Modeling and optimization cognitive of financial behavior: case of public investment

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ABSTRACT

Investment is a necessity for the sustainability and prosperity of companies. The investment behavior of companies has been the subject of numerous theoretical and empirical studies. The goal is to identify the determinants of companies' investment, that is, the variables that influence their investment decisions. The study of financial behavior through artificial intelligence, which is a very powerful and recent tool nowadays, enables better decision-making in the field of investment.

The ARIMA model is used for the prediction of purchase/sale values, and by combining these predicted values with investment parameters, we can determine investment behavior using neural networks.

Keywords: *Optimization, prediction, activities, dynamic system, neural networks, ARIMA.*

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1 INTRODUCTION

In cognitive sciences, the definition of the mind is based on the conception of the human mind as a natural phenomenon intrinsically linked physically to the brain.

To study the multiple facets of the human mind, different approaches have been adopted in various fields, including biological, neurological, and symbolic.

Modeling financial behavior is an analytical approach aimed at mathematically representing the actions and reactions of actors in financial markets. This modeling can take various forms, ranging from simple models to more complex ones, and it is used to understand, predict, and interpret movements in financial markets.

Often, modeling a complex system raises questions about optimization for the forecast of a dynamic system. The question asked is whether analytical models can solve truly complex problems. "A dynamic system is a sustainable arrangement of interconnected elements forming a unified whole," as stated by Josh Kaufman (2013, p. 377). This raises questions about its modeling.

Optimization is considered as the action of developing an activity in the most efficient way possible, that is, with the fewest resources and in the shortest possible time. In other words, optimization means accomplishing a task in the best possible way and can be applied to various fields such as business administration, economics, and information technology. Optimization, in general, involves achieving the best performance of something by using resources in the best possible way.

How can cognitive sciences impact and supervise the dynamic system, thus facilitating decision-makers' adaptation to the optimization context?

The objective of this article is to explain modeling methods based on the combination of ARIMA transformation and perceptron neural networks, in order to represent a dynamic system of financial behavior applicable to public investment.

The rest of this article is organized as follows. Section 2 presents various previous works related to this question. In section 3, we detail the application models we used to find solutions. Finally, we conclude this article and present our future work in section 4.

2 LITERATURE REVIEW

2.1 Dynamic system

The study of systems leads to the development of models. These models allow the analysis of a complex situation or subject and are used for communication purposes. There are several definitions of the term "system," and two key definitions highlighting the essential qualities of this concept have been selected (Jean-Christophe POUSSIN, 1987) [1]:

In their study titled "Risk Assessment and Management in Public Investment Projects: A Critical Analysis" (Linas Jasiukevicius & Asta Vasiliauskaite, 2015), the authors examined the importance of risk assessment in public investment projects. They emphasized that risk analysis is crucial for making informed decisions and minimizing potential negative impacts on projects. The researchers also highlighted the importance of developing methods suitable for the complexity and specificity of public investment projects. [2]

A study by researchers in the document "A Review on Risk Assessment Methods in Public-Private Partnerships (PPP) Projects" (Hrytsenko, Larysa/Boiarko, Iryna et al. 2021) examined risk assessment methods specifically in the context of public-private partnerships (PPP). They identified risks associated with these projects, such as financing risks, return risks, regulation risks, and partnership risks. The researchers also examined different approaches used to assess these risks, including sensitivity analysis, scenario analysis, and risk network analysis. [3]

In their article titled "Risk Evaluation of Public Investment Projects in Developing Countries" (Anand Rajaram, Tuan Minh Le, Nataliya Biletska, and Jim Brumby. 2010), the authors examined specific challenges related to risk evaluation in developing countries. They emphasized the importance of considering the unique political, economic, and social contexts of these countries when evaluating risks. The researchers also explored methods such as cost-benefit analysis, probabilistic modeling, and scenario-based approach to evaluate risks associated with public investments in these countries. [4]

2.2 Modeling

First of all, a model is the representation of a phenomenon constructed for the purpose of facilitating its study, better understanding its behavior, predicting its properties, and envisioning its evolution. As for modeling, it involves constructing a model based on the objectives of a particular study.

