of the elements pq occurring in direct succession within the sequence $S(\beta)$. This probability is estimated as

$$P_{[pq]} = n_{[pq]}/n, \tag{16}$$

where $n_{[pq]}$ denotes the frequency of the elements pq occurring in direct succession within $S(\beta)$. The expressions in (14) and (15) are called the *first entropic measure* (FEM) (indicative of ruggedness) and the *second entropic measure* (SEM) (indicative of smoothness), respectively.

If based on the direct analogy with traditional fitness landscape analyses within the realm of optimisation, the information captured in the FEM and SEM would be computed over the entire time series, generating single values for $\mathrm{H}(\beta)$ and $\mathrm{h}(\beta)$. This time frame is, however, impractical in the context of financial market analyses, and so additional adjustments are made. A look-back window is selected which is offset backwards from the current point in time. The window size dictates the amount of information under consideration and acts as a fixed-size sliding window, shifting on by one position forward with each increment of time. The sliding window ensures that the entropy analyses are carried out in respect of the latest data and creates two separate time series, $\mathrm{H}_t(\beta)$ and $\mathrm{h}_t(\beta)$, for separate inspection.

Although smoothness provides useful information, only ruggedness is analysed after a price jump has been recorded. When analysing the newly created time series $\mathrm{H}_t(\beta)$, two expectations prevail:

1. The entropy information should increase at the onset of a price jump, and
2. the entropy information should decrease once market instability has ended.

Based on the second expectation above, a fixed re-entry threshold value j is selected. When the entropy information captured in $\mathrm{H}_t(\beta)$ falls below this threshold value j, the trading algorithm re-enters the market. Varying the value of j determines the sensitivity of the monitoring phase. Larger values of j ensure that the automated price jump exit and re-entry strategy re-enters the market quicker, but at the expense of possibly entering the market during unstable market conditions. On the contrary, smaller values of j increase the confidence of entering the market during stable market conditions, but at the expense of prolonging the time until market re-entry. A threshold value of $j = 0$, therefore, provides the highest confidence of re-entering the market during stable market conditions.

3.3. Real-time implementation of Phases 1 and 2

The complete real-time incorporation of Phases 1 and 2 described above are summarised in pseudo-code form in Algorithm 1 and illustrated graphically in Fig. 9 in the Appendix. As input, the algorithm receives an asset candlestick data stream, a look-back period, an analysis horizon, and a re-entry threshold value as previously discussed. The algorithm first assigns an auxiliary event variable the value "No," indicating that no price jump has occurred and assigns a counter variable the value 1 (used to navigate through the analysis horizon). Upon algorithm initialisation, the VaR confidence interval is determined over the analysis horizon.

If a price series entry falls outside the VaR confidence interval, a price jump is flagged, the trading algorithm is halted, and the event auxiliary variable is assigned the value "Yes." At the point of the price

Input : Asset candlestick data stream F of intraday price movements, a look-back period ℓ, an analyses horizon g, and a re-entry threshold j
Output: A point of market exit once a price jump is observed and a re-entry point once market re-stabilisation is observed.

1 Event $\leftarrow No$
2 $i \leftarrow 1$
3 $v_{t+g} \leftarrow v_t\sqrt{g}$
4 **for** *each new price entry* f_{t+i} **do**
5   **if** $f_{t+i} \geq f_t(1+v_{t+g})$ *or* $f_{t+i} \leq f_t(1-v_{t+g})$ *or* $Event = Yes$ **then**
6   Stop trading algorithm
7   Event $\leftarrow Yes$
8   Determine ruggedness $H_{t+i}(\beta)$ of $f_{t+i-\ell}, \ldots, f_{t+i}$
9   **if** $H_{t+i}(\beta) \leq j$ **then**
10   Re-enter trading algorithm
11       $f_t \leftarrow f_{t+i}$
12   Return to 1
13   **end**
14   **end**
15   **if** $i = g$ *and* $Event = Yes$ **then**
16     $f_t \leftarrow f_{t+g}$
17     $i \leftarrow 1$
18   Return to 4
19   **end**
20   **if** $i = g$ *and* $Event = No$ **then**
21     $f_t \leftarrow f_{t+g}$
22   Return to 1
23   **end**
24   $i \leftarrow i+1$
25 **end**

Algorithm 1: Automated price exit and jump re-entry procedure.

jump onset, the entropy information analysis is initiated and the price series landscape ruggedness is analysed. If the ruggedness SEM falls below the specified re-entry threshold value, the market is deemed to have re-stabilised, and the trading algorithm re-enters the market. Upon re-entry, the start of the analysis horizon is then reset to the current time step, and the entire process is repeated.

If the auxiliary counter reaches the end of the analysis horizon, one of two events may occur: If the auxiliary event variable indicates that no price jump/market re-stabilisation is currently underway, the algorithm terminates and is re-executed; otherwise, if the auxiliary variable indicates that a price jump/market re-stabilisation is underway, the auxiliary counter variable is reset and the entropy analysis continues until the market has re-stabilised.

4. Two practical case studies

The practicality and utility of our exit and re-entry strategy are validated in this section in the form of two case studies. In Case study 1, our exit and re-entry strategy is compared with existing price jump identification methods, whereas in Case study 2 the results obtained from the strategy are compared with the opinion of a *subject matter expert* (SME). Case study 1 is based on one-minute, five-minute, and 15-min interval candlestick data of the AUD/CAD, AUD/USD, EUR/CAD, and EUR/USD currency pairs over the calendar year 2019. The *Standard and Poor 500* (S&P500) index is also included in our analysis with a view to evaluate the robustness of the strategy. The sheer size of the data set applicable to Case study 1 is impractical for manual inspection, and so Case study 2 focuses on one-minute interval candlestick data across the same assets, but over the period 6 January 2019 to 22 February 2019 — totalling 35 trading days. All simulations were conducted in Python in accordance with the procedure described in Algorithm 1.

