Simulating Low and High-Frequency Energy Demand Scenarios in a Unified Framework – Part I: Low-Frequency Simulation

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RESUMO

Previsão de demanda energética é uma ferramenta estratégica para companias de distribuição devido à necessidade de contratar o montante de uso dos sistemas de transmissão e distribuição. Entretanto, a maior parte da literatura é focada em previsão e não em simulação. A geração de cenários futuros é essencial para capturar a incerteza inerente ao processo e para permitir um framework de decisão com aversão a risco. O primeiro artigo dessa série de dois artigos propõe uma metodologia para simular cenários de consumo de energia de longo prazo e baixa frequência através de modelos em espaço de estados. Um pacote open-source em Julia contendo a implementação da modelagem em espaço de estados para séries temporais, o filtro de Kalman e a estimação por máxima verossimilhança é disponibilizado. Finalmente, um estudo de caso com dados reais do sistema elétrico brasileiro é apresentado.

PALAVRAS CHAVE. Demanda de energia. Modelos em espaço de estados. Simulação Monte Carlo.

ABSTRACT

Energy demand prediction is a strategic tool for distribution companies due to the need to contract the amount of use of the transmission and distribution systems. However, most of the literature focuses on forecasting rather than simulation. The generation of future scenarios is essential to capture the inherent uncertainty of the process and to allow for a risk-averse decision making framework. The first of this two-paper series proposes a methodology to simulate long-term, low-frequency energy consumption scenarios through state-space models. An open-source Julia package containing the implementation of the time series state-space modeling, Kalman filter and maximum likelihood estimation is made available. Finally, a case study with real data from the Brazilian power system is presented.

KEYWORDS. Energy demand. State-space models. Monte Carlo simulation.

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1. Introduction

Network expansion is a fundamental part of the planning of power systems. Expansion occurs at all system levels – namely, generation, transmission, and distribution – and is essentially attached to time-variant signals, such as energy consumption. Furthermore, agents that partake in the use of the transmission and distribution systems must pay for the usage of such infrastructure. Consequently, there is a systematic need to predict the behavior of energy consumption and to correctly characterize its uncertainty and to simulate the usage of the system. Moreover, in general, the transmission system cost allocation is based on a regulated tariff for the maximum value of power consumption. The Brazilian case is an example of such system.

In Brazil, the transmission system cost is allocated through long-term demand contracts, whose amounts are monthly cleared. The contract clearing is based on the maximum power imported in each interconnection bus of each distribution company with the transmission network and contracted amount. The objective of the distribution company is to minimize contracting expenses by precisely balancing between the benefit of reducing the direct contract cost while avoiding paying high penalties for exceeding contract amounts. This means low-frequency signals, such as monthly data on energy consumption, are not good predictors for the MUST, since these don't offer much information on high-frequency demand peaks. It also presents a further difficulty due to the typical power system structure, which contains a large number of low-level buses at the distribution level. These low-level buses, when added together, are ultimately responsible for the total amount of energy being transmitted at the higher levels. Because the moment of maximum demand at the high-level buses is not necessarily the moment when low-level buses are at their maximum, predicting monthly maximum values of the low-level buses and then adding them together won't suffice – it is necessary to account for all low-level buses in hourly frequency in order to accurately predict the MUST. The first paper of this two-paper work (the other being Bodin et al. [2018]) will deal with the long-term, low-frequency modeling.

Various studies have been conducted to investigate the modeling and forecasting of energy consumption, both in long and short terms. Methodologies range from classic ARIMA models (Box et al. [2015]) to state-space models (Durbin and Koopman [2012]) and neural networks (Park et al. [1991]), as well as hybrid models (Zhang [2003], Liu et al. [2014]). In the long-term framework, Hamzacebi and Es [2014] and Hsu and Chen [2003] presented grey prediction models to forecast yearly power demand and electricity consumption in Turkey and Taiwan, respectively. Also in Taiwan, Pao [2009] employed a state-space model to investigate monthly electricity consumption and its relation with economic growth. Similarly, Hunt et al. [2003] utilized a state-space model to study the long-term trend and seasonality of energy demand in the United Kingdom. Tsekouras et al. [2007] proposed a non-linear multivariate regression model for midterm energy forecasting and applied it to the Greek power system.