Furthermore, simulation is the use of a model to predict the properties and forecast the behavior of the modeled object. Indeed, modeling has gained importance in cognitive psychology. This is primarily because one cannot seriously claim to achieve the goal of describing cognitive functioning without being able to produce explicit models of this functioning, namely models that allow computation and simulation.

3 MODELING OF FINANCIAL BEHAVIOR

3.1 Time series by ARIMA

ARIMA models allow the combination of three types of time processes: autoregressive processes (AR), moving average processes (MA), and integrated processes (I). When dealing with a non-stationary series (Xt), it is appropriate to model it using an ARIMA(p,d,q) model, where d denotes the order of differencing and p, d, and q respectively represent the order of the autoregressive process, the order of integration, and the order of the moving average.

The ARIMA(p,d,q) model is represented as:

$$\Phi(L)\Delta^d X_t = \Theta(L)\epsilon_t.$$

where

$$\begin{cases}\Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p, & \phi_p \neq 0,\\ \Theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q & \theta_q \neq 0.\end{cases}$$

Estimating the parameters of the ARIMA(p,d,q) process for the non-stationary series (Xt) involves estimating the coefficients of the ARMA(p,q) process to create a new stationary series (Yt).

The Box-Jenkins methodology allows for determining the appropriate ARIMA model for modeling a time series, aiming to construct a model that best represents the behavior of the time series. This methodology suggests four steps:

- Identification,
- Estimation,
- Validation,
- and Forecasting of the model.

Identification involves specifying the three parameters p, d, q of the ARIMA model. The stationarity of the model is first tested through graphical analysis, autocorrelation analysis, and the augmented Dickey-Fuller test. If the series is not stationary, it should be transformed into a stationary series. The order of integration "d" represents the number of times the initial series was differenced to achieve stationarity. Autocorrelations and partial autocorrelations are used to estimate the orders p and q for the AR and MA models, respectively.

- The partial autocorrelations are zero beyond order p.
- The autocorrelations are zero beyond order q.

Simple Dickey-Fuller test: Dickey and Fuller were the first to provide a set of formal statistical tools to detect the presence of a unit root in a first-order autoregressive process. This test allows for testing the hypothesis:

$$\begin{cases} H_0: The\ model\ has\ a\ unit\ root \\ H_1: The\ model\ does\ not\ have\ a\ unit\ root\end{cases}$$

Dickey and Fuller extended this test procedure to autoregressive processes of order p, resulting in the augmented Dickey-Fuller (ADF) test. Determining a unique model is often not easy. The chosen model is the one that minimizes one of the criteria based on T observations. The information criteria used are:

1. Akaike (1969) : $AIC(p,q) = \log(\hat{\sigma}_\epsilon^2) + 2\frac{p+q}{T}$
2. Schwarz (1977) : $BIC(p,q) = \log(\hat{\sigma}_\epsilon^2) + (p+q)\frac{logT}{T}$
3. Hannan_Quinn(1979) : $\varphi(p,q) = \log(\hat{\sigma}_\epsilon^2) + (p+q)c\left(\frac{\log(\log(T))}{T}\right), avec\ \epsilon > 2$

The selection of an ARIMA model (p, d, q) is the result of the following four main steps:

Step 1: Identification, where initial values for the orders p, d, and q are determined based on the simple and partial autocorrelation analysis.

Step 2: Estimation of the parameters θi and φi through the maximization of the likelihood functions using iterative procedures.

Step 3: Once the parameters are estimated, the estimation results should be examined with reference to tests on the significance of the parameters and the quality of the residuals (absence of autocorrelation).

Step 4: The choice of the most appropriate model among all the estimated models is based on two criteria: Akaike (AIC) and Schwartz (SC), which measure the quality of the model in approximating reality.

