Estimating the environmental impact of Data Centers

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***Abstract*—The demands of performance, availability and storage of new technologies have increased significantly the energy consumption of data centers. This consumption is rising both the environmental impact and operational costs of computational systems that support those technologies. Assuming the electricity consumption and CO_2 emissions, the adopted utility power source is of substantial importance. This work estimates the availability, and conducts an evaluation of cost and CO_2 emissions of electrical infrastructures in data centers, considering different energy sources. We use a multi-layered artificial neural network, which is able to forecast consumption over the following months, based on the energy consumption history of the data center. All these features are supported by a tool, the applicability of which is demonstrated through a case study that computes the CO_2 emissions and operational costs of a data center using the energy mix adopted in Brazil, China, Germany and the US.**

***Index Terms*—ANN, EFM, sustainability, data center.**

I. Introduction

Data center power consumption has increased significantly over recent years influenced by the increasing demand for storage capacity and data processing [1]. Moreover, critical elements in the performance of daily tasks, such as social networks, e-commerce and data storage, also contribute to the rise in energy consumption across these systems.

In China, burning coal generates 65% of the electricity consumed [2], which is a very high level of non-green power generation when compared with Brazil, where the level is 3%. In Germany, 14.7% of the energy produced comes from nuclear fission, whereas in China this figure is only 1%.

This work represents the power subsystem electrical flow by an energy flow model (EFM) [3], and uses SPNs [4] and MCs [5] to estimate the Tier III data center availability.

The main focus of this work is to propose an integrated strategy to evaluate the availability, operational costs and estimate the environmental impacts (CO_2 emissions) of data centers. We propose to integrate the energy flow model (EFM) with an artificial neural network (ANN). The ANN is applied to the EFM metrics, which forecasts the values in the future, based on the consumption of data center electrical architectures and by considering different energy sources. To demonstrate the applicability of the proposed strategy, a case study computes the availability, compares costs and environmental impacts, according to the Brazilian, Chinese German and US energy mixes adopted.

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II. Related Works

Over the last few years, considerable research has been conducted into energy consumption in data centers. This section presents studies related to this research field.

Silva [6] affirmed that the higher demand for energy is an issue that has impacted the way systems are conceived, in the sense that designers need to verify several trade-offs and select the feasible solution considering energy utilization and other metrics, such as dependability. They present an integrated environment for quantification of sustainability impact. However, the authors do not consider CO_2 emissions from the environment and do not use ANNs, to predict energy consumption.

Liu [7] propose to reduce electricity cost and environmental impact of a data center, using a holistic approach that integrates renewable supply, dynamic pricing and cooling supply. The goal is to provide an integrated workload management system for data centers. However, the focus was on the low level of the environment. In our proposal, we enable to conduct a global analysis of the energy consumption.

Reddy [8] presented various metrics related to data center classification, for instance, they defined the core dimensions of data center operations. In our proposal, we use one of the metrics pointed out by Reddy (Efficiency of energy use) and propose a new, considering an integrated analysis of the energy cost and CO_2 emissions.

Dandres [9] affirmed that cloud computing technology enables real-time load migration to a data center. The author proposed a novel approach to minimize GHG emissions cloud computing relying on distributed data centers. The work proposed in our research may be used as support for decision making regarding the need for service migration.

III. Considering energy mix in the EFM

The inclusion of the energy mix in the EFM is proposed for a more detailed analysis of the operational costs and the estimation of CO_2 emissions in the atmosphere, according to the energy consumed. Data center designers may consider more than one energy source, which represents the energy mix of the utility. Additionally, this EFM extension allows operational costs and the environmental impacts of the electricity consumption to be calculated, as well as the CO_2 emissions from the adopted energy mix. Table I presents the relation between the source used to produce the energy and the amount of CO_2 emitted by each [10].

TABLE I: Material used in energy generation x CO_2 emissions

Energy Source	CO_2 **(g/kWh)**
Wind	10
Coal	950
Hydroelectric	20
Nuclear	150
Oil	510

The designer only needs to inform the amount of energy consumed by each source and the corresponding CO_2 emissions in the atmosphere will be calculated. In order to compute the amount of CO_2 emissions, the percentage of each energy source is multiplied by its factor of aggression. This process is described by the following equation (1):

$$CO_2Emissions = \sum_{i=1}^{n}(P_i \times F_i) \quad (1)$$

where: i is the energy source (wind, coal, hydroelectric, nuclear or oil), P_i is the percentage of energy source and F_i is the factor of aggression to the environment.

