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Affective Algorithm for Controlling Emotional Fluctuation of Artificial Investors in Stock Markets

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ABSTRACT This paper presents the design of an affective algorithm for implementing autonomous decision-making systems that incorporate an emotional stabilizer mechanism for the use in the stock market domain. Emotions have a direct influence on human decision-making processes. Non-deterministic behavior in humans can be partially explained by emotions. In this sense, an artificial emotion can be implemented as a synthetic abstraction derived from the observation of human emotions. This paper presents studies related to emotional stability and emotional regulation. However, to the best of our knowledge, it is not possible to identify studies that define a relationship between the regulation of artificial emotions and the decision effectiveness of autonomous decision-making systems, specifically for the stock market domain. With the aim to improve investment results in the stock market domain, a mechanism based on artificial emotions is presented that was designed as a single layer of decision criteria defined by both rational and emotional perspectives. Along with the proposal of an emotional stabilizer mechanism, different values of emotional bandwidths and emotional update rates were tested, aiming to explore the degree of influence of these parameters on the effectiveness of investment decisions made by artificial investors. Our proposal considers the definition of an experimental scenario based on official data from the New York Stock Exchange. The results are promising and include a linear regression analysis. The test results suggest that the use of autonomous affective decision-making systems with emotional stabilization can improve the effectiveness of the decision made.

INDEX TERMS Affective algorithm, artificial investor, emotional fluctuation, stock market.

I. INTRODUCTION

People always have emotions, and they express them every day. Each emotional reaction depends, in turn, on several types of variables: the specific circumstances observed or lived, the current individual risk level, equivalent past experiences, knowledge available, and social influence, to name a few. Emotional states have an important influence on decision-making processes. Emotion may act as a promoter or suppressor of specific actions or decisions. In fact, emotions have a continuous influence on human acts, that is, humans are frequently in a rational-emotional state.

Neuroscience offers evidence that the decision-making process is a unified rational-emotional process [1], [2]. According to Mayer and Salovey, emotional intelligence can be understood as the capacity to reason about emotions and the enhancement of thinking by emotions; in addition, emotional intelligence allows the individual to reflectively regulate emotions to promote emotional and intellectual growth. Emotional intelligence implies knowing and managing one's own emotions, self-motivation, recognizing the emotions of other people, and managing social relationships. In this sense, because emotions have an influence on both individual and social decisions, the emotional regulation process has a critical impact on human behavior. For example, people with low self-esteem have a low motivation to improve their negative moods [4], generating a very different perception of reality relative to people with high self-esteem. The central idea behind emotional regulation is to identify and control the emotions felt by a person [5]. Studies related to emotional regulation and decision-making have shown that emotions derived from specific choice situations can be controlled or regulated through an intentional effort, which allows changes in the parameters that influence decision-making and, consequently, the decisions made [6]. There exist several techniques to modify emotional reactions, which include, e.g., the suppression of negative emotions and thinking about pleasant things or circumstances. During emotional regulation, people may increase, maintain, or decrease emotional intensity. Emotional regulation often involves changes in emotional responses [7].

On the other hand, a market corresponds to a physical or nonphysical space where suppliers and demanders interact over any good or service. When talking about financial markets, the traded instruments correspond to financial assets. A financial market is a mechanism that brings together buyers and sellers of financial instruments, which allows transactions to be made through their systems [8]. Stock markets are a representative example of a decision environment under uncertainty, where it is not possible to exactly determine what will happen with the behavior of a company, a sectorial industry, the economy of a country, or, specifically, with a stock. In this sense, an investor who has several kinds of information about market behavior, future economic expectations, and information about his own investments makes each investment decision. Using available information, which can be partial, incomplete and not necessarily reliable, each investor configures his own notion of confidence and then decides about his own investments. Investor confidence is based on a unified perception along a rational dimension (e.g., analytical indicators) and an affective dimension (e.g., emotions derived from the performance of an investment). Thus, each investment decision is made under an uncertain scenario, where uncertainty has two different sources: one external to the investor, that is, the high complexity of financial markets, and the other internal to the investor, that is, his own behavior conditioned by emotions.

The use of affective systems has increased in recent years, shaping new research initiatives in the domain of text mining [9], [10], tutoring systems [11], recognition of human expressions [12]–[15], or the relationships between humans and robots [16], to name a few. The incorporation of the affective dimension within automated systems has extended the scope and capabilities of these systems. This incorporation represents a novel approach to designing and implementing new technology, where two different objectives can be addressed. First, there is the recognition of emotions and moods in humans, where the use of specific hardware components and software architectures, image processing algorithms and rules allows the interpretation of signals obtained from each human expression [17], [18]. Second, there is the design of decision-making systems with an artificial affective dimension that can be used as an additional criterion in decision environments. Examples of this type of technology are available in [19], [20].

The increased use of home automation systems, the emergence of concepts such as the ‘‘Internet of Things’’ and the ‘‘Smart City’’, and the high business integration (e.g., investment platforms) are current examples of the need to further deepen the study and development of autonomous decision-making systems. In the stock market domain, the current trading platforms and commercial systems are highly dependent on instructions defined in each trading period by a human investor. In this context, it is not possible to observe a commercial trading platform with autonomous behavior devoted to stock markets. Having autonomous decision-making systems in the stock market domain could enable the autonomous systems themselves to make an autonomous decision, negotiate or reach alliances in order to improve returns on investment instruments, or to share relevant information in the event that there is any imminent risk in the market. A preliminary approach to the above was presented in our past research in [21].

Because affective decision-making systems are bio-inspired on the human affective dimension, it is important to analyze how to incorporate the affective dimension within decision-making systems in terms of selecting the type of emotions, defining emotional transition functions, and defining the degree of influence of the affective dimension in decision-making systems. Regarding the above, a new emotional model that incorporates emotional stability theories was developed. The main thrust of the current study was to explore how the stabilization of the affective dimension influences the effectiveness of the decision-making system. Thus, the novelties of our current work are that (1) it defines an emotional stabilizer mechanism for affective artificial investors devoted to making autonomous decisions in the stock market domain, (2) it defines an affective algorithm to invest in the stock market, which allows an emotional stabilizer mechanism to be implemented, (3) it defines an experimental scenario for the affective algorithm, based on official data from the New York Stock Exchange, and (4) by use of the affective algorithm, it analyzes promising experimental results with statistical relevance. Thus, with the ability to design and implement autonomous decision-making systems based on artificial emotions, the role of emotional stabilization within an affective algorithm on these systems can be a key to the success and effectiveness of each investment decision under uncertainty.

The remainder of this work is organized as follows: Section 2 presents related literature. Section 3 explains the use of artificial emotions within autonomous decision-making processes on stock markets, describing an emotional stabilizer mechanism and an affective algorithm for artificial investors. Section 4 shows the scenario description and experimental results. Section 5 presents a discussion of the obtained results, and finally, Section 6 presents conclusions of the work done and future work.

II. RELATED WORK

Among works related to the stock market domain, one research area addresses automated trading platforms [22]–[26], which operate based on instructions defined by human investors. Every decision made by these platforms is based exclusively on human instructions, for example, sell a stock when its price reaches a value X (where X is the price indicated by the human investor). It is important to mention that these platforms do not consider human affectivity as an investment profile parameter. In the same sense, these platforms do not use artificial affectivity in their internal operating mechanisms.

In contrast, other types of studies associated with the stock market domain are devoted to, e.g., predicting the behavior of stock markets [27]–[29], simulating the stock market using agents [30]–[32], defining trading rules based on genetic network programming [33], and developing a decision support system for intraday investment recommendations [34]. In all reviewed cases, it has not been possible to observe the use of artificial emotions as part of the internal components of the systems and tools or as part of the decision criteria.

Bertella *et al.* [35], within an artificial capital market, studied the behavior of an investor agent that modifies its investment strategy considering the number of successes or failures observed in previous investments. Several memory lengths and degrees of confidence are observed in the investor agent. However, it was not possible to observe a formal modeling of an affective dimension, particularly a set of artificial emotions with their model of emotional transition. In another sense, the type of decision an agent can make corresponds to a binary choice between a risky stock that gives a variable return (stochastic) or selecting a stock without risk that gives a steady profit. In contrast, in our work, an investor agent can choose a stock at different levels of risk using its own and independent evaluations of the stock based on analytical-affective criteria.

Several studies in the fields of emotional stability and emotional regulation have been developed to explore the role of emotional stability in the use of the Twitter social media platform [36]; to determine the efficacy of special teaching methods for young children in learning emotional self-regulation [37]; to examine the correlations between the types of adult attachment, self-esteem level and emotional intelligence [38]; or to study the relationships between verbal and non-verbal intelligence in connection with generalized anxiety disorder, depression and social anxiety symptoms [39]. Laakasuo *et al.* [40] studied the influence of emotional stability on decisions in the game of poker. The results suggest that poker players with better emotional stability are associated with better financial success in the game. Emotional stability predisposes poker players to continue playing poker, which in turn leads to increases in experience and in the ability to play. In the same sense, poker players with more experience tend to develop the ability to tolerate high levels of emotional pressure and the ability to remain calm during the decision-making process that involves large sums of money.