Step 5 (Forecasting): Once the ARIMA model is estimated and validated, it can be used to make predictions about future time series data.

3.2 Multilayer Perceptron:

The structure of the multilayer perceptron used is presented in Figure 1, which is composed of interconnected neurons in three successive layers.

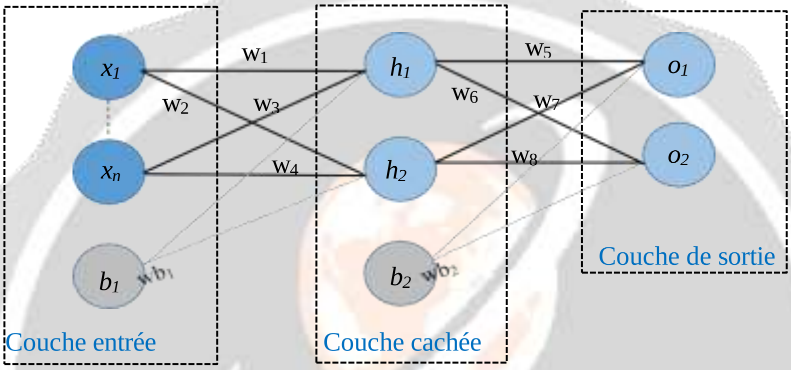


Figure 1 Multilayer Neural Network

The first layer consists of "transparent" neurons that do not perform any calculations but simply distribute their inputs to all neurons in the next layer called the hidden layer. The neurons in the hidden layer (Figure 1), with one example represented by Figure 2, receive the n_0 inputs $\{x_1^0, 000, x_n^0\}$ from the input layer with associated weights $\{w_{i_1}^0, 000, w_{i_{n0}}^0\}$. This neuron starts by calculating the weighted sum of its n_0 inputs:

$$Z_i^1 = \sum_{h=1}^{n_0} w_{ih}^1 * x_h^0 + b_i^l$$

Where b_i^1 is a bias (or threshold).

The output of the hidden neuron is obtained by transforming the sum (1) through the activation function g:
$x_i^1 = g(z_i^1)$. (2)

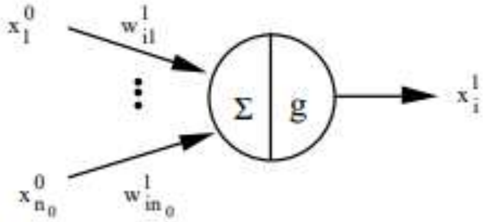


Figure 2: Neuron i in the hidden layer

Although many activation functions have been proposed, the function g(.) is generally the hyperbolic tangent [X]

$$g(x) = \frac{2}{1+e^{-2x}} - 1 = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (3)$$

The neuron in the last layer (or output layer) uses a linear activation function and therefore only performs a simple weighted sum of its inputs:

$$Z = \sum_{i=i}^{n_l} w_i^2 * x_i^1 + b \quad (4)$$

Where w_i^2 are the weights connecting the outputs of hidden neurons to the output neuron and b is the bias of the output neuron.

3.3 Performance Evaluation:

The indicators used in this study are:

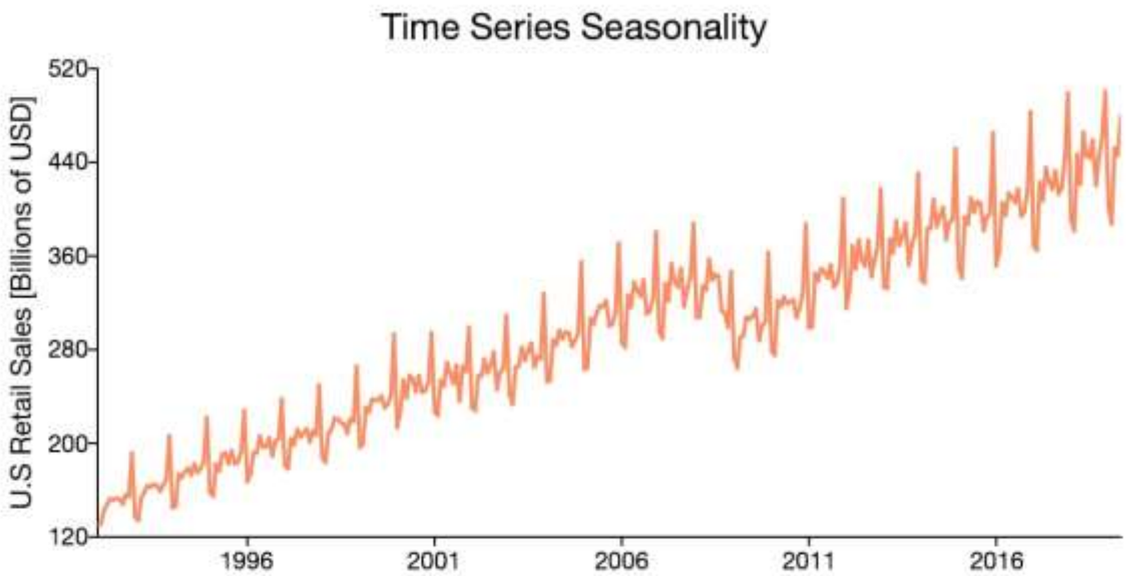
- Nash-Sutcliffe Efficiency (NSE): $NSE = 1 - \frac{\sum_i^N (Y_i^{obs} - \left(Y_i^{sim}\right)^2}{\sum_i^N (Y_i^{obs} - (Y_i^{mean\ obs})^2}$
- Mean Squared Error (MSE) : $MSE = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t^2$
- Coefficient of Determination: $R^2 = \frac{Cov^2(Y_i^{sim}, Y_i^{obs})}{V(Y^{sim}) * V(Y^{obs})}$
- Mean Absolute Error : $MAE = \frac{1}{T}\sum_{t=1}^{T} |\epsilon_t|$.
- Root Mean Square Er-ror : $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \epsilon_t^2}$
- Mean Absolute Percent Error : $MAPE = \frac{100}{T}\sum_{t=1}^{T} \left|\frac{\epsilon_t}{X_t}\right|$

4 CONTRIBUTION

4.1 Representation of Financial Data as Time Series

Time series data often exhibit a common characteristic, where they frequently conform to multiple underlying movements that overlap. These movements typically include a long-term trend observed over an extended period, a possible cycle that gives a wave-like pattern to the trend, one or more periodic or seasonal components, and business fluctuations, which can be either random or unexplained. These elements can add up or have multiplicative effects on each other.

Example of time series



4.2 Modeling Financial Behavior Applicable to Investment

The behavior of the prices of call and put options at the current time is modeled by:

$$C(S,t) = S_0 N(d_1) - Xe^{-r(T-t)} N(d_2)$$

$$P(S,t) = Xe^{-r(T-t)} N(-d_2) - S_0 N(-d1)$$

Where:

C(D,t) is the price of the call option

P(S,t) is the price of the put option

S is the current price of the asset

S_0 is the initial price of the asset

X is the strike price

T is the current time

r is the risk-free interest rate

N(d_1) and N(d_2) are standard normal distribution functions

$$di = \frac{\ln\left(\frac{S}{S_0}\right) + (r + \frac{\sigma^2}{2})(T-t)}{\sigma\sqrt{(T-t)}}$$

$$d_2 = d_1 - \sigma\sqrt{(T-t}$$

4.3 Resolution Methodology

Hybrid models that combine ARIMA with artificial neural networks are models that use, as inputs, the subseries components derived from ARIMA transformations applied to the original time series data. Some key advantages of hybrid modeling with artificial neural networks may include:

- Improved forecast accuracy: Hybrid models can leverage the strengths of both ARIMA and neural networks to improve forecast accuracy, especially for time series data exhibiting multiple underlying patterns.