The operational cost considers the data center operation period, the energy consumed, the cost of energy and the data center availability. Expression (2) denotes the operational cost:

$$OpCost = (\sum_{i=1}^{n}(P_{Input(i)} \times C_{Energy(i)}) \times T \times (A + \alpha(1-A)) \quad (2)$$

where: i is the energy source (wind, coal, hydroelectric, nuclear or oil), $P_{Input(i)}$ is the percentage of power supply for the source i, $C_{Energy(i)}$ is the energy cost of power energy unit, T is the considered time period, and A is the system availability; α is the energy percentage that continues to be consumed when the system fails.

IV. Applying ANNs to the EFM

The multi-layer perceptron (MLP) [11] is adopted, and basically consists of a layer of nodes, one or more layers of hidden processor or computational nodes and an output layer also composed of computational nodes. ANN was implemented in the Mercury tool [12] and is composed of 5 phases.

Load and Normalize Data - Mercury has been extended to accept spreadsheets in *odt*, *xls* and *csv* formats, with three columns (year, month and power consumption, respectively). Thus, users may upload a file with the monthly levels of power consumption from the previous years of a data center.

Create an Artificial Neural Network - In this phase, the basic parameters for creating the artificial neural network are set (e.g., number of neurons in the input layer, number of neurons in the first hidden layer and the number of neurons in the output layer).

ANN Training - The backpropagation training algorithm is the most popular algorithm for training multi-layer ANNs. The algorithm consists of two steps: propagation and backpropagation. In the first step, an input vector is applied to the input layer and its effect propagates across the network producing a set of outputs. The response obtained by the network is subtracted from the desired response to produce an error signal. The second step propagates this error signal in the opposite direction to the synaptic connections, adjusting them in order to approximate to the network outputs. Additionally, using the EFM with ANN, it is possible to set the training stop criteria for a specific error rate or a fixed number of iterations.

Prediction - This option produces forecasts related to the energy consumption of the environment over the next twelve months. At the end of the forecasts, the mean absolute percentage error is displayed.

Graph - This option graphically displays a comparison between the measurements, with a blue line for the actual data and with a red line for the expected monthly consumption values.

A. Models

A data center infrastructure may be classified based on the redundancy features and fault tolerance [13]. This classification provides metrics for data center designers that identify the performance of the electricity and strategies adopted. This subsection presents an analysis of the proposed models to represent configurations of the tier III data center.

The RBD model is used to obtain the dependability metrics of the electrical infrastructure of data center Tier III, meantime due to the system complexity of the redundancy, the utility power and generator subsystem where modeled in SPN (Fig. 1).

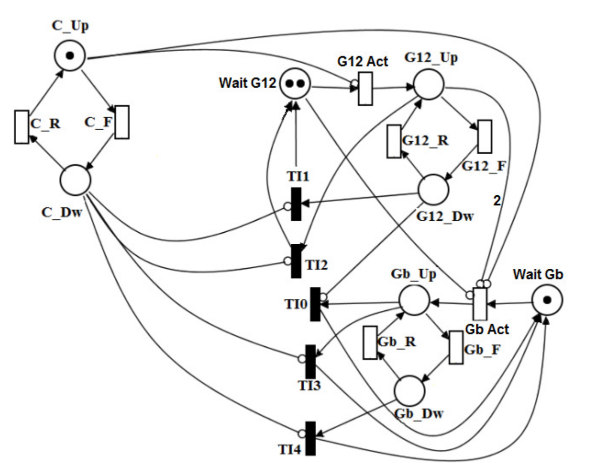

Fig. 1: SPN model for utility power and generator system

This model represents the operational mode of the utility power and generator system, in which the system is operational if the power supply utility ($\#C\_UP = 1$), the two main generators are operating ($\#G12\_Up = 2$) or if one main generator and one backup is running (($\#G12\_Up = 1$) and ($\#Gb\_Up = 1$)).

