BULGARIAN ACADEMY OF SCIENCES

PROBLEMS OF ENGINEERING CYBERNETICS AND ROBOTICS • 2021 • Vol. **75**, pp. 43-50
p-ISSN: 2738-7356; e-ISSN: 2738-7364
https://doi.org/10.7546/PECR.75.21.05

Incremental Sinusoidal Approximation of Time Series with LibreOffice Calc Solver

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Abstract: Financial time series forecasting has high importance in many decision-making situations. There are many methods and approaches for time series forecasting. Artificial Neural Networks are widely used. Support Vector Machines are giving even better results than artificial neural networks. Both tools are pretty complicated and have their advantages and disadvantages. This research proposes an approximation based on cumulative sinusoids. From the Fourier Transform, it is well known that each signal can be represented as a sum of sine functions. Optimal coefficients for the sine functions and the linear component, in this research, are searched with the Solver module of LibreOffice Calc. The search of the optimal values is done on an incremental basis. The result show that the time series can be successfully handled as signals.

Keywords: *Differential evolution, financial forecasting, particle swarm optimization, time series.*

1. Introduction

Time series are widely used in the financial world. Time series forecasting has its place in the soft computing state of the art [1]. In many situations, the financial data are presented as values that change with time passing. The prices of the stocks are changing with time (gas and oil for example [2]). The prices of companies' shares are changing with time. The rates between the national currencies are changing with time. Taking financial decisions manly when it comes to investments is very dependent on reliable forecasting which is mathematically augmented [3]. In the last two centuries, many forecasting tools and approaches are developed. Econometrics is the branch of science responsible for giving empirical content to economic relationships. Thousands of financial indicators/oscillators are created [4]. Thousands of trading strategies are built around the financial indicators/oscillators. In the last few decades, the algorithms of the field of Artificial Intelligence and Machine Learning are also involved in trading decision making [5]. Artificial Neural Networks [6] and Support Vector Machines [7] became very popular in the field. For example, artificial neural networks can be used for financial time series forecasting implemented in Android service and widgets [8] and a proposed modified support vector machine classifier can be used to forecasting short-term trends on the stock market [9].

All forecasting tools in the field of financial times series forecasting depend on the fact that economic processes depend on what happened in the past periods [10]. This branch of forecasting is known as Technical Analysis [11]. It does not count news. It does not count intuitive relationships. It only counts the exact numbers from the past. Fundamental Analysis [12] is another approach for financial forecasting. It relies on intuitive relationships and empirical experience. Such software components could be reusable via service interfaces realized as Service Oriented Architecture [13]. In addition, some of the processes could be automated by using of proper analysis of requests [14]. This research is concentrated on the Technical Analysis and finding of ways to make forecasting with the tools of mathematics and global heuristic optimization algorithms.

Time series in this research is taken as signals [15] in the temporal domain. The measured values are used for building approximation curves. The hope is that when a particular curve fits the known data it will have some forecasting capabilities for the future unknown values. Finding coefficients for the chosen mathematical formulas is a complex optimization problem. The size of the variable space rises with the model refinement process. This fact makes the optimization problem even harder.

The paper is organized as follows: After the literature review part, the incremental sinusoidal approximation is presented. The theoretical proposal is followed by an experimental section. The paper finishes with conclusions and directions for future work.

2. Incremental Sinusoidal Approximation

Fast Fourier Transform is the most used method for signal decomposition met in the literature [16, 17]. It is fast as time consumption and efficient because it is in the group of the exact numerical methods. Even with these advantages, it does not give an answer to what is the minimum of sine functions to be used in the process of interpolation and after that extrapolation. The generalization capability of a sinus approximation tool is closely related to small in number calculations and optimal values for the coefficients used.

