



FINTECHNEXT

SCIENTIFIC EXCELLENCE
INDUSTRY IMPACT

Leveraging Cloud, Big Data and ML for FX and Treasury applications

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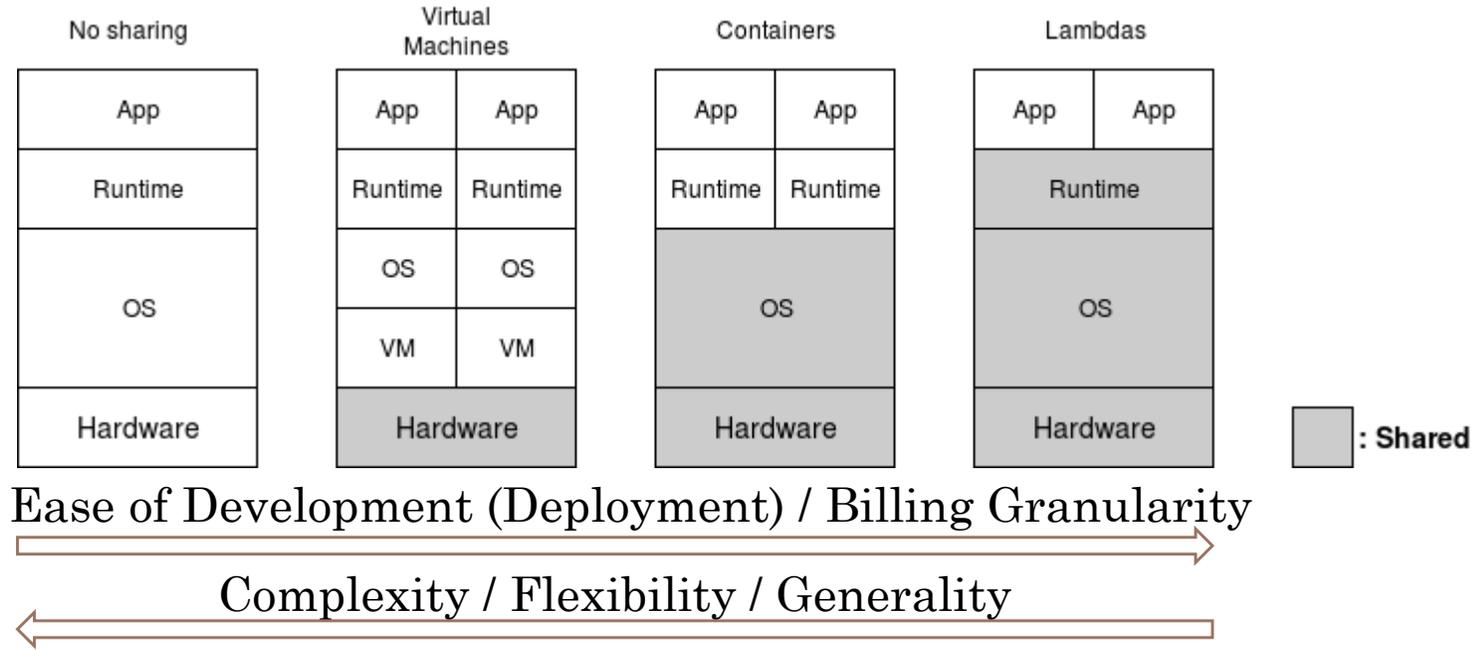
Overview

1. Trends and state of the art in Cloud Computing, Big Data and Machine Learning
2. Treasury applications based on modern technology
3. Tools and methods for FX rate forecasting: Issues, Advantages and Disadvantages
4. Proposed Approach for FX rate forecasting

Trends in Cloud Computing

- Cloud Computing, according to NIST, is defined as a computing model that enables ubiquitous, convenient and on-demand network access to a shared pool of configurable computing resources.
- Basic delivery models: Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS) and Software-as-a-Service (SaaS).
- New more flexible service delivery models: Container-as-a-Service (CaaS), Function-as-a-Service (FaaS) and Everything-as-a-Service (XaaS) boost utilization abstracting away extensive configuration.
- Lightweight instances used as hosts for service, allowing complex and flexible workloads to be executed with more flexible and granular billing.
- Combinations of lightweight services (Microservices) residing in Containers or in the form of stateless Functions, communicate through APIs invoked by different products (reusability).
- This advances led to substantial acceleration in development and use of advanced technologies in a large set of products and services.
- Major providers have adopted this technologies offering a wide variety of tools (Amazon, Microsoft, Google). Notable Open Source tools include: **Kubernetes, Docker and OpenWhisk.**

Serverless Computing (FaaS)