4.1. Case study 1: Validation against the status quo

In this case study, our exit and re-entry strategy is compared with two different existing price jump identification methods, employed as baselines. Each method is executed in respect of the same data set, and is allowed to identify price jumps. The performance of our strategy is then calculated as the proportion of positive price jump identifications made according to the strategy, compared against those identified by the existing methods, and is referred to as the hit rate. The existing methods considered are the Lee and Mykland test (Lee & Mykland, 2008) and the Aït-Sahalia and Jacob test (Aït-Sahalia & Jacod, 2009) (more specifically their centiles method). These two tests were selected for their respective Type II and Type I biases towards identifying price jumps.

The Lee and Mykland test was implemented at a significance level of $\alpha = 0.001$. For the Aït-Sahalia and Jacob test, each asset's return series was fitted against 105 different continuous distribution functions encountered in the SciPy Python package (Virtanen et al., 2020), of which the best fit was selected. Based on the best fitting distribution function, a price jump was selected as any return value falling outside the 0.5% or 99.5% centile value.

During Phase 1 of our exit and re-entry strategy, the close price of each asset was selected and the return series was calculated as the logarithmic difference between two consecutive close price values. In order to determine the variance σ_t^2 for each one-minute interval, a look-back period of one day was utilised and the value of λ was arbitrarily selected as 0.95 (adjustments to the value of λ have a negligible impact on performance due to the small variation in sequential price values at an intraday data resolution). The VaR $v_t(p)$ was determined over the risk level probability subset $p = \{0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95\}$, spanning a time analysis horizon of $g = 60$ min. During the entropy analysis of Phase 2, a look-back period of 60 min was employed, thereby analysing 59 potential price fluctuations. The sensitivity of the entropy analysis β was taken between 0.0001 and 0.0006 in increments of 0.000025 for the one-minute interval candlestick data, totalling 21 different sensitivity considerations. These sensitivity values were then adjusted to 0.001 and 0.006 in increments of 0.00025 to accommodate the larger price movements observed for the five-minute and 15-min interval candlestick data. The larger price movement induced by different candlestick data intervals is more prominent in the S&P500 data, and so β was set between two and seven for the one-minute interval candlestick data, four and nine for the five-minute interval candlestick data, and nine and 14 for the 15-min interval candlestick data (all in increments of 0.25). Furthermore, the re-entry threshold value was set to $j = 0$.

4.1.1. Results

As discussed in the previous section, our exit and re-entry strategy has two parameters (p and β), both of which contribute towards the sensitivity of the exit strategy. It was, therefore, required to analyse the performance of our strategy over a wide spectrum of parameter values in order to be able to select a combination of values for these parameters that best conforms to the trading algorithm's risk-utility.

By adjusting the value of p, the confidence interval width is altered, thereby changing the sensitivity with which price jumps are identified and the number of price jump intervals during which positive identifications can be made. Adjusting the value of β, on the other hand, affects the market re-stabilisation analysis interval length which directly impacts the trading duration available during which returns can be generated. This parameter, however, also contributes to the positive identification of price jumps when compared with the existing models, as a price jump falling within the confidence interval is also recorded as a positive identification.

As an example, the results returned by our exit and re-entry strategy for $p = 0.8$ and $\beta = 0.0003$, based on the AUD/CAD currency pair over a subset of 10 000 min (implemented on one-minute price time steps), are illustrated graphically in Figs. 3 and 4 in comparison with the Lee and Mykland test and with the Aït-Sahalia and Jacob test, respectively. In these figures, the proposed market halt times (identified by our strategy) are denoted by the grey-shaded areas, while the red dots indicate the price jumps identified by the existing methods.

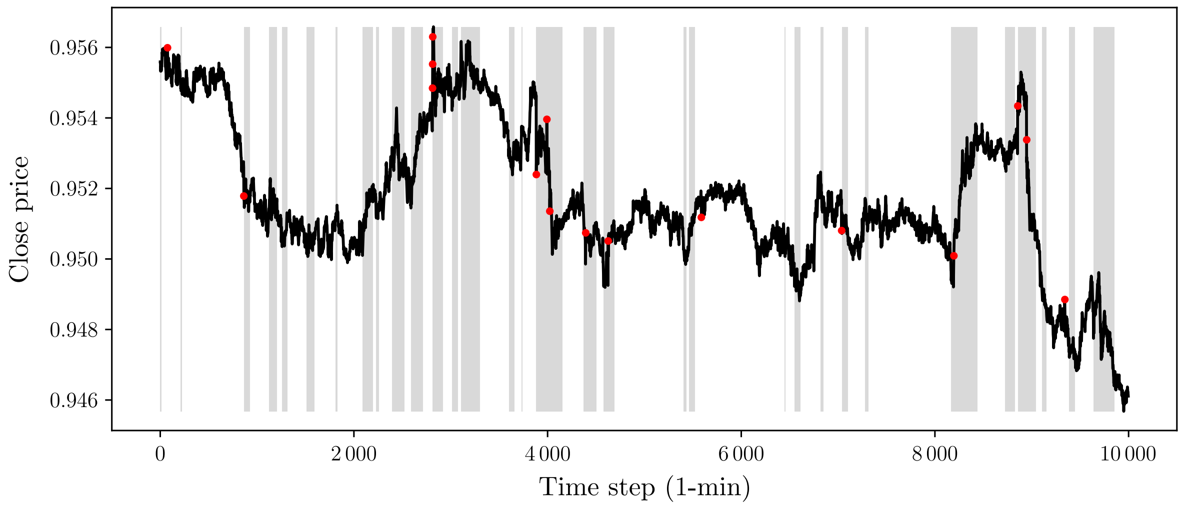


Fig. 3. A market close price series of the AUD/CAD currency pair with trading algorithm halt intervals identified according to our exit and re-entry strategy shaded (in grey) and price jumps identified by the Lee and Mykland test (the red dots) for one-minute price time steps.