Time series are points measured in a temporal order. Using these discrete measures, curves can be fitted according to them. For example, Lagrange Interpolating Polynomial is one of the most popular tools in this field. It is well known that an infinite number of curves can be fitted to a finite number of discrete points. In the field of signal processing, it is a very common curve fitting to be done by the usage of sine functions. In most financial time series there are many ups and downs. Financial time series are perfect candidates for approximation with sine functions. Almost all time series have a linear component known as trend. The trend can be easily approximated with the equation of a line (Eq. 1). The sum of sine functions after that can approximate the ups and downs.

$$y(t) = B.t + C + A_1.sin(\omega_1.t+\varphi_1) + A_2.sin(\omega_2.t+\varphi_2) + A_3.sin(\omega_3.t+\varphi_3) + ... \qquad (1)$$

Where B is the slope of the linear component, C is the intercept of the linear component. Also, A_n is the amplitude of the n sine function, ω_n is the angular velocity of the n sine function, and φ_n is the phase of the n sine function. The incremental part of the approximation consists of the fact that the linear component is optimized alone by itself first. All sine amplitudes, angular velocities, and phases are given to zero. When the linear component is estimated the coefficients of the first sine function are optimized. The optimization process stops when there is no more convergence. After the first sine function, the second sine function is optimized, and so on as a kind of hierarchy [18]. Sine functions are added until there is a significant difference in the achieved minimum of the mean square root error. The mean square root error is calculated between time series measures and the approximated values.

3. Experiments and Results

All experiments are done on a single processor desktop machine – Intel Core i5, 2.3 GHz, 2 Cores, 8GB RAM with macOS High Sierra 10.13.6 and LibreOffice 7.0.5.2. As financial time series, publicly available rates of Bitcoin to USD is taken on a daily interval (Fig. 1).

The optimization starts with all variable cells full with zeros. In the column, A time is presented as an Excel numerical value for the date. Column B holds the value of Bitcoin for 31 days' period. Column C holds the forecasted value. Column D holds the square root difference between the measured and the forecasted value.

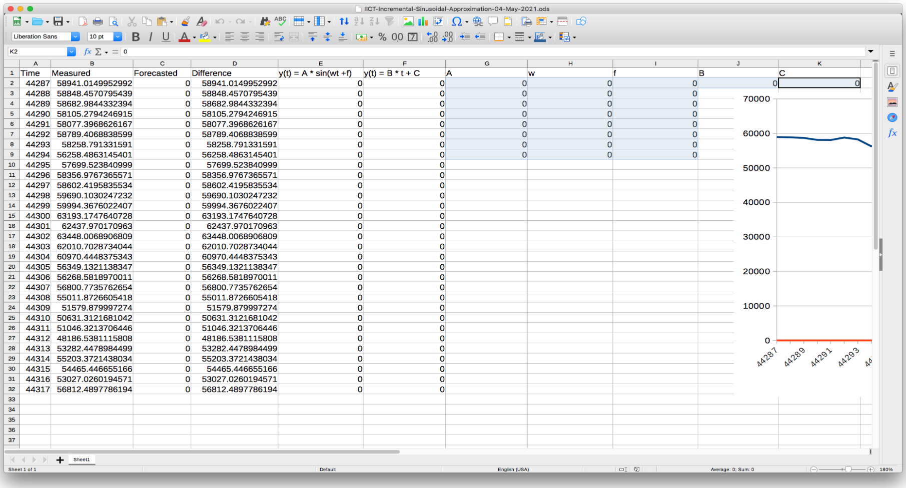

Fig. 1. Initial values as an optimization starting point.

The mean square root error value is accumulated in cell $M2$ and this is the cell subject to minimization (Fig. 2).

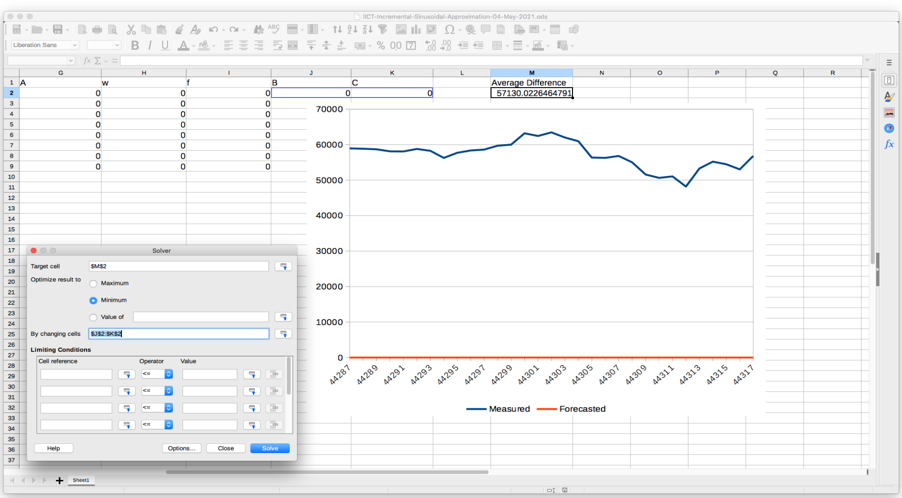

Fig. 2. Start incremental optimization by finding optimal values for the linear component.