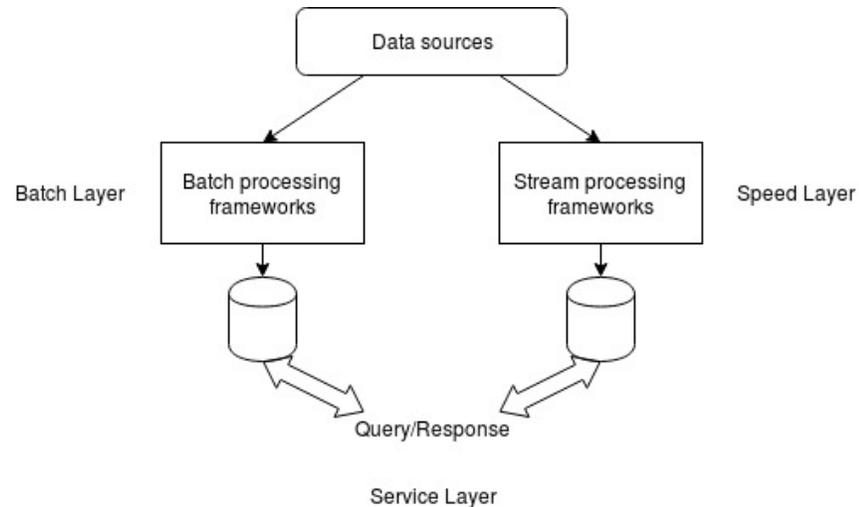


- Function-as-a-Service (FaaS): Provisioning of lightweight services, reacting on event and billed on per-request basis. **Open-source and enterprise tools exist and are already used across multiple domains** (Analytics, UI/UX, ML,..).

Trends in Big Data

- Big data represents the information assets characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value (3Vs models).
- The old model was based on Relational Database Management Systems (RDBS). However, these systems do not have the throughput to support modern needs such as Stream or Near real-time processing for computing analytics. Enterprise Data Warehousing and Data Lakes in Clouds lead to substantial cost reduction.
- Efficient distributed storage (HDFS, GPFS or PVFS) and NoSQL type databases enable processing of large volumes using novel architectures combining stream and batch-processing such Lambda (Batch and Stream (Speed) processing combined with Service layer) and Kappa (Stream processing combined with Service layer) architectures.
- Major Cloud providers support most of open source frameworks such as Apache Storm, Apache Spark, Apache Kafka and Apache Flink as well as custom stream analytics environments. Moreover, they support the design of BDA workflows and architectures.
- **The future directions for Big Data include fields such as Data Warehouse Optimization, Forecasting, Customer/Social Analysis, Predictive Maintenance, Fraud Detection, Clickstream Analytics, Internet of Things and Supply Chain Optimization**

Lambda Architecture



- **Data warehousing and lambda architecture.** Enterprise Data Warehouses (EDW) allow for unification of storage and processing (not easily adaptable to new formats). *Data Hubs based on NoSQL databases* are another alternative. Enterprise software and services are provided by the big providers. Lambda architecture is a **hybrid scheme for combined processing (Batch and Stream) by a single system allowing for improved results by combining past and current.**

Trends in Machine Learning

- Machine Learning (ML) refers to the related algorithms and statistical models used by computer systems relying on inference and patterns, without being explicitly instructed.
- Three basic types of learning: Supervised, Unsupervised and Reinforcement Learning.
- Plethora of ML techniques and methods are included to Open Source packages that in turn have been gradually migrating to the Cloud. Automated workflows are offered by major Cloud providers for analyzing data. These leverage Big Data techniques to offer reusable solution that empower new and existing products.
- The most popular distributed frameworks are Apache Mahout, Apache Spark MLlib and Apache FlinkML. These frameworks support several ML methods such as Recommendation Systems, Classification, Clustering, Dimensionality Reduction, Topic Models, Regression, Decision Trees, Optimization, Natural Language Processing, Neural Networks and others.
- Cloud based tools include: Microsoft Azure ML Studio, Google AI & Machine Learning, IBM Watson ML and Amazon ML. **The future directions in Machine Learning with respect to Fintech includes fields such as Automated Customer Support through ML and AI, Client Risk Profile formation, Trading and Money Management, Regulatory compliance and Fraud detection**

Cloud based IDEs (ML-as-a-Service)

- Popular tools include ANNs, Decision trees, Support Vector Machines, Bayesian Networks and Genetic Algorithms.
- ML-as-a-Service is already provided by major Cloud providers.
- Combined with Big Data capabilities, analysis of ever-growing amounts of data can be performed.
- Novel services allow for analyzing and training based on dynamic data or even use ML as part of UI/UX type services in real-time (Shopping suggestion, smart advertising, recommendations, prediction).
- Such services are Google AI & Machine Learning, Microsoft Machine Learning Studio.

Convergence of Cloud, Big Data and ML

- These three enablers are gradually being adopted in industry and research in a wide range of applications:
 - By 2021 73% of all workloads will be executed in Public Clouds while the remaining 23% will be executed in Private Clouds. SaaS (82%) and 73% of all workloads is Enterprise (Cisco)
 - Big Data adoption is steadily rising in the Enterprise sector from 17% in 2015 to 59% in 2018 (Forbes)
 - AI and ML have become a critical factor of success in enterprises: 27% of Financial Services & Insurance, 25% of Healthcare and 24% of Retail/Wholesale (Forbes)
- These three enablers are coupled in the sense that Cloud is a vast pool of resources for storing and processing data using Big Data techniques and extract useful insights through ML.
- Adoption of these enablers to new and existing products is gradually becoming easier through “APIs” offered by major providers. These providers also offer out of the box solutions though libraries populated constantly with new tools. These solutions auto scale utilizing service delivery models such as (FaaS) to accommodate consumer needs and require less configuration and tuning.