As seen above, there is plenty of literature concerning the forecasting of long-term energy consumption. On the other hand, the liaison between the long and short-term frameworks is generally unexplored and strongly connected to the problem of contracting the optimal MUST. Nonetheless, it is challenging to accurately predict the hourly behavior of demand months ahead through either long or short-term models, as the problem involves high-dimensional data in high frequency. A possible strategy is to reduce the dimension and frequency of the original problem, simulate low-frequency signals that dictate the long-term behavior of the multiple signals, and then disaggregate the low-frequency signal back into the high-dimensional and high-frequency framework. Therefore, a methodology is needed in order to successfully connect long and short-term variability in energy consumption, both in a macro environment, such as the total monthly energy consumed in a region, and micro environments, such as the hourly demand occurring in low-level buses. This paper focuses on the first part, while the companion paper Bodin et al. [2018] focuses on the second.

Furthermore, the vast majority of the literature and the industry deals with forecasting, which only provides a prediction of the mean electricity consumption. As opposed to forecasting, the simulation of future scenarios allows the description of the uncertainty in the process, the characterization of a probability distribution and the implementation of a risk-averse framework. This work proposes a methodology to simulate long-term energy consumption scenarios using historical data and exogenous climatic and economic variables. Additionally, an initial version of the Julia package `StateSpaceModels.jl` by Saavedra and Souto [2018], utilized in the studies presented in this paper and currently under work, is made publicly available on GitHub.

The remainder of this paper is organized as follows. Section 2 contains the problem description and utilized notation. Section 3 presents the state-space model employed in this paper. Section 4 describes the process of estimation and simulation done in order to obtain the future scenarios. A case study with real data from the Brazilian system is presented in Section 5. Section 6 raises the relevant conclusions. Finally, the high-frequency modeling, starting from the monthly energy consumption scenarios obtained in this paper, which represents the second stage of this methodology, comprises the companion paper (Bodin et al. [2018]).

2. Problem description

The first stage of the methodology presented in this work consists of generating monthly scenarios of energy consumption, which will be later used as inputs in the high-frequency model. Energy consumption series have several stylized facts which must be considered in the model. To name a few, these series are often non-stationary and contain a well-defined trend, due to population and economic growth over time; they also generally present yearly seasonality, which is caused mostly by the variation of temperature and precipitation patterns. Let E_m, for $m = 1, ..., M$, denote the energy consumption during month m. The objective is to obtain scenarios

$$E_{M+k}(\omega), \quad k = 1, ..., K, \ \omega \in \Omega, \tag{1}$$

where $M + K$ represents the last simulated month and Ω is the set of simulated scenarios. In order to do so, a state-space model (Durbin and Koopman [2012]), fully described in the next section, is employed. The model utilizes historical consumption data as well as exogenous variables. These explanatory variables can range from economic indices, such as GDP and employment rates, to climatic data such as temperature and precipitation.

3. Structural model with exogenous variables

State-space models represent a set of time series models in which the evolution of the process is assumed to be determined by a set of unobserved vectors $\alpha_1, ..., \alpha_m$, which are called the states, or collectively called the state. These states can often have a physical interpretation, representing behaviors such as trend and seasonality. Our problem can be formulated in the linear Gaussian state-space form as

$$E_m = Z\alpha_m + \varepsilon_m, \quad \varepsilon_m \sim N(0, H), \tag{2}$$

$$\alpha_{m+1} = T\alpha_m + R\eta_m, \quad \eta_m \sim N(0, Q), \quad m = 1, ..., M, \tag{3}$$

where α_m is the state vector, matrices Z, T, R, H and Q may contain unknown, fixed parameters present in vector ψ, which will be estimated, and error terms ε_m and η_m are assumed to be serially independent and independent of each other. In our case, E_m is univariate, so matrix H reduces to a single element σ^2_ε. Equations (2) and (3) are called observation equation and state equation, respectively. The observation equation describes how the state α_m contributes to the actual observation E_m, while the state equation describes the evolution of the state over time. Matrices Z, T and R can be time-varying in a more general framework, but in practical cases they are generally constant.

In this work, we utilize a specific instance of state-space models, usually called the basic structural model with exogenous variables. A state-space time series model is generally called a structural model in the literature when its components have well-defined, physical interpretations (Harvey [1990]). Under this framework, one can write Equation (2) as

$$E_m = \mu_m + \gamma_m + \theta^\top X_m + \varepsilon_m, \tag{4}$$

where μ_m is a slowly varying component called the trend, γ_m is a periodic component with fixed periodicity called the seasonal, X_m is a set of exogenous variables, θ is a vector of parameters related to the exogenous variables, and ε_m is referred to as the irregular or error component.