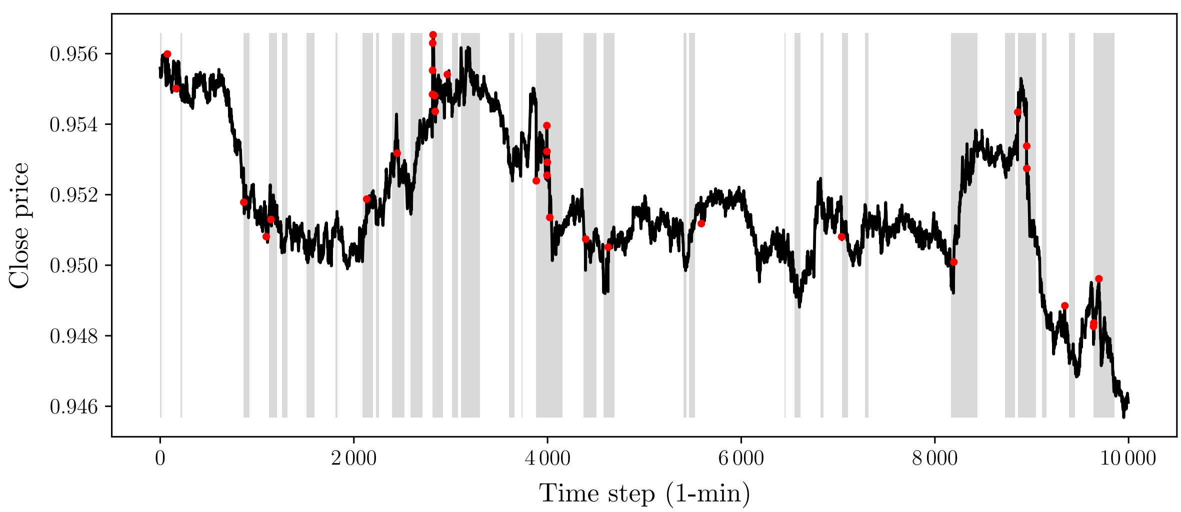


Fig. 4. A market close price series of the AUD/CAD currency pair with trading algorithm halt intervals identified according to our exit and re-entry strategy shaded (in grey) and price jumps identified by the Aït-Sahalia and Jacob test (the red dots) for one-minute price time steps.

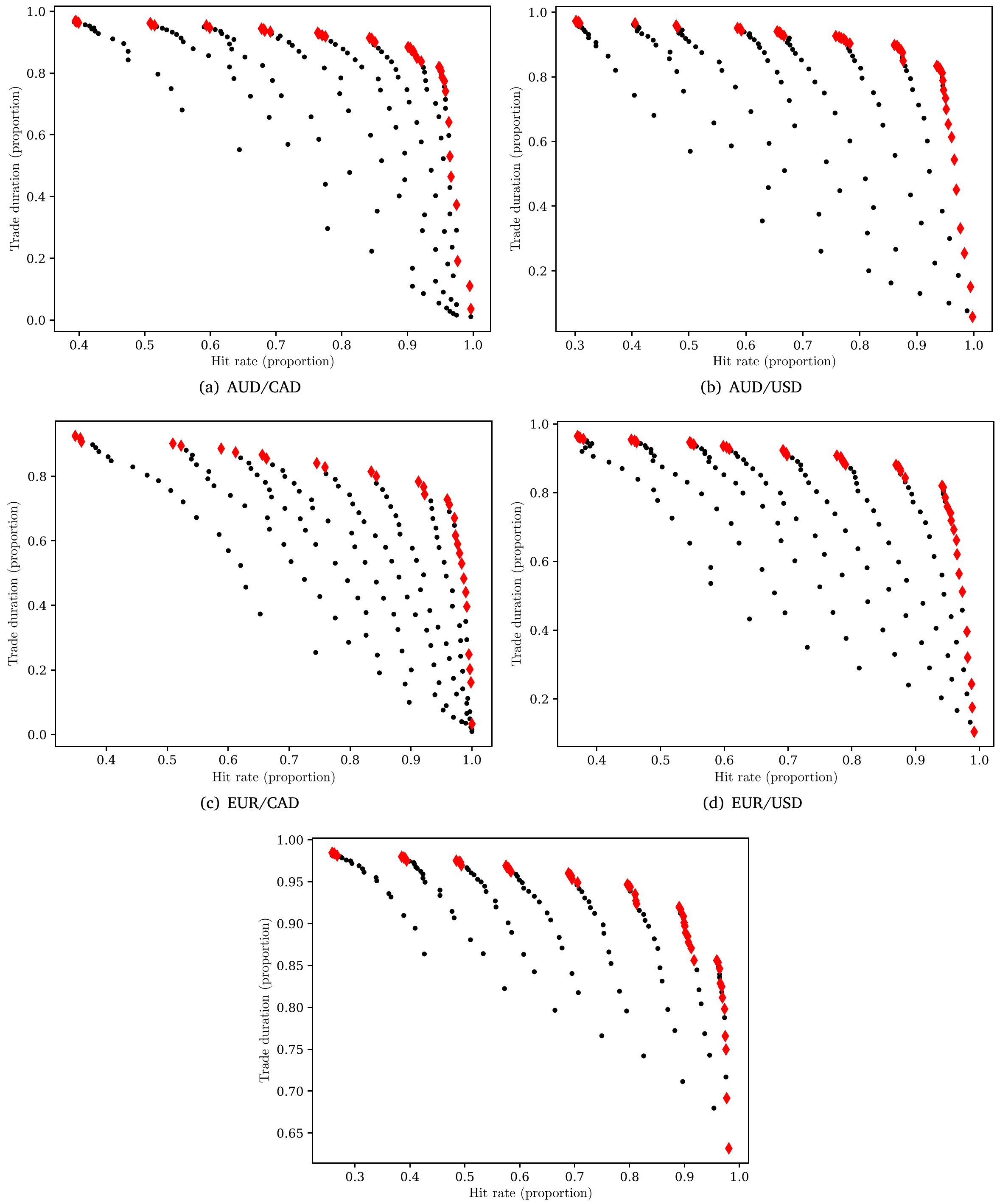
In all practicality, however, these two plots do not provide any indication as to which combination of values for the two parameters best fits the trading algorithm's risk-utility. As a solution to this predicament, all distinct combinations of values for the two parameters were plotted together, from which a Pareto front was extracted for the purpose of identifying suitable trade-offs between maximising the hit rate and maximising the trading duration. (The different time steps considered in this analysis did not drastically alter the shape of the Pareto fronts and, therefore, only the one-minute time step Pareto fronts are illustrated and discussed here. All remaining Pareto fronts are accessible at: https://github.com/CoetzeeKoegelenberg/ESWA-EntropyPriceJump.git.) These plots may be found, for each of the five different assets in Fig. 5 for the Lee and Mykland test comparison and in Fig. 6 for the Aït-Sahalia and Jacob test comparison, with identified Pareto fronts plotted as red diamonds.