Examples of adoption

- Serverless computing realized through the Function-as-a-Service (FaaS) service delivery model, have already been adopted by companies such as **Stripe (serverless payment solutions), Crowd Valley (finance back office as a service), Capital One (banking services based on AWS Lambda), Thomson Reuters and Finra.**
- Adopting Big Data processing and analytics, in the financial sector are: **Santander, ATB financial, Bank of America, ADP and Bank of England.** Examples of adoption of the **Lambda architecture for Big Data processing include Metamarkets, Netflix and Yahoo.**
- ML adoption examples include: **Dataminr, Automation Anywhere, Throughspot and DataRobot,** which leverage ML for analytics, Business Intelligence, predictions and metrics as well as Natural Language Processing. Examples of companies that leverage Cloud based ML tools include **RMI Insights (Google Cloud Platform), TransferWise (Amazon AWS) and Finastra (Microsoft Azure ML).**

Treasury applications based on modern technology

- Treasury is a vital component for businesses in the financial sector, especially those offering services in multiple regions, such as Foreign Exchange companies, Travel agencies, Logistics companies etc.
- Treasuries serve a multi-purpose role spanning from asset management to cash flow, handling of foreign exchange, loan management, derivatives, hedging and risk management.
- A Treasury is usually surrounded by a multitude of businesses of an enterprise, which they service in terms of funds and management.
- The Treasury is responsible for collecting and analysing multiple types of data collected by businesses and external sources and combine them for the purpose of providing business insights and minimize risk, while enhancing functionality and other business performance indicators.
- An important factor for extracting business insights and design strategies while minimizing risks is extrapolation. Extrapolation and forecasting are useful tools used across many applications (volume and price forecasting) especially in multi-currency treasuries.

FOREX rate prediction

- Foreign Exchange (FOREX) rate is defined as the price of one currency exchanged for another.
- FOREX rate is crucial for countries as well as enterprises since it affects policies and decisions.
- FOREX rate is a financial time series and is composed of chronologically ordered observations of a financial variable(s) e.g. daily FOREX rate.
- Financial time series have distinct characteristics such as non-stationary and nonlinear behavior, while they usually are deterministic and sensitive to initial conditions, behaving like random walks. They are noisy with random frequent variations and varying statistical properties at different points in time.
- Predicting time-series with these characteristics is challenging and traditional stand alone models usually fail.

Hybrid models and Soft Computing

- Over the last decade hybrid models have been considered to suppress modelling failures based on combination of prediction methods.
- Hybrid models are categorized to homogeneous, when composed only by non-linear models, or heterogeneous, when both linear and non-linear models are considered.
- Hybrid or ensemble models have been shown to outperform traditional stand-alone models utilizing multiple forecasting models or combinations of artificial neural networks.
- The tools, methods and models involved in the formation of hybrids belong to scientific field of Soft Computing (SC).
- Soft Computing has been used extensively in FOREX rate prediction in the last decades utilizing ANN (Artificial Neural Networks) based, EC (Evolutionary Computing) based, Fuzzy logic based, SVM (Support Vector Machines) based and Chaos based hybrid approaches.

Popularity of Techniques

- In recent reports (Ryll et al. 2019) it is evident that the majority of methods and techniques in the broader field of Financial Market Forecasting and more specifically FOREX rate prediction utilize (in order of popularity):
 - Support Vector Machines (SVMs)
 - (Recursive) Artificial Neural Networks (ANNs) including Long-Short Term Memory (LSTM) Networks
 - Fuzzy Logic models (FL)
 - Generalized Autoregressive Conditional Heteroskedasticity models (GARCH)
 - Auto-Regressive Integrated Moving Average (ARIMA) models
 - Random Walk (RW) models
 - Linear Regression models
 - Autoregressive models
 - Buy and Hold models (BH)
- The two best performing approaches are based on either SVMs or the wider class of RANNs.

Advantages and Disadvantages

- The aforementioned methods and techniques, however, require:
 - substantial amount of data
 - substantial computational work to train and maintain especially for time series with varying behavior
 - large number of computationally intensive tests to fine tune the large number of hyper-parameters
 - usage of those models requires intervention of an expert to determine, usually by experience, the size and complexity of the model
- In hybrid models the number of parameters becomes even larger rendering optimization even more difficult and time consuming.
- Moreover, for financial time series which have chaotic characteristics the set of the determined hyper-parameters should be updated regularly further increasing computational work.

Harmonics based forecasting

- Despite the extensive use of spectral analysis and harmonic modelling in various scientific fields such as Engineering, Physics and Digital Signal Processing, the potential of such techniques has been rarely been exploited in finance i.e. FX rate forecasting
- Only a few notable contributions exist with the most recent model being Dynamic Harmonic Regression (DHR) (1999).
- Initial techniques include Fast Fourier Transform based extrapolation. While other approaches include estimation of frequencies (harmonics) and fitting based on Ordinary Least Squares. More computationally expensive approaches require the solution of a non-linear Least Squares problem to determine frequency and weights simultaneously.
- There are several issues with these models which include:
 - Determination of the adequate number of harmonics
 - Accurate determination of frequencies
 - Avoid blow-ups due to non-linear nature of the model
 - Effect of noise in the data
- An important advantage of such models is that forecasting is a straight forward procedure and is performed by simply advancing the time variable of a series of periodic functions.