Incremental optimization starts with searching for optimal values used as coefficients of the line equation. LibreOffice Calc Solver uses a hybrid implementation of Differential Evolution and Particle Swarm Optimization as optimizers. Coefficients for the linear approximation are found in 10.11 seconds (Fig. 3).

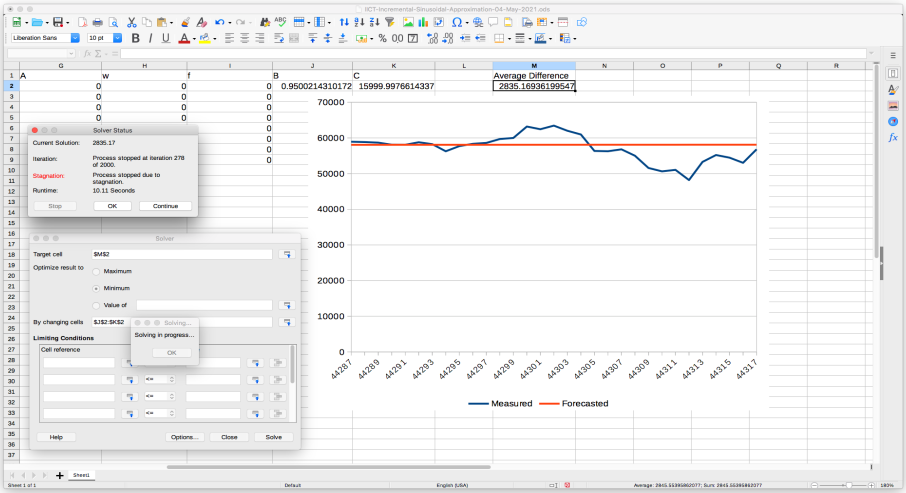

Fig. 3. Coefficients for linear approximation.

After the trend has been estimated, the coefficients for the first sine function are taken for optimization. Stagnation of the optimization with the first sine function is achieved after 150 seconds (Fig. 4).

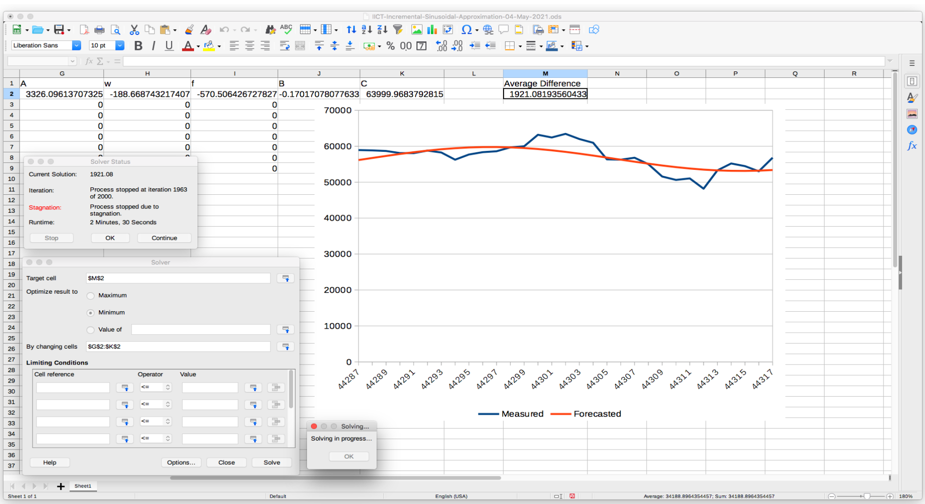

Fig. 4. Coefficients for the first sine function.

After achieving the most accurate possible approximation with a single sine function, the second one is added. Stagnation of the optimization with the two sine functions is achieved after 526 seconds (Fig. 5).

