


Is the Metaverse Dead? Insights from Financial Bubble Analysis

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Abstract: This paper explores the economic trends and identifies speculative bubbles within the emerging metaverse, based on the specific example of Decentraland, which is represented by its underlying native token MANA. For comparability, we consider three further tokens: SAND, ETH, and BTC. The study shows price prediction and provides further insight into bubble behavior to provide a deeper insight into the real trend and situation of the metaverse. When comparing all considered tokens, evidence of comovement and positive as well as negative bubbles is identified. This paper makes use of proven modeling techniques, such as SARIMA, for price prediction and LPPLS for financial bubble identification, visualization, and time stamping.

Keywords: metaverse; Decentraland; MANA; SARIMA; LPPLS; financial bubbles; cryptocurrency

JEL Classification: F3; F360; G1; G150; G170

1. Introduction

The first time the term “metaverse” emerged was in a novel of speculative fiction named *Snow Crash*, written by Neal Stephenson in 1992 [1]. Stephenson’s novel introduced the metaverse concept, a vast virtual environment that runs parallel to the physical world, where users engage with one another using digital avatars. Since its inception, the metaverse has been defined through a multitude of different concepts, reflecting its evolution as a computer-generated universe. At present, the implementation of the metaverse pertains exclusively to the crypto-metaverse and Web3 (Web3 refers to a novel version of the Internet that integrates principles like decentralization, blockchain-based technologies, and economy driven by tokens), signifying the integration of blockchain technology and economy, along with the associated advantages of decentralization [2], such as ease of communication, tighter security, and being community-driven. In a decentralized system, users create freely and are given the rights to their creation. In a centralized system, users create freely; however, the rights remain with the entity behind the virtual world—see Bodò et al. [3] for more details.

In October 2021, the CEO of Facebook, Mark Zuckerberg, officially disclosed his company’s new name: “Meta” [4], a bold statement towards his ambitions beyond social media and the attempt to provide a comprehensive vision for the industry.

In the same year, on 23 November 2021, a piece of land measuring 6090 square feet was bought in the Decentraland metaverse for 618,000 MANA (at the time: USD 2.4 million) (Decentraland is an Ethereum blockchain-based virtual-reality platform that enables its users to generate, encounter, and profit from content and applications [5]); MANA is Decentraland’s native cryptocurrency and hence, represents its economic performance. This land span, acquired by Tokens.com, lies in the Fashion Street area of Decentraland; the acquisition aims to exhibit fashion shows and vend avatar clothing, which is part of the acquirers’ digital strategy [6]. Many more companies have followed suit and are investing heavily in virtual worlds; some are pursuing their visions (e.g., Nvidia, Microsoft), and many others partner with third-party metaverses, such as Decentraland, “The Sandbox”



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(a virtual gaming world built on blockchain technology allowing players to buy, sell, and create digital assets [7]), and many more (which are not subject to consideration in this study). Based on the interest, engagement (media coverage, events, and popular artists), and being fully “decentralized”, Decentraland is well known among all existing metaverses. Therefore, this paper concentrates on Decentraland (MANA).

A recent decline in coverage (mainly media) and big tech turning away from metaverse projects has installed a public opinion of the metaverse being “dead” [8,9]. For more details on the metaverse, especially emerging challenges, opportunities, literature review, and technological singularity, please see [2,10,11]. Here, public opinion and real-investment inflows paint a quite different picture (please see Section 3.1 for the current state of the metaverse). This diverse picture must be analyzed to comprehend the metaverse market’s impact, stability, and outlook.

In this study, first, we analyze the trend of MANA and predict a future price trend using a Seasonal ARIMA model, which is one of the most widely used time-series predictors. Furthermore, we apply the Log-Periodic Power Law Singularity (LPPLS) model to estimate the most probable time of a crash and rapidly accelerating price behavior, which we visualize with a Bubble Confidence Indicator and subsequently time stamp [12]. Based on these results, we show the practical relevance of the LPPLS bubble identification using the indications as buy and sell signals.

Economic history entails ample evidence for speculative bubbles—the Dutch Tulip Mania (1624–1634), the South Sea Bubble (1716–1720), British Railway Mania (1840), the Stock Market Crash (1929), the Dot-Com Bubble (2000) and most recently the US Housing Bubble (2008).

All these disastrous wealth-eradicating events are caused by a persistent increase in the underlying asset’s price above the asset’s fundamental value (mispricing) driven by investor optimism, herd mentality, and speculation. These increases are then followed by an abrupt fall in price and may cause market crashes [13–17]. Economics and finance go back to the Efficient Markets Hypothesis (EMH), as proposed by Fama [18]. Fama argues that enough sophisticated investors may cause bubbles to burst before they have a chance to really inflate and become dangerous [18]; this belief, however, has lost ground since the Dot-Com Bubble in 2000 [19].

Bitcoin, the most famous cryptocurrency with an estimated market capitalization of USD 728 billion (coinmarketcap.com accessed on 20 November 2023), has shown substantial fluctuations, which render it difficult to suggest a fundamental value [20] and therefore contains a component suggesting it to be highly speculative. This speculative characteristic usually signifies bubbles [21] and is caused by three major market issues: market instability (rapid increases or decreases in price), market integrity (fraudulent activities, pump-and-dump schemes), and macro-prudential policy considerations (risks in monitoring and mitigating by authorities) [21]. According to Kumar and Ajaz [22], all cryptocurrencies are driven by the market-maker Bitcoin; we suspect bubble-like behavior in MANA as it is subject to identical issues.

Looking at the development of economic bubbles allows this paper to gather insights into the validity of the metaverse, its stability, and future price movements. It dissects the metaverse asset class to enhance its understanding and build an initial point for future research for further literature on the metaverse. This study aims to determine whether the metaverse is still a viable investment option or has passed its prime.

The further structure of this paper is divided into seven sections. First, we provide an overview of related research. We further provide a look into the current state of the industry and a descriptive and statistical introduction to our choice of data and derivation of the dataset in Section 2.1. Subsequently, we explain and rationalize our applied methodology in Section 2.2. Furthermore, we present our results based on our applied methodology in Section 3, which we then discuss based on empirical findings in Section 4. Lastly, we conclude our study in Section 5.

1.1. Literature Overview

1.1.1. Forecasting Using (Seasonal) ARIMA

Stock forecasting has been a long-standing and intriguing practice, not solely in academia but anywhere. It comes as no surprise that articles and reviews evaluate different statistical techniques to compare accuracies. The Autoregressive Moving Average (ARIMA) is a widely used model for time-series forecasting.

Mondal et al. [23] released a study regarding the efficiency of ARIMA time-series analysis, predicting stock values of 56 different stocks in India. Their findings show the prediction of stock movement with an 85% accuracy. This makes the application of methodology significant for this kind of data (stock price time series).

As many scholars have applied this model to diverse forecasting fields, the literature focuses more on Bitcoin (BTC) than any other segment within the digital asset market.

Poongodi et al. [24] used the ARIMA model to estimate BTC closure rates, covering 28 April 2013 to 31 July 2017. Their study highlights that BTC is difficult to predict due to its high volatility. Nonetheless, [24]'s efforts result in a satisfactory accuracy of 49% between observed and predicted prices. Seasonality was consciously left out in this study, as it is supposed to enhance the predictions based on not giving misleading results [24].

To our knowledge, at the time of writing this paper, the only other literature using a SeasonalARIMA model on MANA is the study of Sahay et al. [25]. Here, they take into consideration four metaverse cryptocurrencies, of which two overlay with ours, MANA and SAND, from March 2021 to March 2022. The results predict a growing price trend for the future. Sahay et al. [25] further concludes that their analysis shows evidence of continuous profitability of the metaverse even though it is a hot topic.

1.1.2. Theory on Bubbles

The idea of the existence of bubbles may come from the description of equity markets by John Maynard Keynes (1936). Keynes states that the environment of equity markets focuses on speculators' opinions rather than the fundamentals of the market. Bubbles, therefore, exist when the asset's price deviates significantly from its fundamental value [15,17,26]. Flood and Hodrick [15] show that the fundamental value does not determine an asset's price because of the violation of variance bounds (see LeRoy [27] for the variance bounds test). The current price of an asset is based on the expectation of its price in the future, whereas the future price depends on the current price; this alone cannot determine the fundamental value of an asset and can only determine sequences of the price [15]. One sequence is the fundamental value, and other sequences will exhibit bubbles.