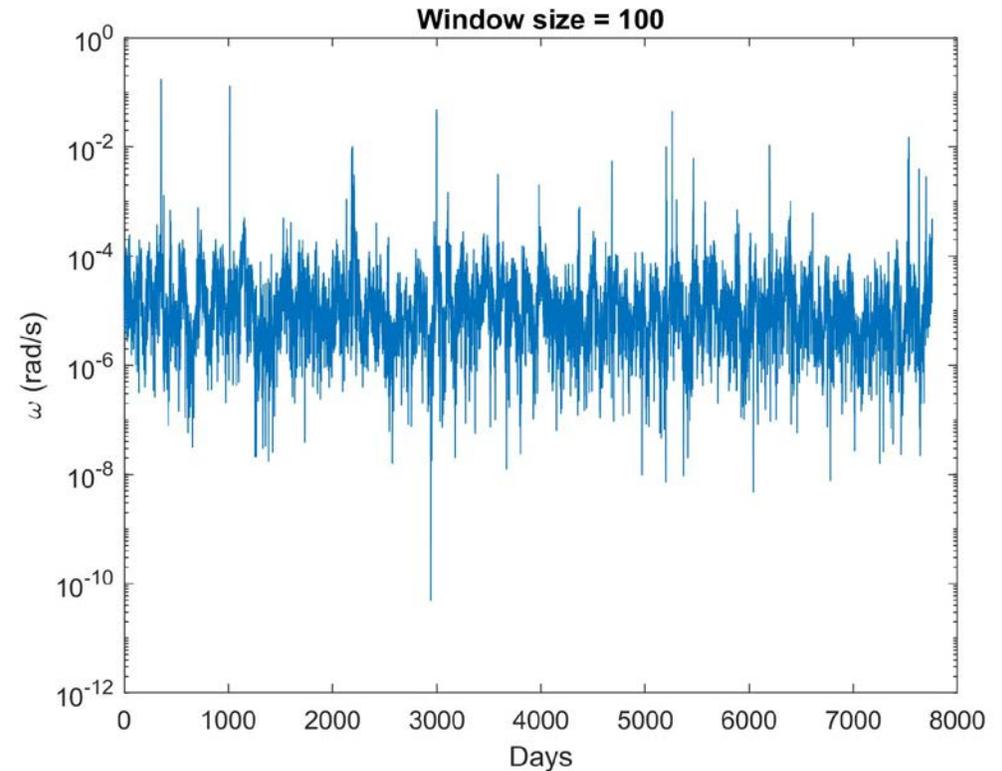
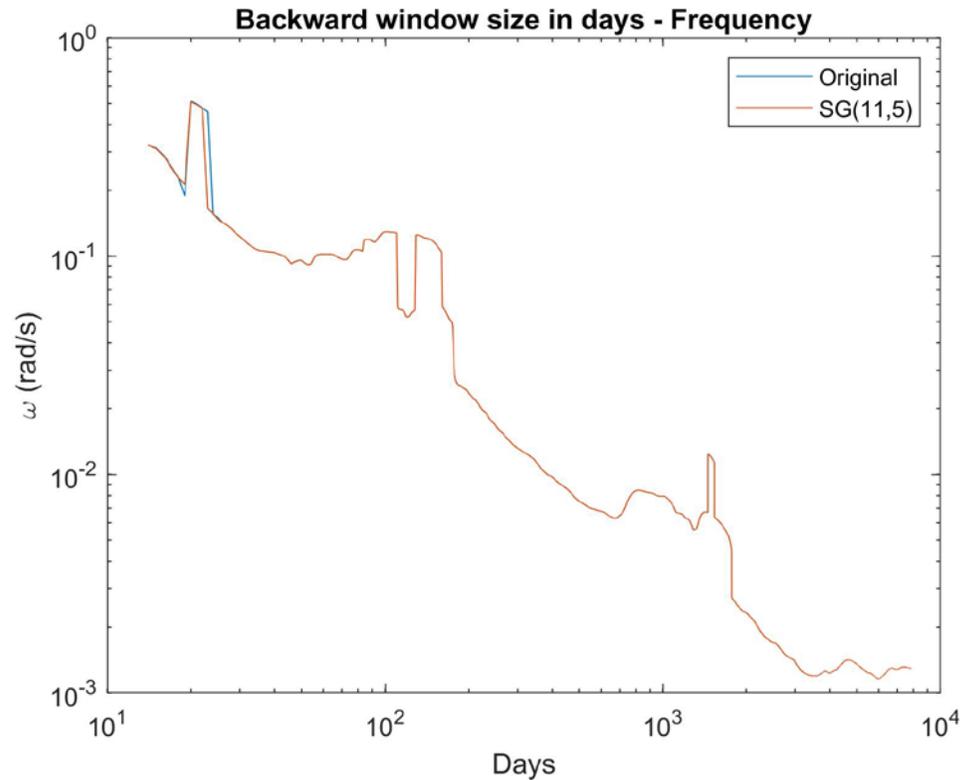
Proposed Harmonics based forecasting

