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ORIGINAL RESEARCH

Deep Heterogeneous AutoML Trend Prediction Model for Algorithmic Trading in the USD/COP Colombian FX Market Through Limit Order Book (LOB)

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Abstract

This study presents a novel and competitive approach for algorithmic trading in the Colombian US dollar inter-bank market (SET-FX). At the core of this strategy is an advanced predictive model, developed using the Tree-based Pipeline Optimization Tool (TPOT). TPOT, an automated machine learning platform based on strongly-typed genetic programming, incorporates the Non-dominated Sorting Genetic Algorithm II (NSGA-II). This multi-objective evolutionary algorithm is instrumental in identifying machine learning models that strike an optimal balance between high accuracy and low complexity, thereby advancing the field of predictive modeling in financial markets.

Keywords Algorithmic trading strategy · AutoML · Genetic programming · TPOT

Introduction

The efficacy of algorithmic trading strategies critically depends on accurately forecasting the future price or price direction of financial assets. These forecasts are informed by discerning patterns in market data, supplemented by various ancillary sources of information. Typically, this data encompasses transaction time series, detailing elements such as negotiation times and price points (open, close, high, and low), along with volume figures. Available in diverse temporal resolutions (ranging from tick-by-tick to daily intervals), the granularity of these series correlates with the data accessibility of the respective entities.

In advanced financial markets, participants have the added advantage of accessing limit order data, encompassing buying and selling price points and volumes. In contexts like the Colombian US dollar inter-bank bulk market SET-FX, traders employ limit orders to express their trading intents. This capability enriches their decision-making process, enabling strategies based not only on transactional data but also on the nuanced dynamics and current state of limit orders.

This study aims to devise and evaluate a bespoke algorithmic trading strategy for SET-FX. The proposed strategy integrates a plethora of variables from SET-FX's transactional time series and limit order book (LOB) dynamics, facilitating systematic trading decisions on a second-by-second basis.

The structure of the paper is laid out as follows: We begin by introducing the Colombian US dollar inter-bank bulk market SET-FX, followed by a detailed examination of its LOB dynamics. Subsequently, we delve into an exploration of TPOT and its role in shaping the predictor for our trading

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strategy. The paper culminates with an analysis of the strategy's profitability.

Exchange markets are broadly categorized into dealership markets, order-driven markets, or hybrid forms, each with distinct operational characteristics.

Dealership markets operate through specialists or institutional investors who provide liquidity by quoting a consistent price for an asset, irrespective of the quantity. These markets are exemplified by entities such as NASDAQ and the London Stock Exchange (LSE).

Conversely, order-driven markets function without dedicated dealers. Here, market participants submit limit orders to quote prices and use market orders to react to the prevailing buy and sell dynamics. A prime example of this market type is EURONEXT.

The Colombian US dollar inter-bank bulk market, SET-FX, exemplifies a single asset order-driven market. Here, institutional brokers and banks engage in US dollar and Colombian peso transactions, leveraging data from both the limit order and transaction books. Managed by the Bolsa de Valores de Colombia (BVC) in collaboration with TP ICAP, SET-FX comprises 43 institutions, with an average daily trading volume of approximately 1.5 billion US dollars. Participants are permitted to place limit orders at any desired price, with volumes in multiples of 250,000 US dollars.

In SET-FX, institutional participants are charged a flat fee of about US $2,000 monthly per client, rather than per transaction. Additionally, a central counterparty clearinghouse mandates a 10% deposit of the total permissible long or short positions by institutions to address various risks, including counterparty, operational, settlement, market, legal, and default risks. Initially, trades in SET-FX were conducted manually via a visual user interface. The introduction of FIX clients in the second quarter of 2019 marked the advent of algorithmic trading in this market.

The next section provides a general description of the dynamics and information within the SET-FX Limit Order Book (LOB).

SET-FX Limit Order Book (LOB) Dynamics and Information

At any given time, the Limit Order Book (LOB) serves as a detailed ledger of prices and volumes for buyers and sellers in the financial market [1]. It is essentially composed of two orderly queues: the bid queue for potential buyers and the ask queue for potential sellers. Each limit order within these queues clearly states the price and volume for the intended trade.

The organization within each queue is primarily price-based. Orders sharing a price are then sorted based on their time of entry [2]. The bid queue arranges orders in descending price order, giving precedence to the highest bids, while the ask queue is in ascending order, favoring the lowest asking prices. This arrangement allows for a clear visualization of supply and demand across different price points, as depicted in Figs. 1 and 2.

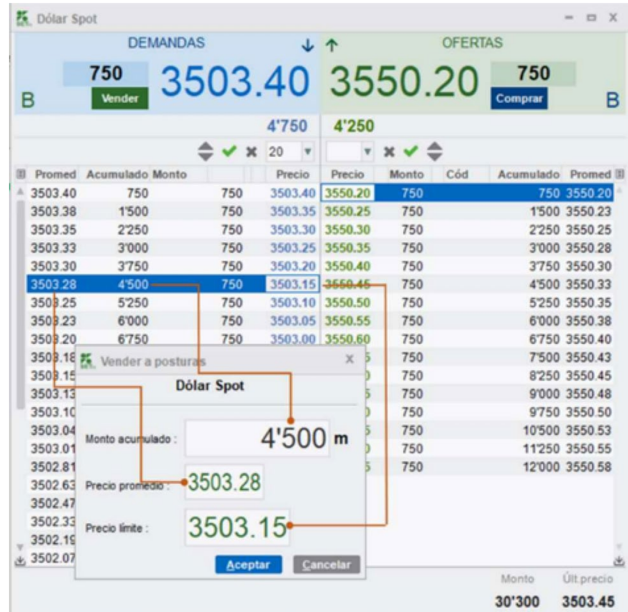

Fig. 1 Snapshot of the limit order book on February 4th 2019 at 10:20:09 A.M extracted from the SET-FX, the inter-bank exchange platform. The best fourteen prices and volumes are presented. first column shows average prices, second column shows cumulative volume, third column shows order volume and forth column shows order prices. Demandas, ofertas, monto, precio stand for bids, offers, quantity and price respectively

Figure 1 captures a moment in the SET-FX's LOB, specifically on February 2nd, 2011 at 10:20:09 A.M. Consider a scenario where a market agent wishes to sell 750 thousand dollars at a rate of 1852.32. The appropriate approach would be to place a limit order, which would be positioned on the sell side of the LOB, nestled between orders at 1852.3 and 1852.33. For this order to be executed, preceding orders must be fulfilled or canceled.

