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# A bottom-up bayesian extension for long term electricity consumption forecasting☆

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ABSTRACT

Long term electricity consumption forecasting has been extensively investigated in recent years in different countries due to its economic and social importance. In this context, the long term electricity consumption projections of a country or region are highly relevant for decision-making of companies and organizations operating in any energy system. In this paper, it is proposed a methodology that combines the bottom-up approach with hierarchical linear models for long term electricity consumption forecasting of a particular industrial sector considering energy efficiency scenarios. In addition, the Bayesian inference is used for model parameter estimation and, enabling the inclusion of uncertainty in the forecasts produced by the model. The model was applied to the Brazilian pulp and paper industry and it was able to capture the trajectory of the real consumption observed during the 2008–2014 period. The model was also used to generate long term point and probability distribution forecasts for the period ranging from 2015 until 2050.



## 1. Introduction

The long term future scenarios of electricity consumption are important for energy planning and development of a country. According to Ardakani and Ardehali [1], the long term energy consumption forecasting is very important for the energy systems expansion planning of developing and developed economies.

Currently, the bottom-up and top-down approaches are used to forecast the long term electricity consumption. The top-down approach treats the variables of interest as a whole, providing direct results for them, while the bottom-up approach separates these variables into components; their results are then aggregated to compose the variables of interest. This decomposition can be done at various levels if it is organized in a hierarchical structure. Due to the detailed hierarchical structure of a given variable, the energy efficiency measures (EEMs) can be better understood and evaluated through a bottom-up approach than a top-down one. The EEMs are very important as they allow reducing future electricity consumption and, consequently, to improve the productivity of industrial processes [2]. According to Rajbhandari and Zhang [3], the energy efficiency is recognized as a key policy option for climate change mitigation and also as an industrial policy to boost economic competitiveness.

This paper presents a methodology that combines the bottom-up approach with hierarchical linear models for long term energy consumption forecasting of an industrial sector considering energy efficiency scenarios. In particular, this methodology was applied to the Brazilian pulp and paper sector to predict the annual electricity consumption until 2050.

In the context of energy efficiency scenarios and long term electricity consumption forecasting, Farla et al. [4] evaluated the energy efficiency measures for eight OECD (Organization for Cooperation and Development) countries in the pulp and paper industry. Then, Fleiter et al. [5] adopted a deterministic bottom-up approach to obtain the long term electricity consumption forecasts taking into account the energy efficiency scenarios in the German pulp and paper industry, without considering the cross-cutting technologies. Similarly, Huang et al. [6] used the same deterministic model for long term electricity projection in the Taiwanese cement industry. Silva et al. [7] extended the deterministic bottom-up model presented by Fleiter et al. [5] and Huang et al. [6]

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considering the cross-cutting technologies and applied this deterministic model to the Brazilian industry sector. This deterministic approach provides point forecasts and the uncertainty associated with these results should be estimated when they are used for decision making [8]. In this context, an extension of Silva et al. [7] was proposed through a stochastic Bayesian approach, able to measure and evaluate the uncertainty of electricity consumption forecasting. To do so, a probability distribution was estimated for each year of the forecast horizon.

The paper is organized as follows. Section 2 brings a review of the literature on relevant works on long term forecasting and about the EEMs effects on these forecasts. Section 3 outlines the structure of the modelling approach and lists the data required for modelling. Section 4 presents the application of the proposed model. This section describes the pulp and paper sector in Brazil and the results obtained. Finally, section 5 provides the main conclusions and some possibilities for future researches.

## 2. Literature review

This section presents a review of studies about bottom-up and top-down approaches that are used for long term forecasting. Particularly, for the bottom-up approach it is shown the effects of EEMs. According to Zellner and Tobias [9], these approaches are used when a variable is organized in a hierarchical structure. Similarly, Athanasopoulos et al. [10] explored hierarchical time series with these approaches.

Herbst et al. [11] presented a detailed description of top-down and bottom-up energy models. According to Wene [12], the development of bottom-up models for energy system analysis started in the 1970s. Dunn et al. [13] showed that the forecasts developed by the bottom-up approach are preferable to those obtained via the top-down approach, especially due to the detailing of the data structure. Dangerfield and Morris [14] also reported that the bottom-up model resulted in more accurate forecasts. Fliedner [15] presented a study about the information required for hierarchical forecasting. Hyndman et al. [16] presented a method for reconciling forecasts of all series in a hierarchy.

Jacobsen [17] studied long term household electricity consumption in Denmark using a model that integrates the bottom-up and top-down approaches. Koopmans and Velde [18] modelled the long term energy consumption in Netherlands using approaches top-down, bottom-up and combined approaches. This study showed that the results of integrating bottom-up and top-down approaches depends on the type of models. Swan and Ugursal [19] presented a review of techniques used for modelling the residential sector energy consumption. The authors concluded that the bottom-up models are more appropriate to incorporate new technologies. On the other hand, Ghedamsi et al. [20] adopted only a bottom-up model to obtain the residential sector energy consumption up to 2040 in Algeria.

Georgiou [21] presented a deterministic bottom-up Mixed Integer Linear Programming model for long term energy planning in Greece. Yi et al. [22] modelled the inter-regional power grid planning up to 2030 in China using a bottom-up approach. Lee and Huh [23] used a bottom-up model for long term forecasting of new and renewable energy supply in South Korea. Berntsen and Trutnevyte [24] presented a bottom-up energy system model with Modeling to Generate Alternatives (MGA) to analyze the Swiss long term electricity supply scenarios. MGA is a technique that can generate different energy scenarios [25]. Hall and Buckley [26] presented a review of bottom-up energy models used in the UK.

Due to the importance of the long term electricity consumption forecasting, several studies have been performed. The linear regression and artificial intelligence models adopted by Ardakani and Ardehalli [1], the Holt-Winter and autoregressive integrated moving average models employed by Hussani et al. [27], Pegels exponential smoothing method used by Maçaira et al. [28] and econometric models presented by He et al. [29], were used for long term electricity consumption forecasting. Perwez et al. [30] employed LEAP (Long-range Energy Alternate Planning) model for Pakistan's electric power sector. Thangavelu et al. [31] adopted a multi-period stochastic energy model to obtain future energy demand in Southeast Asia. Koltsaklis et al. [32] applied the Monte Carlo (MCA) method based on multi-period mixed-integer linear programming (MILP) to the Greek power system. Hong and Fan [33] presented a tutorial review of long term probabilistic electric load forecasting. García and Carcedo [34] used a decomposition model for long term electricity forecasting in Spain. Wierzbowski et al. [35] presented an energy mix optimization method using Polish power sector data. Kaboli et al. [36] used an artificial cooperative search algorithm for long term electric energy consumption forecasting in Iran. Kaboli et al. [37] adopted an optimized gene expression programming model based on particle swarm optimization, cuckoo search algorithm, and backtracking search algorithm for long term electrical energy consumption forecasting applied to countries of the Association of Southeast Asian Nations (ASEAN).

In the context of energy efficiency, Worrell and Price [38] studied existing potentials for further efficiency improvements in industry. Tanaka [39] presented a review about EEMs in industry implemented by governments in IEA countries, Brazil, China, India, Mexico, Russia and South Africa. Fleiter et al. [40] presented a review of bottom-up energy demand models for the industrial sector in order to show how these models consider barriers to the implementation of new efficiency measures.

Giraldo and Hyman [41,42] developed a study about the end-use energy models based on energy flows for the US paper industry. Since the oil crisis in the 1970s, Beer et al. [43] showed a method to identify and characterize technologies that can improve long term energy efficiency for the paper and pulp industry based on the OECD countries, but did not investigate their long term effects.

Fracaro et al. [44] studied the energy consumption of the Brazilian pulp and paper industry through an energy decomposition analysis and an energy efficiency index approach between 1979 and 2009. Camioto et al. [45] investigated the energy efficiency of Brazil's industrial sectors (pulp and paper, foods and beverages, chemical, mining, nonmetallic and metallurgical, textiles) from 1996 to 2009 using a mathematical programming method called Data Envelopment Analysis (DEA). These studies did not show the impact of the long term efficiency measures. Silva et al. [46] presented a preliminary study for the electricity consumption of the Brazilian pulp and paper sector up to 2035 using a bottom-up model. This work did not present the particularities of the model used.