- The general form of a harmonics based model is as follows:
- $y(t) = \mu + \sum_{i=1}^M (A_i \cos(\omega_i t) + B_i \sin(\omega_i t)) + u(t)$
- where μ is the average value, ω_i is the i -th frequency and $u(t)$ are the residuals.
- Direct fitting of this model based on the data requires the solution of Nonlinear Least Squares and “a-priori” knowledge of the number of harmonics, while progressive fitting may result in excessive increase in computational work and instabilities due to increase in frequencies and presence of noisy data.
- To avoid these issues ω_i can be estimated using a frequency estimator such as: FFT, Pisarenko’s method, MUSIC, Quinn, Macleod, Quinn-Fernandes, etc. In general available techniques belong in two groups: Eigenvalue based or ARMA based.
- ARMA based methods are fast and quite reliable under (in some cases) low Signal to Noise ratio. The Quinn-Fernandes technique is fast and very reliable technique if an initial estimation is available (Zemba et al. 2014). Initial estimations can be acquired through FFT.

Proposed Harmonics based forecasting

- In the proposed forecasting model we estimate ω_i with an adaptive modified version of the Quinn-Fernandes algorithm to ensure improved accuracy up to desired tolerance, since after theoretical analysis the error is bounded by:
- $|E| \leq C_1 + C_2 \left(\max_i \delta_i \right) t$
- where δ_i is the error in frequency estimation. Thus, the error increases analogously to the product of time variable with δ_i . This imposes a limit also in the amount of data that can be used for estimating frequencies and building the model.
- Thus, the accuracy of the model is enhanced when accurate estimations can be extracted by fewer (or more current) samples.
- Another important issue is noise in the initial data and especially high-frequency components, that significantly affect estimation especially when fewer samples are available.
- In order to avoid the effects of noise, Savitzky-Goley filter has been chosen to filter out (random) noise components.
- The SG filter, which is a generalization of the MA filter, has substantial advantages compared to the MA filter including higher SNR and preservation of shape.