In this case study, a standard risk-utility of *at least* 0.6 hit rate proportion is selected for comparison purposes. The best matching hit rate proportion on the Pareto front and the corresponding parameters are provided in Table 1 for each asset and their respective time step size.

4.1.2. Discussion

Upon analysing the results of the price jumps identified by both existing price jump identification methods in Figs. 3 and 4, the differences between the two existing methods and our newly proposed exit and re-entry strategy may be observed. Over the course of the 10 000 min sample size, sixteen price jumps were identified by the Lee and Mykland test and thirty-two price jumps were identified by the Aït-Sahalia and Jacob test. Although this is a relatively small sample relative to the size of the entire data set of one year across all five different assets, Figs. 3 and 4 provide a representative estimate of the overarching results across all data points. Upon inspection, it may be observed that the Lee and Mykland test adopts a conservative approach towards identifying price jumps, while the Aït-Sahalia and Jacob test identifies all the price jumps identified by the Lee and Mykland test, along with numerous additional jumps. Due to the vagueness inherent in what is considered to be an actual price jump, it is not possible to determine which one of the two existing methods is the superior method in the context of the data set considered. In light of this vagueness, the two models are, therefore, rather considered as benchmarks against which to compare the Type I or Type II error bias of our newly proposed exit and re-entry strategy (Hanousek et al., 2014).

By analysing the Pareto fronts in Figs. 5 and 6, the hit rate of our strategy can be compared against the corresponding trading duration.



(a) AUD/CAD (b) AUD/USD (c) EUR/CAD (d) EUR/USD (e) S&P500

Fig. 5. Pareto fronts (red diamonds) indicating optimal combinations of proportion trading duration and proportion hit rate for four currency pairs and the S&P500 when compared with the Lee and Mykland test for one-minute time steps.

At first glance, it is evident that the Pareto fronts consist of curved lateral lines of points which increase in their degree of curvature from Figs. 5 to 6. Upon closer inspection each line represents the eight distinct p-values. A first conclusion may, therefore, be made that the p-value dictates the horizontal position of these lines. Furthermore, it may be observed that along these lines an increase in the hit rate proportion is accompanied by a steep decline in trading duration. This downward slope is caused by a decrease in the value of β. Once our strategy identifies the first price jump corresponding to the value $\beta = 0.0001$, for a Forex currency pair, for instance, the entropy analysis never identifies a point of market re-stabilisation, because the over-sensitive value of the parameter β results in a situation where normal market volatility is mistakenly anticipated as representing unstable market conditions. Our strategy, therefore, seldom, or never, triggers re-entry into the market, thereby providing the false sense of security associated with a near-perfect hit rate proportion as observed at the bottom right of the Pareto fronts. At the other extreme of the Pareto fronts, high levels of trading duration are observed, paired with low hit rates. These high levels of trading duration are attributable to in-sensitive p- and β-values. As a consequence, unstable market conditions