Worrell et al. [2] showed the benefits of energy efficiency measures in the iron and steel industry in the US. Neelis et al. [47] studied energy efficiency in the petrochemical industry of Western Europe, Netherlands and the world. Saygin et al. [48] analysed the energy efficiency potential in the global chemical and petrochemical industry. Flues et al. [49] investigated energy efficiency in the European iron and steel industry. These works were developed via a bottom-up approach, but the long term energy savings potential was not investigated. On the other hand, Szabó [50] incorporated several technological details of the pulp and paper industry for 47 world regions. Fleiter et al. [5] presented energy efficiency measures for the German pulp and paper industry. Karali et al. [51] studied energy efficiency measures in the US iron and steel industry. Brunke and Blesl [52] investigated energy efficiency in the German cement industry. These works analysed the long term energy consumption and $CO_2$ emission using the bottom-up approach. They also showed that the $CO_2$ reduction is related to energy savings.

Boβmann and Staffel [53] showed the evolution of load curves until 2050 in Germany and Britain. The energy demand used in the evolution of load curves was obtained by the FORECAST[1] model [54]. This model is a deterministic system and is used to project long term energy demand. It follows a hierarchical structure, i.e., it follows a bottom-up approach. Recently, the FORECAST model was used for the long term energy demand forecasting in the German pulp and paper industry [5], Taiwanese cement industry [6] and Brazilian pulp and paper industry [46].

In Brazil, the Energy Research Company (EPE) is the federal agency responsible for energy planning and the electricity demand forecasting in the medium and long term using both bottom-up and top-down approaches. It does not show the details of the model used. One of the reports presented by EPE shows the electricity consumption projection up to 2050 [55]. Pao and Tsai [56], using a top-down approach, and Cabral et al. [57] via a spatial econometrics approach showed the importance of energy consumption forecasting in Brazil.

In this review, the bottom-up models presented for long term energy consumption forecasting are all deterministic models. According to Uusitalo et al. [8], the uncertainty in the results of deterministic models must be estimated when they are used for decision making. Hagan [58] concluded that the uncertainty present in deterministic models can be viewed as a probability distribution of an unknown quantity.

In the context of stochastic models, hierarchical linear models were presented by Bryk and Raudenbush [59], but according to Lindley and Smith [60] these hierarchical linear models have emerged in the development of Bayesian estimation methods for linear models.

Lindley and Smith [60] pointed out that the best strategy for specifying an a priori distribution to describe an experimental situation is to define a priori distributions to the lowest levels of the hierarchy.

This section presented an overview of different works that have used the bottom-up and top-down approaches for long term energy consumption forecasting, and a brief review of hierarchical linear models. It was observed in this review that, when comparing these two types of models, the top-down uses less data to achieve the results; but the interpretation of the influence of some agents in the results is less explicit. On the other hand, the bottom-up approach allows a better interpretation of the influence of such factors in the results at the expense of a larger amount of data.

This study presents a modelling structure that combines the bottom-up approach with linear hierarchical models, estimated via Bayesian inference, which estimates a probability distribution for the electricity consumption for each year of the forecast horizon. This methodology was not proposed in any previously published work, to the best of our knowledge.

## 3. Modelling approach

In this section, it is presented the model for long term electricity consumption forecasting of an industrial sector. This model combines the forecasting generated by the bottom-up approach with linear hierarchical models.

The proposed stochastic model to obtain the long term electricity consumption of an industrial sector is based on the work of Silva et al. [7], and is defined by

$$S_t = \sum_{j=1}^{n} P_{j,t} + R_t - E_t + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_s^2\right), \tag{1}$$

$$P_{j,t} = g(Prod_{j,t}) - E_{j,t} + \delta_{j,t}, \qquad \delta_{j,t} \sim N\left(0, \sigma_p^2\right), \tag{2}$$

for time $t = 1, 2, \ldots, T$, $j = 1, 2, \ldots, n$, where $n$ represents the number of processes of a sector; $S_t$ represents electricity consumption of the sector; $P_{j,t}$ represents electricity consumption of the process $j$; $g(Prod_{j,t}) = SEC_{j,t_r} \times Prod_{j,t}$, $SEC_{j,t_r}$ is the specific electricity consumption of process $j$ at a fixed time, $t_r$, and $Prod_{j,t}$ denotes production of process $j$; $R_t$ is a component that was not identified prior in the bottom level of the hierarchy, i.e., this term is known as the gap of the sector; $E_t$ corresponds to the saved energy by applying EEMs to cross-cutting technologies of the sector, and $E_{j,t}$ represents the saved energy obtained by EEMs applied in process $j$; $\varepsilon_t$ and $\delta_{j,t}$ are random disturbances of the sector and process, respectively, both following a normal distribution with zero mean and variances $\sigma_s^2$ and $\sigma_p^2$. Furthermore, it is assumed that the errors $\varepsilon_t$ and $\delta_{j,t}$ are internally and mutually independent. The hierarchical structure of the proposed model presented in equations (1) and (2) is schematically illustrated below in Fig. 1.

The energy savings due to EEMs can be calculated by the following equations,

i) For processes:

$$E_{j,t} = \sum_{e_j=1}^{m_j} \left(sp_{j,e_j} \times \alpha_{j,e_j,t,x} \times Prod_{j,t}\right), \tag{3}$$

where $e_j$ is an energy efficiency measure (EEM) for process $j$, $m_j$ is the number of EEMs of process $j$, $sp_{j,e_j}$ is the specific potential reduction of the electricity consumption of $e_j$ to process $j$, $\alpha_{j,e_j,t}$ is the percentage of reduction of the electricity consumption in time $t$ obtained with $e_j$, and $x$ is a path of $e_j$ with time.

ii) For cross-cutting technologies:

$$E_t = \sum_{k=1}^{Z} (\phi_k \times \Delta_{k,t}), \quad \Delta_{k,t} = \sum_{e_k=1}^{m_k} \left(sp_{k,e_k} \times \alpha_{e_k,t,x}\right) \tag{4}$$

where $k$ is a cross-cutting technology (fans, pumps, lighting, compressed air, other motors, cold appliances), $Z$ is the number of cross-cutting technologies, $e_k$ is an EEM to technology $k$, $m_k$ is the number of EEMs of technology $k$, $sp_{k,e_k}$ is the specific potential reduction of

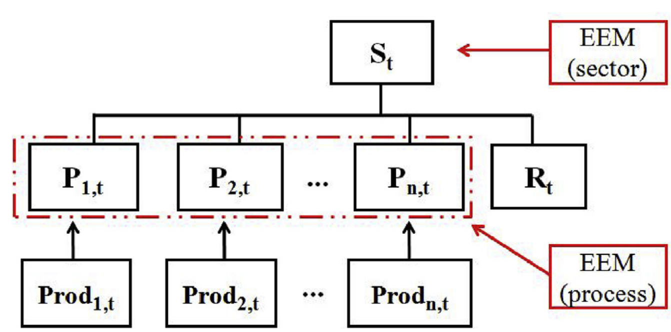



**Fig. 1.** A hierarchical structure with energy efficiency measures.

[1] Further information about the model is available from http://www.forecastmodel.eu/forecast-en/content/methodology.php.

the electricity consumption of $e_k$ to technology $k$, $\alpha_{e_k,t,x}$ is the percentage of reduction of the electricity consumption at time $t$ obtained with $e_k$, $x$ is a path of $e_k$ with time, $\phi_k$ is the electricity consumption of the cross-cutting technology $k$ of the sector, and $\Delta_{k,t}$ corresponds to achieved percentage of energy saving to $k$.

The paths of $x$ with time come from diffusion curves [61]. According to this author, the values of a diffusion curve can be estimated by a logistic function. This function is defined in this study by

$$d_x(t) = \frac{D_{x,0}\, D_{x,f}\, e^{\lambda_x(t-t_{x,0})}}{D_{x,f} + D_{x,0}\left[e^{\lambda_x(t-t_{x,0})} - 1\right]} \tag{5}$$

where $x$ is diffusion type (path), $t$ is the target year; $\lambda$ is the slope of the logistic curve, $t_{x,0}$ is the initial year, $t_{x,f}$ is the last year, $D_{x,0}$ is the diffusion value at $y_{x,0}$ and $D_{x,f}$ is the diffusion value at $t_{x,f}$.