The literature has presented studies related to emotional stability and emotional regulation. However, to our knowledge, it is not possible to identify studies that define a relationship between artificial emotional stability and how it is addressed in autonomous decision-making systems applied to the stock market domain. In the field of decision-making research, the flexibility of emotion implies that its impact on choices may also vary [41]. In this sense, regarding the stock market domain, it is important to explore how variation in emotional reactions can influence the choices of artificial investors. Specifically, in our study, we used different emotional parameters (e.g., emotional bandwidth, emotional update rates) with the aim of exploring the degree of influence of these parameters on the effectiveness of investment decisions. For the purposes of the present study, an emotional band corresponds to a continuous numerical range (not discrete) bounded by an upper limit and a lower limit on which an emotional variable can fluctuate. In the same sense, each rate of emotional update (i.e., the value that an emotional variable can have over time) accords with a specific mechanism of emotional updating, which is explained in section IV.

III. ARTIFICIAL EMOTIONS FOR AUTONOMOUS DECISION-MAKING PROCESSES ON STOCK MARKETS

This section includes an explanation of how investment decisions in stock markets are made, the influence of the affective dimension, and the configuration of bio-inspired artificial emotions within autonomous decision-making processes.

A. DECISION-MAKING ON STOCK MARKETS

To invest is to put money into financial schemes, shares, properties, or a commercial venture with the expectation of achieving a profit [42]. In this sense, an investment corresponds to an acquisition of an asset to which it is possible to allocate funds with the aim of protecting or increasing its value over time. A market corresponds to a physical or non-physical place where suppliers and demanders interact over any good or service (buying and selling). Within a stock market, a stock represents a non-tangible good that corresponds to a fragment of a specific company.

Investors seek to increase the value of their investments over time. However, knowing the future value of an investment is very difficult (or perhaps impossible). To address this difficulty, two different analysis techniques can be used by investors to support their own decision-making: technical analysis and fundamental analysis. Technical analysis focuses on predicting the behavior of the investor and market through the movements of shares, in both volume and price, ignoring the use of tools for fundamental analysis [43]. In technical analysis, three principles are followed. First, the price evolves according to certain movements or patterns. Second, the market provides the necessary information to predict possible changes in trend. Third, what happened in the past will be repeated in the future. The use of technical analysis is incorporated into several automated platforms available on the market. For example, MetaTrader 5 [44], an online platform that enables real-time stock trading, offers an ''automatic trading systems'' option that allows trade operations without the intervention of a human investor. With this option, the investor must configure a set of operating parameters so as to define the price at which to buy or sell a particular stock. In addition, the tool allows the use of ''investment strategies'' based on widely known investment indicators, such as MACD, Stochastic, ADX, RSI, and all numerical and analytical indicators. For example, RSI (Relative Strength Index) is an oscillation indicator that describes the movements of single stocks using sequences of the closing price [45]. An indicator value equal to or less than 30 indicates the stock is "on-sale": it is convenient to buy. Conversely, if the indicator is equal to or greater than 70, the stock is "overbought": it is convenient to sell.

On the other hand, fundamental analysis is the examination of the underlying forces that affect the wellbeing of the economy, industry groups and companies. As with most analysis, the goal is to develop a future price movement forecast and increase the value of the investments. While technical analysis is strongly used, fundamental analysis has become more important over time, since its line of study provides a comprehensive perspective on market behavior within a global context [46], [47].

Whereas in technical analysis, the market provides the best information quality related to the behavior of a stock, fundamental analysis studies the evolution of the company over a given period through a comparison between the company's performance and the industry average. It is important to mention that in both cases, an investor needs to outline an own notion of confidence in order to accept the analysis results and then make an investment.

The above allows explaining, for example, a situation where two investors who have the same investments and use the same analytical information (which can be obtained from technical, fundamental or mixed analysis) can finally make different investment decisions. Since each investor configures an own notion of confidence, in practice, the affective dimension associated with each investor has a very high degree of importance and incidence in each investment decision. Although it is possible to separate analytical processes, the analytical results are ultimately subjected to an internal and personal evaluation by the investor. The final investment decision is made considering both analytical and affective criteria.

An investor can buy or sell stocks along time, and the stock price can vary depending on several factors, e.g., investments by and/or in the company, economic indicators, the country's risk environment, the international behavior of commodities, and the investor's confidence, to name a few. A proposal to model the knowledge of the stock market using an affective-oriented ontology was presented on our past research [48]. Because each choice depends on affective and analytical factors, which can vary over time, it is possible to classify the stock market domain within the broader domain of decision-making under uncertainty, where the probabilities and magnitudes of expected rewards and punishments are not explicitly known [49].

B. ARTIFICIAL EMOTIONS AS AN INFLUENCE FACTOR ON AUTONOMOUS DECISION-MAKING PROCESSES

For Wooldridge [50], an agent is "*a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its delegated objectives*". An agent has the capabilities of reactivity, pro-activeness, and social ability. Several applications have been developed using agent technology. Nevertheless, agent software has no capability to feel genuine emotions. The software has no somatic components and has no human life experience. Human cognition depends on experiences associated with a body, which has several sensorimotor capabilities, and these individual sensorimotor capabilities are embedded in a wider context that includes biological, psychological and cultural aspects [51]. The embodiment concept implies that if a researcher wants to study some characteristics of a physical system (for example, how humans walk on the street), it is necessary to build an own physical system, that is, build a physical robot [52]. However, the inclusion of emotions within agents could allow the building of more-lifelike, believable, and helpful agents [53]. The future machines should be designed to allow fluent communication with people, because the ability to recognize and express emotions are inherent in human-like high-level communications [54]. Several researchers are trying to model emotions and to show how they affect human behavior and how environmental changes affect human emotions. However, there is no standard emotional model to represent such relationships. These models might have to be complex, and the effects of emotions in human behavior might differ individually [55].

To design and implement artificial emotions, it is first necessary to know how emotions are understood within the human dimension. Lerner *et al.* [56] distinguished integral and incidental emotions. An integral emotion is associated with the configuration of a judgment or choice using a strong and routine characteristic of personality (e.g., not flying by plane due to a dislike of heights). Conversely, an incidental emotion emerges from daily life circumstances and often generates unexpected and non-conscious influences (emotional reactions). Specifically, when emotional reactions are unexpected, it is possible to consider three different techniques to reduce their effects: intentionally decrease the intensity of the emotion; intentionally reduce the importance of the emotion as an input within a decision-making process; and intentionally use an emotional bias opposite the emotional reaction observed. Because stock behavior can change each day and each hour, the type of emotional reaction that can be observed in the stock market domain corresponds to incidental emotions. In our work, an improved version of our affective algorithm is presented that incorporates a stabilizing mechanism to decrease the intensity of emotional reactions (more details about the mechanism are available in the next section).

The current work considers the use of three specific pairs of emotions: joy and sadness; fear and trust; and tranquility and anger. The criteria for selecting and using the mentioned emotions correspond to a basic choice among emotions with clear and distinguishable emotional states [57]. The formation of emotion pairs seeks to reflect opposite emotional reactions. In other words, it is not possible to simultaneously be in two opposite emotional states, such as joy and sadness.

Each pair of emotions receives an initial configuration, and their values depend on business performance. Compliance with the objectives (or non-compliance with them) promotes the updating of emotional values, that is, generates emotional reactions.

Within an artificial investor (implemented as a software agent), artificial emotions act as a high-level behavior regulator, promoting the maintenance of stocks with good profitability, low risk or low probability of loss (depending of investment strategies) and influencing the selling of stocks that show a behavior that is not in accordance with the defined investment strategy. Regarding the criteria used in each decision, the current work proposes and defines a dual rational-emotional perspective. For this purpose, each investment decision needs both the analytical results obtained from the market (profitability, risk, the probability of loss) and the reactions generated in an investor agent through the behavior triggered by his artificial emotions. These two different but complementary dimensions give rise to a global perception of what happens in the market and allows the artificial investor to adapt his investment behavior.

IV. DEFINING AN AFFECTIVE ALGORITHM FOR INVESTMENT PROCESSES

This section includes an explanation of rational-emotional decision criteria used in the stock market; a description of how emotional behavior in artificial affective investors can be stabilized; and, finally, an explanation of an affective algorithm for application in an experimental scenario.