The discussion surrounding speculative bubbles has identified two categories of investors: speculators, who focus primarily on the future selling price of financial securities, and sophisticated investors, who evaluate the market price of the asset's intrinsic value. Based on the different investment approaches, a favorable environment for asset bubble formation is created in the circumstance of several speculators surpassing that of sophisticated investors [28].

Abreu and Brunnermeier [16] show that when speculators coexist with sophisticated investors, who gradually become aware of a bubble formation, these sophisticated investors tend to exit the market just before the burst for maximum capital gains. Scheinkman and Xiong [29] add a layer of overconfidence, which results in disagreement of the fundamental value of the asset among investors, which leads to deviation of the price from the fundamental value.

The first studies to mention the term "bubble", based on the characteristics of the "hypothesis of financial instability" by Minsky [30] are Blanchard [31] and Flood and Garber [32]. The "financial instability hypothesis" argues that during extended periods of economic stability, individuals and institutions tend to seek higher levels of risk, resulting in the accumulation of financial vulnerability and raising the prospect of a systemic financial crisis [30].

Tirole [14] and Blanchard and Watson [13] set the basis for subsequent developments in terms of bubble identifications. Tirole [14] put special emphasis on the conditions needed for bubbles to occur and their consequence for the economy (mainly interest rates and economic growth). For Blanchard and Watson [13], on the other hand, the approach is purely empiricist and, therefore, focuses on the discrepancy between the market value and the fundamental value.

Due to the limitations of these techniques, mainly because of market fundamentals being unobserved and the explosiveness of prices being undetected, bubbles may stay unidentified (esp., periodically collapsing bubbles).

A somewhat novel approach is Johansen et al. [33], who propose a slow build-up of long-range time correlations, which is the result of all investors leading to a collapse in one critical instant. This model is called the Log-Period Power Law (LPPLS). Sornette and Johansen [34] suggests that log-periodicity can be linked with bubbles and, therefore, is a tool to detect them (see the following section for more details).

1.1.3. Bubble Identification Using LPPLS

Predictions of bubbles have been popular on many subjects (e.g., [35–38]). When looking at the cryptocurrency market, it did not take long for academics to leverage traditional and proven techniques to grasp an understanding mainly of BTC.

Bianchetti et al. [39] analyze BTC and ETH, in particular, using various models, including the LPPL model. Their data covers the time frame of 1 December 2016 to 16 January 2018. The study finds that the LPPL shows strong bubble signals for BTC, which are consistent with the other models applied; ETH aligns with the models, including LPPL showing bubble signals corresponding to the crash on 12 June 2017.

Yao and Li [40] have applied the model as mentioned above onto a wider range of time; 1 January 2014 to 30 March 2020. The study applies two methods for bubble identification, LPPL and GSADF; the LPPL shows stable results when shifting the time window. In line with the research of Yao and Li [40], is Shu et al. [41]. Shu et al. [41] uses a shorter time frame (1 December 2019 to 24 June 2021) and identifies positive as well as negative bubbles which are clustered. The research stretches the “outstanding performance” of the LPPLS model, which can provide useful insights into times of price fluctuations [41]. To our knowledge, at the time of writing, the first to make use of the LPPLS bubble identifications containing MANA is the study of Ito et al. [42]. Ito et al. [42] uses weekly moving-average prices of non-fungible tokens (NFTs), covering 23 June 2017 to 20 December 2021—MANA (Decentraland) and SAND (“The Sandbox”) are included. The results show MANA in a “medium bubble” (predicting price decline); no concrete dates are given. Ito et al. [42] acknowledge this being an initial step to bubble prediction and recommend considering heterogeneity for further research.

2. Materials and Methods

2.1. Data

2.1.1. Current State of the Metaverse

The term “metaverse” is omnipresent and was on everyone’s lips; what precisely the concept of it entails, however, is still largely incomprehensible to most of the general public [43]. As time goes by, the metaverse is less often mentioned, as the “hype” has seen a drastic decline since the peak of interest in early 2022. Looking at Figure 1, the metaverse search trend started an explosive upward trend before Facebook’s name change announcement—in fact, interest peaked at Meta’s announcement in October 2021 (see Figure 1).

Investors, policymakers, and enthusiasts share a common opinion on the inability of business leaders to describe the metaverse meaningfully; Microsoft sees it as “a merge of the physical and virtual”, Nvidia as an “overlay on the physical world” [44]. The initial unveiling of numerous unstructured and diverse ideas was a great debut, becoming the tech world’s obsession and winning over investors quickly [9]. Due to the overpromising of single business leaders with the underlying technology not being ready for the grand

visions sold, firms such as Microsoft put a stop to its virtual-reality platform (AltspaceVR) in early 2023. They continued to cut departments associated with virtual worlds [9]. Other big companies followed suit quickly; Disney and Walmart canceled their metaverse projects in the second quarter of 2023. The final push came when Meta (formerly Facebook) announced its strategy shift onto “advancing AI” [8].

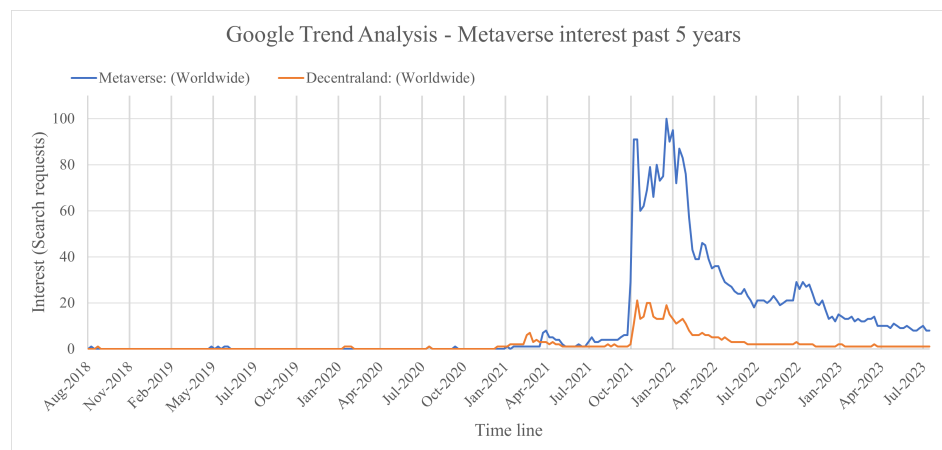


Figure 1. Google Trend Analysis—Interest Over Timeshows a peak in interest from October 2021 until February 2022; since then, interest has been declining and approaching pre-hype levels. Interest over time represents search interest relative to the highest point on the chart for the given region and time; Timeline: 2 February 2018, to 15 March 2023.

At the time of this study, the countries with the most interest in the metaverse and Decentraland (according to Google Trends) are Pakistan, Egypt, Thailand, and Indonesia. In these developing nations, individuals perceive the metaverse as a virtual realm transcending geographical and geopolitical boundaries, offering interconnectedness [45]. Moreover, they envision economic prospects within a gamified and innovative economy facilitated by the metaverse, extending its impact globally.

As interest in the term declines and the shift of big tech shies away, economic outlooks are surprisingly stable, and the metaverse industry is forecast to grow. Estimates of potential economic value vary; however, McKinsey&Company [46] suggest it may generate up to USD 5 trillion in impact by 2030, placing it equally with the third largest economy in the physical world today: Japan. For comparison, in 2022, the global stock market amounted to USD 102 trillion, and the global bond market to USD 130 trillion (according to SIFMA (Securities Industry and Financial Markets Association (2023))). Precedence Research, a well-respected research institution, predicts a market size just above USD 1 trillion with a CAGR of 44.5% from 2022 to 2030 [47]. Of course, the impact per se varies by industry; however, it is set to be around USD 2 trillion in e-commerce, approximately USD 200 billion in academic virtual learning, roughly USD 150 billion in advertising, and USD 120 billion in gaming by 2030 [46].

In 2022, over USD 120 billion in investment has flowed into the metaverse space, which is more than double than the year before—2021: USD 57 billion [46]. This shows significant growth compared to the global equity markets, which were down USD 18 trillion by the end of 2022 compared to 2021 (USD 120 trillion), according to SIFMA. Venture Capital funds drive this inflow of investments, e.g., the Games Fund One launched by Andreessen Horowitz, dedicating USD 600 million into this development area [48].