The parameters $(\alpha_{e_j,t,x}, \alpha_{e_k,t,x})$ of equations (3) and (4) are derived from these curves, resulting in

$$\alpha_{e_j,t,x} = d_{e_j,x}(t) - d_{e_j,x}(t_{x,0}) \tag{6}$$

$$\alpha_{e_k,t,x} = d_{e_k,x}(t) - d_{e_k,x}(t_{x,0}) \tag{7}$$

Finally, based on the FORECAST model [54], the component $R_t$ was calculated by

$$R_t = \begin{cases} S_t - \sum_{j=1}^{n} P_{j,t}, & t = 1, \cdots, t^*; \\ R_{t^*} \times \left[1 + \left(\dfrac{VA_t}{VA_{t^*}} - 1\right) \times \rho\right], & t = t^* + 1, \cdots, T; \end{cases} \tag{8}$$

where $t^*$ represents the calibration year (in particular, $t^* = 2014$), $VA_t$ is the value added of a sector at time $t$ and $\rho$ is a factor of correlation between the energy demand and value added of the sector. The correlation factor was calculated from the data observed (value added and electricity consumption) in the period 2007–2014. For more details on this factor, see Soytas and Sari [62].

### 3.1. Required data

In this study, it was considered only electricity as energy source for the sector. The main variables required for the study are: sector electricity demand (GJ), process identification, production by process (t), specific electricity consumption (SEC) by process (GJ/t), value added of the sector, percentage electricity consumption of each cross-cutting technology of the sector (%), EEMs for the sector and their processes, electricity price, and annual forecasting of production and value added until 2050.

The annual data of electricity consumption of the Brazilian industrial sector were obtained at the website of EPE [63]. The historical data ranged from 1995 to 2016. The value added data of the sector were obtained from the Brazilian Institute of Geography and Statistics (IBGE) [64]. It was used the annual data from 2007 to 2014. The production of processes, from 2007 to 2014, were obtained from EPE [65], IBGE [64] and FAO [66]. The electricity price projection until 2050 was obtained by a stochastic hydrothermal dispatch model (SDDP). For more details on the SDDP see Calili et al. [67].

The specific electricity consumption (SEC) for some individual processes was particularly difficult to obtain from the official sources. Thus, the SEC was estimated using the procedure proposed by Silva et al. [7] and available data from EPE [63], National Electrical Energy Conservation Program (PROCEL) [68]. This procedure to obtain the SEC can be written by

$$SEC_{j,t,L} = \theta \times SEC_{j,t,C}, \tag{9}$$

where $L$ represents a country whose SEC of the processes are unknown, $C$ represents a country whose SEC of processes are known; and

$$\theta = \frac{S_{t,L} - R_{t,L}}{\tilde{S}_{t,C}}, \tag{10}$$

where $\tilde{S}_{t,C}$ is the energy consumption estimation of a sector of country $C$ corresponding to their processes, and is calculated by

$$\tilde{S}_{t,C} = \sum_{j=1}^{n} (SEC_{j,t,C} \times Prod_{j,t,L}), \tag{11}$$

and

$$R_{t,L} = \left(\frac{R_{t,C}}{S_{t,C}}\right) \times S_{t,L} \tag{12}$$

The individual electricity consumption percentage of each cross-cutting technology in Brazil was estimated based on the data from PROCEL [68] and on the procedure proposed by Silva et al. [7].

### 3.2. Scenarios definition of technological diffusion

The technological diffusion scenarios were defined considering efficiency policies, innovation barriers, costs of EEMs and investment costs.

According to Fleiter et al. [5] in German industry, Huang et al. [6] in Taiwanese industry and Silva et al. [7] in Brazilian industry, there is a baseline scenario and three others of technological diffusions. The diffusion curve values were estimated using the logistic function (equation (5)). These scenarios are defined as follows.

- Frozen scenario (baseline) is defined as the one where no further improvement in efficiency takes place. The distance from any scenario to the frozen one in a given year is defined as the saving potential of the scenario.
- Autonomous scenario (auto) assumes that these technological barriers remain high and the technology diffusion is based on past development without promotion policies.
- Maximum scenario (max) is based on the assumption that barriers are very low or even non-existent.
- Cost-effective scenario (cost) is based on the cost of EEMs and certain assumptions of corporate investment decisions. It is assumed in this scenario that companies investments are based on turnaround time of EEMs. The higher the turnaround time is, the closer it is to the lower limit (auto), while the shorter the turnaround time, the closer it gets to the upper limit (max). The value of cost-effective diffusion is defined by

$$d_{cost}(t) = d_{auto}(t) + \psi(t)(d_{max}(t) - d_{auto}(t)), \tag{13}$$

where $d_{auto}(t)$ is the value of autonomous diffusion, $d_{max}(t)$ is the value of maximum diffusion, and $\psi(t)$ is a parameter that depends on the energy price, discount rate, investment costs, running costs and economic lifetime for each efficiency measure. The values of $\psi(t)$ vary in the interval $[0, 1]$. For more details about the calculation of $\psi(t)$, see Worrell et al. [2].

The construction of the diffusion scenarios can be seen in more detail in Silva et al. [7].

### 3.3. Parameter estimation for the proposed model

The model parameters were estimated using Bayesian inference due to the that it allows measuring the uncertainty. Thus, the Monte Carlo Markov Chain (MCMC) method was used to generate samples of each parameter [69], with emphasis on Gibbs sampling [70].

For an industrial sector, the interest is to estimate the parametric vector of the proposed model, which is given by $\Theta = (\sigma_s^2, \sigma_p^2, \mathbf{P}_t)$, where $\mathbf{P}_t = (P_{1,t}, P_{2,t}, \cdots, P_{n,t})$ and $P_{j,t} = (P_{j,1}, \cdots, P_{j,T})$. Following the proposed model (equations (1) and (2)), the likelihood function for the parameters is given by

$$l\left(\sigma_s^2, \sigma_p^2, \mathbf{P}_t \middle| \mathbf{S}_t\right) = p\left(\mathbf{S}_t \middle| \sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) = \left(2\pi\sigma_s^2\right)^{-T/2} \exp\left\{ -\frac{1}{2\sigma_s^2} \sum_{t=1}^{T} \left(S_t^* - \sum_{j=1}^{n} P_{j,t}^*\right)^2 \right\},$$

such that $\mathbf{S}_t = (S_1, S_2, \cdots, S_T)'$, $S_t^* = S_t - R_t - E_t$ and. $P_{j,t}^* = P_{j,t} - E_{j,t}$

Let $p(\sigma_s^2, \sigma_p^2, \mathbf{P}_t)$ be the prior distribution of the parametric vector $\Theta$. It was assumed prior independence between the components of the parametric vector. For the parameters $\sigma_s^2$ and $\sigma_p^2$ it is usual to specify an inverse gamma (IG) prior distribution, due to the conjugacy [71], independent and not very informative prior. For a more detailed explanation of the vague or not very informative prior distributions, consult Box and Tiao [72] and the study of reference posterior distributions by Bernardo [73]. Thus, the independent prior distributions were adopted $\sigma_s^2 \sim IG(\alpha_1, \beta_1)$, where $\alpha_1$ and $\beta_1$ are known, and $\sigma_p^2 \sim IG(\alpha_2, \beta_2)$, where $\alpha_2$ and $\beta_2$ are known.

The complete model for the electricity consumption of an industrial sector is specified by

$$\begin{aligned}
&\left(\mathbf{S}_t \middle| \sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) \sim N\left(\sum_{j=1}^{n} P_{j,t} + R_t + E_t,\ \sigma_s^2\right) \\
&\left(\mathbf{P}_t \middle| \sigma_p^2, Prod_{j,t}\right) \sim N\left(g(Prod_{j,t}) + E_{j,t},\ \sigma_p^2\right) \\
&\sigma_s^2 \sim IG(\alpha_1, \beta_1) \\
&\sigma_p^2 \sim IG(\alpha_2, \beta_2)
\end{aligned}$$

where $\alpha_1$, $\beta_1$, $\alpha_2$ and $\beta_2$ represent the prior distribution's known hyperparameters. The values of $Prod_{j,t}$ and $R_t$ were generated exogenously up to the forecast horizon.