- Better handling of nonlinearity: Artificial neural networks are well-suited for capturing nonlinear relationships in the data, which can be particularly useful when dealing with complex time series patterns.
- Enhanced adaptability: Hybrid models can adapt to changing data patterns and evolve over time, making them suitable for dynamic and evolving time series data.
- Increased robustness: The combination of ARIMA and neural networks can make the model more robust, enabling it to handle different types of time series data.
- Ability to model multivariate relationships: Hybrid models can be extended to handle multivariate time series data, where the relationships between multiple variables need to be captured and predicted.

From a historical sales/purchase database, the first phase involves data preprocessing followed by separating the available data into training and test sets.

The algorithm automatically calculates the ARIMA model's p, q, and d parameters and predicts the future behaviors of the studied series.

Resolution algorithm

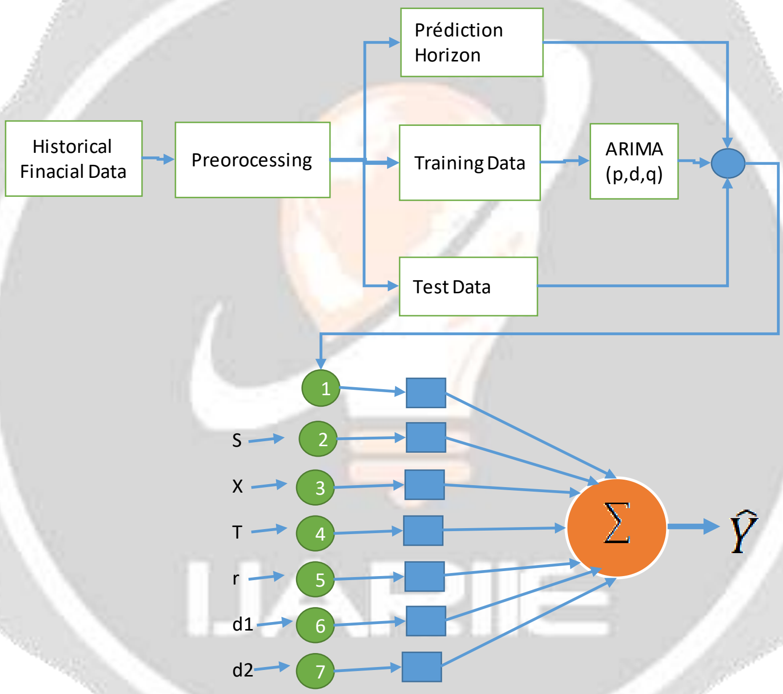


Figure 2: Resolution algorithm diagram

5 CONCLUSION

The implementation of the current hybrid model follows a process that involves data collection, data preprocessing, data splitting, model structure selection, model training, model validation, optimization and tuning, cross-validation, interpretation of results, model utilization, and potential updates if necessary.

In conclusion, hybrid modeling is a powerful tool for predicting behavioral value in finance and applying it to investment. ARIMA allows for the prediction of buying/selling values, and with the use of a perceptron neural network, the model also enables the determination of the interaction between finance and treasury, as well as the search for a balance between self-financing, investment, and financial structure. Financial behavior of an economic entity: Seeking a balance between self-financing, investment, and balance sheet structure.

The remaining part of the article focuses on analyzing investment-related risks.

Bibliography

[1]A. A. Beaujean, *Factor Analysis using R*, Practical Assessment, Research & Evaluation,

Volume 18, Number 4, February 2013

[2] Chaput L., (2006), Contemporary model in management, Press of Québec University

[3] Délignières D. Times series : model ARIMA, seminary EA "sport- Performance – health"

[4] G . Dreyfus , Neural Networks, Mechanical Manufacturer and Material, sept 1998

[5] Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. Journal of Behavioral Decision Making,