The LOB is characterized by its dynamic nature, with orders constantly being placed, executed, modified, or removed throughout the trading period. These actions reflect the evolving buying and selling intentions of market agents, as illustrated in Fig. 3. The dynamics of the LOB are also significantly influenced by trading events or transactions, which lead to the removal of negotiated orders from the LOB, as further detailed in Fig. 4. Order execution adheres to the Best Price First (BPF) principle, with a First In First Out (FIFO) rule applying to orders at identical prices.

The dynamics of the LOB have been modeled, analyzed, and visualized using various mathematical [3, 4], statistical [5–7], and visual [8–11] approaches. Figure 5 showcases

Fig. 2 LOB information

a visual interpretation of the USD/COP SET-FX LOB dynamics, with the *y*-axis representing exchange rates and the *x*-axis denoting one-minute aggregation intervals. The red and green intensities indicate sell and buy volumes, respectively. This visualization also highlights how certain segments of LOB volume dynamics can serve as indicators for price trends. Additionally, Fig. 6 presents another heatmap visualizing the LOB dynamics from March 21, 2012. Here, the red shades represent volume levels, with blank spaces indicating zero volume. Each unit of volume corresponds to 250 thousand US dollars, with the maximum volume depicted being 15 million US dollars, represented by the number 60 on the color bar. Solid black lines trace the evolution of the best buy and sell prices [12].

TPOT

The significant surge in big data generation has propelled the application of Machine Learning (ML) across diverse sectors, notably in finance, to solve increasingly complex challenges. This trend highlights the complexities encountered in the development of robust ML models. Addressing these challenges, the field has witnessed the emergence of Automated Machine Learning (Auto ML) tools in recent years. These tools harness advanced computational capabilities and sophisticated algorithms, including genetic algorithms, genetic programming, simulated annealing, and tabu search [13]. They offer a broad spectrum of solutions through automated exploration. Among these, the Tree-based Pipeline Optimization Tool (TPOT) [14] stands out. TPOT employs genetic programming for the automated creation of ML

Fig. 3 LOB events

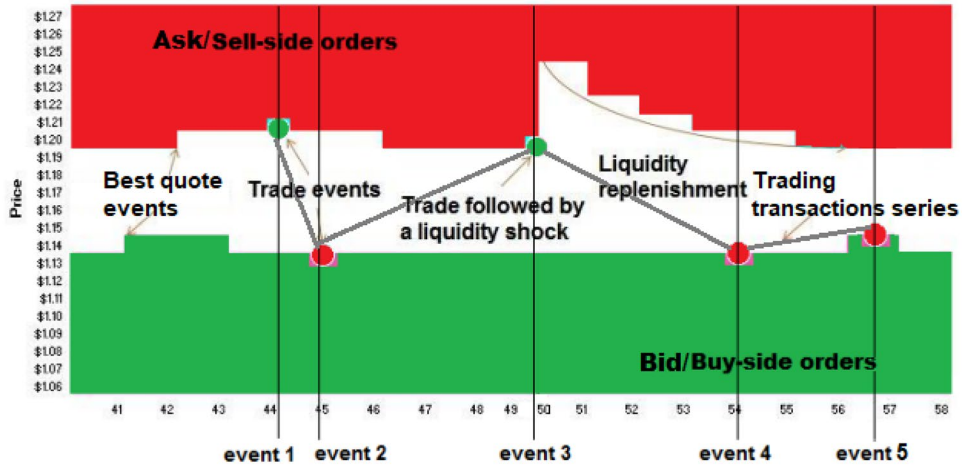

Fig. 4 LOB events that have an impact on liquidity and spread

models, placing a strong emphasis on model interpretability as a key evaluation parameter.

The process of constructing a machine learning model encompasses several key stages, as detailed below [15]:

1. Purification of data
2. Engineering of features
   (a) Preprocessing of features
   (b) Selection of pertinent features
   (c) Construction of new features
3. Choosing the appropriate model
4. Training the model
   (a) Optimization of hyperparameters
   (b) Fine-tuning of model parameters
5. Validating the model's efficacy

TPOT,[1] an innovative, open-source AutoML tool based on genetic programming, streamlines this workflow. It refines a variety of feature preprocessors and machine learning models, targeting optimal performance in classification or regression tasks [14]. Notably, models devised by TPOT frequently surpass expert-crafted counterparts. TPOT automates every phase of this workflow, as illustrated in Fig. 7.

In essence, TPOT operates as a sophisticated overlay for the scikit-learn library in Python [16], progressing through NSGA-II enhanced scikit-learn pipelines [17]. These pipelines are representable as syntactic trees, offering a visual understanding of the process (see Fig. 8).

Trading in financial markets demands the identification and exploitation of subtle patterns hidden within vast and complex datasets. Traditional methods often rely on manual feature engineering and model selection, which are inherently limited by human biases and computational inefficiencies. Despite the wide use, TPOT offers a solution by automating the entire machine learning pipeline, from feature selection to model optimization, thus enabling the discovery of nuanced trends that may elude human intuition.

By leveraging TPOT's capabilities, we can efficiently sift through financial data to uncover patterns indicative of profitable trading opportunities. One of the primary objectives in financial time series analysis is the detection of trend patterns, which can signal potential market movements. TPOT excels in this regard by leveraging ensemble methods and sophisticated feature selection techniques to extract meaningful patterns from noisy data. References such as [18, 19] highlight the effectiveness of TPOT in identifying complex patterns in various domains, reinforcing its potential utility in financial markets.