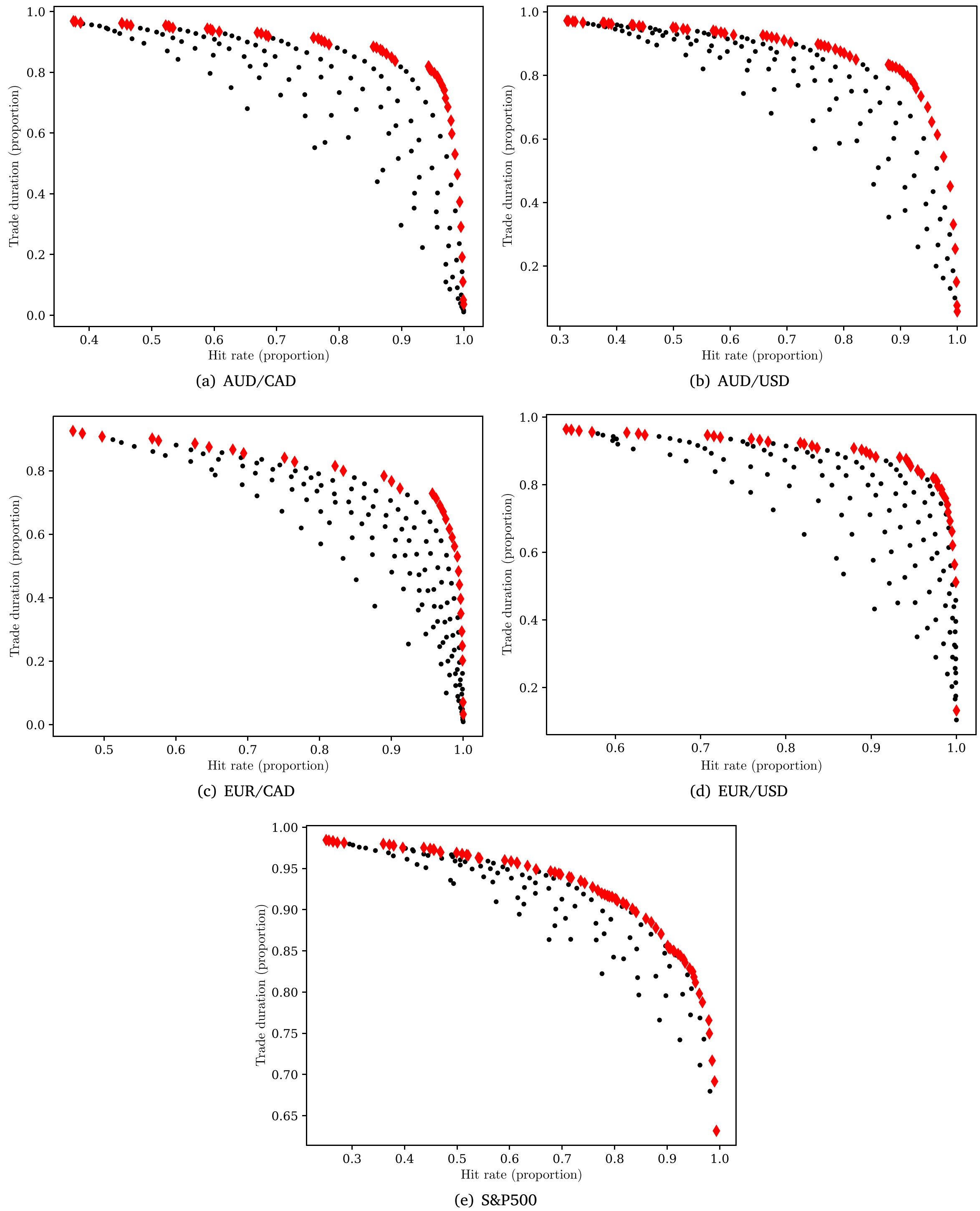


Fig. 6. Pareto fronts (red diamonds) indicating optimal combinations of proportion trading duration and proportion hit rate for four currency pairs and the S&P500 when compared with the Aït-Sahalia and Jacob test for one-minute time steps.

are considered stable, and the entropy analysis identifies an immediate point of market re-entry once a price jump has been identified. This immediate market re-entry causes many price jumps originating within unstable market conditions to be omitted, decreasing the hit rate proportion. The logical conclusion is that at high levels of trading duration, the hit rate proportion is governed by the confidence interval parameter p and a near-perfect hit rate proportion is attributable to an over-sensitive β-parameter value. One can, therefore, move from one extreme point on the Pareto front to the other by decreasing the values of p and β, or increasing the values of p and β.

Upon further review of the Pareto fronts obtained for our strategy, when compared with that of the Lee and Mykland test (illustrated graphically in Fig. 5), the plots would seem to indicate promising performance in the form of triangularly dispersed clusters of data points. Analysing the Pareto fronts from the top left-hand corner to the bottom right-hand corner, it is evident that the Pareto set experiences large improvements in hit rate proportion without significant reductions in trading duration. This trend continues until a steep drop-off is reached at a hit rate proportion of approximately 0.95. The gradual decline in the Pareto front trading duration indicates that the confidence interval

Table 1
The parameter values and corresponding proportions of trading duration associated with our exit and re-entry strategy in order to fulfil a risk-utility requirement of at least 0.6 for both the Lee and Mykland test and Aït-Sahalia and Jacob test.

	1 min				5 min				15 min			
	p	β	Hit rate proportion	Trading duration proportion	p	β	Hit rate proportion	Trading duration proportion	p	β	Hit rate proportion	Trading duration proportion
	Lee and Mykland											
AUD/CAD	0.8	0.0006	0.6779	0.9441	0.8	0.0055	0.6216	0.9841	0.8	0.0055	0.6533	0.9796
AUD/USD	0.75	0.0006	0.6548	0.9409	0.75	0.0055	0.6699	0.9758	0.8	0.00525	0.6076	0.9808
EUR/CAD	0.85	0.00055	0.6121	0.8745	0.7	0.006	0.7055	0.9590	0.8	0.00575	0.6441	0.9538
EUR/USD	0.8	0.000575	0.6035	0.9322	0.75	0.00525	0.6034	0.9766	0.75	0.00575	0.6307	0.9583
S&P500	0.75	7	0.6886	0.9600	0.75	9	0.6371	0.9120	0.8	14	0.6300	0.8904
	Aït-Sahalia and Jacob											
AUD/CAD	0.8	0.000525	0.6081	0.9341	0.7	0.0055	0.6408	0.9612	0.7	0.0055	0.6689	0.9544
AUD/USD	0.75	0.0005	0.6061	0.9271	0.7	0.004	0.6058	0.9554	0.7	0.00525	0.6093	0.9573
EUR/CAD	0.85	0.0006	0.6265	0.8859	0.7	0.006	0.6293	0.95897	0.75	0.006	0.6606	0.9433
EUR/USD	0.9	0.0006	0.6135	0.9541	0.75	0.0025	0.6114	0.9628	0.75	0.004	0.6080	0.9603
S&P500	0.75	6.75	0.6028	0.9586	0.75	9	0.6844	0.9120	0.85	14	0.6230	0.9114

is the main driver of hit rate improvements until a drop-off occurs. During the drop-off, however, a marginal improvement in hit rate is achieved by gradually increasing the sensitivity of the parameter β, indirectly increasing the length of the stability analysis interval. Supporting this interpretation, Table 1 reveals that the desired risk-utility is comfortably achieved by utilising an insensitive value of β.