A. DECISION CRITERIA ON STOCK MARKETS

Within the context of the stock market domain, this work considers that the artificial investors make investment decisions only by determining the configuration of portfolios composed of stocks. A stock represents a nominative property associated with a specific company and has a value that can vary over time. This price variation (in terms of percentage) can be called profitability, and it is calculated from the returns observed over time. Thus, profitability can be positive or negative. When a stock maintains its price, the profitability value is zero. Markowitz affirmed that the behavior of stock markets follows the pattern of a normal probability distribution [58]. In other words, the profitability value will tend to average the daily profitability observed over time. Equation (1) shows that the return is the benefit or gain (price difference) divided by the amount of investment. Depending on each company, a dividend (Dj) may be delivered to investors.

$$r_t = \frac{D_t + P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

Considering an investment portfolio, the global return is according to (2):

$$E[R_P] = \sum_{i=1}^{n_p} w_i \overline{R_i} \tag{2}$$

Subjected to:

$$\sum_{i=1}^{n_p} w_i = 1 \tag{3}$$

Where:
w_i : Weight of the ith stock in the portfolio.
n_p : Number of stocks in the portfolio.
$\overline{R_i}$: Average return of the ith stock.

When the price associated with a stock varies over time, the stock exhibits volatile behavior. Technically, the volatility is represented by the risk, which corresponds to a measure of the variability of observed returns along time. The risk of a stock is given by the value of its standard deviation. Equation (4) shows how risk is calculated for a portfolio of two stocks:

$$\sigma_p = \sqrt{\sum_{i=1}^{n_p} \sum_{j=1}^{n_p} w_i w_j \sigma_i \sigma_j C_{ij}} \tag{4}$$

Where:
σ_i : Risk of the ith stock in the portfolio.
σ_j : Risk of the jth stock in the portfolio.
w_i : Weight of the ith stock in the portfolio.
w_j : Weight of the jth stock in the portfolio.
C_{ij} : Covariance between the ith and jth stocks in the portfolio.

A third decision criterion used in buying or selling stocks corresponds to the probability of loss associated with each stock. In this context, the probability of loss represents the probability that the price of a stock will decrease from a specific trading period to the trading period immediately following. Stock prices can increase or decrease over time. When the price decreases, a loss is observed. In each trading period, an artificial investor must consider the three decision criteria described above (profitability, risk, and the probability of loss) with three possibilities: maintain the current investment portfolio, sell all stocks contained in the investment portfolio, or change a specific stock in the investment portfolio. To do this, the artificial investor must determine the behavior of its investment portfolio, calculating a selectivity index associated with each stock according to (5):

$$\begin{aligned} S_{ij} = {} & F_{1ij} \cdot (q_p + E_{1j}) + F_{2ij} \cdot (q_r + E_{2j}) \\ & + F_{3ij} \cdot (q_{pl} + E_{3j}) \end{aligned} \tag{5}$$

Equation (5) indicates that the selectivity of a stock i in a period j is determined from considerations of three different dimensions: profitability (F_{1ij}), risk (F_{2ij}), and probability of loss (F_{3ij}). The components (q_p), (q_r), (q_{pl}) represent influence factors associated with profitability, risk, and probability of loss, respectively. These influence factors are user parameters. In contrast, the components (E_{1j}), (E_{2j}), (E_{3j}) represent emotional factors directly associated with a specific financial dimension. The component (E_{1j}) corresponds to the "joy-sadness" emotional band; the component (E_{2j}) corresponds to the "trust-fear" emotional band; and the component (E_{3j})

corresponds to the ''tranquility-anger'' emotional band. Each emotional band behaves independently and contains an opposite emotion whose value depends directly on the behavior of the financial dimensions. For a trading period j, if the profitability is positive, the component (E_{1j}) increases its value to a positive emotion, i.e., the emotional value is shifted in the direction of joy. Conversely, if the profitability is negative, the component (E_{1j}) decreases its value to a negative emotion, i.e., the emotional value is shifted in the direction of sadness. Furthermore, if the risk increases in value, the component (E_{2j}) decreases its value to a negative emotion, i.e., the emotional value is shifted in the direction of fear. Conversely, if the risk decreases in value, the component (E_{2j}) increases its value to a positive emotion, that is, the emotional value is shifted in the direction of trust. Moreover, if the probability of loss increases its value, the component (E_{3j}) decreases its value to a negative emotion, i.e., the emotional value is shifted toward anger. Conversely, if the probability of loss decreases its value, the component (E_{3j}) increases its value to a positive emotion, that is, the emotional value is shifted toward tranquility. In any case, if the profitability, risk or probability of loss do not vary in a specific trading period, their respective emotional components do not change but rather retain their previous value.

It is important to mention that every emotional band is influenced exclusively by the behavior of a single financial dimension. If the evolution of a financial dimension is positive for the artificial investor, its emotional value will be increased favorably, turning into a positive emotion (joy, trust, tranquility, as appropriate). In contrast, if the evolution of a financial dimension is negative for the artificial investor, its value will change to a negative emotion (sadness, fear, anger, as appropriate). Equation (6) illustrates the emotional update method used in each test.

$$E_{xj} = E_{xj-1} \pm EIF_k \cdot Rand\,[0, 1] \tag{6}$$

This equation shows that the new emotional value (E_{xj}) depends directly on the immediately preceding emotional value (E_{xj-1}), together with an updated emotional factor called EIF (*Emotional Influence Factor*), where X corresponds to each different emotional band available for use. This factor is a user parameter that does not change throughout the test run. To achieve a non-deterministic behavior (near emotional behavior in humans), a random factor is added so that in two or more similar financial scenarios, the emotional reaction is not necessarily identical.

Each emotional band has an independent behavior that depends on the behavior of the financial dimension associated with it and the rate of emotional update observed in each trading period. In terms of implementation, each emotional band is defined as a continuous numerical scale, where zero on the scale represents emotional neutrality, a positive value on the scale represents a positive emotion, and a negative value on the scale represents a negative emotion. For example, considering the emotional band (E_{1j}), an emotional value 0.2 represents a weak emotional state of joy over a state of emotional neutrality, an emotional value 1.5 represents a clear state of joy, and an emotional value of -0.9 represents a state of sadness. Therefore, changes in the financial dimension ''profitability'' do not generate binary emotional states in the artificial investor but rather make it possible to generate behavior patterns that are correlated between financial and emotional dimensions.

B. STABILIZING EMOTIONAL BEHAVIOR IN AFFECTIVE ARTIFICIAL INVESTORS

Because emotions show flexible behavior (in terms of the internal and external context), a mechanism to define ranges of emotional behavior is proposed with the aim of observing whether emotional stabilization has any impact on the decisions of an artificial investor. This mechanism is according to (7):

$$f(E_x) = \begin{cases} ULim_x, & E_x \geq ULim_x \\ E_x, & ULim_x > E_x > LLim_x \\ LLim_x, & E_x \leq LLim_x \end{cases} \tag{7}$$

The above equation indicates that if the value of an emotional function is equal to or greater than an upper emotional limit, the value of the emotional function will be the upper emotional limit (*ULimit*). On the other hand, if the value of an emotional function is equal to or less than a lower emotional limit, the value of the emotional function value will be the lower emotional limit (*LLimit*). Otherwise, the emotional function retains its value. Fig. 1 shows that the emotional behavior (represented by a continuous line) varies between the upper limit located at point (0, 1) on the vertical axis and the lower limit located at point (0, -1) on the same vertical axis. The broken lines observed above the upper limit and under the lower limit represent a potential emotional behavior not contained within the emotional bandwidth.

C. AFFECTIVE ALGORITHM FOR INVESTMENT DECISION PROCESSES

Table 1 shows an affective algorithm used by the investor agent in its investment decision-making process. In each trading period j, the investor agent obtains market information about stock behaviors (price variation). Then, if the investor agent does not have an investment portfolio, he configures one, considering for this purpose the selectivity index of each candidate stock belonging to available stocks of the capital market. If the investor agent has an investment portfolio, go to step 3: check the performance of its portfolio. This process implies determining the variation in profitability, risk, and probability of loss for all stocks contained in the investment portfolio. The emotional state is then updated according to (6). If the emotional fluctuation reaches the upper or lower emotional limit, the emotional band is stabilized according to (6). Step 5 then determines whether the performance observed in the portfolio meets the investment criteria of investor agent k. If the above is true, the investor agent maintains its portfolio. Otherwise, step 6 is performed and changes are applied to the portfolio, calculating the

TABLE 1. Affective algorithm of investor agent.

Consider the following notation: Pkj: Investment portfolio of investor agent k in period j; Sij: Selectivity of stock i in period j; MDj: Market data available in period j; Exj: Emotional behavior of emotional band x in period j; ULimx: Upper limit of emotional band x; LLimx: Lower limit of emotional band x.

