OPTIMIZATION FOR THE FORECASTING OF A DYNAMIC SYSTEM

TSISAROTINA Maminiaina René Alexandre – Dr RABENORO RAKOTONIAINA Barry – Pr ANDRIAMANOHISOA Hery Zo

Ecole Supérieure Polytechnique Antananarivo (ESPA) - Université d'Antananarivo BP 1500, Ankatso – Antananarivo 101 – Madagascar

¹ cgpmtp@gmail.com, ² barryrakotoniaina2017@gmail.com, ³aheryzo@gmail.com

Abstract

Optimization is considered as the action of developing an activity as efficiently as possible, i.e., with the least amount of resources and in the shortest possible time. In other words, optimization means performing a task in the best way and can be applied to various domains such as business management, economics, and information technology. Optimization, in general, involves achieving the best performance of something by using resources in the most efficient manner. ARIMA is a statistical model considered reliable for analyzing time series and/or chronological data for the purpose of making predictions. Artificial neural networks are an organized set of interconnected neurons that enable the resolution of complex and dynamic problems. The combination of these two models forms the hybrid model, the subject of this article.

Keywords : Optimization, prediction, activities, system, resources.

1 INTRODUCTION

Often, modeling a complex system leads to questions about optimization for forecasting a dynamic system. The question raised is whether analytical models can solve genuinely complex problems. "A dynamic system is a lasting arrangement of interconnected elements that form a unified whole," as stated by Josh Kaufman (2013, p. 377). This raises questions about its modeling.

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How can cognitive sciences influence and manage the dynamic system, assisting decision-makers in better adapting to the field of optimization? The objective of this article is to describe modeling methods based on the combination of ARIMA transformation and Artificial Neural Networks for modeling a dynamic system.

The study and understanding of dynamic systems, especially economic systems, require the development of innovative mathematical and computational methods and models. Thus, a hybrid approach ensures the improvement of the performance of modeling complex systems.

2 DYNAMIC SYSTEM MODELING 2.1 System

The study of systems leads to the development of models. These models allow for 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 that highlight the essential qualities of this concept have been selected (Jean-Christophe POUSSIN, 1987) :

- "An organized whole, composed of interrelated elements that can only be defined in relation to each other, based on their position within this whole." (F. de SAUSSURE)
- "A set of elements in dynamic interaction, organized with a purpose in mind." (J. de ROSNAY)

A system possesses four key properties: organization, totality, interaction among its elements, and complexity. Certainly, the complexity of a system requires that it be modeled in the most pragmatic manner possible. This will enable better monitoring of the process and subsequently the detection of any disturbances that could lead to instability and system malfunction.

2.2 Model and Modeling

Firstly, a model is the representation of a phenomenon constructed for the purpose of facilitating its study, better understanding its behavior, predicting its properties, and foreseeing its evolution. As for modeling, it involves the construction of 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. Certainly, modeling is gaining increasing importance in cognitive psychology. This is primarily because one cannot seriously claim to achieve the goal of describing cognitive functioning without being capable of producing explicit models of this functioning, namely models that allow for calculation and simulation.

3 TIME SERIES MODELING

The primary objectives of time series modeling are focused on describing and comparing two time series in order to predict the future evolution of the time series based on the observed values.

3.1 Econometric Model

Econometrics is a discipline that combines economic theory and statistical analysis. Dynamic econometrics, in particular, focuses on econometric theory based on the use of data from time series. Econometric analysis is primarily based on two elements, namely, empirical evidence on the one hand, and economic theory on the other. The regression model can be written as follows :

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_k X_{kt} + \varepsilon_t$$

Finite-sample and asymptotic properties need to be identified while solving the variance and covariance matrix. The goal is to ensure the quality of fit and variance analysis while considering the unbiased estimator of error term variances. The confidence interval is then expressed as follows :

$$IC(\beta_i, 1-p) = [\hat{\beta}_i \pm t(T-k-1)_{p/2} \times S_{\widehat{\beta}_i}]$$

For the resolution, it is sufficient to determine the level of risk and the confidence level. The steps to follow are translated as follows: the hypothesis test, the level of risk, the statistical test, as well as the decision and conclusion. The general methodology of an econometric analysis is presented as follows :



Source : The Limitations of Econometric Models in Forecasting, Emanuel NIBITEGEKA Econometric models in forecasting face challenges, including:

a) Data-Related Challenges:

• Data quality: The objective of econometric techniques is to obtain equations with unbiased, consistent coefficients, and optimal estimations. If the data is seriously deficient or incomplete, all efforts to adopt estimation methods are of limited utility.

• Interpretation of coefficients: This relates to the interpretation of coefficients and specification errors. Data must be measured without errors for a good model. However, even if they are unbiased and cover a sufficiently long period, the interpretation of coefficients in regression equations can be very limited.

b) The Mathematical Form of Equations: Another way in which a model may not satisfy is when the modeler incorrectly specifies the relationships between endogenous variables and the set of independent variables.

c) Technical Issues : To solve equations, one must rely on a series of assumptions that facilitate their resolution. These assumptions primarily concern the error term. Faced with these restrictions, the natural question to ask is whether the results we obtain pertain to their properties when the assumptions are violated, including those related to the error term, explanatory variables, and the model. We will focus on the three main cases, namely :

• Autocorrelation, which arises from the violation of the assumption that the error term is not temporally correlated.

 \bullet Heteroskedasticity, originating from the violation of the assumption that the variance of "t" is constant and finite for all "t"

• Multicollinearity, a problem resulting from the failure to satisfy the assumption that explanatory variables are neither highly nor totally correlated.