When compared against the Aït-Sahalia and Jacob test (illustrated in Fig. 6), the results of our strategy would seem to indicate roughly the same performance with the only noticeable decrease experienced in the case of the S&P500 asset. Fig. 6 contains a more compacted and convex Pareto front than does Fig. 5. Due to the convex nature of the Pareto front, an increase in hit rate proportion is paired with a gradually steeper decline in trading duration. This gradual decline, however, still surpasses the 0.95 hit rate proportion drop-off point observed in Fig. 5. Recalling that the Aït-Sahalia and Jacob test identifies more price jumps than does the Lee and Mykland test, one would expect an overall noticeable decrease in performance when analysing the Aït-Sahalia and Jacob test. It is, however, apparent that the increase in price jumps identified has no negative effect on the performance of our strategy, thereby confirming that our strategy is biased towards Type I errors.

Further analysis of Table 1 indicates that our strategy is robust with respect to different time step sizes and is compatible with varying candlestick data intervals. Apart from the S&P500, it provides improved performance for larger time steps than for one-minute time steps. These larger time steps are, however, susceptible to more substantial price movements during stable market conditions which should be compensated for when choosing a value for β.

It is clear that the three methods compared are completely different and hence it is impossible to comment on the superiority or otherwise of our strategy over the two existing methods. Our strategy, however, resolves the three main problems identified in the introduction to this paper. Furthermore, it was found that our strategy identifies additional price jumps not identified by the existing methods, as illustrated in Figs. 5 and 6. Identifying these additional price jumps cannot be seen as correct or incorrect as neither of the two existing methods can necessarily be associated with a 100% success rate. This case study, therefore, ultimately indicates that our strategy provides an alternative perspective on price jump identification and may even identify additional price jumps missed by the existing methods, without sacrificing performance.

4.2. Case study 2: Subject matter expert validation

During the second case study, an SME[1] was asked to identify intervals containing price jumps (according to the definition in Section 2.1) and the period of market instability observed after those price jumps. These price jump intervals correspond to the time steps during which the SME would ideally suspend market ranged-based trading activity.

The data set considered in Case study 2 was a sub-sample of the data utilised in Case study 1 and only consisted of one-minute time steps. (Case study 1 indicated that our strategy improves with larger time steps at our risk-utility. Case study 2, therefore, tests our strategy in a *worst case scenario*.) The SME was presented with a printout of each asset's close price series. Through manual inspection, the SME labelled each interval by hand during which a price jump was perceived to have occurred. Our strategy's performance was measured as a relative hit rate proportion, corresponding to the number of instances positively identified by our strategy against those instances identified by the SME. The price jump intervals identified by the SME reduced the total available trading duration (the *ground truth*). In light of this, a relative trading duration was considered, comparing the trading duration of the strategy with that of the ground truth. Furthermore, the experimental design was identical to that employed during Case study 1.

4.2.1. Results

The results generated by our strategy are illustrated in Fig. 7. This figure contains five Pareto fronts (represented by diamonds), revealing each asset's optimal combinations of parameters p and β with the goal of maximising the relative hit rate and maximising the relative trading duration.

For Case study 2 a relative hit rate proportion risk-utility of *at least* 0.6 was employed. The best matching hit rate proportion on the Pareto front and the corresponding parameters are provided in Table 2 for all assets. Utilising the best-fitting parameters of each asset, five confusion matrices were generated, shown in Fig. 8, with the following labels:

$True\ positive$ (TP): Proportion of SME instances which were positively identified by the strategy as forming part of the price jump interval.

$False\ negative$ (FN): Proportion of SME instances which were not identified by the strategy, but formed part of a price jump interval.

[1] Suzzette van Niekerk (CFP) is a financial planner with 22 years of experience. At the time of writing, she was employed at Efficient Wealth (PTY) LTD. (Email: suzettevn@efw.co.za).