When speaking about the metaverse, it entails much more than what most people envision; BMW built a digital twin in the Nvidia Omniverse based on one of its existing factories to drive efficiency improvements across the supply chain [49].

Promising may best describe the traction of the metaverse. The Metaverse Fashion Week, which is held in Decentraland in March of every year, has received, once again, more interest and attention than any other metaverse event before; it attracts high-end luxury

brands such as Dolce & Gabbana, Estèe Lauder, and many more. The fashion show creates a blockchain-based experience and is sold as NFT, meant for your virtual avatar (partially in connection with real-life products) [50].

Decentraland, which this paper focuses on as a representation of the metaverse cosmos, is showing growth (based on released statistics of 2022), counting 2.7 million NFTs minted (+440% YoY), 1 million Unique Active Users (+12.9% YoY), 2800 Events created (+169% YoY) and 755 Creators receiving royalties (For details please see <https://decentraland.org/blog/announcements/decentraland-2022-recap>, accessed 3 September 2023). Additionally, monthly LAND units sold are gaining transactions in Q1 2023 with 74 units per month (compared to 49 the months before); New addresses and active addresses are gaining traction as well with 10,552 and 27,674, which is an improvement of 11.83% and 2.34%, respectively.

Furthermore, the sports giant Nike is ahead of its competition and leading in terms of NFT sales—67,251 NFTs sold, generating revenue of approximately USD 185 million.

Fifth on the list, behind Nike, Dolce & Gabbana, Tiffany, and Gucci, is Adidas, with 51,449 NFT sales, resulting in approximately USD 11 million (this information is retrieved from Dune.com), the German company that bought a presence in “The Sandbox” in 2021.

2.1.2. Data Sample and Descriptive Statistics

Decentraland’s financial system is underpinned by its digital currency, MANA, which operates as an ERC-20 token based on the Ethereum blockchain. Ethereum Request for Comment 20 (ERC-20) are fungible tokens that are indistinguishable from any other token in the set (basically, like every dollar is the same as the other). The token refers to standards defining a set of rules, i.e., how the token may be transferred and the total supply of tokens. MANA is the primary mode of transaction within the Decentraland metaverse, allowing users to purchase virtual property, commodities, and services. MANA may be obtained through cryptocurrency exchanges like Crypto.com, Coinbase, and Binance. It can then be used to acquire virtual real estate (i.e., LAND) or invest in other digital assets (i.e., wearables) offered in the digital world.

Additionally, MANA acts as a governance token (the building block of a decentralized system). By holding a governance token, individuals gain the ability to vote on proposed modifications to smart contracts within the issuing protocols. This grants them the power to actively participate in decision-making processes that determine the operational changes in the protocol. In essence, utilizing MANA as the primary means of exchange within the Decentraland virtual universe provides a decentralized and secure mechanism for conducting economic transactions while encouraging user involvement and contributions. Therefore, MANA is the real-time representation of Decentraland’s economy. For our analysis, we use daily price data from the earliest possible date of historical data of MANA up to the most recent data point; 2 February 2018, to 15 March 2023.

To compare our findings in subsequent sections with relatable representations of metaverses and underlying technologies (blockchains), we choose to consider the following: SAND, ETH, and BTC.

SAND is the native token of Decentraland’s competitor, “The Sandbox”, which works almost identically to Decentraland, with the significant difference being the focus of the virtual world. Decentraland focuses on user-generated content and art, whereas “The Sandbox” is mostly gaming-focused. It is important to note that SAND was launched on 13 August 2020, and therefore, our dataset holds daily price data from 14 August 2020, to 15 March 2023. This shortens our time series and results in our analysis.

Ether (ETH) price is considered the representation of the underlying technology of both metaverses in this study. “The Sandbox” considers a multi-chain strategy, which enables developers to build multiple independent blockchains on top of each other. Ether is still considered to substantially impact the “The Sandbox” and is the primary basis for Decentraland.

Bitcoin (BTC) is considered a reference point for Ether (ETH) and is also the best-known cryptocurrency. All the obtained price data series are traded all year round (365 days), regardless of weekends or bank holidays. The observations add up to 1868 for MANA, ETH, and BTC and 944 for SAND (due to it being launched later).

Introducing our data with descriptive statistics, in Table 1, we can see comparability. All the considered cryptocurrencies share a similar characteristic; the mean is not close to the maximum value nor the minimum value of the respective token. The four tokens may not be compared by simply looking at the values, much more so by looking at the comparability among them.

Table 1. Descriptive statistics of price data for MANA (Decentraland), SAND (“The Sandbox”), ETH (Ether), and BTC (Bitcoin) covering the entire time series 2 February 2018, to 15 March 2023. SAND, due to a later launch covers 14 August 2020, to 15 March 2023.

<i>n</i> =	MANA 1868	SAND 944	ETH 1868	BTC 1868
Minimum	0.0179	0.0308	84.31	3228.700
Mean	0.5625	1.2402	1163.9481	20,509.0342
Maximum	5.1950	8.4022	4812.0900	67,527.9000
Median	0.0960	0.7165	557.6200	11,337.8499
Standard Deviation	0.8783	1.5007	1189.0905	16,762.4430
Skewness	2.3304	1.9036	1.1213	1.0097
Kurtosis	5.3721	3.1073	0.1991	−0.2605

The standard deviation is relatively similar across the different considered tokens (based on perspective); the lower standard deviation in BTC is noticeable and signifies that the data are clustered around the mean, meaning it shows less volatility than the other considered tokens and results in lower investment risk. On the contrary, MANA and SAND show a higher standard deviation and are, therefore, associated with higher volatility and, subsequently, higher risk. All considered tokens show positive skewness, indicating a price distribution towards higher values. MANA and SAND exhibit higher values compared to their peers, meaning these two are particularly skewed to the right—long right tail. MANA and BTC exhibit relatively high kurtosis values, indicating heavier tails in their price distributions compared to a normal distribution, suggesting extreme price events are more likely. SAND and ETH have their price distribution closer to a normal distribution based on lower values.

Overall, the tokens considered in this study show comovement in their main descriptive characteristics (this will be discussed further in Results; Section 3).

2.2. Methodology

2.2.1. Seasonal ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) method is widely used in time-series forecasting, particularly in the field of finance, for predicting market movements (among other stock prices). Numerous researchers have applied this model, including Poongodi et al. [24] and U et al. [51]. The ARIMA model was introduced by Box and Jenkins [52]; therefore, it is also known as the Box-Jenkins Model.

The model is comprised of three components: Autoregression (AR), differencing (I), and Moving Average (MA). This combination allows a flexible approach to analyzing and forecasting time series, such as linear and nonlinear trends, and seasonal and non-seasonal fluctuations based on statistical methods and theory.

The model, however, requires stationary data, which means that the statistical characteristics of the time series remain constant throughout time (e.g., mean and standard deviation). When this is not the case, data are non-stationary (i.e., stock price data) and need to be transformed. Hence, it is necessary to check before using the model.

The Augmented Dickey–Fuller (ADF) test is mainly used for this, identifying whether a time series is stationary or non-stationary by checking for the presence of a unit root [25]. In this test, the null hypothesis assumes that the time series is non-stationary. If the p -value of the test is smaller than the significance level (0.05), the null hypothesis may be rejected, and the time series is considered stationary. In our case, the ADF test yields a p -value of 0.78 for MANA, leading us to conclude that our data are non-stationary; we fail to reject the null hypothesis. To convert non-stationary data into stationary, we use differencing; this involves subtracting consecutive observations from one another. By doing so, our ADF test rejects the null hypothesis, and the time series is considered stationary—the p -value is smaller than the significance level (0.05).

Given the presence of seasonal effects in our dataset, which we base on analyzing the Autocorrelation Function (ACF) and several other hypotheses, such as increased trading and blockchain activity during winter months (internet usage shadow) and the effect of public holidays (i.e., Christmas). An upgraded version of the model is used to capture the seasonality aspect:

$$\text{SeasonalARIMA}(p, d, q)(P, D, Q)_s \quad (1)$$

where:

p = autoregressive—allows incorporating the effect of past values;

d = integrated—allows incorporating differencing (i.e., the number of past time points to subtract from current values);

q = moving average—allows setting the error of the model as a linear combination of the error values observed at previous time points in the past;

“ s ” = the subscripted letter shows the length of the seasonal period. P, D, Q follow the exact definition only for the seasonal component of the time series.