Other problems exist, but these are the most important ones. This insufficiency has allowed us to fairly comprehensively identify the primary challenges that economists face when planning, as well as the limitations of these models, which can lead to erroneous results and flawed planning in our investigations.

The ARIMA model is a generalization of the ARMA model that allows working with non-stationary time series, which can be made stationary through differencing. To facilitate the equation representation of the ARIMA model, the concept of a lag operator, denoted as *B*, is introduced :

ou encore

$$By_t = y_{t-1}$$
 ou encore $(By_t) = B^2y_t = y_{t-2}$
It then becomes very easy to represent the differencing process. For example, the second-order differencing of a time series yt is given by :

$$y_t - 2y_{t-1} + y_{t-2} = (1-2B+B2)t = (1-B)^2y_t$$

The equation representing the ARIMA model is as follows :

$$A(p, d, q): (1 - \alpha_1 B - \ldots - \alpha_p B_p)(1 - B)dy_t = c + (1 + \theta_1 B + \ldots + \theta_q B_q) \varepsilon_t$$

Where p, d, q are respectively the order of the autoregressive part, the degree of differencing, and the order of the moving average part. $\alpha 1, \ldots, \alpha p$ and $\theta 1, \ldots, \theta q$ are the parameters of the autoregressive and moving average parts, and εt is white noise.

3.2 Artificial Neural Networks

In the field of artificial intelligence, an artificial neural network is an organized set of interconnected neurons that allows for the resolution of complex problems. An artificial neuron functions in a way inspired by biological neurons. A node in a network of multiple neurons typically receives several input values and generates an output value.

Artificial neural networks require real cases as examples for their learning. These cases should be more numerous when the problem is complex and its topology is less structured. There are problems that are well-suited for neural networks, especially those involving classification in convex domains. Specifically, if points A and B are part of the domain, then the entire line segment AB is also part of it.

A neural network learns from the examples provided to it. The goal of this learning is to allow the network to derive generalities from these examples and apply them to new data in the future. In artificial intelligence, overfitting occurs when a model has learned too much about the specifics of each example provided as training data. This can result in very high success rates on the training data but may harm its actual general performance.

If most of the parameters are trainable, there are also constant, non-trainable parameters whose values are set before the learning process. These can be defined as hyperparameters and have a crucial influence on the model's performance. For a basic artificial neural network, the following are some typical hyperparameters :

- The network structure such as the number of layers, the number of neurons per layer, and the type of activation function.

- Optimization parameters like the optimization method, learning rate, and batch size.

Hyperparameter tuning is a problem of non-linear, non-differentiable, and non-convex optimization that cannot be solved using traditional optimization methods. For each combination of hyperparameters, a complete training must be performed to evaluate performance. If the number of hyperparameters is high, the number of trainings required can be enormous.

The general regression model is not very effective for analyzing non-stationary time series data. The Autoregressive Integrated Moving Average (ARIMA) model has a significant advantage in handling non-stationary time series. However, the ARIMA model supports univariate prediction problems, and it is difficult to establish multivariate predictive models. As an intelligent prediction method, artificial neural networks provide a fast and flexible way to create models for time series prediction. In recent years, artificial neural networks have generated a lot of interest in research across various domains due to their strong self-organization, self-learning capability, and robust fault tolerance. Neural networks can learn patterns and capture hidden functional relationships in data, even when those relationships are unknown or difficult to identify. This capacity is applicable to the prediction of non-linear time series with satisfactory prediction results. Considering the different advantages and limitations presented by econometric

models and artificial neural networks, this article opts for the combination of these two concepts, giving rise to the hybrid model.

4 CONTRIBUTION : HYBRID MODEL

Time series data often exhibit a common characteristic wherein 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 imparts a wave-like pattern to the trend, one or more periodic or seasonal components, and conjunctural fluctuations, which can be either random or unexplained. These elements can either add up or have multiplicative effects on each other.

The power of hybrid modeling with artificial neural networks lies in its ability to combine the strengths of neural network models with other modeling approaches to achieve enhanced performance. Hybrid models often incorporate complementary machine learning methods to leverage available data effectively and address complex problems.

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

• Improved Forecasting Accuracy : Hybrid models can harness the strengths of both ARIMA and neural networks to enhance forecasting accuracy, particularly for time series data with multiple underlying patterns ;

• Better Handling of Non-linearity : Artificial neural networks are well-suited for capturing non-linear relationships in data, which can be especially 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, allowing it to handle various types of time series data ;

• Ability to Model Multivariate Relationships : Hybrid models can be extended to address multivariate time series data, where the relationships between multiple variables need to be captured and predicted.

The specifics of the advantages and the methodology for implementing these hybrid models would depend on the particular application and the data being analyzed.

Hybrid modeling is a type of time series model that can be used in machine learning to predict or model sequences of temporal data. It is an extension of various models that take into account feedback and exogenous inputs to improve predictive capabilities. This model can be constructed using various machine learning techniques, including recurrent neural networks, long short-term memory networks, gated recurrent neural networks, and other deep learning models, as well as traditional statistical learning methods like ARIMA models.

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 summary, hybrid modeling is a powerful tool for time series prediction, especially when dealing with non-linear relationships and exogenous inputs. There are numerous machine learning libraries and frameworks available that make it easier to implement hybrid models, enabling their use in various application domains.

5 CONCLUSION

Hybridizing Artificial Neural Networks and the ARIMA model is highly recommended for time series prediction, financial modeling, demand forecasting, weather modeling, and many other fields. However, it is essential to note that building these hybrid models can be complex and requires expertise to select the best components and integrate them optimally. Furthermore, rigorous model validation is crucial to ensure that the hybrid model delivers good predictive performance. This approach demands a deep understanding of the data, modeling skills, and a robust methodology to succeed.

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