While the last trading period is not reached, for each investor agent:

Step 1. Obtain MD_j

Step 2. If the *trading period* = 1
- Configure initial P_{kj}
  - Determine S_{ij} $\forall$ $i \in$ {*available stocks*} according to the investment profile of investor agent *k*
  - Prioritize and select the best stock candidates for P_{kj}

Otherwise: go to step 3

Step 3. Check *performance* of P_{kj}
- Determine *profitability* of stock *i*, $\forall \in P_{kj}$
- Determine *risk* of stock *i*, $\forall \in P_{kj}$
- Determine *probability of loss* of stock *i*, $\forall \in P_{kj}$

Step 4. Update emotional state of investor agent *k*

$$E_{xj} = E_{xj-1} \pm EIF_k \cdot Rand[0,1], \; \forall \; E_x \in \{emotional\ bands\}$$

If E_{xj} reaches $ULim_x$ or $LLim_x$, apply the stabilizer mechanism of emotional behavior

Step 5. If the performance of P_{kj} meets the investment criteria of investor agent *k*
- Maintain P_{kj}
- Go to Step 1

Otherwise: go to step 6

Step 6. Apply changes on P_{kj}
- Determine S_{ij} $\forall$ $i \in$ {*available stocks* - $i \in P_{kj}$} according to the investment profile of investor agent *k*
- Prioritize and select the best stock candidates for P_{kj}

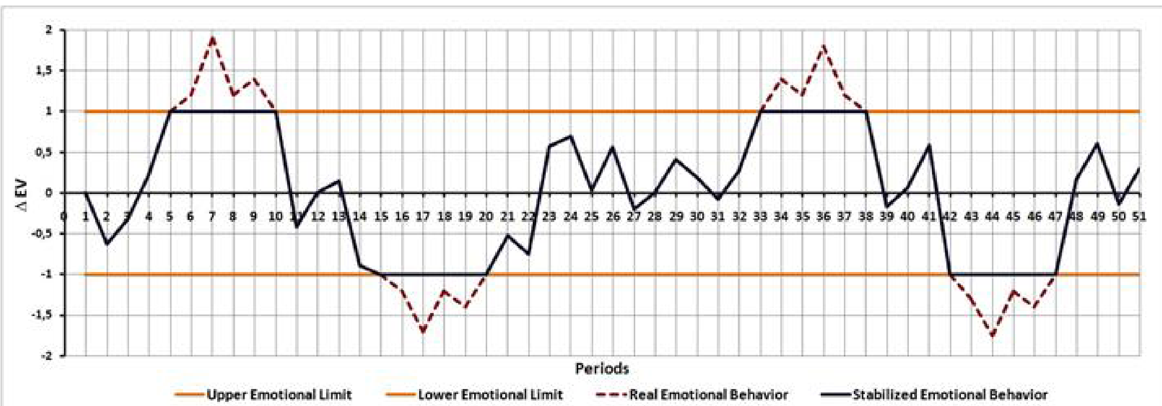

FIGURE 1. Graphical example of a stabilized emotional behavior.

selectivity for all candidate stocks (not considering the stocks that compose the portfolio in that moment), obtaining a modified investment portfolio. It must be considered that the algorithm is run during active trading periods.

V. SCENARIO AND RESULTS

This section includes a description of an experimental scenario and the experimental results obtained from two different tests.

A. SCENARIO DESCRIPTION

The experimental scenario considers official data from the New York Stock Exchange corresponding to daily data on trading operations during the years 2012 and 2013 [58] (New York Stock Exchange Data, 2017). For this purpose, 50 companies were selected randomly and are represented by stocks. Investor agents with artificial emotions must configure investment portfolios (composed of two stocks) and check the market conditions during each trading period and with the capacity to maintain the investment portfolio or make changes to it. Investor agents used stock market data of 2012 when they made their first decision, that is, to configure the initial investment portfolio. In turn, the stock market data of the year 2013 was used to evaluate the performance of each investment portfolio. Each investor agent had an initial capital of US$ 10.000. Regarding the behavior of stock prices associated with the companies considered in the experimental scenario, it is observed that during 2012, the companies as a whole presented an annual average profitability of 7.7%, with the greatest profitability at 100.17% and the least at −56.2%. In the same year, an average risk level of 27.47% was observed. In 2013, the companies

TABLE 2. Results of initial comparison between investor agents.

LSP	Initial (US$) IA-NL	Initial (US$) IA-L	Min (US$) IA-NL	Min (US$) IA-L	Max (US$) IA-NL	Max (US$) IA-L	Final (US$) IA-NL	Final (US$) IA-L	Differenc e (Value)	Differenc e (%)
1	10.000	10.000	8.520	8.759	11.939	11.366	8.815	9.661	846	9,60%
2	10.000	10.000	8.920	9.658	12.151	12.587	9.859	11.451	1.592	16,15%
3	10.000	10.000	10.000	10.000	13.135	13.328	12.606	12.645	39	0,31%
4	10.000	10.000	10.000	10.000	16.311	16.424	15.767	15.894	126	0,80%
5	10.000	10.000	10.000	10.000	18.307	18.135	17.563	17.410	152	0,88%
6	10.000	10.000	10.000	10.000	18.799	18.272	18.000	17.556	444	2,53%
7	10.000	10.000	10.000	10.000	18.917	19.169	18.149	18.365	216	1,19%
8	10.000	10.000	10.000	10.000	19.169	19.169	18.365	18.365	0	0,00%

presented, as a whole, an annual profitability average of 29.67%, with the greatest profitability at 124.61% and the least at −50.38%. In the same year, an average risk of 32.26% was observed.

B. TEST 1: INITIAL COMPARISON

The initial test considers two types of investor agents: an investor whose emotional behavior does not have limits (IA-NL) and an investor who does have emotional behavior limits (IA-L). The emotional behavior of the second type of investor agent is stabilized according to (7). The emotional amplitude allowable has a value of 1. This means that from a neutral emotional state (emotion valued at zero), emotional behavior can achieve a maximum positive value of 1 (a positive emotion) or a minimum negative value of −1 (a negative emotion). The above definition generates a continuous range of emotional behavior [−1, 1] in a similar manner to Fig. 1. The objective of test 1 corresponds to observing whether the use of a stabilizer mechanism on the artificial emotional behavior has a positive impact on the effectiveness of the investment decisions, understanding effectiveness as an increase in investment capital during the trading periods.

The investment profile used by the investor agents is ''aggressive'', that is, they seek high profitability. In this sense, to begin the initial test, and considering equation (3), the components (q_p), (q_r), and (q_{pl}) are given the values 1, 0, and 0, respectively. This means that stocks with high profitability are strongly preferred in contrast to other types of financial behavior.

Meanwhile, the components E_{1j}, E_{2j}, E_{3j} are initially valued at zero with the idea of representing a neutral emotional state. These values are updated according to (6) (applied in each trading period), considering the behavior of each financial dimension separately. In the initial test, the emotional influence factor (EIF) is defined as 0.3 for E_{1j}, E_{2j}, E_{3j}, a value that is considered adequate.

Table 2 shows the results obtained in the initial test. It is important to mention that because the investor agents have emotional components in their decision criteria (which propagate non-deterministic behavior), each experiment was performed 30 times independently. Thus, each value included in table 2 corresponds to an average of 30 different but equivalent experiments.

The column LSP represents the number of weeks in which an investor agent can tolerate an adverse investment scenario (considering its investment criteria). For example, a configuration with an LSP value of 3 implies that the investor is able to withstand 3 weeks without observing favorable results in its investment. Because investors can have different frustration tolerances, the LSP value offers a range of tolerance, from 1 week without observing favorable results to 8 weeks without observing favorable results. Each ''Initial (US$)'' column represents the initial investment capital available for each investor agent. Each ''Min (US$)'' column represents the minimum valuation of the investment portfolio associated with each investor agent. Each ''Max (US$)'' column represents the maximum valuation of the investment portfolio associated with each investor agent, and each ''Final (US$)'' column represents the final valuation of the investment portfolio, that is, the final investment capital available for each investor agent following all the trading periods.

The results show that investor agents IA-L obtain better available final investment capital than investor agents IA-NL for LSP 1, 2, 3, 4, and 7. For the first investment strategy (LSP 1), both profiles lose investment capital during the trading periods: in the case of IA-NL, there is a capital loss of 11,85%; in the case of IA-L, there is a capital loss of 3,39%. The difference in the final capital obtained by both profiles is 9,6% (in favor of IA-L). Investor agent IA-L obtains positive results from LSP 2 onwards. In contrast, investor agent IA-NL obtains positive results from an LSP of 3 onwards. When LSP has a value of 2, the investor agent IA-L obtains a final profitability of 11,45%; meanwhile, investor agent IA-NL obtains a capital loss of 1,41%. For LSP 2, the difference in the final capital obtained by both investment profiles is 16,15% (in favor of IA-L). From an LSP value of 3 to an LSP value of 8, both investment profiles obtain positive profitability, showing a maximum of US$18.365 (IA-L for LSP 7 and LSP 8; IA-NL for LSP 8). This implies an annual profitability of 83,65%. From LSP 3 onwards, an essentially equivalent performance is observed, where the largest difference corresponds to 2,53% (observed for LSP 6). Fig. 2 graphically shows the final capital obtained by both investment profiles for all LSP values.

The results obtained by the initial test furnish a preliminary indication that the use of an emotional bandwidth has a

TABLE 3. Comparison of investor agents using a restricted emotional bandwidth.