To meet our aim of predicting future price trends, we follow a machine learning approach; this means splitting the data set into train and test. The common ratio of the split is 75% train and 25% test; which is not conducted randomly but more so by taking the first 75% of the time series as train set and the remaining 25% as test set in order to maintain temporal order.

The seasonal component is derived by analyzing the time series graphically and with further techniques, such as ACF, which specifies the average relationship between successive data points within a time series—we will not describe this further; however, it is a necessary step in deriving the right seasonal ARIMA fit. Now, to evaluate and compare the fit of different models with varying parameters, it is essential to rank each model against each other.

For this purpose, we utilize the Akaike Information Criterion (AIC), which measures the goodness of fit of a model while considering its overall complexity. AIC is frequently used in machine learning practice for time series or small data sets in cases where evaluating the model’s performance on the test set is challenging. The primary objective is to minimize the AIC value, signifying an optimal trade-off between model fit and generalizability; this aims to enhance the model’s capacity to perform well on out-of-sample data. The model uses the maximum logarithmic likelihood estimation as a measure of fit (high log-likelihoods tend to yield lower AIC values).

To identify the best fit, we use a grid search (Grid search involves exhaustively exploring a predefined subset of hyperparameter space for the targeted algorithm [53]) approach, which iteratively explores combinations of the parameter (p, d, q, P, D, Q) showing the AIC value.

The seasonal ARIMA model may be written mathematically as follows:

$$\phi_p(B)\phi_p(B^s)z_t = \delta + \theta_q(B)\theta_Q(B^s)a_t \quad (2)$$

where:

B = backward shift operator

z_t = level of differencing

δ = notated constant

ϕ = autoregressive operator

a = random shock corresponding to time t

θ = moving-average operator

To assess the model's accuracy, we compute the Mean Squared Error (MSE) and the Mean Absolute Percentage Error (MAPE). Both measures give us comparability with our peers.

2.2.2. Log-Periodic Power Law Singularity (LPPLS)

As put forward by Johansen et al. [54], bubbles are considered to be the result of unsustainable growth (faster than exponential), obtaining an infinite return in finite time (singularity). This, in turn, forces a correction of the regime in the real world.

We employ the Log-Periodic Power Law (LPPL) model to describe specific complex systems' behavior during market crashes. Johansen, Ledoit, and Sornette first introduced the model in 2000 [54]. This model is based on the concept that the price dynamics of systems exhibit recognizable patterns characterized by logarithmic periodic oscillations leading up to a critical point, such as a bubble burst [12,33,54,55]. In light of our data's characteristics (i.e., abrupt price changes), we choose to use an extended version of the LPPL model called the Log-periodic Power Law Singularity (LPPLS) model. The LPPLS model incorporates the notion of singularities to account for abrupt and discontinuous changes in price dynamics. This extension provides more flexibility in modeling extreme events or nonlinear behavior. The LPPLS model acknowledges that price dynamics can exhibit non-smooth behavior, deviating from the continuous and smooth oscillations assumed by the standard LPPL model, particularly during periods of intense market stress or systemic shocks. By including singularities, the LPPLS model offers a more accurate representation of market dynamics when sudden and significant shifts in sentiment or market conditions occur. In other words, positive (negative) bubbles are distinguished by a rate of price growth (decline) that surpasses exponential patterns, as opposed to a simple exponential increase (decrease) in price [56,57]. Essentially, the focus of the LPPLS model is on identifying bubbles and forecasting turning points in the market. It can be written as follows:

$$E[\ln p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln(t_c - t) - \phi) \quad (3)$$

where:

$E[\ln p(t)]$ = expected log price at a given time t

A = expected log price at the peak at t_c

B = amplitude of power law acceleration

C = amplitude of log-periodic oscillations

m = degree of super-exponential growth

ω = scaling ratio of the temporal hierarchy of oscillations

ϕ = time scale of oscillations

t_c = critical time, transitions to another regime

According to the theory of the Log-Periodic Power Law (LPPL) model, it is claimed that the following relationship remains valid during a bubble period

$$\ln[p_i] = LPPL(t_i; A; B; C; t_c; m; \omega; \phi) + \epsilon_i \quad (4)$$

where t_1, \dots, t_n and p_1, \dots, p_n correspond to the historical data of the considered time series, while ϵ_i , for $i = 1, \dots, n$, are the discrepancies or errors between the predicted values and the actual values in the analysis.

To fit the LPPLS model, we utilize the Ordinary Least Squares (OLS) method. This optimization technique minimizes the squared residuals to estimate the parameters of our LPPLS model, namely A , B , C , m , ω , ϕ , and t_c , within a defined time range $[t_1, t_2]$.

Our calibration process follows the approach described by Filimonov and Sornette [58], where we eliminate a nonlinear parameter ϕ . As a consequence of eliminating the quasi-periodicity from the cost function (The cost function evaluates a machine learning model's performance on given data by quantifying the discrepancy between the predicted and expected values and expressing this discrepancy as a single real number), the primary property that previously necessitated the application of non-rigorous metaheuristic searches no longer holds, and rigorous search (Non-rigorous metaheuristic search methods prioritize computational efficiency and flexibility over ensuring optimality, while rigorous search methods focus on achieving optimality but may encounter feasibility challenges in problems with extensive search spaces) methods become adequate for the task—we, therefore, expand Equation (3):

$$E[\ln p(t)] = A + (t_c - t)^m \{B + C_1 \cos[\omega \ln(t_c - t)] + C_2 \sin[\omega \ln(t_c - t)]\} \tag{5}$$

where $C_1 = C \cos \phi$ and $C_2 = C \sin \phi$.

When employing the LPPLS model, commonly, conditions for nonlinear parameters (m, ω, t_c) are based on empirical evidence from past bubbles [12]. These conditions are defined in the literature and build reliability and validity of the model itself (see [34,59,60]).

$$\max \left\{ t_2 - 60, \frac{t_2 - 0.5}{t_2 - t_1} \right\} < t_c < \min \left\{ t_2 + 252, \frac{t_2 + 0.5}{t_2 - t_1} \right\},$$

$$0 < m < 1, \tag{6}$$

$$2 < \omega < 15. \tag{7}$$

We iterate the calibration by shrinking the time frame to make bubble predictions at each data period. In this context, t_1 corresponds to an earlier day of t_2 , while t_2 represents a fictitious present day. Initially, the window range is set at 120 days, with a shrinking interval of t_1 as 5 days. Since the prediction relies solely on historical data as input, the outcome for t_2 solely depends on data from t_2 to the last 120 days.

To compute the results of the LPPLS model, we use a Confidence Indicator. This indicator predicts and visualizes positive and negative bubble indications for a given t_2 , with a total of 24 outcomes. The Confidence Indicator counts the number of $B < 0$ and $B > 0$, where the former implies a positive bubble (price increases faster than exponential), and the latter indicates a negative bubble (price decreases faster than exponential).

The 24 outcomes now classified into $B < 0, B > 0$ are filtered, based on empirical evidence of previous bubble investigations [34,60]. The filter in Equation (8) ensures that the time it takes for the oscillation to complete is big enough. Moreover, as you approach the critical time (t_c), the frequency of oscillations (ω) increases. The filter in Equation (9), as derived by [60,61], is set by definition.

$$\frac{\omega}{2\pi} \cdot \ln \frac{t_c - t_1}{t_c - t_2} > 2.5 \tag{8}$$

$$\frac{m|B|}{\omega|C|} > 0.5 \tag{9}$$

We group the outcomes, which satisfied the filter conditions above, into $[B < 0]_{\text{count}}^*$ and $[B > 0]_{\text{count}}^*$. Our Confidence Indicator of a given t_2 is computed as

$$\text{confidenceindicator}(\text{pos}) = \frac{[B < 0]_{\text{count}}^*}{[B < 0]_{\text{count}}} \tag{10}$$

$$\text{confidenceindicator}(\text{neg}) = \frac{[B > 0]_{\text{count}}^*}{[B > 0]_{\text{count}}} \quad (11)$$

Here, the Confidence Indicator shows how much of a bubble has formed in the $[0, 1]$ range based on the price at time t_2 . This quantifies the possibility of a price movement in the near future; in the case of a negative bubble, it suggests a price decline, whereas in the case of a positive bubble, it suggests a price increase—regime changes. The LPPLS model derives these values for all t_2 and visualizes its predictions.