The stochastic trend is formulated in the state equation in the following manner:

$$\mu_{m+1} = \mu_m + \nu_m + \xi_m, \quad \xi_m \sim N(0, \sigma_\xi^2), \tag{5}$$

$$\nu_{m+1} = \nu_m + \zeta_m, \quad \zeta_m \sim N(0, \sigma_\zeta^2). \tag{6}$$

where ν_m is called the slope, while the stochastic seasonal component can be formulated as follows:

$$\gamma_{m+1} = -\sum_{j=1}^{p-1} \gamma_{m+1-j} + \chi_m, \quad \chi_m \sim N(0, \sigma_\chi^2), \tag{7}$$

where p represents the periodicity of the seasonal component, which means the sum of seasonals over a period must be zero, except for an error. Note that all components change stochastically over time, and therefore add further flexibility to this model in capturing time series variations. If variances $\sigma_\varepsilon^2, \sigma_\xi^2, \sigma_\zeta^2, \sigma_\chi^2$ are null, then the model reduces to a deterministic process with well-defined trend, slope and seasonality.

Naturally, it is necessary to formulate Equations (4)–(7) in the state-space matricial form so that they can be inserted in the framework of Equations (2) and (3). The necessary manipulations, as well as the estimation and simulation functions, are implemented in the Julia package `StateSpaceModels.jl` by Saavedra and Souto [2018], which we make publicly available on GitHub. The package also contains an implementation of the square-root Kalman filter (Van Der Merwe and Wan [2001]), square-root smoother, parallelized maximum likelihood estimation (Scholz [1985]), and Monte Carlo simulation.

4. Estimation and simulation

The model contemplated in Equations (2)–(7) depends on a set of hyperparameters, namely the variance of the observation error (σ_ε^2), and each of the variances associated with the errors of the states ($\sigma_\xi^2, \sigma_\zeta^2, \sigma_\chi^2$). Therefore, for the proposed model, ψ contains the following elements:

$$\psi = \begin{bmatrix} \sigma_\epsilon^2 & \sigma_\xi^2 & \sigma_\zeta^2 & \sigma_\chi^2 \end{bmatrix}^\top. \tag{8}$$

Estimation of the fixed parameters is done via maximum likelihood (MLE, Scholz [1985]). Additionally, given that we're dealing with a state-space model, the use of the Kalman filter (Bishop et al. [2001]) is necessary. In particular, we utilize the square-root Kalman filter (Van Der Merwe and Wan [2001]) in our implementation due to its advantages in the state-space time series framework, such as guaranteed positive semi-definiteness of the estimated state covariances. The MLE problem can be formulated as

$$\psi^\star \in \arg\max \ \ell(\psi;\ E_1, ..., E_M) \tag{9}$$

where $\ell(\psi;\ E_1, ..., E_M)$ denotes the log-likelihood concerning vector ψ and observations $E_1, ..., E_M$, such that

$$\ell(\psi) = \sum_{m+1}^{M} \log p(E_m | E_1, ..., E_{m-1}; \psi), \tag{10}$$

where $p(E_m|E_1, ..., E_{m-1}; \psi)$ is obtained through the Kalman filter equations (for the derivation of the Kalman filter equations, see Chapter 4.2 of Durbin and Koopman [2012]). Among the Kalman filter outputs is the smoothed state $\tilde{\alpha}_m = \mathbb{E}[\alpha_m|E_1, ..., E_M]$, which can be interpreted as the extracted components of the series, and the predictive state $a_m = \mathbb{E}[\alpha_m|E_1, ..., E_{m-1}]$, which is used when computing goodness-of-fit statistics and diagnostics.

Algorithm 1 Monte Carlo simulation in a state-space framework

for $\omega \in \Omega$ **do**
  for $k = 1$ **to** K **do**
    1. Sample random innovations from their distributions:
      $\varepsilon_{M+k}(\omega) \sim N(0, \hat{\sigma}^2_\varepsilon)$,
      $\xi_{M+k}(\omega) \sim N(0, \hat{\sigma}^2_\xi), \;\; \zeta_{M+k}(\omega) \sim N(0, \hat{\sigma}^2_\zeta), \;\; \chi_{M+k}(\omega) \sim N(0, \hat{\sigma}^2_\chi)$
      where $\hat{\sigma}^2_\varepsilon, \hat{\sigma}^2_\xi, \hat{\sigma}^2_\zeta, \hat{\sigma}^2_\chi$ are the maximum likelihood estimates of the error variances.
    2. Obtain the state using sampled state innovations:
      $\alpha_{M+k}(\omega) = T\alpha_{M+k-1}(\omega) + R\eta_{M+k}(\omega)$
    3. Obtain energy scenario from simulated state and sampled observation innovation:
      $E_{M+k}(\omega) = Z\alpha_{M+k}(\omega) + \varepsilon_{M+k}(\omega)$
  end for
end for
return $\{E_{M+k}(\omega)\}, \; k = 1, ..., K, \; \omega \in \Omega$