LSP	Initial (US$) LUR	Initial (US$) HUR	Min (US$) LUR	Min (US$) HUR	Max (US$) LUR	Max (US$) HUR	Final (US$) LUR	Final (US$) HUR	Difference (Value)	Difference (%)
1	10.000	10.000	8.369	9.217	11.794	12.131	8.481	9.688	1.207	14,2%
2	10.000	10.000	8.969	9.677	12.636	12.441	10.396	10.910	515	5,0%
3	10.000	10.000	10.000	10.000	11.972	13.101	11.282	12.256	974	8,6%
4	10.000	10.000	10.000	10.000	15.397	16.503	14.654	15.927	1.273	8,7%
5	10.000	10.000	10.000	10.000	18.103	19.018	17.376	18.165	789	4,5%
6	10.000	10.000	10.000	10.000	18.272	19.169	17.556	18.365	809	4,6%
7	10.000	10.000	10.000	10.000	19.169	19.169	18.365	18.365	0	0,0%
8	10.000	10.000	10.000	10.000	19.169	19.169	18.365	18.365	0	0,0%

TABLE 4. Comparison of investor agents using an extended emotional bandwidth.

LSP	Initial (US$) LUR	Initial (US$) HUR	Min (US$) LUR	Min (US$) HUR	Max (US$) LUR	Max (US$) HUR	Final (US$) LUR	Final (US$) HUR	Difference (Value)	Difference (%)
1	10.000	10.000	7.640	8.623	11.524	11.338	7.716	9.532	1.816	23,5%
2	10.000	10.000	9.323	9.364	12.392	11.738	9.708	10.033	325	3,3%
3	10.000	10.000	10.000	10.000	11.892	11.950	10.749	11.426	677	6,3%
4	10.000	10.000	10.000	10.000	15.765	16.371	15.125	15.782	657	4,3%
5	10.000	10.000	10.000	10.000	18.600	18.532	17.851	17.767	84	0,5%
6	10.000	10.000	10.000	10.000	18.496	19.169	17.758	18.365	607	3,4%
7	10.000	10.000	10.000	10.000	19.169	19.169	18.365	18.365	0	0,0%
8	10.000	10.000	10.000	10.000	19.169	19.169	18.365	18.365	0	0,0%

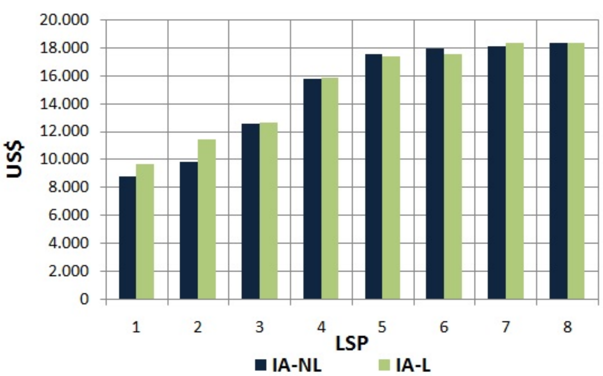

FIGURE 2. Final investment capital for initial test.

positive impact on investor agents. Considering the above, it is necessary to explore in more detail how to vary the behavior and effectiveness of investment decisions in investor agents when the characteristics of the emotional bandwidth vary.

C. TEST 2: VARYING THE CHARACTERISTICS OF EMOTIONAL BANDWIDTH

The second test considers variation in two different characteristics: the amplitude of the emotional bandwidth and the value of the emotional influence factor (EIF). The amplitude of the emotional bandwidth can have two values: 1 for a restricted emotional limit and 2 for an extended emotional limit. Note that in both cases, the emotional limit is defined in a symmetric manner, i.e., the restricted emotional bandwidth is defined by a continuous range $[-1, 1]$, and the extended emotional bandwidth is defined by a continuous range $[-2, 2]$. Relative to EIF, the values are 0.1 (for a Low Update Rate - LUR), and 0.5 (for a High Update Rate - HUR). The above definitions generate four different configurations of emotional bandwidth: a restricted emotional bandwidth using LUR and HUR separately and an extended emotional bandwidth also using LUR and HUR separately.

Table 3 shows the results obtained by the use of a restricted emotional bandwidth, and Table 4 shows the results obtained by the use of an extended emotional bandwidth. Considering Table 3, it is possible to observe that, in general, the configuration used by HUR obtains better final results than the configuration used by LUR. For the first investment strategy (LSP 1), both profiles lose investment capital: in the case of LUR, the investor agent loses 15,19%; in the case of HUR, the investor agents lose 3,12%. For LSP 1, the difference in the final capital obtained by both investor agents is 14,2% (in favor of HUR). From LSP 2 onwards, both configurations of investor agents (LUR and HUR) obtain positive results. When LSP is valued at 6 (using HUR), 7 and 8 (using LUR and HUR), a final investment capital of US$18.365 is observed, representing the maximum level of profitability of investor agents. In other cases, the difference between LUR and HUR has an average of 6,7% (in favor of HUR).

Considering Table 4, in general, the final investment capital obtained by investor agent HUR is better than that obtained by investor agent LUR except for strategy LSP 5. If LSP has a

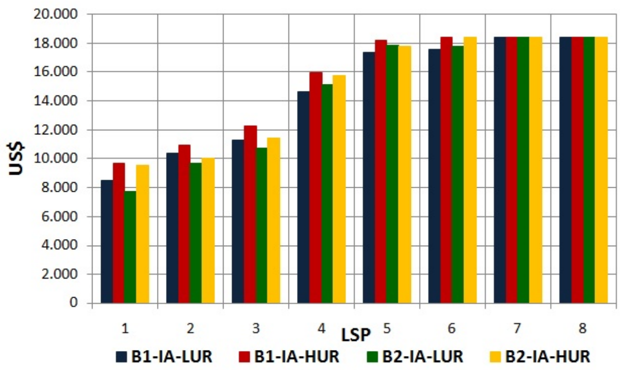

FIGURE 3. Final investment capital for restricted and extended emotional bandwidth.

value of 1, the investor agent LUR loses 22,84% of its investment capital. In contrast, the investor agent HUR loses 4,68%. The difference between the investor agents in the final capital obtained is 23,5%. If LSP has a value of 2, investor agent LUR loses 2,92%. In contrast, investor agent HUR finished with virtually the same initial investment capital, obtaining a marginal profitability of 0,33%. From LSP 3 onward, both types of investor agent obtain positive profitability. For LSP 3 and 4, investor agent HUR obtained a better profitability than investor agent LUR: 6,3% versus 4,3%, respectively. For LSP 5, investor agent LUR obtained 0,5% more profitability than investor agent HUR. In contrast, for LSP 6, investor agent HUR obtained 3,4% more profitability than investor agent LUR. For LSP 7 and 8, both types of investor agent obtained the same final investment capital of US$18.365.

Fig. 3 graphically shows the final capital obtained by the use of a restricted emotional bandwidth (B1) and an extended emotional bandwidth (B2) for investor agents HUR and LUR. Note that if the value of LSP is 1, all configurations lose investment capital. In this case, the investor agents that use HUR obtain better results than do the investor agents that use LUR. If the value of LSP is 2, the investor agents that use a restricted emotional bandwidth (B1) obtain positive profitability. In addition, the investor agents that use an extended emotional bandwidth (B2) obtain marginal positive results (using HUR) and suffer a loss (using LUR). From LSP 3 onward, all configurations yield a positive profitability. For LSP 7 and 8, all configurations obtain the same final result, representing a maximum of profitability. In other cases, the investor agents that use B1 and HUR always obtain the highest profitability compared with other configurations. In particular, they always obtain better results than investor agents that use B1 and LUR. Investor agents that use B2 and HUR obtain better results than investor agents that use B2 and LUR, with the exception of LSP 5. The above considerations and findings indicate that the use of a high update rate over EIF has a positive influence on the effectiveness of the investment decisions.

Table 5 shows the number of excesses observed in the emotional behavior of investor agents when a restricted emotional bandwidth is used. In the same sense, Table 6 shows the number of excesses observed when an extended emotional bandwidth is used.

An excess means that the emotional behavior reaches and exceeds the emotional limit established by the emotional bandwidth. For example, for an emotional bandwidth with a value of 1, an upper limit excess is represented by an emotional value greater than 1, and a lower limit excess is represented by an emotional value less than -1. Whenever the emotional limit is exceeded, the emotional stabilizer mechanism is activated according to (7).

Note that because the excesses were recorded during the same experimental tests explained above, each row of data associated with a specific LSP strategy corresponds to results obtained from a set of 30 different and independent experiments. For example, note that in table 5, row LSP 1, 5 lower limit excesses were observed for IA-LUR; this observation implies that in 30 experiments, 5 excesses were observed. In the same sense, the average of 0, 17 corresponds to the number of excesses (on average) per each of the 30 different experiments. Therefore, it is possible that some experiments do not show excesses in their behavior or, alternatively, that an experiment can show more than one excess in its behavior.