Although the LPPLS model can effectively capture the rapid price dynamics and exponential growth rates linked to market bubbles, it lacks a specific mechanism to identify or distinguish structural breaks as explosive phenomena. The primary objective of the LPPLS model is to recognize crucial inflection points and forecast the possible collapse or reversal of the bubble rather than explicitly characterizing explosive behavior.

To further distinguish the severity of impact caused by identified price accelerations, we follow a common definition of percentage changes in price throughout the bubble duration (beginning to end price). Now we choose three categories: (i) market dip (price change of less or equal than 10%), (ii) market correction (price change between 10% and 20%), (iii) market crash (price change of greater or equal 20%). Therefore, when referring to financial bubbles (positive and negative), the definition of a price change of 20% or more holds throughout this paper.

3. Results

3.1. Results from SARIMA Model

As we have already mentioned in the Methodology section, we used differencing to transform our data into stationary. The Augmented Dickey–Fuller (ADF) test results in (-21.62) , which is smaller than the critical values (-3.43) and (-2.86) at the 5% and 10% significance levels, respectively. Therefore, our data were transformed correctly into stationary.

Since we chose to follow the machine learning approach and split our data into training (first 75%) and testing (remaining 25%), we aim to analyze how well we can predict the prices of the unseen data (test). While fitting the model to the data, the seasonality component is set at $s = 4$. This is derived using various factors, for example, Autocorrelation Function (ACF). The best model fit, based on Akaike Information Criterion (AIC), is SARIMA $(1, 0, 0)(1, 0, 1, 4)$, which we explored using grid search, choosing the one with the smallest AIC (-3190.6981) —the model results are as follows:

Based on the results in Table 2, we can interpret that the model indicates a strong positive autocorrelation with *ar.L1* coefficient being positive (0.9985); this shows a strong tendency for the values being positively related to their immediate past values. Furthermore, the seasonal components *ar.S.L4* and *ma.S.L4* with the derived order of 4 suggest a strong seasonal positive autocorrelation. This means *ar.S.L4* (0.9936) positively influences the current value by its seasonal counterpart from four periods ago; on the other hand, however, *ma.S.L4* (-0.9904) indicates a negative influence of the error term from previous seasonal periods on current values. *Sigma2* (0.0063) represents the variance of the error term, which suggests a good model fit due to a relatively low amount of unexplained variability.

Table 2. SARIMA model results using SARIMA $(1, 0, 0)(1, 0, 1, 4)$ on the train data (75% of dataset).

	Coefficient	Standard Error	Z-Value	p-Value	0.025	0.975
ar.L1	0.9985	0.002	514.157	0.000	0.995	1.002
ar.S.L4	0.9936	0.021	46.338	0.000	0.952	1.036
ma.S.L4	-0.9904	0.023	-43.214	0.000	-1.035	-0.945
sigma2	0.0063	7.73×10^{-5}	81.816	0.000	0.006	0.006

Overall, the high significance of the coefficient estimates (as the p -values indicate) suggests a well-fitted model, which provides a good representation of the underlying data; this, in turn, is confirmed by our accuracy measures, an MSE of 0.0083 and a MAPE of 0.2909%; this in turn results in 70.91% accuracy.

Considering the goodness of fit achieved by the model, we have used the train data fit to predict the unseen test data (remaining 25%). The result shows that the model can capture the trend but not accurate price points, with an MSE of 1.6530 and accuracy of 30.12%—Figure 2.

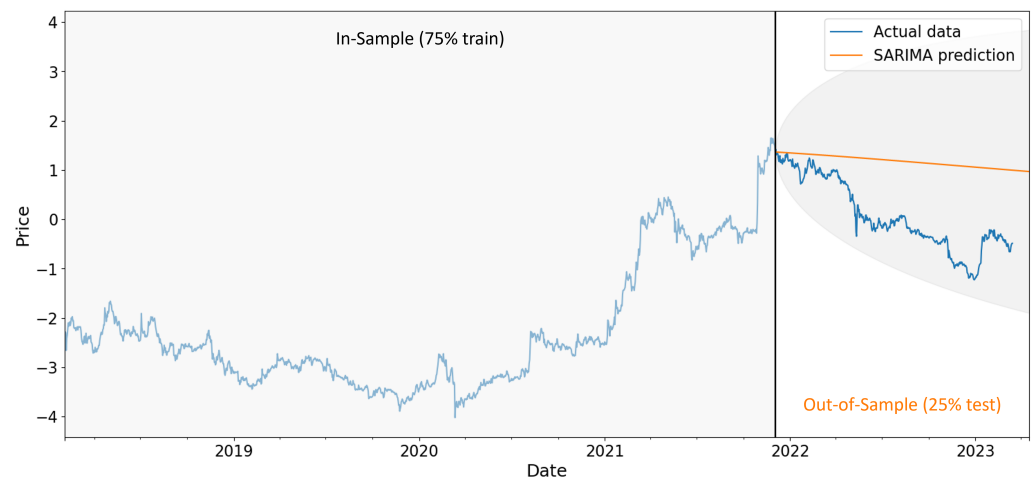


Figure 2. SARIMA model prediction on unseen data. The Out-of-Sample data (remaining 25%) was predicted by a SARIMA model based on the train data (first 75%). The trend is captured; however, an accurate price development is not captured.

Based on our analysis using Seasonal ARIMA, we derive that MANA expresses a declining price trend, showing signs of instability. This, in turn, means we can estimate if and when the price starts to decrease; however, we cannot precisely estimate price points.

3.2. Result from LPPLS Model

Overall, the LPPLS model shows a good fit and accurately captures the MANA trend (see Appendix A Figure A1); in Table 3, the model raw results are given for all considered cryptocurrencies.

As the critical time (t_c) for SAND and ETH are projected to enter into a bubble at a date that has passed at the time of writing this paper (see Table 3, t_c), we are able to undermine the prediction with real-world data. The predicted regime change (t_c) for SAND on 23 April 2023 indicates, as depicted in Table 3, a negative bubble (A shows the expected value at t_c being $e^{-0.4327}$, which is USD 0.6487). Looking at the actual price chart, we see that SAND accurately enters a negative bubble, the expected price (A) being achieved four days before our prediction 19 April 2023 (Please see actual price chart as reference <https://coinmarketcap.com/currencies/the-sandbox>, accessed 12 June 2023).

Table 3. Prediction results of LPPLS model of all considered datasets across entire time series 2 February 2018 to 15 March 2023, using daily data frequency. A represents the expected value at the peak time t_c . B states the steepness of the oscillation within the time range of t and t_c ; C is the amplitude of log-periodic oscillations; m is the degree of super-exponential growth; ω is the oscillations frequency and c_1, c_2 are constants determining the shape..

	A	B	C	m	ω	c_1	c_2	t_c
MANA	-12.1341	143.1350	-1.2134	-0.3516	8.1304	-6.0181	17.1913	5 July 2025
SAND	-0.4327	2.0597	4.8706	1.6765	3.2276	4.8597	3.2634	23 April 2023
ETH	7.3582	2.0270	0.0015	1.0310	3.1468	0.0014	0.0005	12 April 2023
BTC	-4.3041	23.1065	1.3118	-0.0688	5.4534	1.2861	0.2583	20 July 2024

The critical time (t_c) for *ETH* is, as shown in Table 3, projected to be on 4 April 2023, suggesting a positive bubble (A shows the expected value at t_c being $e^{7.3582}$, which is USD 1569.01). Comparing our LPPLS prediction with the actual data, *ETH* enters a positive bubble. The predicted price (A), however, is reached four weeks earlier on 12 March 2023 (Please see actual price chart as reference <https://coinmarketcap.com/currencies/ethereum/>, accessed 12 June 2023).

Our model works well, considering the “LPPLS model fit” (Appendix A—Figure A1) and the real-world proof of regime changes (t_c), which already makes this technique reputable for investors and policymakers alike.