Proposed Harmonics based forecasting



EUR/USD Pair

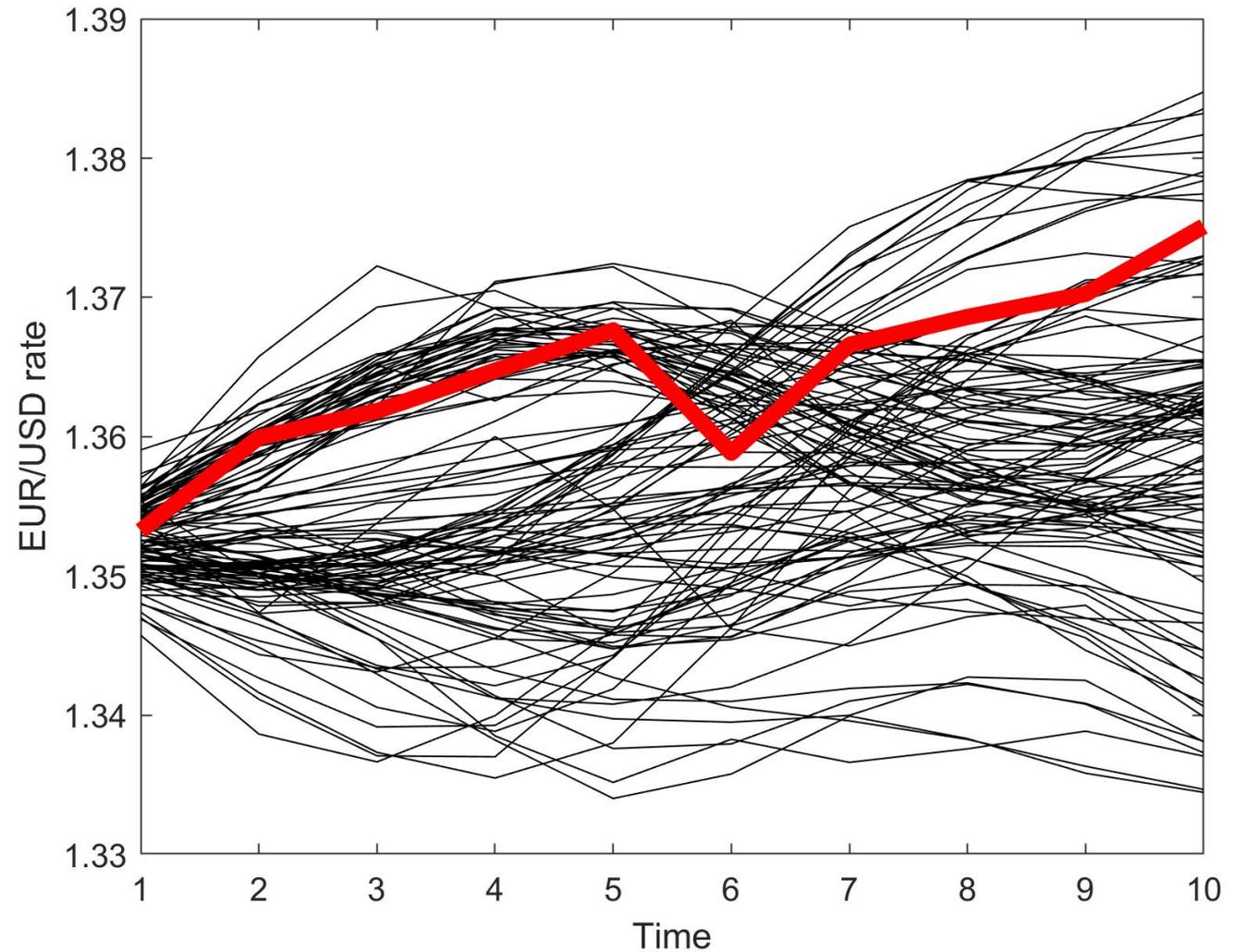
Proposed Harmonics based forecasting

- The estimation of frequency ω_i is performed after filtering the input time series with SG filter.
- Following estimation of ω_i a harmonic $H_i(t) = A_i \cos(\omega_i t) + B_i \sin(\omega_i t)$ is fitted to the time series and removed from the initial signal. The process continues until a threshold is achieved. Thus, no “a priori” knowledge of the number of harmonics is required.
- Moreover, to avoid instabilities the estimation of parameters A_i and B_i is performed with **theoretically proven closed formulas**, which substantially reduce computational work involved in the repetitive solution of OLS problems.
- Furthermore, **stability analysis in terms of condition number of the coefficient matrices** of the linear systems has been carried out, leading to conditions in order to avoid break down of the model due to ill-conditioning, as well as alternative (stable) formulas to compute A_i and B_i .
- To further improve stability **monotonic reduction of the norm of the residual** is enforced, since iterative removal of harmonics may result in the formation of high frequency components.
- **An important issue in such a model is the amount of data that will be used to extract frequencies and estimate harmonics.**

Proposed Harmonics based forecasting

10-step ahead forecast for EUR/USD using a variable window ranging from 15-120 samples. Thick red line represents the observed values.

There is substantial variance between results, since the dominant frequencies are different for different numbers of samples.