Table 5 shows that when using a low update ratio, the number of upper limit excesses is zero and the number of lower limit excesses is very low, with excesses observed for LSP 1, 5 and 8. Meanwhile, the same table shows that using a high update ratio, the number of upper limit excesses increased substantially, with the greatest number of excesses observed for LSP 2 and 1. Similarly, the number of lower limit excesses increased, with the greatest number of excesses observed for LSP 7, 5 and 8. In contrast, Table 6 shows that using a low update ratio, the number of excesses (upper and lower) is zero. Furthermore, using a high update ratio, the number of upper and lower limit excesses shows an increase, but less so than in Table 5. The number of upper limit excesses is greatest for LSP 1 and 2, and the number of lower limit excesses is greatest for LSP 6, 4 and 8.

On the other hand, Fig. 4 and Fig. 5 show an example of behavioral alignment between the average profitability and emotional behavior, using HUR with LSP 1 and HUR with LSP 2, respectively.

Note that in each trading period and based on the profitability behavior, the emotional reactions are calculated separately for each component of the investment portfolio. In this sense, each stock in the portfolio generates an independent emotional reaction, modifying the values of the last existing emotional state. Recall that one of the components included in (7) corresponds to a random value from the interval [0, 1], used with the aim to prevent the deterministic emotional behavior. Therefore, if a specific stock of the portfolio has a negative profitability, this implies a decrease in the valuation of the emotional band specifically associated with profitability.

In turn, observing a positive value of profitability, the valuation of the specific emotional band associated with the profitability also increases. Furthermore, not every change in

TABLE 5. Number of excesses for a restricted emotional bandwidth.

LSP	IA-LUR Upper limit excesses	IA-LUR Average	IA-LUR Lower limit excesses	IA-LUR Average	IA-HUR Upper limit excesses	IA- HUR Average	IA- HUR Lower limit excesses	IA- HUR Average
1	0	0	5	0,17	94	3,13	51	1,70
2	0	0	0	0	107	3,57	80	2,67
3	0	0	0	0	58	1,93	131	4,37
4	0	0	0	0	42	1,40	173	5,77
5	0	0	6	0,20	26	0,87	195	6,50
6	0	0	0	0	15	0,50	174	5,8
7	0	0	0	0	12	0,4	214	7,13
8	0	0	1	0,03	22	0,73	184	6,13

TABLE 6. Number of excesses for an extended emotional bandwidth.

LSP	IA-LUR Upper limit excesses	IA-LUR Average	IA-LUR Lower limit excesses	IA-LUR Average	IA-HUR Upper limit excesses	IA- HUR Average	IA- HUR Lower limit excesses	IA- HUR Average
1	0	0	0	0	35	1,67	52	1,73
2	0	0	0	0	16	0,53	37	1,23
3	0	0	0	0	4	0,13	50	1,67
4	0	0	0	0	5	0,17	93	3,1
5	0	0	0	0	8	0,27	66	2,2
6	0	0	0	0	3	0,1	97	3,23
7	0	0	0	0	4	0,13	71	2,37
8	0	0	0	0	5	0,17	80	2,67

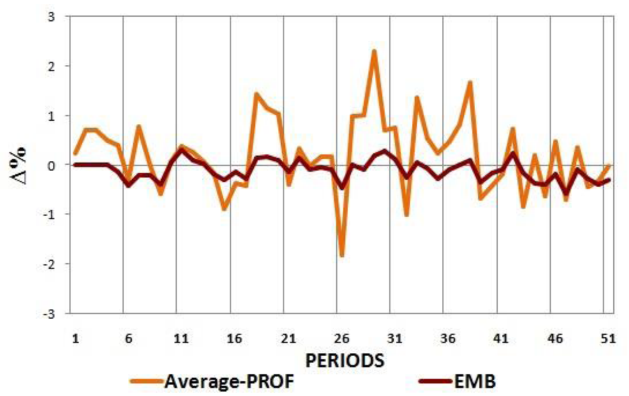

FIGURE 4. Emotional and profitability behavior aligned on a restricted emotional bandwidth: Using HUR and LSP 1.

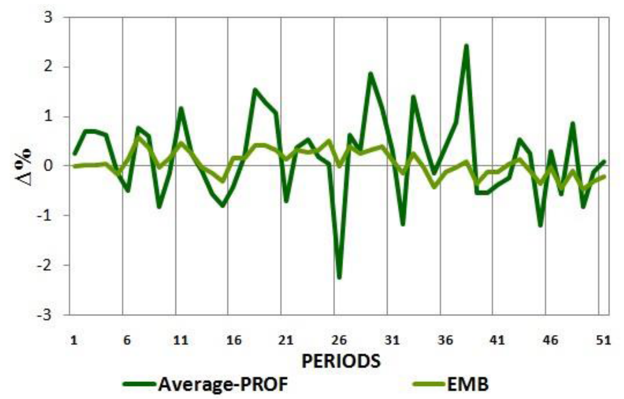

FIGURE 5. Emotional and profitability behavior aligned on a restricted emotional bandwidth: Using HUR and LSP 2.

the profitability of a stock will necessarily generate the same emotional reaction in value or in proportion. For a specific trading period, given a portfolio of two stocks, namely, a stock with positive profitability and another stock with negative profitability, it is possible that the average profitability is positive.

However, the average behavior of emotional reactions is not necessarily symmetric with respect to the average behavior of profitability, since eventually the negative profitability of the first stock could generate an emotional reaction to a downward movement that is more intense than the emotional reaction to the upward movement generated by a positive profitability of the second stock of the portfolio. The above observation can also be applied in the opposite sense: a positive profitability of the first stock, with a percentage value of X, could generate an emotional reaction to an upward movement that is more intense than the emotional reaction to a downward movement generated by the negative profitability of the second stock, also with a percentage value of X. An example of a non-symmetric behavior can be observed from trading period 23 to trading period 25 in Fig. 5.

Finally, the simulations that generated the data of Tables 2, 3 and 4 were subjected to a linear regression analysis

TABLE 7. Linear regression analysis.

			R-squared = 0.6072
r	Coef.	Robust Std. Err.	p-value
LSP	.1497036	.0034659	0.000*
EB	-.0289713	.0164424	0.078
EIF	.1494459	.0449974	0.001*
_cons	-.1901127	.347822	0.000*

*99% confidence interval for regression coefficient

(see Table 7), taking the final profitability percentage of the investment portfolio as a dependent variable (r), with the initial investment capital (US$10.000) as the reference value. In addition, different values of explanatory variables were considered: the breadth of the emotional bandwidth (EB), with values of 1 and 2; the LSP parameter with values from 1 to 8; and EIF, with values of 0.1, 0.3, and 0.5. A sample of 1200 independent observations was used. Table 7 shows the linear regression model obtained (r). In this analysis, the regression explains 60,72% of the total variance of the final profitability percentage obtained from the initial investment portfolio. The estimators LSP and EIF are significant at a 95% confidence level. Each additional unit of LSP (holding other variables constant) contributes, on average, an increase of 14,97% of the final profitability obtained. Similarly, each additional unit of the EIF factor contributes an increase of 14,94% of the final profitability obtained.

Each additional unit of the EB variable contributes, on average, a 2,9% decrease in final profitability. However, this variable was not statistically significant at the 5% level. The distribution of the model errors is nearly normal (symmetry close to zero and kurtosis value close to 3) according to the STATA test. The covariance between the errors and the independent variables are close to zero, and the low correlation between the independent variables reduces the presence of multicollinearity. Furthermore, the regression was corrected for heteroscedasticity [60].

VI. DISCUSSION

The results obtained in test 1 show that in general, applying an emotional stabilizer using an affective autonomous decision-making system improves the effectiveness of the decisions. In addition, the results of test 2 show that using a restricted band and HUR can positively affect the final results. More precisely, the linear regression analysis shows that the value of LSP and the EIF are relevant to the percentage of final profitability obtained. In terms of the influence of LSP on the percentage of final profitability obtained, one possible explanation is that the assessment of this factor facilitates the definition of strategies for short-term investment (low value of LSP) and for long-term investment (high value of LSP). In this respect, the combination ''aggressive strategy'' and short-term horizon (i.e., LSP value 1-2) is less effective than the combination ''aggressive strategy'' and long-term horizon (i.e., LSP value 6-8). Therefore, for the same investment strategy (in the experiment realized, ''aggressive strategy''), the LSP valuation can be effective if this factor is defined relative to a long-term horizon, but it can be ineffective if this factor is defined relative to a short-term horizon.

In contrast, the influence of EIF on the percentage of final profitability obtained can be explained by the impact of the value of each artificial emotion in equation (3) associated with the calculation of portfolio selectivity. Each fluctuation observed in the value of the investment portfolio generates an update in the emotional state of the artificial investor. In this sense, a low EIF value (e.g., 0.1) can generate small emotional changes in each trading period. In turn, a high EIF value (e.g., 0.5) can generate more-important emotional changes in each trading period. In any case, the rate of emotional update has a clear impact on how the artificial emotions are valued, which in turn influences the calculation of the portfolio selectivity.

In another sense, although the linear regression analysis was inconclusive regarding the relevance of the emotional bandwidth value band in the final percentage of profitability, the use of a high update rate (HUR) with a restricted emotional bandwidth shows a better effectiveness than other combinations, as indicated in table 5. Each time an artificial emotion reaches a limit of the emotional band, the emotional stabilization mechanism is activated.