Using the shrinking window calibration, starting at 120 days with a shrinking interval of 5 days, the LPPLS Confidence Indicator shows the strength of inflection points rather than explosive behavior. As mentioned earlier in this paper, we focus on bubble detection in Decentraland, which is represented by its currency, MANA. Therefore, an in-depth analysis of other considered datasets is not provided; you can find the LPPLS Confidence Indicator plot for all considered cryptocurrencies in the Appendix A (Figures A2–A4). Looking at the confidence indicators of all considered cryptocurrencies, MANA, SAND, BTC, ETH, it shows significant visual signs of comovement as analyzed in-depth by De Pace and Rao [62]. Due to this close comovement, it comes as no surprise that the applied LPPLS model identifies indications around the same times (distorted, of course, which can be accounted for the difference in price).

In Figure 3, the red color indicates positive bubbles, whereas the green color marks negative bubbles. Overall, both bubble predictions capture the time series well empirically; four detections catch the eye immediately; therefore, we will explain these in more detail. All detected price decreases are shown and categorized in Table 4, and all price increases in Table 5.

The turning of the year 2018 to 2019, we can see a negative bubble indication; this may be traced back to the vote to remove inflation from the virtual world, and a 1% marketplace fee was introduced; the bubble occurred from 30 December 2018 to 11 February 2019.

At the beginning of 2020, in March, to be specific, MANA reached its lowest point to date, trading at USD 0.0237. The model predicts a regime shift (price decline) towards the second quarter of 2022. The strongest indication of a bubble forming is given on 1 May 2022. During the 54 days of decline, the price started to decrease by 41.38% from 1.5262 to 0.8947 (with its lowest point at 0.7700 on 11 May 2022).

It is worth mentioning that the LPPLS model has identified positive bubbles as well. Two major ones, one after the other, which we are able to predict, took place at the beginning of 2021—12 January 2021, until 21 March 2021—where prices surged from 0.1101 up to a, to date, record high of 1.0602.

Our date stamping of both negative and positive bubbles highlights the opportunities the metaverse cosmos has provided. Identifying the raw data of the LPPLS Confidence Indicator, we can time stamp the occurred bubbles and take the price decrease/increase in percentage.

Based on our categorization in the covered time frame, the LPPLS model indicates only two bubbles over the period considered. Other indications by the model are categorized into market dips (four indications) and market corrections (two indications).

Comparing the negatively identified indicators with the positive ones, applying the same categorization, six indications can be labeled as financial bubbles with an average price increase of 71.22% in a much shorter duration than negative bubbles.

Based on our analysis, we demonstrate that the market is not “dead” and has much more upside potential than downside. Based on our SARIMA example, the market is currently decreasing; however, looking at it empirically, the development and time stamping of bubbles allow us to draw a conclusion on the viability of it being a diversifiable asset class/an investment opportunity. Based on our results, it is a long-term investment, which will most likely not be profitable in the short term; nonetheless, price movements identified much more upside (six positive bubbles) than downside (two negative bubbles).

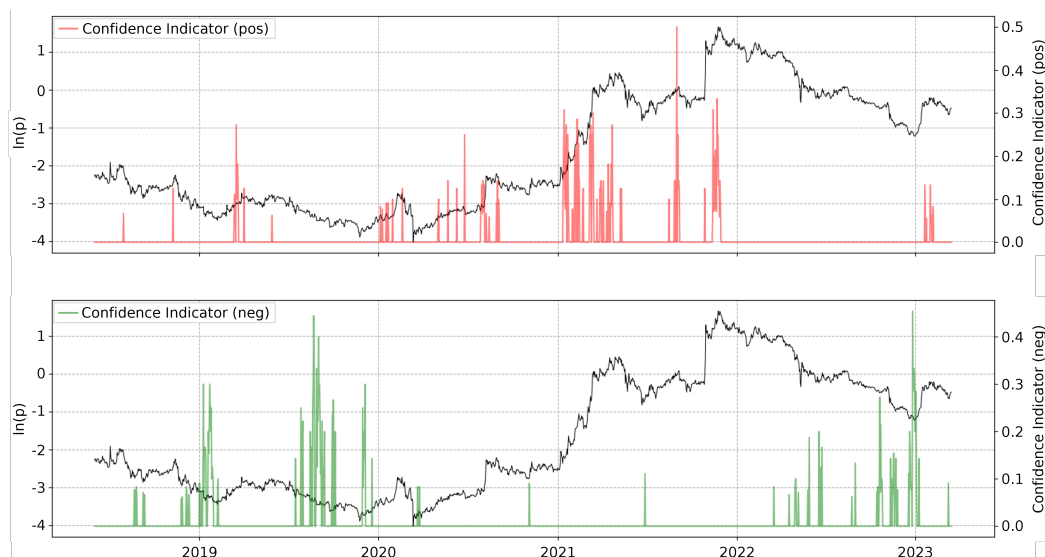


Figure 3. MANA–LPPLS Confidence Indicator visualized. Positive (red) and negative (green) bubbles are depicted separately based on the LPPLS model applied, as discussed in Methodology; Section 2.2.2.

Table 4. Prediction results of LPPLS Confidence Indicator for **negative bubbles** in MANA. In this table, we consider bubbles that are identified by the LPPLS model. Based on the price decline, the categorization into the market dip (<10%), market correction (>10%, <20%), and financial bubble (>20%) is conducted manually.

Bubble (neg)	Start	End	Days	Mean Price	Price Decrease	Bubble Category
1	19-08-2018	26-08-2018	8 Days	0.0680	−7.31%	market dip
2	30-11-2018	12-12-2018	13 Days	0.0593	−7.63 %	market dip
3	30-12-2018	11-02-2019	44 Days	0.0386	−27.51%	financial bubble
4	18-08-2019	15-09-2019	29 Days	0.0332	−13.82%	market correction
5	29-11-2019	07-12-2019	9 Days	0.0246	−4.60%	market dip
6	01-05-2022	23-06-2022	54 Days	1.0511	−41.38%	financial bubble
7	14-10-2022	24-10-2022	11 Days	0.0621	−3.21%	market dip
8	12-11-2022	27-11-2022	16 Days	0.4126	−13.93%	market correction

Table 5. Prediction results of LPPLS Confidence Indicator for **positive bubbles** in MANA. In this table, we consider bubbles which are identified by the LPPLS model. Based on the price increase, the categorization into market dip (<10%), market correction (>10%, <20%), and financial bubble (>20%) is conducted manually.

Bubble (pos)	Start	End	Days	Mean Price	Price Increase	Bubble Category
1	12-03-2019	04-04-2019	24 Days	0.0525	26.60%	financial bubble
2	30-07-2020	06-08-2020	8 Days	0.0482	22.03%	financial bubble
3	12-01-2021	15-02-2021	35 Days	0.1833	169.48%	financial bubble
4	04-03-2021	21-03-2021	18 Days	0.7260	134.64%	financial bubble
5	02-04-2021	23-04-2021	22 Days	1.1491	19.47%	market correction
6	18-08-2021	06-09-2021	20 Days	0.9355	34.26%	financial bubble
7	13-11-2021	01-12-2021	19 Days	4.1629	40.29%	financial bubble
8	21-01-2023	04-02-2023	15 Days	0.7354	9.12%	market dip

It is possible for regulators to use this information and issue signals to stakeholders, such as investors, to preventively mitigate the damage caused by financial bubbles (positive and negative). Additionally, we have identified periods where bubbles are not detected, suggesting that the underlying asset has some intrinsic value and is not merely dismissed as a bubble [63].

3.3. Contextual Considerations: COVID-19

The findings of our financial analysis must be viewed in the context of the unprecedented market conditions during the COVID-19 pandemic, which started in early 2020 and, therefore, is included in our analysis.

The pandemic introduced significant volatility in financial markets, driven by extensive economic shocks and heightened uncertainty. This was further compounded by the response of corporate entities, which, facing demand shocks and financial constraints, significantly delayed investment decisions [64], which resulted in market unpredictability. Moreover, the period of analysis coincides with aggressive fiscal interventions and unconventional monetary policies (UMPs) implemented by central banks around the globe. These policies, while stabilizing, also infused substantial liquidity into financial systems. According to Cortes et al. [65], while UMPs were instrumental in mitigating immediate disaster risks, they simultaneously heightened the risk of market distortions. The increased liquidity and lower borrowing costs combined with decreased spending per individual due to “lockdowns” may have encouraged speculative investment behaviors, potentially contributing to the inflation of cryptocurrency investments (including metaverse ventures) and the, therefore, forming of bubbles.