The values of $Prod_{j,t}$ were obtained by dynamic regression models (DRM) [74] using the industry GDP,[2] and the values of $R_t$ were calculated by equation (8). In this equation, the value added was estimated by DRM using the industry GDP.

Therefore, the posterior distribution to $\Theta$ is obtained as follows,

$$\begin{aligned}
p\left(\sigma_s^2, \sigma_p^2, \mathbf{P}_t \middle| \mathbf{S}_t\right) &\propto l\left(\sigma_s^2, \sigma_p^2, \mathbf{P}_t \middle| \mathbf{S}_t\right) p\left(\sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) \\
&= p\left(\mathbf{S}_t \middle| \sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) p\left(\sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) \\
&\propto p\left(\mathbf{S}_t \middle| \sigma_s^2, \sigma_p^2, \mathbf{P}_t\right) p\left(\mathbf{P}_t \middle| \sigma_p^2\right) p\left(\sigma_s^2, \sigma_p^2\right) \\
&\propto p\left(\mathbf{S}_t \middle| \sigma_s^2, \mathbf{P}_t\right) p\left(\mathbf{P}_t \middle| \sigma_p^2\right) p\left(\sigma_p^2\right) p\left(\sigma_s^2\right),
\end{aligned}$$

assuming prior independence between the components of the parametric vector. It follows that the posterior distribution of the proposed model parameters is given by

$$\begin{aligned}
p(\Theta|\mathbf{S}_t) \propto &\left(2\pi\sigma_s^2\right)^{-T/2} \exp\left\{ -\frac{1}{2\sigma_s^2} \sum_{t=1}^{T} \left(S_t^* - \sum_{j=1}^{n} P_{j,t}\right)^2 \right\} \\
&\times \left(2\pi\sigma_p^2\right)^{-nT/2} \exp\left\{ -\frac{1}{2\sigma_p^2} \sum_{j=1}^{n} \sum_{t=1}^{T} (P_{j,t} - g(Prod_{j,t}))^2 \right\} \\
&\times \left(\sigma_s^2\right)^{-\alpha_1 - 1} \exp\left\{ -\frac{\beta_1}{\sigma_s^2} \right\} \times \left(\sigma_p^2\right)^{-\alpha_2 - 1} \exp\left\{ -\frac{\beta_2}{\sigma_p^2} \right\}.
\end{aligned}$$

The joint posterior distribution has no known form. However, the posterior conditional distributions of each parameter can be obtained as:

(i) The full posterior conditional distribution of $P_{j,t}$:

$$\begin{aligned}
p(P_{j,t}|\cdot) \propto &\exp\left\{ -\frac{1}{2\sigma_s^2} \left(S_t^* - \sum_{j=1}^{n} P_{j,t}\right)^2 \right\} \\
&\times \exp\left\{ -\frac{1}{2\sigma_p^2} \sum_{j=1}^{n} (P_{j,t} - g(Prod_{j,t}))^2 \right\} \\
&\propto \exp\left\{ -\frac{1}{2}\left[ P_{j,t}^2 \left(\frac{1}{\sigma_s^2} + \frac{1}{\sigma_p^2}\right) - 2P_{j,t}\left(\frac{S_t^* - \sum_{k=1,k\neq j}^{n} P_{k,t}}{\sigma_s^2} + \frac{g(Prod_{j,t})}{\sigma_p^2}\right)\right]\right\}.
\end{aligned}$$

Thus,

$$(P_{j,t}|\cdot) \sim N\left(v^{-1}m, v^{-1}\right), \text{ where}$$

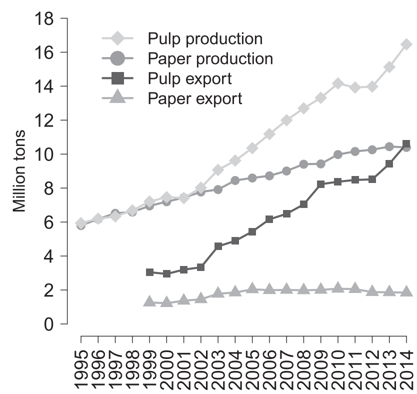
$$v = \left(\frac{1}{\sigma_s^2} + \frac{1}{\sigma_p^2}\right) \text{ e } m = \left(\frac{S_t^* - \sum_{k=1,k\neq j}^{n} P_{k,t}}{\sigma_s^2} + \frac{g(Prod_{j,t})}{\sigma_p^2}\right).$$

(ii) the full posterior conditional distribution of $\sigma_s^2$:

$$p\left(\sigma_s^2 \middle| \cdot\right) \propto \left(\sigma_s^2\right)^{-T/2 - \alpha_1 - 1} \exp\left\{ -\frac{1}{\sigma_s^2}\left[\beta_1 + \frac{1}{2} \sum_{t=1}^{T} \left(S_t^* - \sum_{j=1}^{n} P_{j,t}\right)^2\right]\right\}.$$

Thus,

[2] GDP values were estimated on the basis of BACEN (Central Bank of Brazil) data, https://www3.bcb.gov.br/expectativas/publico/consulta/serieestatisticas.



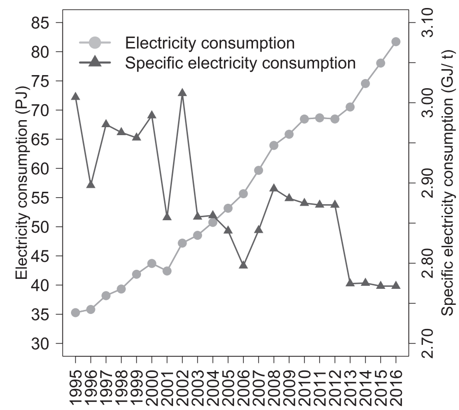




**Fig. 2.** (a) Production and export of pulp and paper for 1995–2014. (b) Electricity consumption and specific electricity consumption of the pulp and paper sector for 1995–2016.

**Table 1**
Annual production by process (million tons) and annual value added of the pulp and paper sector in Brazil (million Reais).

| | Process | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|---|
| Production ($10^6$ t) | Paper | 5.76 | 6.33 | 7.10 | 7.97 | 8.95 | 10.03 | 11.21 | 12.53 |
| | Chemical pulp | 16.69 | 18.34 | 20.57 | 23.11 | 25.96 | 29.09 | 32.50 | 36.32 |
| | Mechanical pulp | 0.48 | 0.53 | 0.60 | 0.66 | 0.74 | 0.83 | 0.93 | 1.04 |
| | Recovered paper | 4.60 | 5.05 | 5.67 | 6.37 | 7.15 | 8.02 | 8.96 | 10.01 |
| Sector | | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
| Value added ($10^6$ REAL) | | 22936 | 25558 | 30048 | 34252 | 38182 | 41826 | 45059 | 48115 |

$$\left(\sigma_s^2\middle|\cdot\right) \sim IG\left(\alpha_1 + \frac{T}{2}, \beta_1 + \frac{1}{2}\sum_{t=1}^{T}\left(S_t^* - \sum_{j=1}^{n} P_{j,t}\right)^2\right).$$

(iii) the full posterior conditional distribution of $\sigma_p^2$:

$$p\left(\sigma_p^2\middle|\cdot\right) \propto \left(\sigma_p^2\right)^{-\frac{nT}{2}-\alpha_2-1}\exp\left\{-\frac{1}{\sigma_p^2}\left[\beta_2 + \frac{1}{2}\sum_{j=1}^{n}\right.\right.$$
$$\left.\left.\times\sum_{t=1}^{T}\left(P_{j,t} - g\left(Prod_{j,t}\right)\right)^2\right]\right\}.$$

Thus,

$$\left(\sigma_p^2\middle|\cdot\right) \sim IG\left(\alpha_2 + \frac{nT}{2}, \beta_2 + \frac{1}{2}\sum_{j=1}^{n}\sum_{t=1}^{T}\left(P_{j,t} - g\left(Prod_{j,t}\right)\right)^2\right).$$

Since the full posterior conditional distributions are known, then samples of the posterior distribution of the specified model parameters can be generated using the MCMC method, in particular, the Gibbs sampler.