Currently, the electronic platforms that allow the management of stock exchange transactions require an initial definition of parameters by the human investor, usually based on technical parameters (for example, a stock price value that, when reached, results in a purchase or sale of stocks). In this sense, electronic platforms do not entail autonomous investment behavior; rather, they must strictly follow the indications defined by a human investor. In contrast, artificial affectivity has emerged as a new step forward in the definition of decision support systems, representing an opportunity to establish new mechanisms to support and provide autonomous behavior in decision-making systems.

The use of an emotional stabilizer can be incorporated into any autonomous system for decision-making that has an affective artificial dimension based on emotions and in which, according to human behavior, the behavior of the affective artificial dimension is based on non-deterministic rules of emotional updating. Thus, emotional stabilization should promote the control of the affective artificial dimension without interfering disproportionately with the non-deterministic nature of the emotional dimension.

The analysis of the use and behavior of artificial affectivity in autonomous decision-making systems facilitates an understanding of their performance and degree of applicability, promoting the detection of weaknesses and potential. This represents a central aspect of the increasing use of the artificial emotional dimension in autonomous systems, opening up possibilities for increasing the number and types of affective criteria used in decision-making and extending the types of application domains.

The delegation of decision-making in autonomous systems represents a challenging and developing field. The design of a decision-support system as a tool that generates indicators and shows it to the user as a set of visual features on a dashboard (where the user makes every decision) has been gradually giving way to the design of an autonomous system that, taking technical knowledge and criteria for the domain, makes decisions on behalf of the user. In this sense, the use of artificial emotions furnishes a promising alternative in the definition of decision-making systems with real autonomy.

VII. CONCLUSION

An affective algorithm that incorporates an emotional stabilizer mechanism for affective artificial investors in a stock market domain was presented. Its importance is that it represents a promising effort towards a definition of stabilization mechanisms for artificial emotions used in autonomous decision-making systems. The affective algorithm for supporting investing operations allows the incorporation of an emotional stabilizer mechanism. The definition of an experimental scenario based on official free-access data from the New York Stock Exchange facilitated the numerical experiments reported in this study.

The limitations of the proposal are as follows: First, the results obtained are not instances of stable behavior, and the effectiveness of the decision-making process does not show the same degree of accuracy in all configurations. In this case, increased experimentation represents a feasible solution.

Second, the artificial emotions considered in this study are not used as a single mechanism to perform a business action (for example, sell a stock) but are used as decision criteria within a mathematical formula for calculating the selectivity of a stock. Considering the above, a possible extension of this study would be to incorporate variations in artificial emotions as signals to an artificial investor. For example, based on the investor's experience, an emotional behavior can represent a signal to buy a stock, wait for another opportunity, or maintain an investment portfolio, without needing to use a mathematical formula to calculate the portfolio performance.

Third, the stabilizing mechanism was tested only in the domain of the stock market, which is associated with three different criteria, namely, profitability, risk, and the probability of loss. In this sense, it is necessary to test this stabilizing mechanism in another type of domain (for example, purchasing decisions in retail), with the aim of exploring how the emotional stabilization can improve the decision-making process. People can reach an elevated and intense emotional state, for example, when observing a special sale. Hence, an autonomous affective decision-making system for purchase decisions can control a possible euphoric state (using an emotional stabilizer mechanism). It is clear that the purchase decision depends on the degree of control applied to the emotional behavior. An initial effort related to the incorporation of the affective dimension within an autonomous decision-making system for purchasing decisions has been presented in [61].

Fourth, the affective decision-making algorithm currently considers three pairs of basic emotions: joy and sadness; fear and trust; and tranquility and anger. In the experimental scenario tested, the initial assessment of these emotional variables tries to represent a neutral emotional state. However, in the real world, the affective dimension varies from investor to investor, so it is certainly possible that there are different affective profiles (e.g., initial valuation of affective variables) as well as different affective reactions to the same investment situation.

One future direction of study would be to extend the proposed stabilizing mechanism, for example, by the incorporation of different stabilization rules (probabilistic or fuzzy rules). Another direction would be to extend the scope of the experimental scenario, e.g., by the incorporation of more artificial investors with the possibility that they can interact with each other. The success or failure of an artificial investor can represent an important source of information for its own investment strategies, which of course, are sustained permanently on the affective dimension.

On the other hand, another future research line would be to extend the experimental base, e.g., by the implementation of an on-line autonomous affective decision-making system with the aim of continuously observing different artificial emotional behaviors and testing different investment strategies in a real-time system.

Another future line of research corresponds to the use of decision-making scenarios that represent special decision conditions (for example, an economic shock scenario), where the use of an affective dimension within a unified rational-emotional decision scheme would allow one to verify different types of reactions and, at the same time, different degrees of effectiveness of the decisions made. In the same way, another line of future research corresponds to the definition of personality profiles for artificial agents of investment, conditioning the initial valuation of affective variables of each artificial agent and guiding the mechanisms of updating the affective state of each of them.

As a general implication of this work, the proposed emotional mechanism could be adapted not only for domains focused on optimizing user profit but also on behavior simulation under circumstances where emotions play a critical role. Consider how people react to natural disasters, or a driver's behavior on streets with high transit volume. These simulations can involve not only a single individual but also multiple individuals with different emotional profiles interacting and influencing the environment at the same time. Like the stock market domain, these applications could benefit from including emotional variables alongside random and rational behavior, with the particularity that the results are evaluated according to the accuracy of the simulation regarding reality.

REFERENCES

[1] A. Bechara, "The role of emotion in decision-making: Evidence from neurological patients with orbitofrontal damage," *Brain Cognit.*, vol. 55, no. 1, pp. 30–40, 2004.

[2] A. Damasio, *Descartes' Error: Emotion, Reason, and the Human Brain*. New York, NY, USA: Putnam, 1994.

[3] J. D. Mayer and P. Salovey, "What is emotional intelligence?" in *Emotional Development And Emotional Intelligence: Educational Implications*, P. Salovey and D. Sluyter, Eds. New York, NY, USA: Basic Books, 1997, pp. 3–31.

[4] J. V. Wood, S. A. Heimpel, L. A. Manwell, and E. J. Whittington, "This mood is familiar and i don't deserve to feel better anyway: Mechanisms underlying self-esteem differences in motivation to repair sad moods," *J. Personality Soc. Psychol.*, vol. 96, no. 2, pp. 363–380, 2009.

[5] S. Robbins and T. Judge, *Organizational Behavior*. Englewood Cliffs, NJ, USA: Prentice-Hall, 2013.

[6] A. Grecucci and A. G. Sanfey, "Emotion regulation and decision making," in *Handbook of Emotion Regulation*, J. J. Gross, Ed. New York, NY, USA: The Guildford Press, 2014, pp. 140–153.

[7] S. L. Koole, "The psychology of emotion regulation: An integrative review," *Cognit. Emotion*, vol. 23, no. 1, pp. 4–41, 2009.

[8] E. Court and J. Tarradellas, *Mercado de Capitales*. Englewood Cliffs, NJ, USA: Prentice-Hall, 2010.

[9] I. Perikos and I. Hatzilygeroudis, "Recognizing emotions in text using ensemble of classifiers," *Eng. Appl. Artif. Intell.*, vol. 51, pp. 191–201, May 2016.

[10] J. Sun, G. Wang, X. Cheng, and Y. Fu, "Mining affective text to improve social media item recommendation," *Inf. Process. Manage.*, vol. 51, no. 4, pp. 444–457, 2015.

[11] A. Kaklauskasa *et al.*, "Affective tutoring system for built environment management," *Comput. Edu.*, vol. 82, pp. 202–216, Mar. 2015.

[12] M. S. Hossain and G. Muhammad, "An emotion recognition system for mobile applications," *IEEE Access*, vol. 5, pp. 2281–2287, 2017.

[13] J. Deng, S. Frühholz, Z. Zhang, and B. Schuller, "Recognizing emotions from whispered speech based on acoustic feature transfer learning," *IEEE Access*, vol. 5, pp. 5235–5246, 2017.

[14] A. Azazi, S. L. Lutfi, I. Venkat, and F. Fernández-Martínez, "Towards a robust affect recognition: Automatic facial expression recognition in 3D faces," *Expert Syst. Appl.*, vol. 42, no. 6, pp. 3056–3066, 2015.

[15] L. Malatesta, S. Asteriadis, G. Caridakis, A. Vasalou, and K. Karpouzis, "Associating gesture expressivity with affective representations," *Eng. Appl. Artif. Intell.*, vol. 51, pp. 124–135, May 2016.

[16] I. Leite, A. Pereira, S. Mascarenhas, C. Martinho, R. Prada, and A. Paiva, "The influence of empathy in human—Robot relations," *Int. J. Hum.-Comput. Stud.*, vol. 71, no. 3, pp. 250–260, 2013.

[17] Y. Zhang, L. Zhang, and M. A. Hossain, "Adaptive 3D facial action intensity estimation and emotion recognition," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1446–1464, 2015.