These observations suggest that the COVID-19 pandemic and subsequent monetary expansion have been critical factors affecting market volatility, spending habits, and, hence, price dynamics during the period under study. Recognizing these influences is essential for interpreting our results in Sections 3.1 and 3.2.

3.4. Practical Relevance

To understand how we may leverage our bubble identification knowledge to yield positive returns, we use the results of the previous sections as indicators to simulate trading actions.

Based on the LPPLS Confidence Indicator in Figure 3 and, subsequently, Tables 4 and 5 in the previous (Section 3.2 Results from LPPLS model), we define our strategy to be a straightforward buy-and-sell approach.

The returns are calculated on a simulated portfolio with the strategy of going long. We purchase MANA on 26 June 2018 on the second official trading day of the cryptocurrency at USD 0.1062 (equal to 1 MANA). Our portfolio holds USD 100 worth of MANA. Whenever a negative bubble is signaled, we choose to sell the day before the bubble; on the other hand, when a positive bubble is signaled, we hold until the peak of that bubble. This approach is subject to standard market volatility as we experience some losses even when selling in time.

Figure 4 depicts this, for convenience, with the detected bubbles (Section 3.2—Tables 4 and 5) as well as the buy and sell signals.

Our approach, following the LPPLS Confidence Indicator, yields at the end of our time series (15 March 2023) 15,428.16% with an average of 1028.54% per trade (based on 8 positive trades and 7 negative ones). The calculated Sharpe Ratio of 0.6017 indicates a sub-optimal return ratio (10-year US Treasury Rate of 3.51% taken as the risk-free rate, accessed on 1 December 2023).

In comparison, a standard Buy-and-Hold (B&H) strategy within the same time frame (26 June 2018 to 15 March 2023) yields 477.87%.

This shows how lucrative bubble identification may be, taking into account the limitations (as discussed in previous sections); the LPPLS model can signal us the next critical time (t_c) for which our next trade would be made.

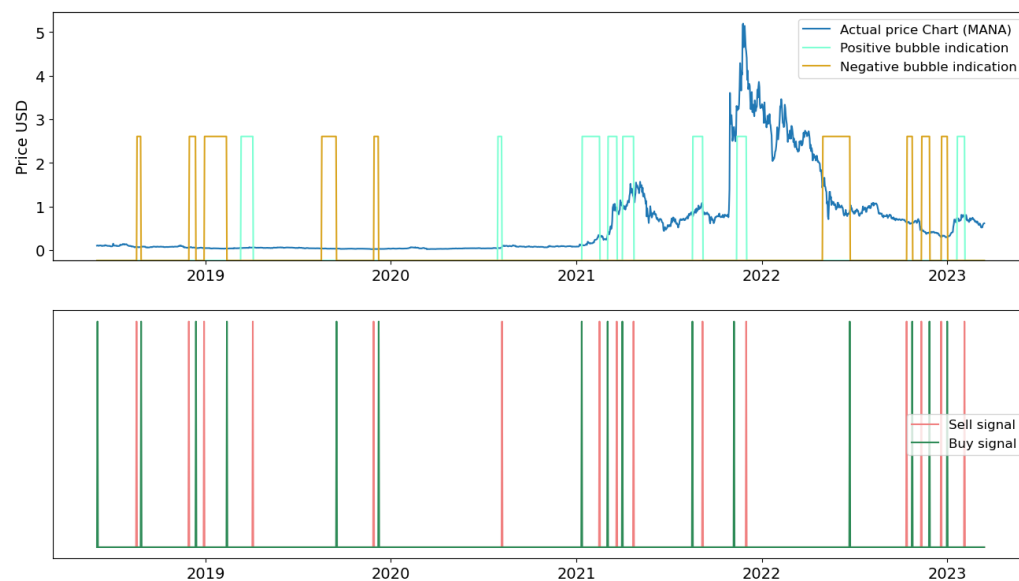


Figure 4. MANA—Buy and Sell based on *LPPLS Confidence Indicator* outcome. We go long and depict our Buy (green) and Sell (red) signals based on the identified bubbles: negative bubble (gold) and positive bubble (turquoise). The first investment is on 26 June 2018 at USD 0.1062.

4. Discussion

4.1. Discussion of SARIMA Results

Previous studies focused exclusively on predicting future price trends of cryptocurrencies or bubble identification, focusing on Bitcoin.

A study conducted in 2014 by Mondal et al. [23] examined the effectiveness of time-series analysis in forecasting stock values in India. The researchers analyzed data spanning 23 months and found that the ARIMA model predicted stock market fluctuations with an accuracy rate exceeding 85%.

Furthermore, Daryl et al. [66] predict Apple stock prices using SARIMA; as stocks are not static and prices vary over time, the SARIMA model can work with these data. Their final result amounts to 36% accuracy, claiming the model works as intended; nonetheless, it is unable to predict the real-time stock value due to its volatility. Based on the finding of Mondal et al. [23]; Poongodi et al. [24] used the ARIMA model without seasonality to estimate Bitcoin closure rates in 2021. In comparison, their analysis resulted in 49% accuracy. Sahay et al. [25], conducted a research-based analysis on the metaverse. They have taken various metaverse crypto tokens, among which MANA and SAND, and fitted ARIMA as well as SARIMA models, resulting in a fit of 88% accuracy for MANA using the ARIMA model and a 93.6% accuracy for SAND using SARIMA.

Based on Daryl et al. [66] and Sahay et al. [25] results, we have chosen to apply the SARIMA model to our MANA data as it incorporates seasonal effects, i.e., periodic consequences and exogenous factors. Furthermore, we argue that MANA and SAND are equally turbulent, too non-stationary, and may not be fitted into a basic ARIMA model; as mentioned earlier in this paper, the two metaverses move similarly and show significant signs of comovement.

Our outcome reflects Daryl et al. [66] results, as we result in a 30.12% accuracy with a high MSE (1.653) on the test set (remaining 25% of data). The train set (75% of data) shows a good fit with an accuracy of 70.91% and an MSE of 0.0083. As the only comparable study is the paper from Sahay et al. [25], we cannot match their obtained accuracy (MANA with 88%). This can be subject to (i) the exclusion of the seasonal component by Sahay et al. [25], and (ii) the considered time series (April 2021 to April 2022). Both can result in the difference in obtained results, whereby the chosen models are said to be good predictors in the short term but do not uphold the accuracy when predicting long-term with a long time series [25].

Nonetheless, our models' performance is significant and predicts the price trend for unseen future data.

4.2. Discussion on Bubbles

Bubbles have been mostly defined by the deviation of actual price based on the fundamental price [13,15]. Cryptocurrencies, in general, make it difficult to identify their fundamental value [20]; others take a more aggressive position in arguing their fundamental value is zero (i.e., Cheah and Fry [67]).

Based on the disagreement of cryptocurrencies' fundamental value, we choose to follow Johansen et al. [33] and Sornette [12] in terms of focusing not on the deviation but rather on the explosiveness of price as the characteristic of a bubble.

This choice supports our research question of bubble identification instead of bubble heritage (where does the bubble come from). Furthermore, Abreu and Brunneimeier [16] state that sophisticated investors tend to exit the market just before the burst. Based on our presented analysis, we establish that this is not the case for cryptocurrencies (esp. MANA), as investors are driven by speculators. We argue our conclusion to be true with the analysis of Almeida and Gonçalves [68], who establish various trades of cryptocurrency investors, of which one states: "The uncertainty of fundamentals leads to investors' dispersed beliefs, leading to high trading and speculative bubbles".

4.3. Discussion of LPPLS Results

Academic literature offers wider empirical evidence on bubble behavior, mainly on the specific course of Bitcoin (BTC) using the LPPLS model, especially [37,40,41,69]. Directly corresponding with our research is in part Ito et al. [42], which conducted a time-series analysis of selected NFT weekly moving-average prices using the LPPLS model. Their result in terms of Decentraland (MANA) is a price decline prediction, which is not further elaborated upon. Ito et al. [42] have focused not solely on MANA but more on a variety of NFT data. Furthermore, the LPPLS model is applied. However, no in-depth analysis of any considered token is shared, except the confidence indicator charts (such as Figure 3).

When comparing our confidence indicators with Ito et al. [42], we can see how they indicate the same bubbles; however, they moved about on the time axis. This is due to the fact of our time series being longer and including a drastic decline in price throughout 2022 (approx. -92%); here, the Ito et al. [42] study ends and indicates a negative bubble just slightly before 2022 (their data end on 20 December 2021). Our finding is consistent, as we also have a heavy positive bubble identification towards the end of 2021, except our result shows a higher indicator.