## 4. Application

This section presents a description of the pulp and paper sector of the Brazilian industry and some required information for modelling. This is followed by a presentation of the results obtained by the fitting of model to this industrial sector.

### 4.1. The Brazilian pulp and paper sector

The Brazilian industrial sector accounted for 37.6% of total electricity consumption in 2016, reaching a value of 703 PJ [63]. The Brazilian energy balance divides the industrial sector into eleven sectors[3] according to the activity performed [65].

The pulp and paper sector presents one of the highest long term economic expectancy in the country [65]. According to EPE [65], this characteristic is related to the fact that eucalyptus adapts very well to Brazilian soil and climate.

In 2016, this sector accounted for 11.6% of total the Brazilian industrial consumption, reaching 82 PJ. In the period from 1995 to 2014, the sector presented production growth of 124% [75]. Brazil is currently ranked among the top ten world producers of pulp and paper [75] and played an important role in the Brazilian economy in 2014 [76]. In the same period, electricity consumption increased by 111% [65]. This increase was driven by a rise in output from 12 million tons in 1995 to 27 million metric tons in 2014 (see Fig. 2 (a)). For the period from 1995 to 2016, SEC per ton of pulp and paper sector presented oscillation, but showed a decreasing trend (see Fig. 2 (b)).

Table 1 presents the annual projections up to 2050 of production and value added generated by dynamic regression models [74], in multiples of 5 years, starting in 2015. The exogenous variable used in the models was the industry GDP.[4] These projected values complete the information required for modelling.

[3] The Energy Research Company (EPE) ranks them as follows: pig-iron and steel, non-ferrous metals and other metallurgical, pulp and paper, chemical, foods and beverages, cement, iron-alloys, mining and pelletization, textiles, ceramics and other industries [65].

[4] GDP values were estimated on the basis of BACEN (Central Bank of Brazil) data, https://www3.bcb.gov.br/expectativas/publico/consulta/serieestatisticas.

**Table 2**
Summary of energy efficiency measure assumptions for processes: specific energy savings (SES) and costs.

| Process | Energy efficiency measures | SES | Costs | |
|---|---|---|---|---|
| | | Electricity | Initial costs | Lifetime |
| | | (GJ/t) | (R$/t) | (year) |
| 1. Paper | 1.1 Efficient refiners | 0.118 | 33.0 | 10 |
| | 1.2 Optimization of refining | 0.075 | 1.5 | 10 |
| | 1.3 Chemical modification of fibers | 0.164 | 9.2 | 10 |
| 2. Chemical pulp | 2.1 Black liquor gasification | 2.000 | 943.1 | 10 |
| 3. Mechanical pulp | 3.1 High efficiency (GW) | 2.590 | 755.7 | 10 |
| | 3.2 Enzymatic pre-treatment | 1.860 | 929.7 | 10 |
| | 3.3 Efficient refiner (TMP) | 1.550 | 233.6 | 10 |
| 4. Recovered paper | 4.1 High consistency pulping | 0.020 | 5.4 | 10 |
| | 4.2 Efficient screening | 0.065 | 12.6 | 10 |
| | 4.3 De-inking flotation optimization | 0.050 | 1.9 | 10 |
| | 4.4 Efficient disperser | 0.022 | 2.5 | 10 |

R$ - Brazilian currency (R$ 1~ US$ 0.46, in 2013); SES - Specific Energy Savings.

### 4.1.1. *Energy efficiency measures*

In this study it was considered 11 EEMs to reduce the electricity consumption of the processes of the Brazilian pulp and paper sector (see Table 2). These EEMs were defined based on the studies of the German pulp and paper industry [5], Brazilian pulp and paper industry [7], US pulp and paper industry [77], the report of the International Energy Agency (IEA) [78], and information from the Brazilian industry contained in PROCEL [68].

Regarding cross-cutting technologies, 13 EEMs that could be applied in to Brazilian industry were considered. They were defined based on the studies of Silva et al. [7], Brazilian industry energy efficiency [68], energy efficiency in pumping systems [79], fan system efficiency [80], lighting system efficiency [81], and industrial efficiency technologies [82], as shown in Table 3.

The electricity savings obtained over the forecast horizon is related to the diffusion speed of EEMs and their savings potential. These characteristics are given by the $\lambda_x$ factor and the values $D_{x,0}$ and $D_{x,f}$, respectively, of the logistic function (equation (5)). The diffusion values were calculated by the FORECAST model [54].

## 4.2. *Results*

The long term electricity consumption and savings results for the pulp and paper sector in Brazil are presented next.

In this work, it was used the electricity consumption data from

**Table 3**
Summary of the energy efficiency measure assumptions for cross-cutting technologies: specific energy savings (SES) and costs.

| Cross Technology | Energy efficiency measures | SES | Costs | |
|---|---|---|---|---|
| | | Electricity | Initial costs | Lifetime |
| | | (GJ/t) | (R$/t) | (year) |
| 10. Fans | 10.1 High efficiency fans | 0.050 | 0.50 | 15 |
| | 10.2 Regular maintenance | 0.013 | 1.49 | 1 |
| | 10.3 IE2 motors | 0.009 | 0.05 | 20 |
| | 10.4 Variable speed drive | 0.096 | 0.79 | 20 |
| | 10.5 IE3 motors | 0.004 | 0.06 | 20 |
| | 10.6 Direct drive instead of V-belt | 0.029 | 0.01 | 15 |
| 11. Pumps | 11.1 High efficiency pumps | 0.029 | 0.50 | 15 |
| | 11.2 Avoid oversizing | 0.025 | 0.01 | 20 |
| | 11.3 Regular maintenance | 0.013 | 3.58 | 1 |
| | 11.4 IE2 motors | 0.009 | 0.05 | 20 |
| | 11.5 Variable speed drive | 0.113 | 0.74 | 20 |
| | 11.6 IE3 motors | 0.004 | 0.06 | 20 |
| | 11.7 Direct drive instead of V-belt | 0.029 | 0.01 | 15 |
| 12. Compressed air | 12.1 High efficiency compressor | 0.047 | 0.52 | 15 |
| | 12.2 Regular maintenance | 0.177 | 5.54 | 1 |
| | 12.3 IE2 motors | 0.009 | 0.05 | 20 |
| | 12.4 Variable speed drive | 0.026 | 0.82 | 20 |
| | 12.5 IE3 motors | 0.004 | 0.06 | 20 |
| | 12.6 Direct drive instead of V-belt | 0.020 | 0.01 | 15 |
| 13. Cold appliances | 13.1 Improved compressors | 0.022 | 0.51 | 20 |
| | 13.2 Regular maintenance | 0.044 | 3.52 | 20 |
| | 13.3 IE2 motors | 0.009 | 0.05 | 20 |
| | 13.4 Variable speed drive | 0.009 | 0.69 | 20 |
| | 13.5 IE3 motors | 0.004 | 0.05 | 20 |
| | 13.6 Direct drive instead of V-belt | 0.029 | 0.01 | 15 |
| 14. Other motors | 14.1 IE2 motors | 0.009 | 0.06 | 20 |
| | 14.2 IE3 motors | 0.004 | 0.07 | 20 |
| | 14.3 Direct drive instead of V-belt | 0.029 | 0.01 | 15 |
| 15. Lighting | 15.1 Regular maintenance | 0.068 | 12.57 | 1 |
| | 15.2 LEDs | 0.136 | 16.82 | 20 |
| | 15.3 Efficient luminaries | 0.041 | 15.46 | 10 |

R$ - Brazilian currency (R$ 1~ US$ 0.46, in 2013); SES - Specific Energy Savings.