[18] W. Dai, D. Han, Y. Dai, and D. Xu, "Emotion recognition and affective computing on vocal social media," *Inf. Manage.*, vol. 52, no. 7, pp. 777–788, 2015.

[19] R. Katarya and O. Prakash, "Recent developments in affective recommender systems," *Phys. A, Stat. Mech. Appl.*, vol. 461, pp. 182–190, Nov. 2016.

[20] J. Vallverdú, M. Talanov, S. Distefano, M. Mazzara, A. Tchitchigin, and I. Nurgaliev, "A cognitive architecture for the implementation of emotions in computing systems," *Biol. Inspired Cognit. Archit.*, vol. 15, pp. 34–40, Jan. 2016.

[21] D. Cabrera-Paniagua, C. Cubillos, R. Vicari, and E. Urra, "Decision-making system for stock exchange market using artificial emotions," *Expert Syst. Appl.*, vol. 42, no. 20, pp. 7070–7083, 2015.

[22] *Acuity Trading Platform*. Accessed: Oct. 31, 2017. [Online]. Available: http://acuitytrading.com

[23] *Colmex Expert*. Accessed: Oct. 31, 2017. [Online]. Available: http://www.colmexpro.com/about/Colmex-Expert

[24] *VT Trader*. Accessed: Oct. 31, 2017. [Online]. Available: http://vtsystems.com/products/vt-spot-platform/vt-trader.

[25] *XStation*. Accessed: Oct. 31, 2017. [Online]. Available: http://xopenhub.pro/products/xstation

[26] *ZuluTrade Platform*. Accessed: Oct. 31, 2017. [Online]. Available: http://www.fxcm.com/products/zulutrade

[27] F. M. Talarposhti, H. J. Sadaei, R. Enayatifar, F. G. Guimarães, M. Mahmud, and T. Eslami, "Stock market forecasting by using a hybrid model of exponential fuzzy time series," *Int. J. Approx. Reasoning*, vol. 70, pp. 79–98, Mar. 2016.

[28] Z. Guo, H. Wang, J. Yang, and D. J. Miller, "A stock market forecasting model combining two-directional two-dimensional principal component analysis and radial basis function neural network," *PLoS ONE*, vol. 10, no. 4, p. e0122385, 2015.

[29] J. Wang and J. Wang, "Forecasting stock market indexes using principle component analysis and stochastic time effective neural networks," *Neurocomputing*, vol. 156, pp. 68–78, May 2015.

[30] G. Yang, Y. Chen, and J. P. Huang, "The highly intelligent virtual agents for modeling financial markets," *Phys. A, Stat. Mech. Appl.*, vol. 443, pp. 98–108, Feb. 2016.

[31] J. R. Wei, J. P. Huang, and P. M. Hui, "An agent-based model of stock markets incorporating momentum investors," *Phys. A, Stat. Mech. Appl.*, vol. 392, no. 12, pp. 2728–2735, 2013.

[32] C.-X. Yang, R. Wang, and S. Hu, "Modeling and analysis of an agent-based model for Chinese stock market," *Phys. Lett. A*, vol. 377, nos. 34–36, pp. 2041–2046, 2013.

[33] S. Mabu, K. Hirasawa, M. Obayashi, and T. Kuremoto, "Enhanced decision making mechanism of rule-based genetic network programming for creating stock trading signals," *Expert Syst. Appl.*, vol. 40, no. 16, pp. 6311–6320, 2013.

[34] T. Geva, and J. Zahavi, "Empirical evaluation of an automated intraday stock recommendation system incorporating both market data and textual news," *Decision Support Syst.*, vol. 57, pp. 212–223, Jan. 2015.

[35] M. A. Bertella, F. R. Pires, L. Feng, and H. E. Stanley, "Confidence and the stock market: An agent-based approach," *PLoS ONE*, vol. 9, no. 1, p. e83488, 2014.

[36] F. Celli and L. Rossi, "The role of emotional stability in Twitter conversations," in *Proc. 13th Conf. Eur. Chapter Assoc. Comput. Linguistics*, 2012, pp. 10–17.

[37] R. T. Bradley, P. Galvin, M. Atkinson, and D. Tomasino, "Efficacy of an emotion self-regulation program for promoting development in preschool children," *Global Adv. Health Med.*, vol. 1, no. 1, pp. 36–50, 2012.

[38] N. E. Doinita, "Adult attachment, self-esteem and emotional intelligence," *Procedia-Soc. Behav. Sci.*, vol. 187, pp. 570–574, May 2015.

[39] A. M. Penney, V. C. Miedema, and D. Mazmanian, "Intelligence and emotional disorders: Is the worrying and ruminating mind a more intelligent mind?" *Personality Individual Differences*, vol. 74, pp. 90–93, Feb. 2015.

[40] M. Laakasuo, J. Palomäki, and M. Salmela, "Experienced poker players are emotionally stable," *Cyberpsychol., Behav., Soc. Netw.*, vol. 17, no. 10, pp. 668–671, 2014.

[41] K. M. Lempert and E. A. Phelps, "Neuroeconomics of emotion and decision making," in *Neuroeconomics: Decision Making and the Brain*, P. W. Glimcher and E. Fehr, Eds. San Francisco, CA, USA: Academic, 2014, pp. 219–236.

[42] *Oxford Dictionary*. Accessed: Oct. 31, 2017. [Online]. Available: https://en.oxforddictionaries.com/definition/invest

[43] A. Scherk, *Manual de Analisis Fundamental*. Madrid, Spain: Inversor Editores, 2011.

[44] *MetaTrader 5 Platform*. Accessed: Oct. 31, 2017. [Online]. Available: http://www.metatrader5.com

[45] J. Welles, *New Concepts in Technical Trading Systems*. Greensboro, NC, USA: Trend Research, 1978.

[46] A. Silva, R. Neves, and N. Horta, "A hybrid approach to portfolio composition based on fundamental and technical indicators," *Expert Syst. Appl.*, vol. 42, no. 4, pp. 2036–2048, 2015.

[47] K.-Y. Shen and G.-H. Tzeng, "Combined soft computing model for value stock selection based on fundamental analysis," *Appl. Soft Comput.*, vol. 37, pp. 142–155, Dec. 2015.

[48] D. Cabrera-Paniagua, T. T. Primo, and C. Cubillos, "Distributed stock exchange scenario using artificial emotional knowledge," in *Advances in Artificial Intelligence—IBERAMIA*, A. L. C. Bazzan and K. Pichara, Eds. Cham, Switzerland: Springer, 2014, pp. 649–659.

[49] E. T. Rolls, *Emotion and Decision-Making Explained*. London, U.K.: Oxford Univ. Press, 2014.

[50] M. Wooldrigde, *An Introduction to Multiagent Systems*. New York, NY, USA: Wiley, 2009.

[51] F. J. Varela, E. T. Thompson, and E. Rosch, *The Embodied Mind: Cognitive Science and Human Experience*. Cambridge, MA, USA: MIT Press, 1993.

[52] R. Pfeifer and J. Bongard, *How the Body Shapes the Way We Think: A New View of Intelligence*. Cambridge, MA, USA: MIT Press, 2007.

[53] A. Ortony, "Affect and emotions in intelligent agents: Why and how?" in *Affective Information Processing*, J. H. Tao and T. N. Tan, Eds. New York, NY, USA: Springer-Verlag, 2009, pp. 11–21.
[54] T. Nishida, "Modeling machine emotions for realizing intelligence—An introduction," in *Modeling Machine Emotions for Realizing Intelligence: Fundations and Applications*, T. Nishida, L. Lakhmi, and C. Faucher, Eds. Berlin, Germany: Springer-Verlag, 2010, pp. 1–15.
[55] H. Jiang, J. M. Vidal, and M. N. Huhns, "EBDI: An architecture for emotional agents," in *Proc. 6th Int. Joint Conf. Auto. Agents Multiagent Syst.*, 2007, p. 11.
[56] J. S. Lerner, Y. Li, P. Valdesolo, and K. S. Kassam, "Emotion and decision making," *Annu. Rev. Psychol.*, vol. 66, pp. 799–823, Jan. 2015.
[57] S. Bloch, *Surfeando la Ola Emocional*. Santiago, Chile: UQBAR Editores, 2008.
[58] H. M. Markowitz, *Mean-Variance Analysis in Portfolio Choice and Capital Markets*. Oxford, U.K.: Blackwell, 1987.
[59] *New York Stock Exchange Data*. Accessed: Jun. 10, 2016. [Online]. Available: http://finance.yahoo.com
[60] H. White, "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity," *Econometrica*, vol. 48, no. 4, pp. 817–838, 1980.
[61] D. Cabrera-Paniagua, N. Araya, H. Jaime, C. Cubillos, R. M. Vicari, and E. Urra, "Defining an affective algorithm for purchasing decisions in E-commerce environments," *IEEE Latin Amer. Trans.*, vol. 13, no. 7, pp. 2335–2346, Jul. 2015.

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