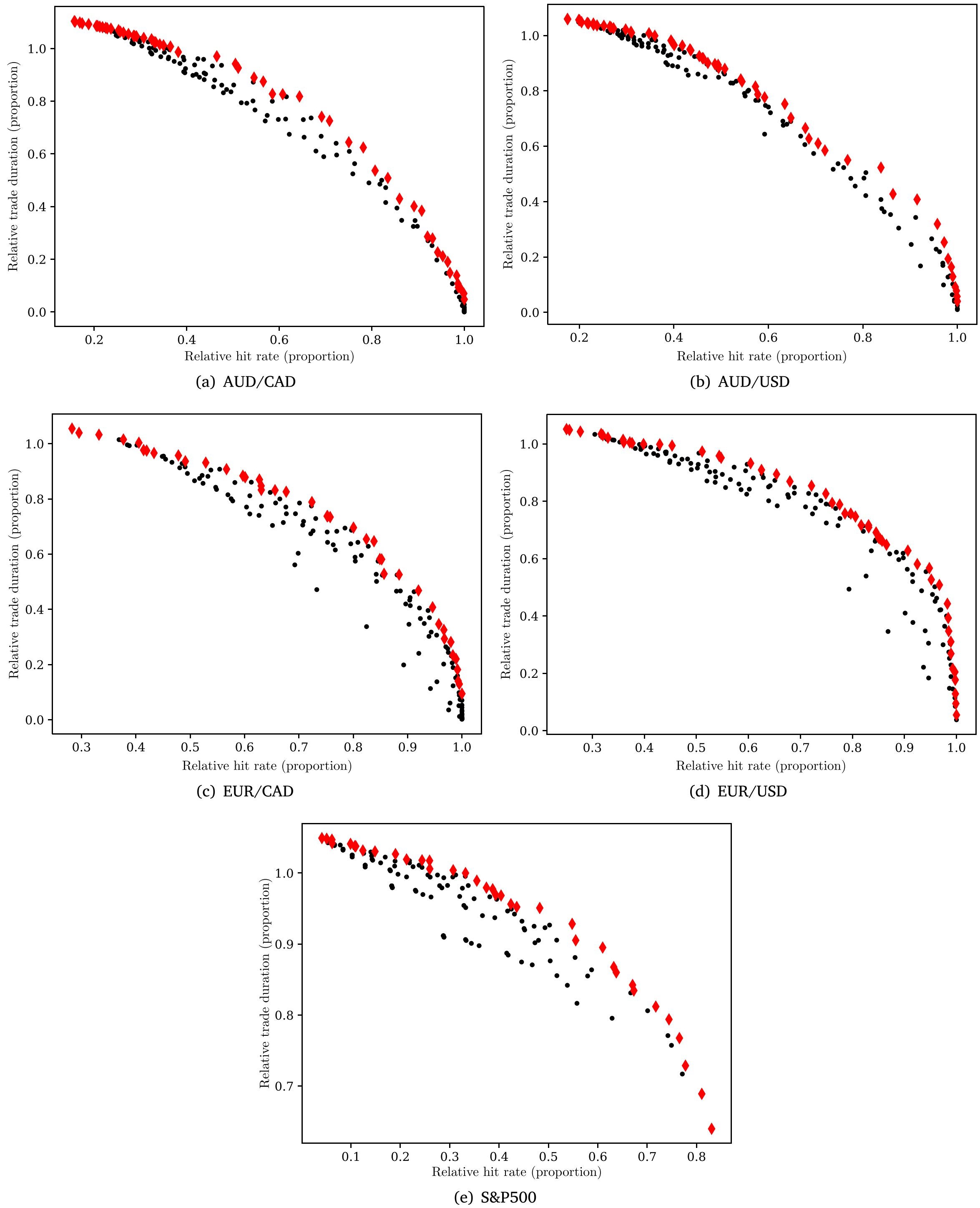


Fig. 7. Pareto fronts (red diamonds) indicating optimal combinations of proportion relative trading duration and proportion relative hit rate for four currency pairs and the S&P500 when compared with price jump intervals identified by a SME.

False positive (FP): Proportion of SME instances which were positively identified by the strategy, but were not part of a price jump interval.

True negative (TN): Proportion of SME instances which were correctly identified by the strategy as not falling within a price jump interval.

4.2.2. Discussion

Upon analysing the plots in Fig. 7, compact (but narrowly dispersed) convex Pareto fronts may be observed. These fronts indicate a reduced performance when compared with those in Figs. 5 and 6 of Case study 1. This comparison is, however, not fair as the benchmark results generated in Case study 1 only included single points identified by a fixed rule-based method, whereas intervals identified by the SME were utilised in Case study 2 which are open to cognitive biases. The plots indicate that large proportions of relative hit rate are paired with

Table 2
The parameter values and corresponding proportions of relative trading duration associated with our exit and re-entry strategy in order to fulfil a risk-utility requirement of at least 0.6.

	p	β	Relative hit rate proportion	Relative trading duration proportion
AUD/CAD	0.9	0.00025	0.6075	0.8265
AUD/USD	0.8	0.000275	0.6348	0.7528
EUR/CAD	0.8	0.0005	0.6012	0.8784
EUR/USD	0.95	0.000325	0.6043	0.9323
S&P500	0.8	2.5	0.6099	0.8951

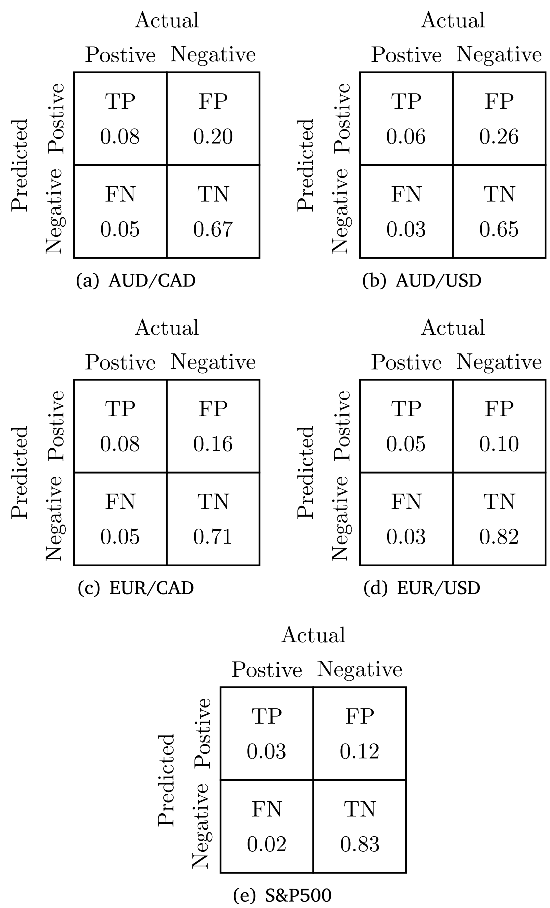


Fig. 8. Confusion matrices illustrating the price jump instance classification performance of our strategy at a 0.6 hit rate proportion risk-utility.

low levels of relative trading duration and *vice versa*. Moreover, from the top left-hand corner to the bottom right-hand corner, a gradual decrease in relative trading duration may be observed (unlike the sudden performance drop-off observed in Case study 1). This decrease in trading duration would seem to indicate that the sensitivity of the parameter β primarily contributes to the performance of our strategy. As discussed in Case study 1, large proportions of relative hit rate are attributable to over-sensitive β-parameter values which cause the exit and re-entry strategy never to trigger a re-entry of the market. Conversely, small proportions of relative hit rate are due to insensitive β-parameter values. One can navigate along the Pareto front by simultaneously decreasing/increasing the values of the parameters p and β.