2000 to 2016. However, the last two years (2015 and 2016) were left out of the sample in order to evaluate the quality of the forecasting by simulation, and to compose the sample until 2050 the values were projected by the deterministic bottom-up model. The data from 2008 to 2014 were used to evaluate the fit of the model by simulation. The reduced size of the sample used for the adjustment was limited by the lack of data, for example, the sector value added, which is only available between 2008 and 2014 [83], the specific electricity consumption, which was obtained for the year 2007, and also by the small size of the time series of production by process. However, it is important to emphasize that the main objective of this study is to insert the uncertainty in the long term forecasting obtained by a deterministic bottom-up model.

First, for each process a sufficiently large chain of 30000 iterations was generated via MCMC method, out of which the 10000 initial iterations were considered as burn-in period and discarded. Hence, the remaining iterations were used to compose the posterior samples of the model parameters after thinning at every 40 iterations. For more details on the MCMC method see Gamerman and Lopes [71]. Fig. 3 shows some chains of process electricity consumption of the paper and pulp sector for 2015 and 2016. The convergence of the chains was evaluated from graphical inspection (Fig. 3).

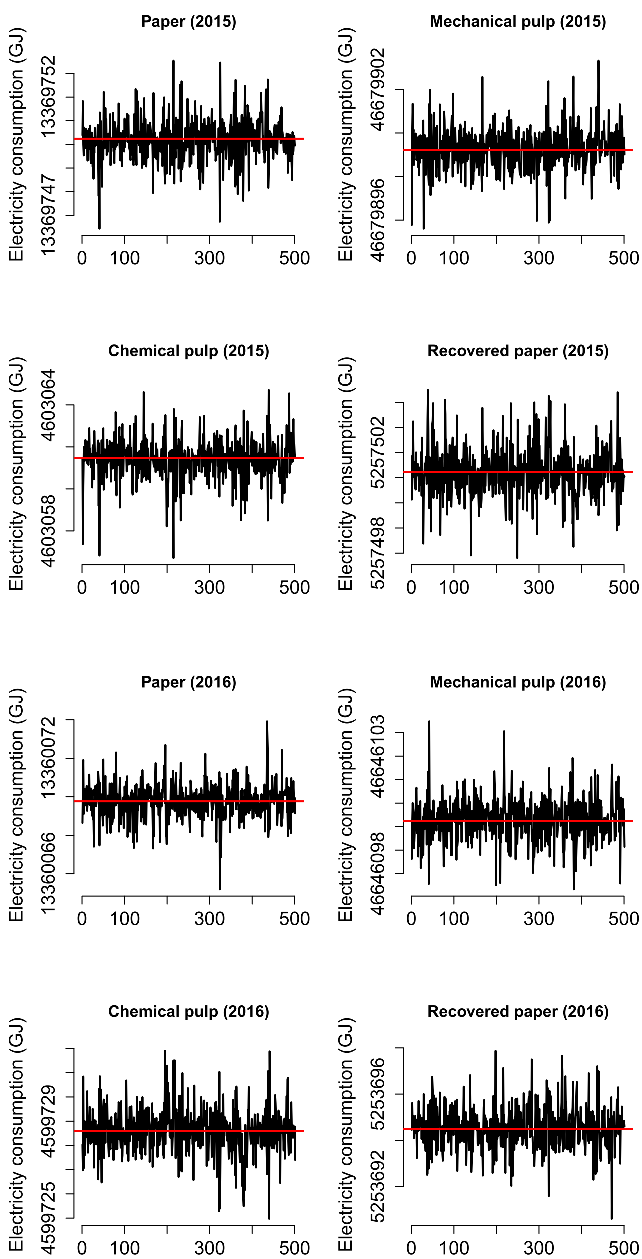



**Fig. 3.** The electricity consumption chain of each process in the pulp and paper sector in Brazil for 2015 and 2016, where the red line is the chain's average. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

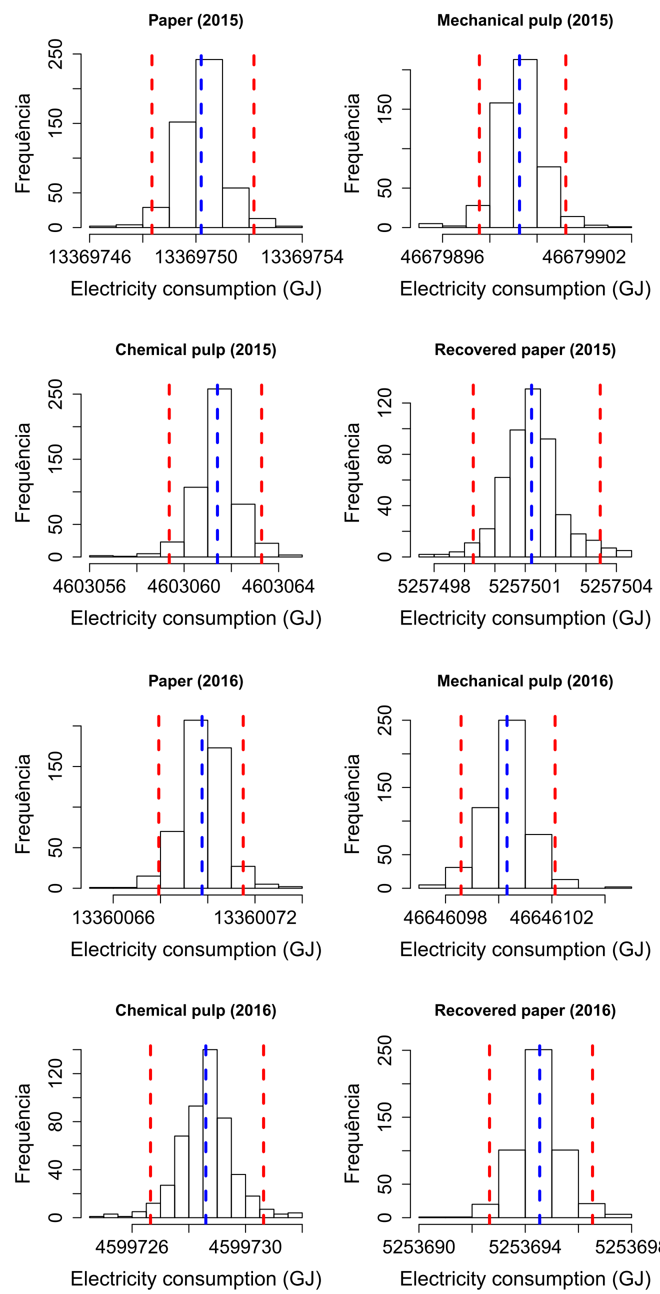



**Fig. 4.** Histograms of electricity consumption of each process in the pulp and paper sector in Brazil for 2015 and 2016, where the blue dashed line is the posterior mean and the red dashed line is the 95% credible interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

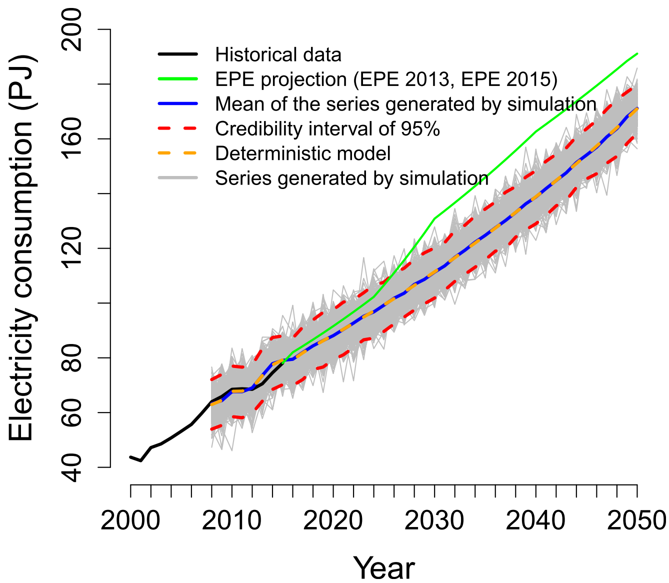



**Fig. 5.** Summary of the posterior predictive distribution of long term electricity consumption of the pulp and paper sector in Brazil with the frozen efficiency measures, i.e., a frozen scenario.