5. Conclusions

This study sheds light on the validity and stability of Decentraland (MANA) as a representation of the metaverse cosmos as a whole. Having analyzed the seasonality and trend of MANA to choose the best model to apply SARIMA, an insight into the dynamics of the cryptocurrency is provided—MANA behaves like any stock price time series (e.g., Daryl et al. [66]). Furthermore, we find common ground by looking at future price predictability and obtain comparable results, which are in line with [23–25,66]; meaning accuracy is reasonable and within the range of empirical studies. None of the studies mentioned above managed to predict exact price data points but solely price trends [25].

Focusing on financial bubble identification, making use of Johansen et al. [54] LPPLS model, this study uses the calibration as put forward by Filimonov and Sornette [58]. Herewith, we identify twelve bubbles, six positive and six negative ones, which we can timestamp.

We conclude the bubble identification with a practical example and derive a 15,428.16% return on investment when selling and buying according to the model identification; this should be investigated in further research.

By closely understanding MANA's dynamics, we are one step closer to comprehending metaverse price behavior. This, in turn, may support investors (speculators and sophisticated), enthusiasts, and policymakers to adjust their risk-management tools and look towards the growing metaverse cosmos as a serious investment class. Financial risk mitigation and minimization of the impact of this asset class can be provided and signaled to the market.

This study has focused on MANA to shed light further light on the metaverse. However, other virtual worlds that are not based on cryptocurrency may be investigated (i.e., Upland).

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Appendix A

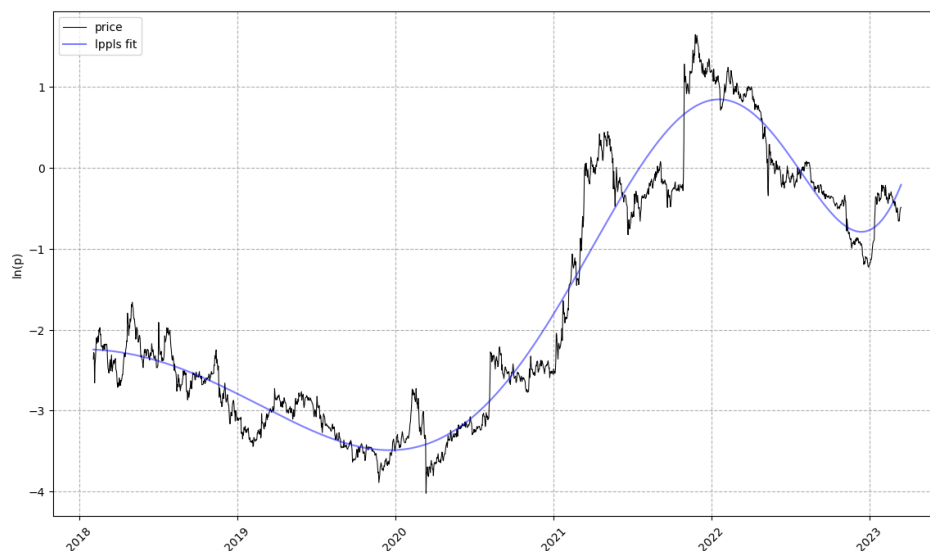


Figure A1. MANA–LPPLS model fit. The model manages to capture the trend well and creates the foundation of bubble indication.

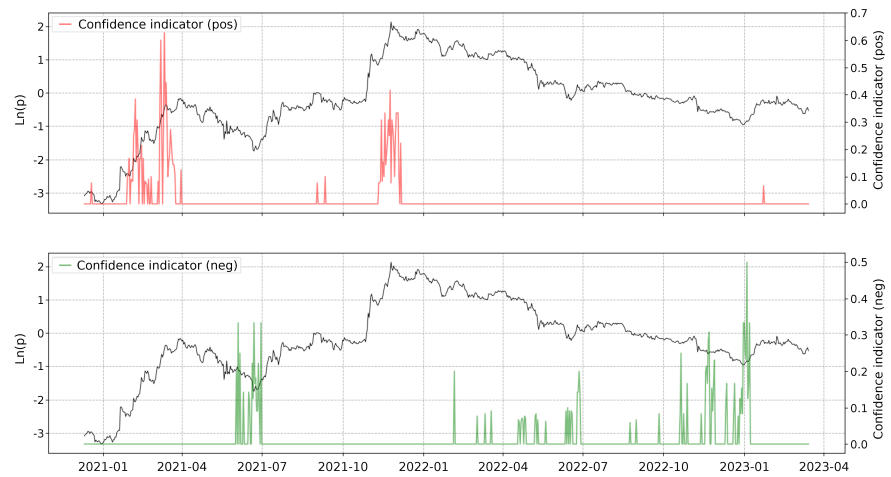


Figure A2. SAND–LPPLS Confidence Indicator visualized. Positive (red) and negative (green) bubbles are depicted separately based on the LPPLS model applied, as discussed in Methodology; Section 2.2.2.

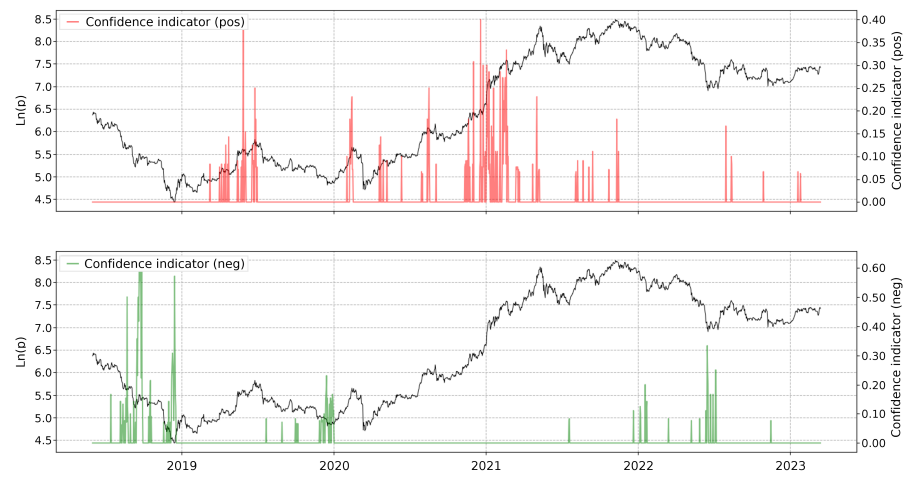


Figure A3. Ether–LPPLS Confidence Indicator visualized. Positive (red) and negative (green) bubbles are depicted separately based on the LPPLS model applied, as discussed in Methodology; Section 2.2.2.

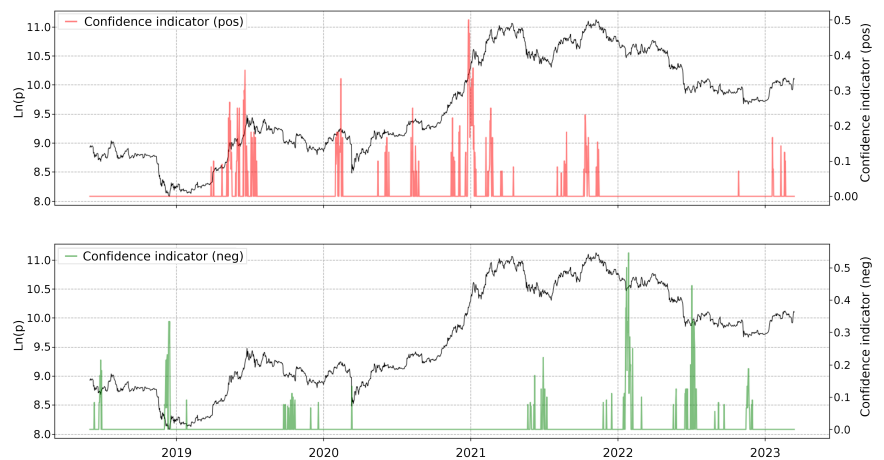


Figure A4. Bitcoin–LPPLS Confidence Indicator visualized. Positive (red) and negative (green) bubbles are depicted separately based on the LPPLS model applied, as discussed in Methodology; Section 2.2.2.

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