TPOT learns from historical data, uncovering trends specific to a particular market or asset class. This data-driven approach can outperform generic, pre-defined indicators that may not capture the nuances of a specific market. In conclusion, TPOT presents a promising avenue for uncovering trend patterns in financial time series data and constructing more effective trading strategies. By automating the machine learning pipeline, TPOT reduces human biases, accelerates model development, and enhances the adaptability of trading strategies to evolving market conditions. Through empirical evaluations and comparisons, we provide compelling evidence for the superiority of TPOT-driven strategies, advocating for its adoption in financial markets [20].

[1] http://epistasislab.github.io/tpot/.

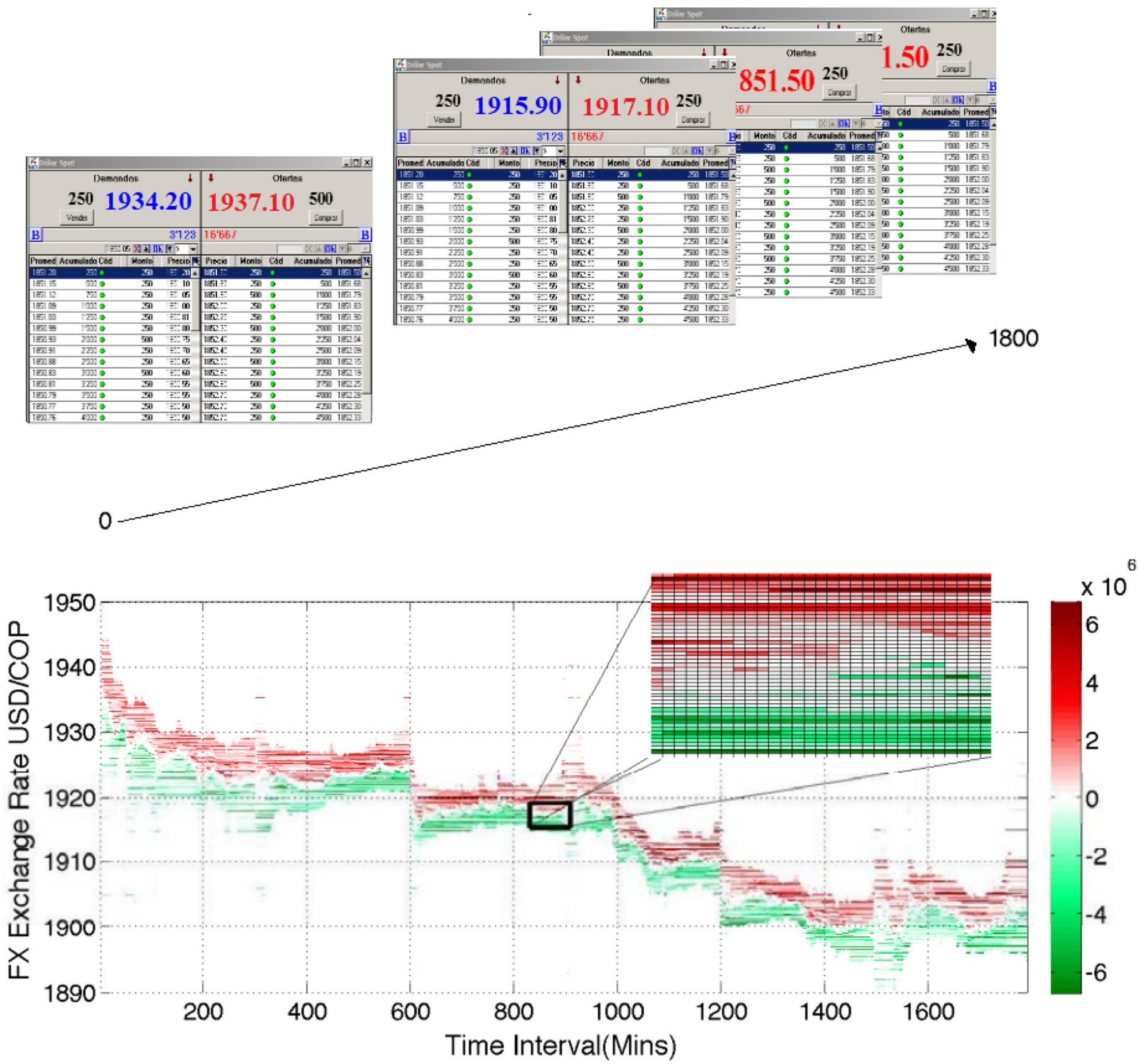

Fig. 5 A heatmap visual representation of USD/COP SET-FX LOB dynamics information, data. *y*-axis represents USD/COP exchange rates and *x*-axis captures time intervals using an aggregating one-min interval. Red intensities represented sell volumes and green intensities represents buy volumes. The zooming shows a segments of the LOB volume dynamics that can be uses as a predictive pattern for the price movement

SET-FX Data Set and Data Exploration

This research utilizes a data set encompassing 6 days of Limit Order Book (LOB) activity, which includes actions like insertions, modifications, and deletions of limit orders, along with transactional elements such as prices, volumes, and LOB sides (refer to Table 1). This data can be accessed for further study.[2] It was sourced from SET-FX's FIX algorithmic engine via Algpocdex, an algorithmic trading entity in Colombia that creates trading algorithms for the SET-FX market on behalf of "Acciones y Valores," a prominent Colombian brokerage firm.

Operating hours for the SET-FX market span from 8 AM to 1 PM, during which approximately 14,000 LOB events occur daily. This translates to roughly one LOB event every 1.29 s. In addition, the market witnesses about 1,500 transaction events each day, averaging one transaction roughly every 12 s.

[2] https://github.com/gjhernandezp/SetFX.