In Fig. 4 are presented the histograms of the posterior distributions for the model parameters $\mathbf{P}_t$, with their respective 95% credible intervals for 2015 and 2016. Therefore, for each year of the forecast horizon it is possible to obtain the probability distribution of electricity consumption.

The results presented below were replicated from the proposed model through the parameter estimates obtained by the MCMC method.

The result presented in Fig. 5 shows that the proposed model was able to capture the trajectory of the electricity consumption observed in the pulp and paper sector from 2008 until 2014. In this period, the forecasting error measure MAPE (Mean Absolute Percent Error) is 2%. In addition, it presents the annual projection of the long term electricity consumption up to 2050. This figure also shows the comparison between the electricity consumption forecasting obtained by the proposed model and the deterministic model. The EPE electricity consumption curve, shown in this figure, was projected using the consumption growth rate provided by EPE reports of energy demand [55] and energy projection [76]. The difference observed in the figure between EPE [55] projections and the proposed model is mainly related to the industrial production growth scenario considered by EPE [55] before the most recent crisis period in Brazilian industry, which started in 2014.

From Fig. 5, it is not possible to observe a difference between the values generated by the proposed model and the deterministic one. But in Fig. 6, one can see the difference between the two projections. Over the forecasting horizon, the difference between the two approaches was less than 1%.

In Fig. 7 are presented the histograms with the replicated values of the electricity consumption projection for 2015 and 2016, as well as the actual values observed by EPE [63]. The replicated values of

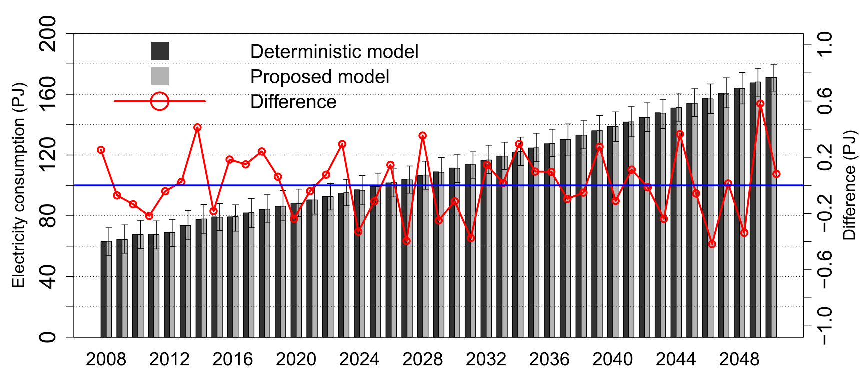



**Fig. 6.** Electricity consumption generated by the proposed model and the deterministic model for the pulp and paper sector in Brazil.

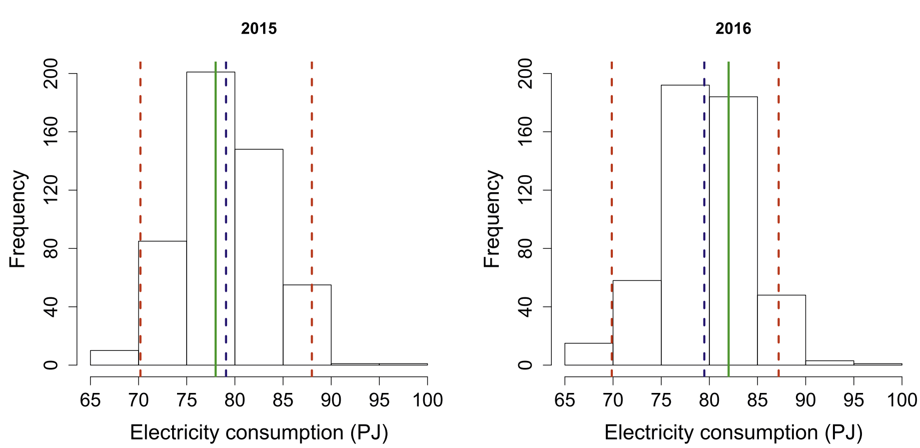



**Fig. 7.** Histograms of electricity consumption of the pulp and paper sector in Brazil for 2015 and 2016. The solid green line represents the actual value obtained by the EPE, the blue dashed line represents the posterior mean and the red dashed lines represent the 95% credible interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the proposed model were obtained from the generated parameter estimates of each iteration via the MCMC method. For example, for 2015, average electricity consumption was estimated as 79 PJ, with a 95% credible interval between 71 and 88 PJ. It can be seen in the figure that the values estimated by the model are close to the real values observed by the EPE, and the real values belong to the 95% credible interval (Table 4).

Fig. 8 shows the evolution of the long term electricity consumption of the pulp and paper sector with the introduction of energy efficiency measures. This figure presents the autonomous and cost-effective technological diffusion scenarios. It can be observed in this figure that the proposed model is able to capture the trajectory of the electricity consumption projected by the deterministic model, besides measuring the uncertainty through a credible interval, which can help make decisions in the sector.

In the frozen scenario, it was estimated that electricity consumption increased from 82 PJ to 170 PJ between 2016 and 2050 (Table 4), an annual growth rate of 2.17% (Table 5), with a 95% credible interval between 161 and 180 PJ for electricity consumption in 2050 (Table 4). For the autonomous diffusion scenario, the electricity consumption increased from 82 PJ to 157 PJ between 2016 and 2050 (Table 4), with an annual growth rate of 1.93% (Table 5). Also, the estimate of electricity consumption is between 148 and 166 PJ in 2050 (Table 4). For the cost-effective diffusion scenario, the electricity consumption increased from 82 PJ to 129 PJ between 2016 and 2050 (Table 4), with an annual growth rate of

**Table 4**
Evolution of electricity consumption, with 95% credible interval, for the pulp and paper sector in Brazil and percentage reduction of electricity consumption from the use of energy efficiency measures, compared to the frozen scenario for 2015, 2016, 2020, 2030, 2040 and 2050.

| Ano | Scenarios | | | | | | |
|---|---|---|---|---|---|---|---|
| | Frozen | Auto | | Max | | Cost | |
| | Cons. (PJ) | Cons. (PJ) | Red. (%) | Cons. (PJ) | Red. (%) | Cons. (PJ) | Red. (%) |
| 2015 | 79.08 [69.96; 88.47] | 76.43 [67.31; 85.60] | 3.26 | 73.14 [64.33; 81.73] | 7.46 | 76.28 [67.66; 86.23] | 3.54 |
| 2016 | 79.45 [70.62; 88.16] | 76.02 [67.02; 85.93] | 4.10 | 71.31 [63.15; 79.11] | 10.04 | 75.79 [66.78; 85.83] | 4.39 |
| 2020 | 88.53 [79.25; 97.34] | 83.93 [74.93; 93.21] | 5.56 | 70.25 [62.46; 78.19] | 20.86 | 79.91 [71.08; 89.33] | 9.95 |
| 2030 | 111.30 [102.01; 121.10] | 103.64 [94.94; 111.91] | 7.08 | 74.08 [68.96; 79.76] | 33.52 | 90.23 [82.81; 98.17] | 19.03 |
| 2040 | 138.95 [129.28; 148.87] | 128.26 [119.93; 136.76] | 7.87 | 85.19 [79.16; 91.65] | 38.59 | 106.33 [98.88; 113.55] | 23.35 |
| 2050 | 170.09 [160.79; 179.66] | 156.89 [147.72; 166.12] | 8.15 | 97.40 [92.29; 102.82] | 43.02 | 128.59 [120.81; 136.12] | 24.77 |

Cons. = Consumption; Red. = Reduction.