Non-linear optimization methods such as BFGS, L-BFGS and Nelder-Mead (Avriel [2003], Liu and Nocedal [1989]) can be employed to solve this problem. It is important to note that this problem is usually non-convex and thus global optimality might not be guaranteed. It is good practice to run several random seeds as starting points in order to reduce the risk of obtaining a local maximum. An extensive discussion on parameter estimation for state-space models can be found in Durbin and Koopman [2012].

After estimating the fixed parameters and running the Kalman filter, generation of future scenarios can be done through Monte Carlo simulation. Given the energy consumption data E_M, the smoothed state $\tilde{\alpha}_M$, and the estimated hyperparameters $\hat{\psi}$ the simulation is conducted as described in Algorithm 1.

5. Case study

This section presents results from a case study based on real data from distribution company Energisa. The study consists of a simulation of 1000 scenarios for the energy consumption in the state of Minas Gerais (MG). We utilize historical consumption dating from January 2006 up to December 2015 as our in-sample period, while the out-of-sample period is set as January 2016 to September 2016. Figure 1 presents the time series of interest. It is visible that the series displays a definite rising trend, which attenuates after 2014, possibly due to the recent Brazilian economic crisis. Additionally, we employ climatic and economic indices as exogenous variables, namely monthly temperature in the Minas Gerais state (specifically in the municipality of Manhuaçu), Brazilian GDP, employment rates, salary of admission, and an industrial production proxy.

Estimation and simulation are done following the methods presented in Section 4 through Julia package `StateSpaceModels.jl`. The extracted smoothed state components are displayed in Figure 2. It shows a stochastic, rising trend with a noticeable dip towards the end, a deterministic, positive slope, and a well-defined but stochastic seasonal component. The simulation results and their comparison with the out-of-sample realization can be seen in Figure 3. The observed series is between the 5% and 95% quantiles of the scenarios except for one observation. The out-of-sample

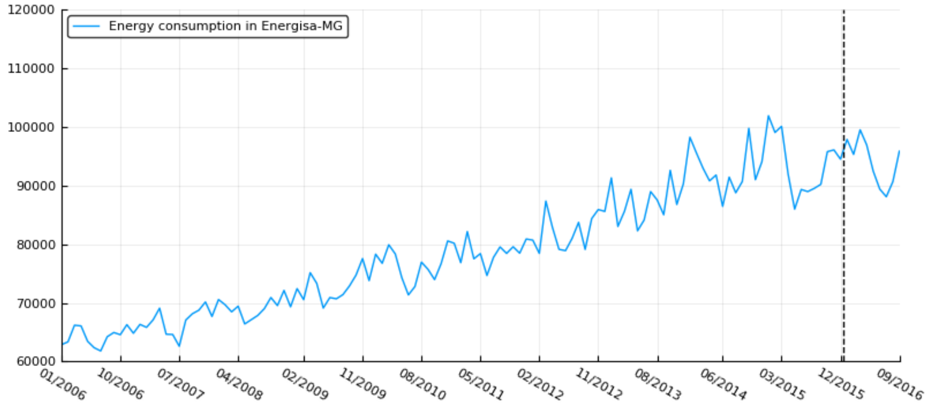

Figure 1: Energisa-MG monthly energy consumption. The dashed line separates the in-sample and out-of-sample periods.