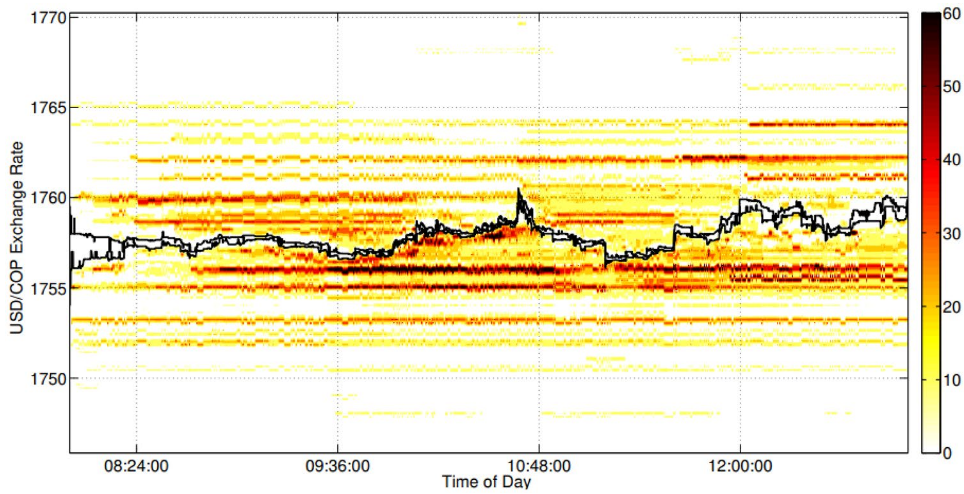

Fig. 6 A heatmap visual representation of USD/COP SET-FX LOB dynamics information from March 21, 2012. Red intensities present volume, white spaces correspond to zero volume with every volume unit equivalent to 250 thousand US dollars. Maximum volume, 60 in the color bar, is equal to 15 million US dollars. Solid black lines show best buy/sell price evolution

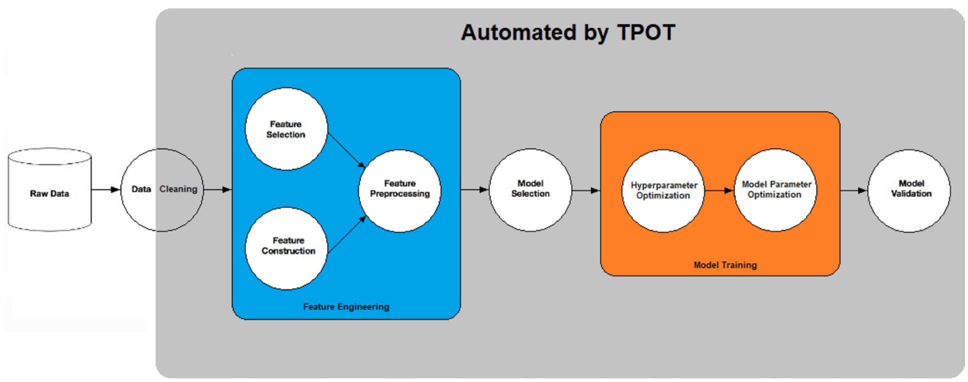

Fig. 7 Where TPOT fits in the ML Model developing workflow

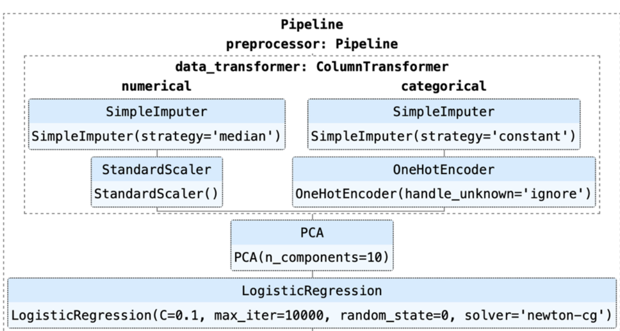

Fig. 8 A example for a pipeline in Scikit-Learn [17]

Table 1 SET-FX data

Day	Number LOB events	Number of transactions
2019-04-25	14,617	1648
2019-05-08	12,988	1346
2019-05-14	21,041	1991
2019-04-24	13,755	1311
2019-06-28	7725	1080
2019-06-26	10,809	1549
Average	13,489.1	1487.5

Data is structured into daily tick-by-tick sequences of LOB events, each characterized by:

- Timestamp
- Unique identifier for each order
- Side of the market (buy/sell)
- Nature of event (e.g., insertion, modification, removal)
- Price of order
- Volume of order

This is supplemented by tick-by-tick transaction sequences, encompassing:

- Timestamp
- Unique ID for each transaction
- Market side

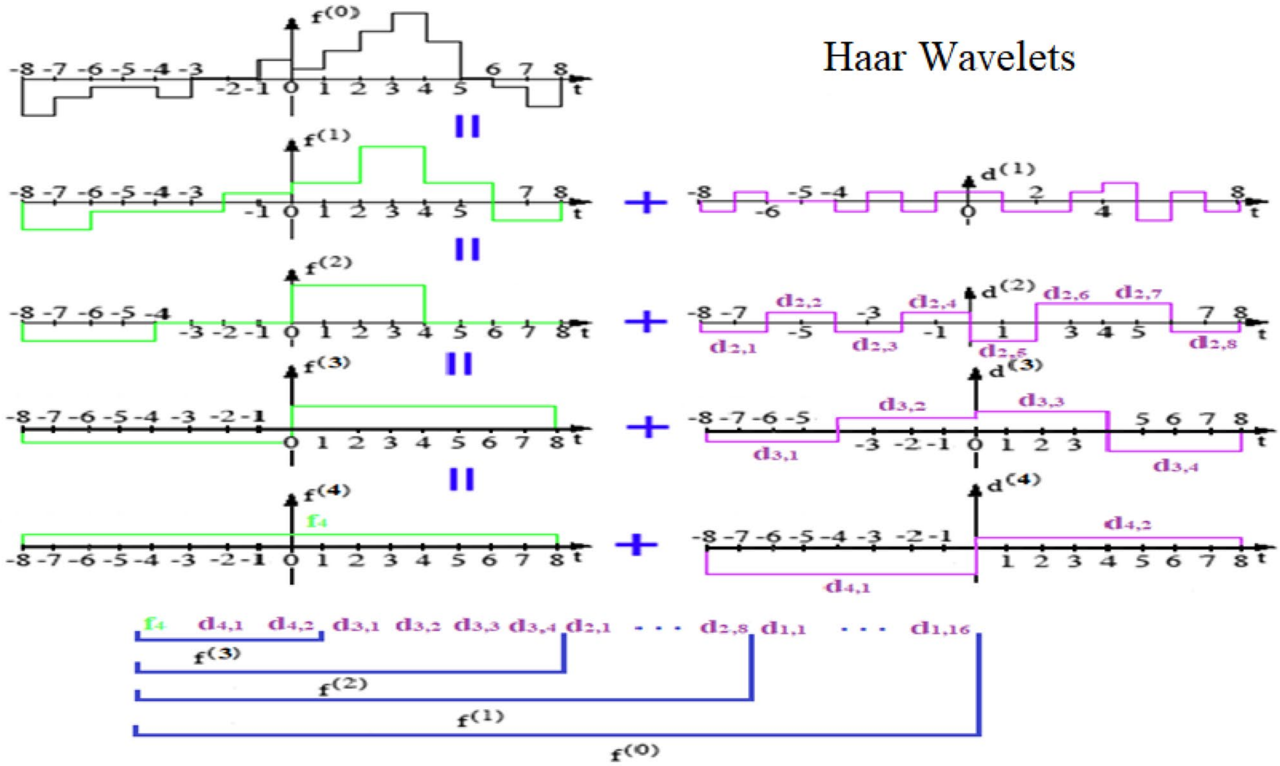

Fig. 9 Haar wavelets applied obtain different time scale (1, 2, 4, 8 and 16 s) average coefficients of a time series

- Transaction category (market, registration)
- Transaction price
- Transaction volume

We refine this data into second-level aggregate time series and visual representations, employing a 64-s moving window on these sequences and images to detect patterns predictive of price trends, as depicted in Fig. 10. Additionally, we conduct a multi-resolution and frequency analysis of these series and images. The data representation utilizes sliding 64-s windows and Haar wavelets. Figure 9 illustrates the application of four levels of Haar wavelets, retaining only average coefficients of different time scales (1, 2, 4, 8, and 16 s) of a time series.

Adopting the methodology outlined in [21], we conduct an analysis and categorization of visual patterns in the LOB (Limit Order Book) volumes, which may be indicative of future price trends (Fig. 10).

Figure 12 depicts the correlation between LOB activities and transactional data with both ascending and descending price movements.

Figure 11 showcases volume windows of 30 × 30, corresponding to 30-min periods and a 3 COP (Colombian Pesos) range above and below the mid-price. The mid-price is derived from the lowest offer price and the highest bid price within the chosen interval. Here, sell volumes are represented in red, while buy volumes are shown in green.

Figure 12 exhibits the grouping of these visual elements through K-means clustering, utilizing 13 distinct clusters. The lowest row in the figure portrays the centroid of each cluster. The positioning of clusters on the *x*-axis is strategic, reflecting their likelihood of being linked with specific market trends. Clusters numbered 12, 8, 7, 4, and 10 correspond to rising market trends, while clusters 5, 6, 9, 3, 13, and 11 indicate falling trends. Clusters 1 and 2 exhibit a mild inclination towards downtrend scenarios.

The features considered for the analysis are categorized into LOB and transaction features. For the LOB, the features are:

- Time series of spreads (relative to the first mid-price)
- Time series of mid-prices (relative to the first mid-price)
- Time series of best buy prices (relative to the first mid-price)
- Time series of best sell prices (relative to the first mid-price)
- Time series of best buy volumes (relative to the first mid-price)