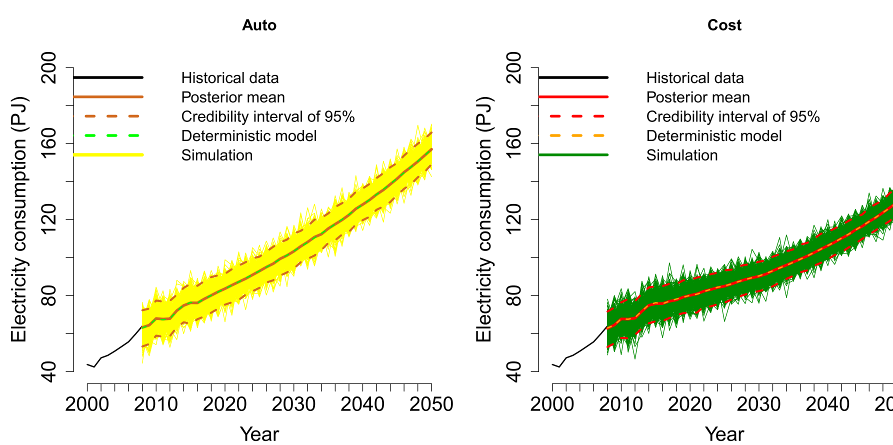



**Fig. 8.** Long term electricity consumption of the pulp and paper sector in Brazil considering the autonomous and cost-effective diffusion scenarios.

**Table 5**
Average growth rate, with the 95% credible interval, of electricity consumption in the Brazilian pulp and paper industry.

| Scenarios | 2016[a]-2050 | 2016[a]-2020 | 2020–2030 | 2030–2040 | 2040–2050 |
|---|---|---|---|---|---|
| Frozen | 2.17 [2.00; 2.33] | 1.93 [-0.85; 4.38] | 2.32 [1.43; 3.18] | 2.24 [1.51; 2.95] | 2.04 [1.47; 2.60] |
| Auto | 1.93 [1.75; 2.10] | 0.58 [-2.23; 3.26] | 2.13 [1.24; 2.92] | 2.15 [1.47; 2.81] | 2.04 [1.42; 2.62] |
| Max | 0.51 [0.35; 0.67] | −3.43 [-6.32; −0.89] | 0.38 [-0.33; 1.13] | 1.41 [0.67; 2.15] | 1.35 [0.80; 1.90] |
| Cost | 1.33 [1.15; 1.50] | −0.64 [-3.51; 2.16] | 1.22 [0.36; 2.08] | 1.66 [0.92; 2.33] | 1.92 [1.28; 2.50] |

[a] Actual value observed by EPE [63], 82 PJ.

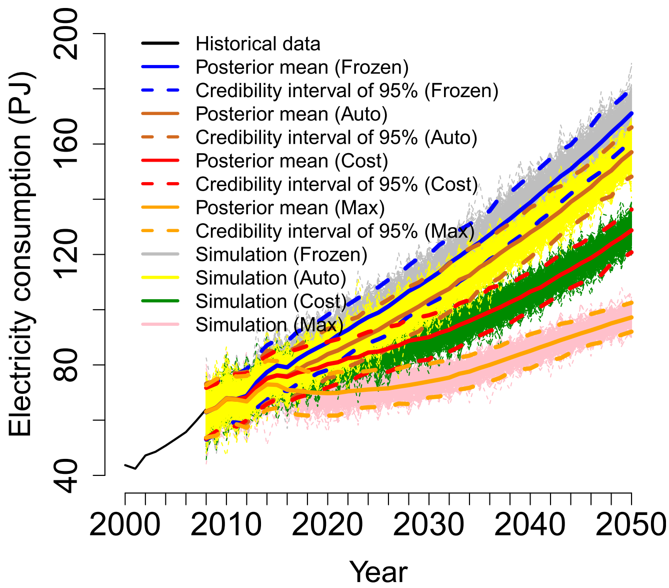



**Fig. 9.** Long term electricity consumption of the pulp and paper sector in Brazil considering the scenarios of frozen diffusion, autonomous, cost-effective and maximum.

1.33% (Table 5). In this scenario, the estimated an interval for consumption of electricity was between 121 and 136 PJ in 2050 (Table 4).

In Table 5, the negative values of the average growth rate of electricity consumption are related to the deceleration of industrial production caused by the economic crisis that began in 2014.

The electricity consumption results of the Brazilian paper and pulp industry up to 2050 considering the scenarios of frozen diffusion, autonomous, cost-effective and maximum diffusion are presented in Fig. 9. In this figure, it can be observed that there are regions of intersection between the simulated series and the credible interval. In addition, it is well known that the electricity consumption in the frozen scenario is always greater than any other efficiency scenario when the economic assumptions are the same. In the frozen scenario, which does not consider energy efficiency, the electricity consumption will increase by about 35.73% between 2016 and 2030, and by 107.43% between 2016 and 2050. But when efficiency measures are applied the electricity consumption is reduced considerably (Table 4). Table 4 shows the percentage of electricity consumption reduction when efficiency measures are employed compared to the scenario where the measures are frozen. For the cost-effective diffusion scenario, electricity consumption will grow by about 10.04% between 2016 and 2030, and 56.82% between 2016 and 2050.

## 5. Conclusions

In this paper, it was proposed a new approach that allows combining the bottom-up approach with linear hierarchical models to forecast the long term electricity consumption of a particular Brazilian industrial sector (pulp and paper) up to 2050. For the model parameter estimation of the proposed model, it was used Bayesian inference.

The use of Bayesian inference allowed the generation of sample values for each parameter of interest and, consequently, their posterior probability distributions. Thus, measures of uncertainty were obtained from the estimated posterior distributions. The MCMC method, more specifically the Gibbs sampler, was used to generate such samples.

The proposed stochastic model is inspired by the deterministic bottom-up model presented in the literature. The proposed model here is able to measure the uncertainty of the electricity consumption forecasting through estimation of a probability distribution for each year of the forecast horizon. Thus, it allows the generation of long term forecasts of electricity consumption, for each year of the desired forecast horizon, with an associated credible interval. The long term forecasting brings with it a high degree of uncertainty in its results, so the proposed model can contribute with new information that allows decision-making on a more solid basis.

In the search carried out in the pertinent literature, it was not found any available model with these characteristics, which allows one to state that the model developed in this work is a novelty for the purpose of long term energy forecasting.

The developed model also allows evaluating the effect of adopting EEMs on future electricity consumption, due to the use of the bottom-up approach. As shown, the EEMs are related to the scenarios of technological diffusion. The detailing of energy efficiency measures used for this sector is also important for the other sectors of the Brazilian industry. The technological diffusion scenarios implemented and defined in this study can be rated as innovative in energy modelling and simulation of energy efficiency scenarios in Brazil. This is another contribution of this work.

The obtained results by the proposed stochastic model were satisfactory, since they help in the interpretation of the annual electricity consumption and especially in decision-making regarding the choice of energy efficiency measures. The probability distributions obtained for the predictions provided expected values similar to those resulting from the equivalent deterministic model (used in predictions of this type) employed here to compare the results (Section 4, Fig. 5). The difference between the values of the two models was less than 1% over the forecast horizon. From these figures, it can be observed that the data from the proposed model brings more information than that coming from the deterministic model, providing more robustness for decision-making by the agencies and companies responsible for the energy planning.

Another demonstration that the results obtained by the stochastic model contain more information was observed in the years of the Brazilian crisis of 2015 and 2016. In these years, the built-in credible intervals contemplate the real observed values provided by EPE, while the deterministic model presents only one-off measures (Section 4, Fig. 7).

In the context of energy efficiency, it was presented a set of EEMs for the Brazilian industrial sector modelled in this work. For sector related cross-cutting technologies, were identified and detailed 16 EEMs, while for process technologies were used 11 EEMs. The impact of these EEMs on the electricity consumption of the sector was evaluated from the defined technological diffusion scenarios. These EEMs are important to save on electricity consumption and are therefore a strategy to reduce costs and increase gains, especially in times of energy price volatility.

For a real scenario (cost-effective), taking into account economic aspects, one can observe a reduction in the electricity consumption that reached 25% in 2050 (Section 4, Table 4), representing savings of 42 PJ for this sector. It was also estimated a 95% credible interval of energy saving between 34 and 50 PJ for the same year.

An interesting question for future research would be to combine the method presented in this article with some reconciliation method of hierarchical time series forecasts. This combination might help to improve the accuracy of the long term projections. Finally, another potential future work would be use a dynamic linear model (DLM) to take into account the hierarchical structure of the data modelled in this study and incorporate the energy efficiency scenarios.

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