Upon further review of the results in Table 2, our strategy would seem to have achieved promising performance. The table indicates that the risk-utility hit rate was satisfied by utilising insensitive values of the parameter p paired with a highly sensitive β-parameter value, thereby supporting the circumstantial evidence that the β-parameter value is the main driver of performance. Furthermore, each asset's relative hit rate risk-utility was comfortably reached at acceptable levels of relative trading duration. Due to the sensitive β-parameter value, however, large proportions of instances were falsely identified as part of price jump intervals, as illustrated in Fig. 8, which causes a decrease in relative trading duration. This proportion is expected to increase at higher levels of risk adversity.

Overall, the results of Case study 2 indicate that our exit and re-entry strategy is capable of identifying price jump intervals to some degree. As results greatly depend on the risk-utility of the SME and her cognitive bias at the time of data labelling, the results are, of course, subject to change from one expert to another. Although the strategy may not provide full protection against all price jump intervals, the results indicate that the newly proposed strategy may contribute to decreasing the risk associated with these market events.

5. Conclusion

In this paper, an automated exit and re-entry strategy was proposed which is capable of identifying price jumps that terminate automated trading activity during unstable market conditions and continue trading activity during stable market conditions. The strategy comprises two underlying phases. During Phase 1, a VaR analysis is performed to identify price jumps. Thereafter, Phase 2 involves carrying out an entropy analysis to identify an appropriate point for market re-entry. The strategy was validated in two case studies. Case study 1 validated that our strategy provides an alternative perspective on price jump identification when compared with two existing methods. The results generated indicate that the strategy was capable of maintaining up to 98.41% of the trading duration proportion of the Lee and Mykland test, and up to 96.28% of the trading duration proportion of the Aït-Sahalia and Jacob test at a risk-utility of 0.6 hit rate proportion. Furthermore, Case study 2 demonstrated that our strategy provides promising results when compared with price jump intervals identified by an SME and was capable of maintaining a relative trading duration proportion of up to 93.23% at a relative hit rate proportion risk-utility of 0.6. The positive results obtained in both case studies suggest that our proposed exit and re-entry strategy satisfies all three problems identified in Section 1, by

1. assigning a monetary value to any potential losses caused by a price jump,
2. identifying strong market trends which have the same effect as a spontaneous price jump, and
3. evaluating market stability after a price jump has occurred.

In future work, the scope of our analyses may be broadened by testing the effect of our exit and re-entry strategy on risk-adjusted returns, when combined with actual range-based trading strategies. Furthermore, the optimisation of our strategy may include the re-entry entropy threshold value to obtain a solution space with parameters p, β, and j which may yield further improvements in strategy performance.

CRediT authorship contribution statement

Dirk Johan Coetzee Koegelenberg: Conceptualization, Methodology, Software, Validation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Jan H. van Vuuren:** Conceptualization, Methodology, Supervision, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors report that financial support was provided by Sonic fund. The paper contained a subject matter expert as a form of validation. The subject matter expert had no input on the contents/analyses of this paper and was only asked to label data for benchmarking purposes. The subject matter expert is not associated in any way with Sonic fund.

Data availability

Data will be made available on request.

Acknowledgements

The authors thank Sonic fund and Basie Kok for their contribution to funding this research. Many thanks also to Suzzette van Niekerk for her willingness to fulfil the role of SME for this paper.

Appendix. Strategy process diagram

The strategy process diagram may be seen in Fig. 9.

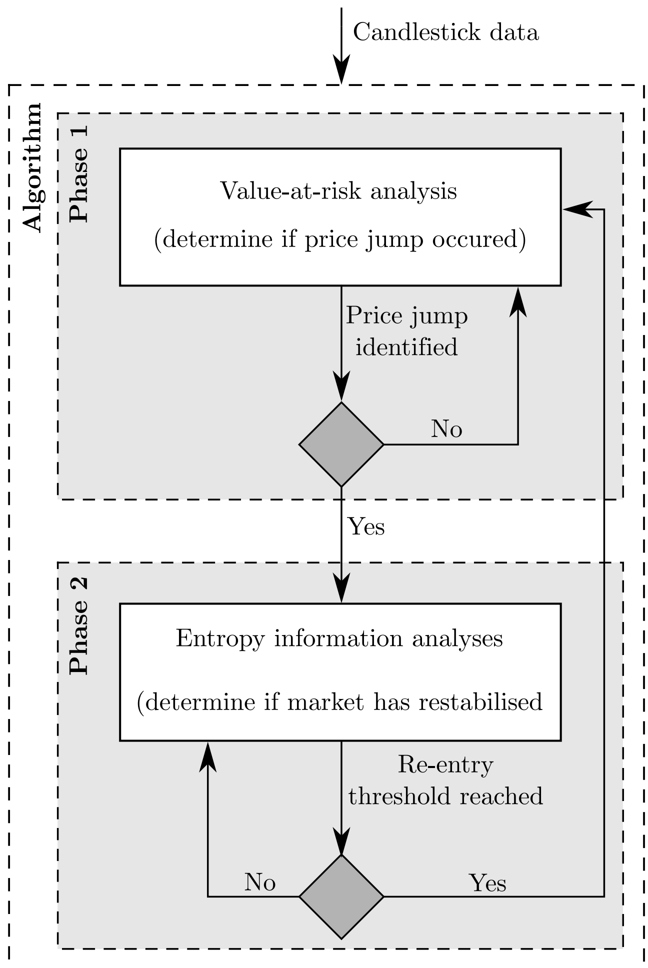


Fig. 9. A process diagram of the proposed automated price jump exit and re-entry strategy.

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