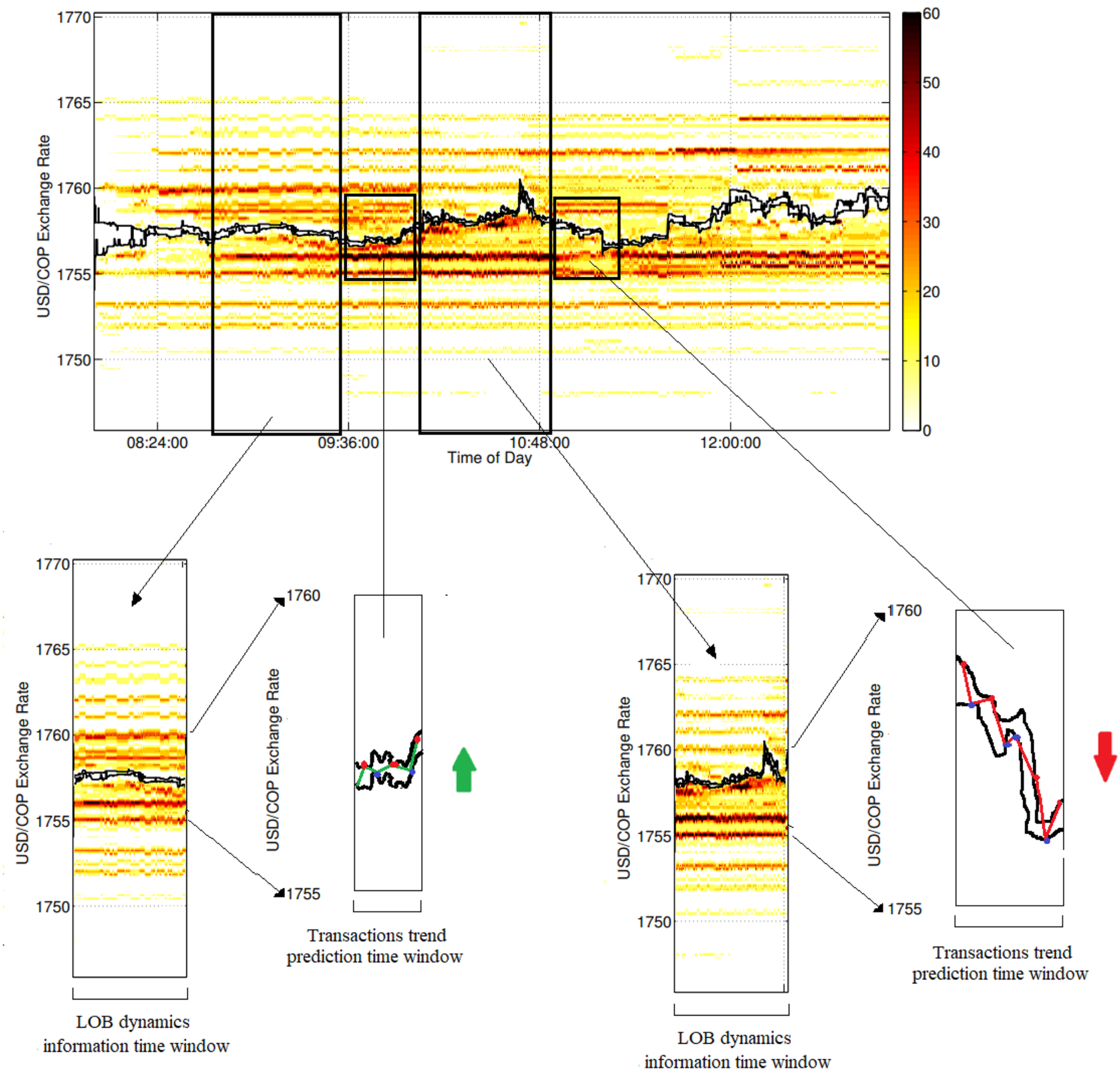

Fig. 10 How LOB and transactions are associated with with up and down price trends

- Time series of best sell volumes (relative to the first mid-price)
- Time series of market sides (B: buy, S: sell)
- Time series of types of events (I: insertion, U: update, D: deletion)
- Time series of order prices (relative to the first mid-price)
- Time series of order volumes (relative to COP 12 M)
- Time series of images representing the LOB dynamics, with a 64-s time window (64 pixels) and $10 COP granularity, quantized at $20 cents (50 pixels)

For the transaction data, the features are:

- Time series of transaction prices
- Time series of transaction volumes
- Time series of transaction market sides
- Time series of transaction types (M: market, R: registration)

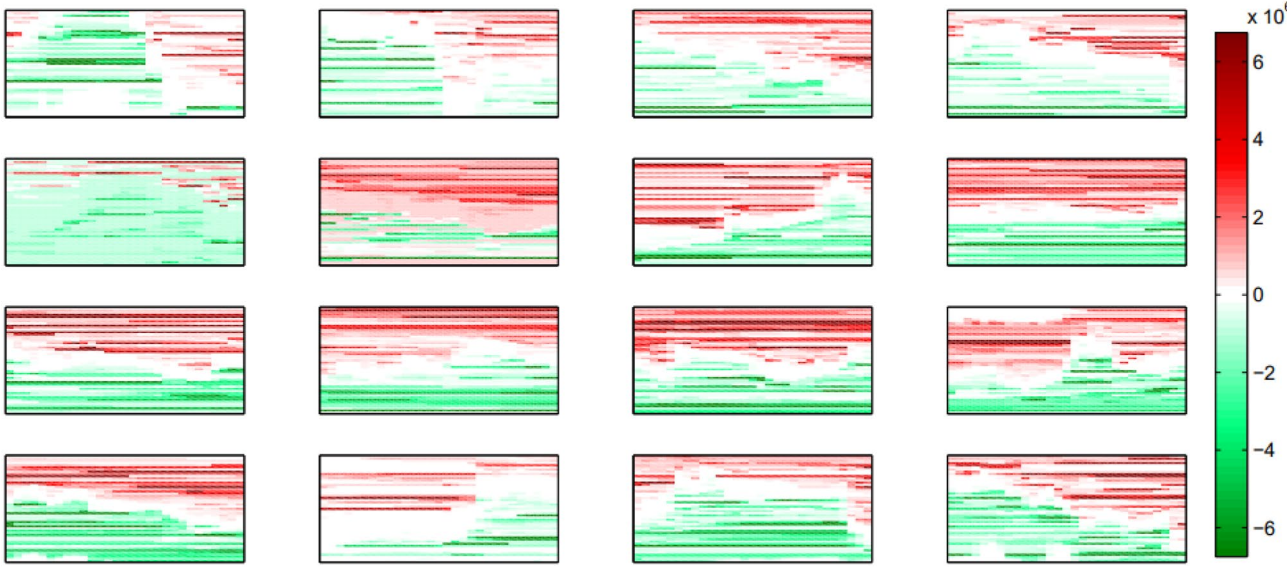

Fig. 11 30×30 volume windows representing 30 min and 3 COP up and down from every mid-price calculated using lowest best buy price and highest best sell price during the selected time window. Red means sell volume and green represents buy volume

Figure 13 illustrates the pattern identification process.

Algorithmic Strategy and Backtesting

Our proposed methodology involves a passive trading approach designed to capitalize on anticipated price movements. The strategy functions based on predictions made by the price trend predictor:

- **Anticipating a rise in price**: In scenarios where a price increase is anticipated, the system places a purchase limit order within the LOB. Owing to the strategy's passive nature, a position is initiated only when a counterparty in the market fulfills the order (in this context, the minimum transaction is US $250,000). Upon successful execution, our algorithm adopts a long position and immediately sets a new selling limit order at an optimal price. This position is maintained until it is bought out by another market participant, thus completing the cycle.
- **Anticipating a decline in price**: Conversely, when a price drop is predicted, the strategy initiates a selling limit order for dollars. The operational mechanism remains identical but is executed in reverse.

The intrinsic passive characteristic of this strategy implies that it engages in trades only when they are executed by other market participants, rather than proactively seeking trading opportunities.

The efficacy of this trading strategy was rigorously tested through backtesting on designated training and testing days, as well as on an independent out-of-sample day. Our simulation approach, which replicates the market behavior for orders placed by our algorithm, presumes execution upon fulfillment of preceding orders in the LOB. Specifically, a lower-priced order should be executed for buy scenarios, and a higher-priced one for sell scenarios.