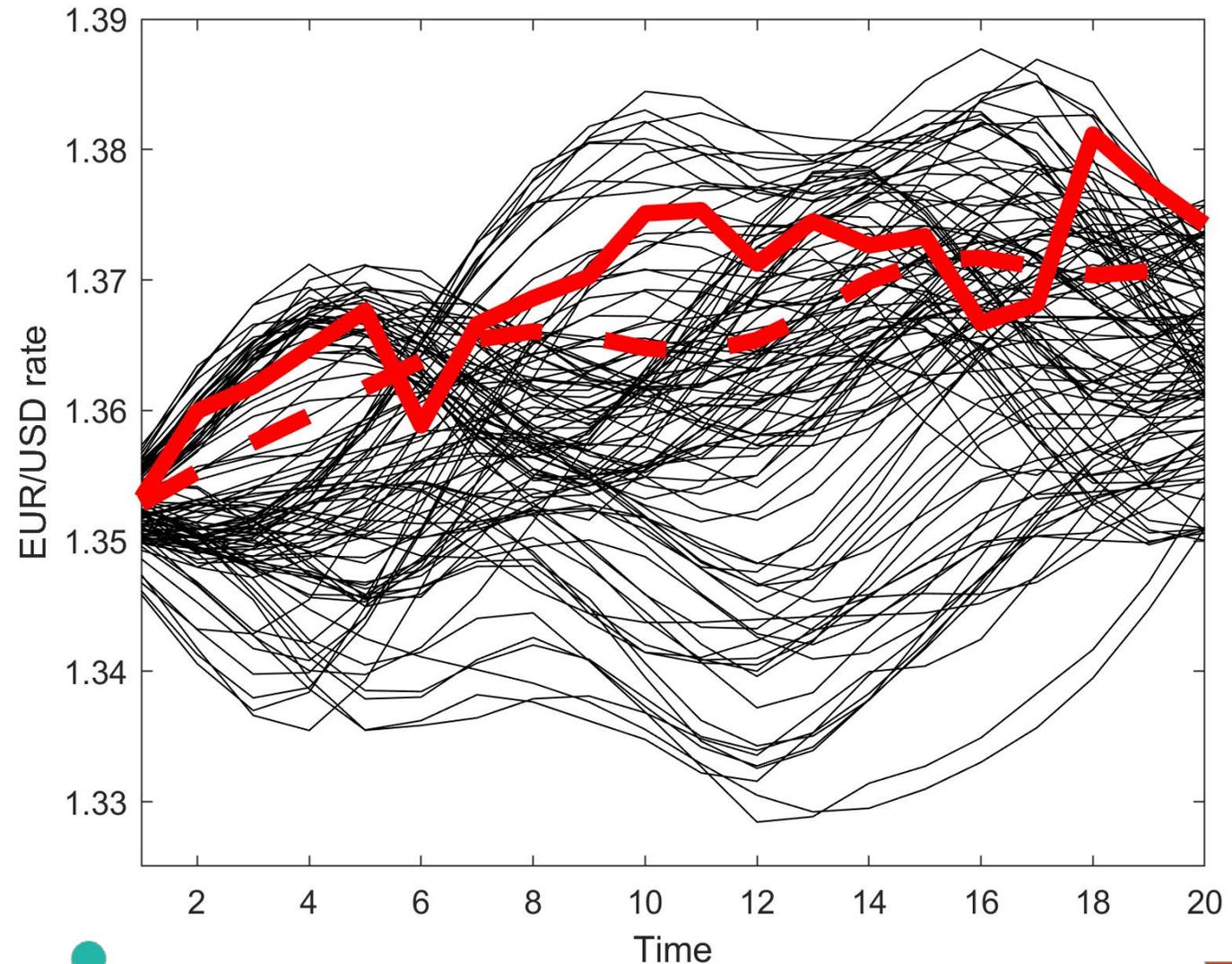


Proposed Harmonics based forecasting

- Determination of the amount of past sample is critical to accuracy of forecasting.
- A large number of past samples might result in a model taking into account the more general behavior smoothing out local phenomena
- While a small number might lead to insufficient capture of a smaller frequency affecting the overall trend.
- Due to the low computational complexity ($\approx O(N \log(N))$) of the proposed scheme, this can be performed by linear search until a local minimum in error is achieved from the most recent values.
- The past values are separated into two subsets (train and test) and several choices are tested allowing for momentum to avoid (sudden) local minima.
- This procedure is terminated if no better value has been achieved or a maximum length has been reached.
- The length of this past window may not be fixed and can be updated in regular intervals, since financial time series tend to change characteristics over time.

Proposed Harmonics based forecasting

20-step ahead forecast for EUR/USD using a variable window ranging from 15-120 samples. Thick red line represents the observed values. Dotted Thick line denotes forecast with the optimal (in terms of MAPE) choice of past values.



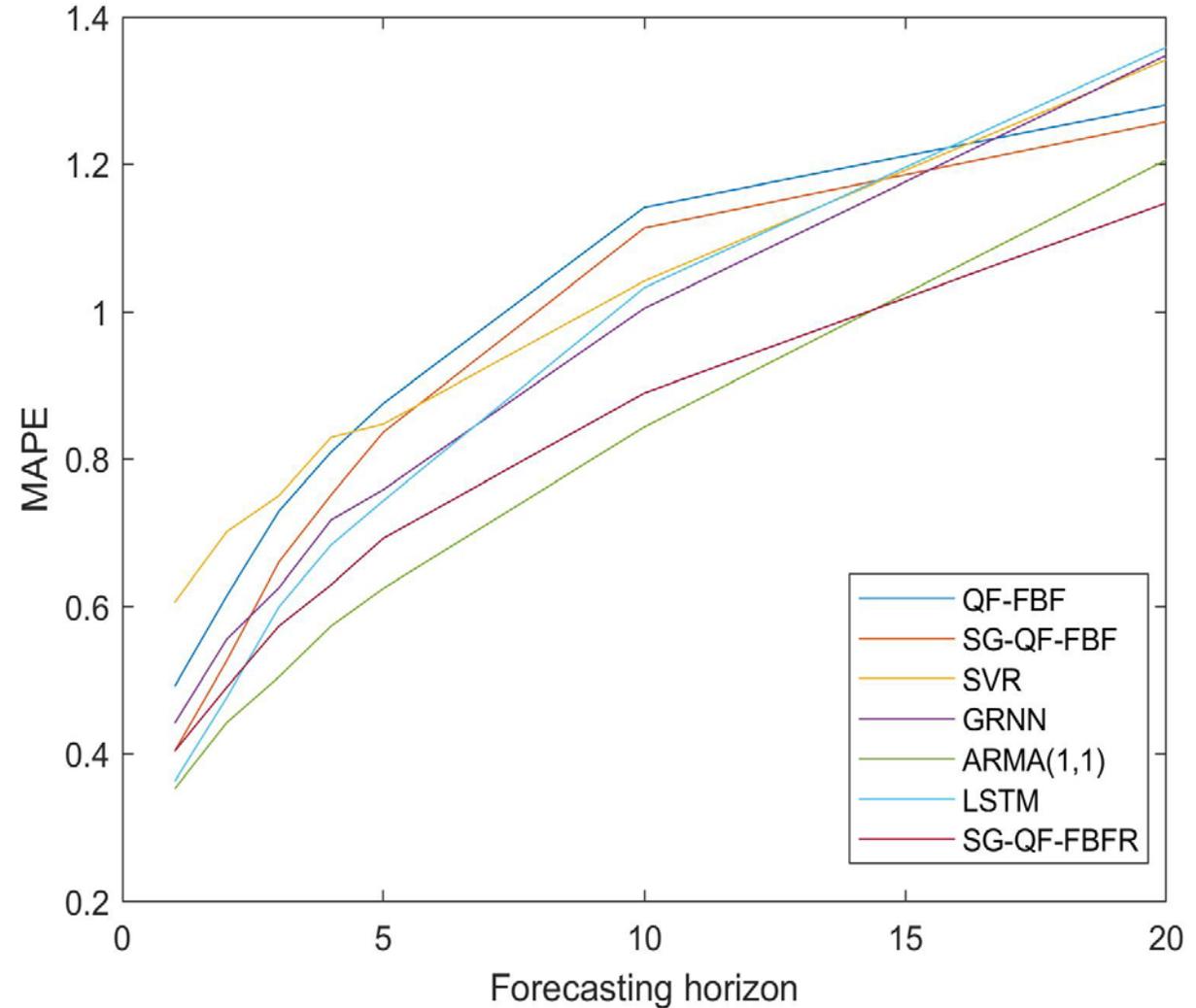
Indicative results

Daily EUR/USD rate (Reuters) for variable forecasting horizons – Train (6288 samples) / Test (1572 samples).