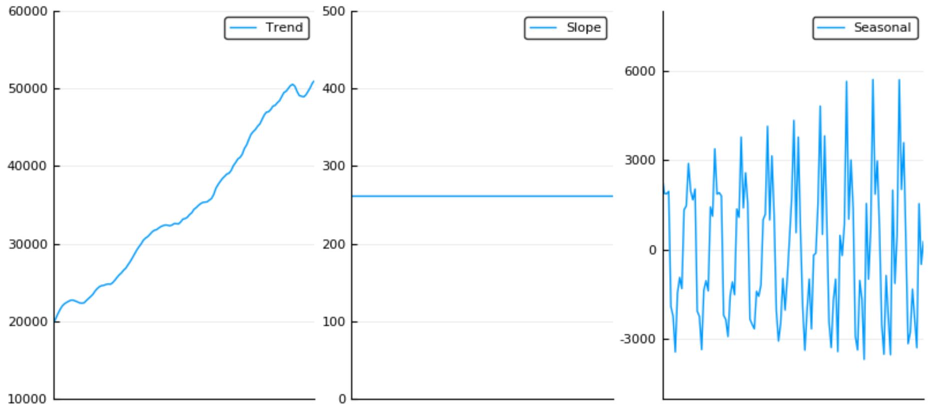

Figure 2: Smoothed state components extracted from Energisa-MG in-sample data.

goodness-of-fit statistics indicate an adequate model fitting, with a mean absolute error[1] (MAE) of 2359.72 MWh and consequent symmetric mean absolute percentage error[2] (SMAPE) of 1.26%. The in-sample predictive estimates show similar results, with a MAE of 2098 MWh and SMAPE of 1.27%.

Finally, as a diagnostic procedure, we analyze the standardized predictive residuals, which are given by

$$e_m = \frac{v_m}{\sqrt{F_m}}, \quad m = 1, ..., M, \tag{11}$$

where $v_m = E_m - \hat{E}_{m|m-1}$ and F_t are the one-step-ahead forecast error and its variance, respectively. $\hat{E}_{m|m-1}$ is the predictive observation given by the Kalman filter, such that

$$\hat{E}_{m|m-1} = \mathbb{E}\big[E_m \big| E_1, ..., E_{m-1}\big]. \tag{12}$$

If the model is well-specified, then e_t follows a standard Normal distribution. Therefore, we conduct a Jarque-Bera test (Jarque and Bera [1987]) in order to test the in-sample forecast errors for normality. The resulting p-value of 0.026 goes against normality at the 95% significance level. However, residuals have been affected by an outlier in June 2015, where the energy consumption drastically dropped. By inserting a manual intervention, correcting that outlier residual and

[1] $MAE = \frac{1}{M}\sum_{i=1}^{M} |\hat{E}_m - E_m|$
[2] $SMAPE = \frac{1}{M}\sum_{i=1}^{M} \frac{\hat{E}_m - E_m}{(|\hat{E}_m| + |E_m|)/2}$

computing once again the Jarque-Bera test, we obtain a p-value of 0.710, which strongly indicates normality.

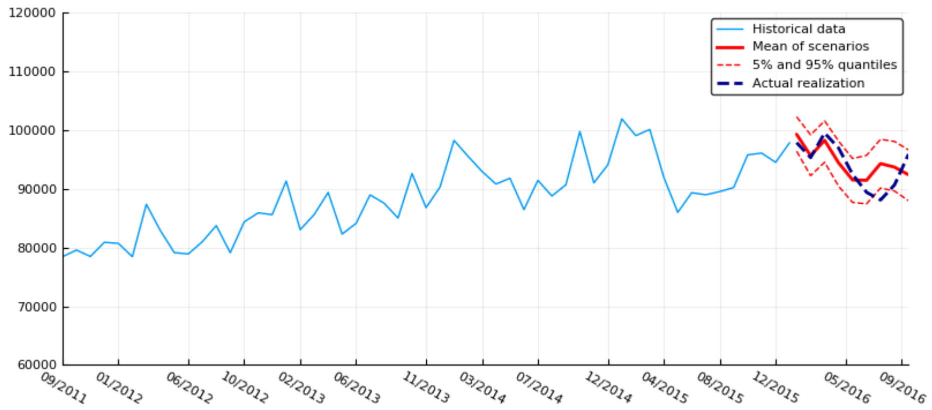

Figure 3: Out-of-sample simulation and comparison with the actual realization for Energisa-MG energy consumption.

6. Conclusions

This paper proposes a methodology to simulate future long-term scenarios of energy consumption based on a state-space framework, as opposed to the majority of the literature, which consists of forecasting. The out-of-sample goodness-of-fit results and diagnostics indicate that the model is well-specified. We also make an initial version of `StateSpaceModels.jl`, a powerful Julia package for modeling time series in state-space form, available on GitHub. Additionally, we make the liaison between low- and high-frequency modeling in demand forecasting together with the companion paper (Bodin et al. [2018]), which starts from the monthly energy consumption scenarios and proceeds to the high-frequency framework.

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