Building upon our initial success in analyzing visual patterns within the LOB (Limit Order Book) volumes, we harnessed the capabilities of TPOT to devise an effective predictor leveraging the insights from LOB dynamics and transactional data [22]. Our approach took into account the data from the preceding minute, applying a trend indicator that assessed whether the average transaction price fluctuated by 20 cents or more compared to the closing price of the previous minute.

```
ExtraTreesClassifier(bootstrap=False, criterion=
    "entropy", max_features=0.8500000000000001,
    min_samples_leaf=3,
    min_samples_split=7, n_estimators=200)
```

For TPOT's deployment, we configured it to run through 20 generations with a population of 10, employing a five-fold cross-validation approach. On analyzing the first 5 days of our dataset with TPOT, we identified a robust predictor exhibiting an overall accuracy of 77%, with specific accuracies of 68% for rising trends and 69% for falling trends.

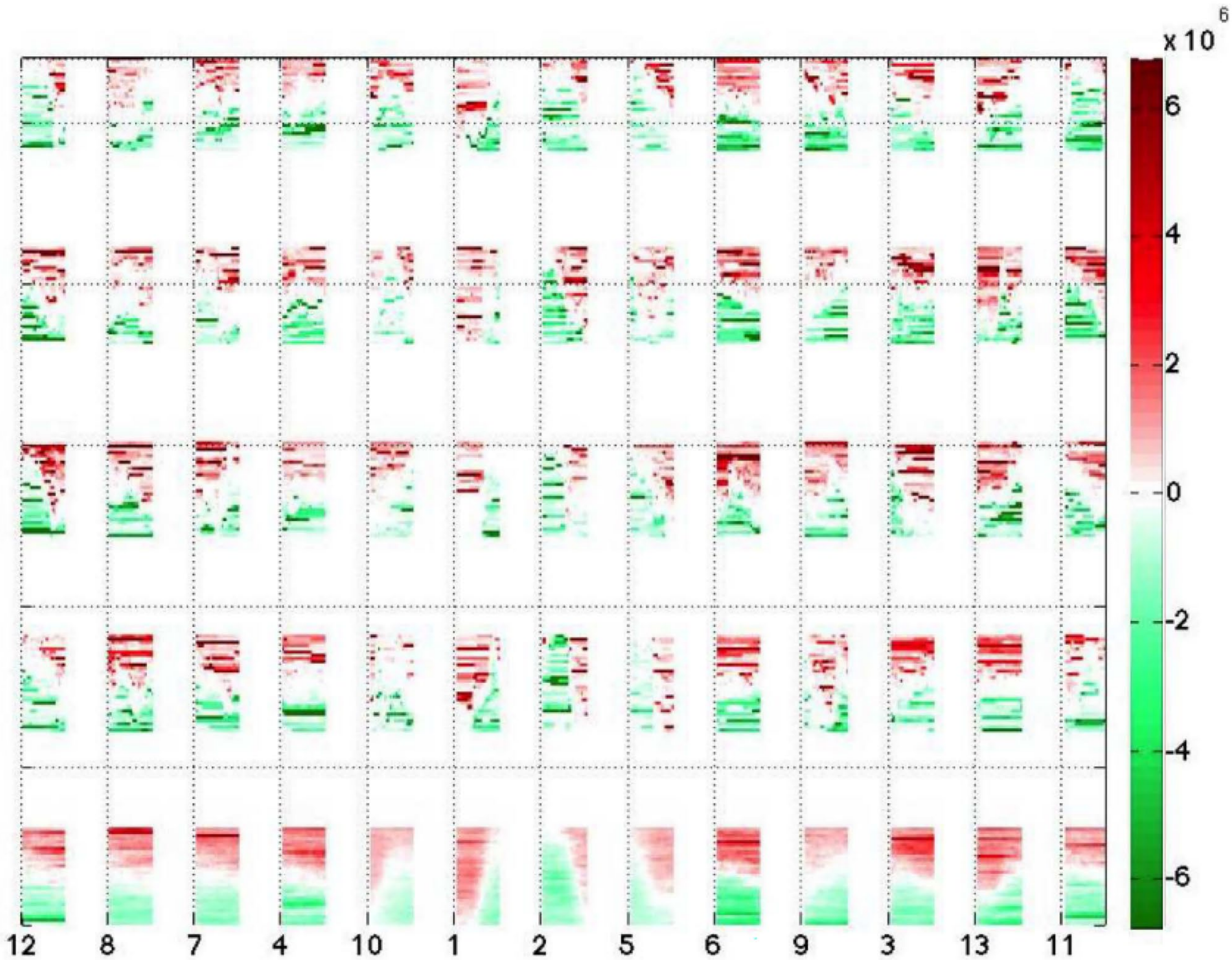

Fig. 12 Clustering of visual patches using K-means and 13 clusters. Bottom-most row presents a visual representation of every cluster's centroid. Clusters in the x-axis are organized according to their probability of being associated to a particular market trend. Clusters 12, 8, 7, 4, 10 are related to uptrend movements, clusters 5, 6, 9, 3, 13, 11 are related to downtrend movements and clusters 1, 2 showed a weak tendency to downtrend regimes

We then proceeded to backtest our algorithmic trading strategy, which incorporated the predictor developed by TPOT. This testing phase was carried out on the sixth day (2019-06-26) of our dataset. The outcomes of this backtesting process are delineated in Figs. 14 and 15.

Conclusion and Future Work

Our development of an algorithmic trading strategy for the SET-FX, the Colombian US dollar inter-bank bulk order-driven market, leveraging an advanced evolutionary model through TPOT, has proven to be highly effective. The strategy achieved a notable gain of COP $14 in the backtest on the data set's sixth day, translating to an estimated daily profit of around US $1000. This figure is particularly significant considering the trade positions were valued at US $250,000, yielding a total of COP $\$14 \times 250{,}000 =$ COP $3.5M, equivalent to approximately US $1000.