200 past values at maximum were allowed since this selection resulted lead to best results for all methods.

Methods:

1. QF-FBF (proposed)
2. SG-QF-FBF (proposed with SG filtering)
3. Support Vector Regression
4. Generalized Recursive Neural Network
5. Auto-Regressive Moving Average (ARMA(1,1))
6. Long-Sort Term Memory Network (LSTM)
7. SG-QF-FBFR (proposed with retraining)



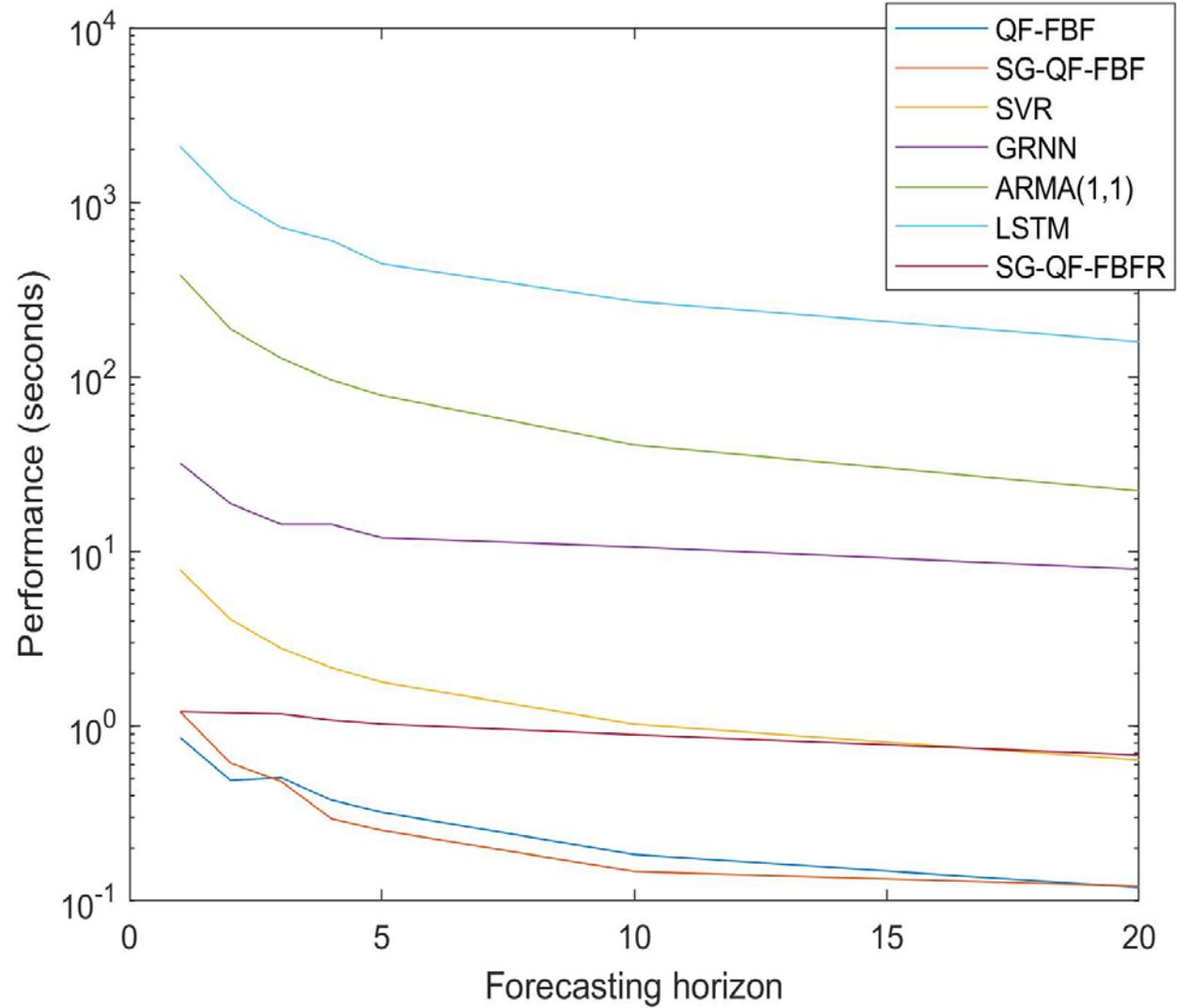
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Conclusions

- Proposed scheme presents accuracy similar to the best of the selected methods (ARMA(1,1)) and far superior performance.
- It does not rely on “heavy” assumptions and can be easily generalized to different time series from other fields.
- It does not require any tuning, since it is automatically tuned in terms of window of past samples and the required parameters are the tolerance in the computation of frequency and the tolerance in the computation of harmonics.
- Due to improved performance the model can be used as a base to design hybrid models.
- The mathematical operations involved in the formation of the model can be easily vectorized or even accelerated efficiently in GPU environments.
- With modifications can be utilized in High-Frequency or as a component in a “what if” engine, due to increased performance.

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Thank you!!!