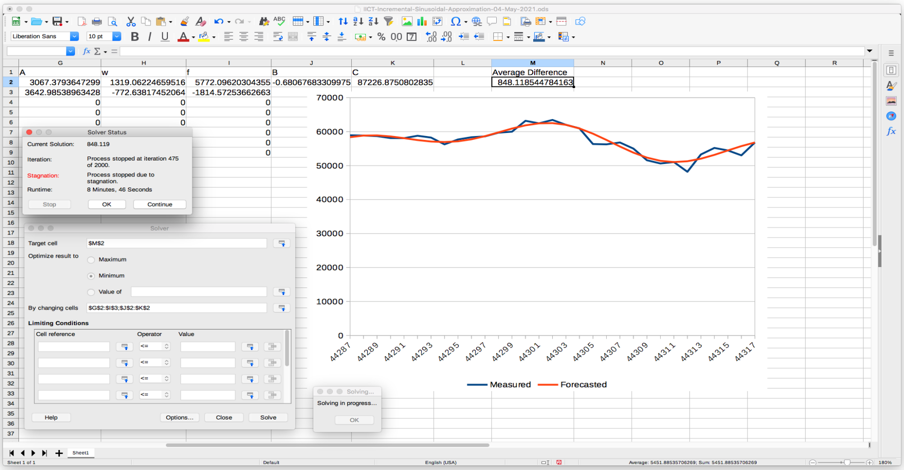

Fig. 5. Coefficients for the second sine function.

Even visually it is clear that a linear component with two sine functions is enough for forecasting with the given input data. Just to prove that two sine functions are enough, a third sine function is added and the optimization target cell is observed that significantly better minimum is difficult to be achieved (Fig. 6).

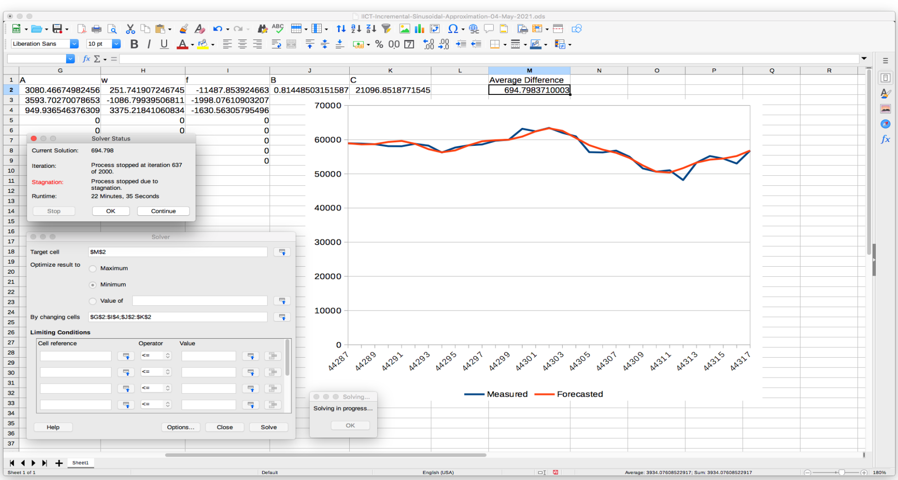

Fig. 6. Coefficients for the third sine function.

Stagnation of the optimization with the three sine functions is achieved after 1355 seconds. The incremental approximation process was stopped on this level because adding too many sine functions can lead to undesired overfitting of the model. The time series used in this experiment is relatively short. For more practical usage much bigger time series should be used.

4. Conclusions

In this paper, incremental sinusoidal approximation of time series with LibreOffice Calc Solver was proposed. The Solver has a hybrid optimizer based on Differential Evolution and Particle Swarm Optimization. The time series are handled as signals. Coefficients for linear component and sinusoids are found by incremental optimization. The experiments and results show that such a forecasting approach can be very promising.

As further work, some automation as LibreOffice Calc macros would be interesting. Incremental optimization is done manually at this stage (human-computer interactions) of the research. From a practical point of view, the proposed forecasting can be implemented as service-oriented software architecture.

Acknowledgments

This work was funded by Velbazhd Software LLC and it was partially supported by the Bulgarian Ministry of Education and Science under the National Research Program Smart Crop Production, approved by Decision of the Ministry Council No.866/26.11.2020.

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