Given these promising results, there is considerable scope for further optimization and refinement. Future endeavors could focus on leveraging specialized time series AutoML tools, like Auto-TS [23] or Auto_TimeSeries [24], to enhance predictive accuracy. Furthermore, incorporating reinforcement learning strategies [25, 26]

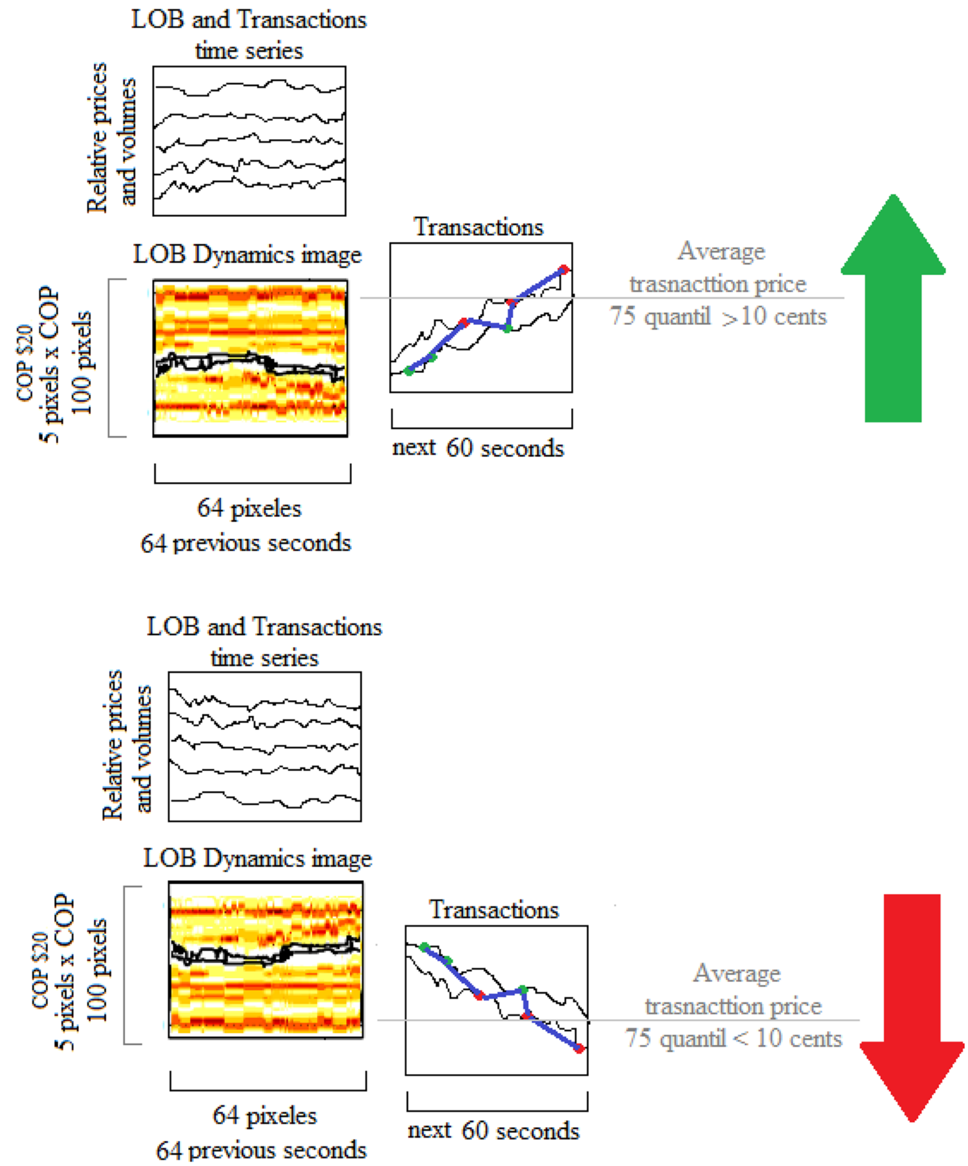

Fig. 13 Pattern identification process

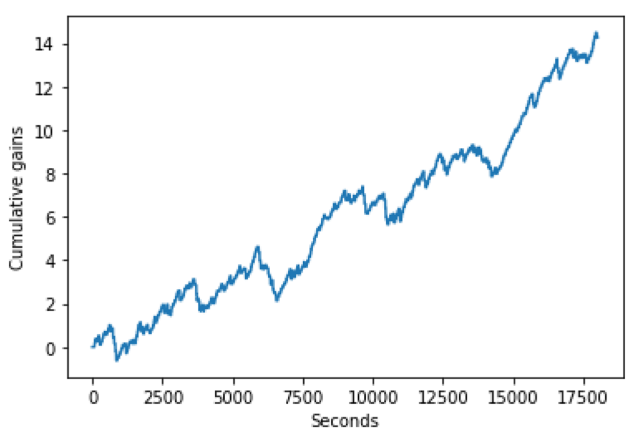

Fig. 14 Backtesting of the algorithmic trading strategy based on an predictive fund by TPOT on the 6th day (2019-06-26) of the data set

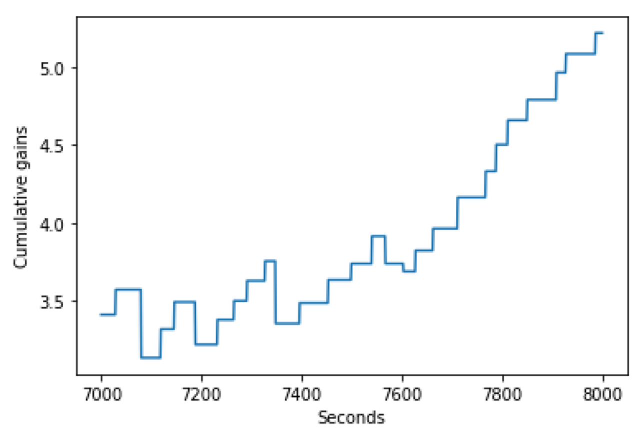

Fig. 15 Zoom between seconds 7000 and 8000 of the backtesting of the algorithmic trading strategy based on an predictive fund by TPOT on the 6th day (2019-06-26) of the data set

could pave the way for even more sophisticated and adaptable trading algorithms.

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Data availability The data supporting the findings of this study are available upon request from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Human and animal rights This article does not contain any studies with human or animal participants.

Informed consent There are no human participants in this article and informed consent is not applicable.

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