The availability expression obtained by SPN model is: A = ($\#C_Up$=1) OR ($\#G12_Up$=2) OR (($\#G12_Up$=1) AND ($\#Gb_Up$=1))

The Tier III model is divided into subsystems, two of them represent the power (Subsystem X) and UPS systems (Subsystem Y). Both provide possible paths to the set of power strip component (Subsystem P). The availability algebraic expressions of each subsystem is shown in 3, 4 and 5.

$$SubsystemX = ATS1 \times UPSSystem \times ATS2 \times SDT1 \times SubPanel1 \times JuctionBox1 \quad (3)$$

$$SubsystemY = SDT1 \times SubPanel2 \times JuctionBox2 \quad (4)$$

$$SubsystemP = \prod_{i=1}^{n}(PowerStrip_{(n)}) \quad (5)$$

where n is 6, in this model. Equation (6) shows the algebraic availability expressions of all subsystem (X, Y, P) that compose the Tier III.

$$TierIII = (1-(1-(UPS\_GS) \times (ATS1 \times UPSSystem \times ATS2 \times SDT1 \times SubPanel1 \times JuctionBox1)) \times (1-(UP2) \times (SDT1 \times SubPanel2 \times JuctionBox2))) \times (\prod_{i=1}^{n}(PowerStrip_{(n)})) \quad (6)$$

Once availability is computed, the EFM model can be analyzed to provide cost and operational exergy as well as to ensure that the power restrictions of each device are respected. Figure 2 presents the EFM model adopted for Tier III.

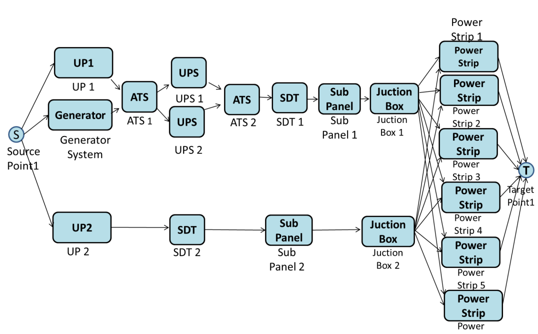

Fig. 2: EFM model of Tier III

B. Energy mixes, Energy cost and CO2 emissions

Table II presents the energy mixes used to estimate CO_2 emissions and cost, obtained from [2], [14]–[16].

TABLE II: Energy mixes, Energy cost and CO_2 emissions

Energy Source	GER	BRA	CHN	USA	CO_2 (g/kWh)
Cost kWh (USD)	0.25	0.18	0.43	0.12	-
Wind (%)	14.3	1.44	6	4.7	10
Coal (%)	42.9	1.5	63	33	950
Hydroelectric (%)	4	69.76	22	6	20
Nuclear (%)	14.7	1.68	1	20	150
Oil (%)	0.94	6	2	1	510
Others (%)	23.16	19.62	6	35.3	-

Figure 3 depicts a comparison of CO_2 emissions according to the energy mix adopted by each country (see Equation 1), considering the same demand per year. China presented the highest CO_2 emissions, with 41,445 tons per year in 2014, followed by the US and Germany, with 37,177 and 35,883, respectively. Due to the number of rivers and topology, Brazil is outstanding in its generation of clean energy, which may represent an interesting option for building a data center when considering only CO_2 emissions.

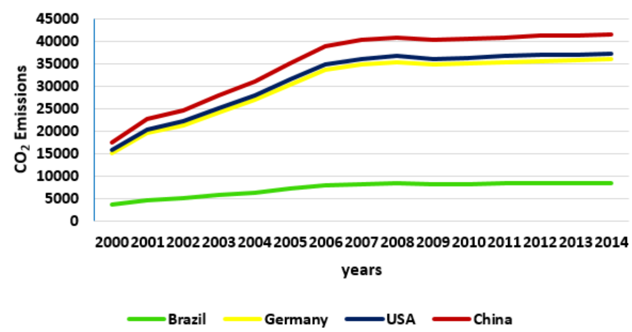

Fig. 3: CO_2 emissions for one year in tons

Figure 4 illustrates the operational costs (in USD, according to the equation 2) of a data center during a period of one year. Additionally, this paper also estimates the operational costs assuming that the same data center consumes energy as if it were in China, Germany and Brazil. Considering the price of energy per kWh, is the US and the worst is China. Considering operational cost and CO_2 emissions, Brazil is the best option.

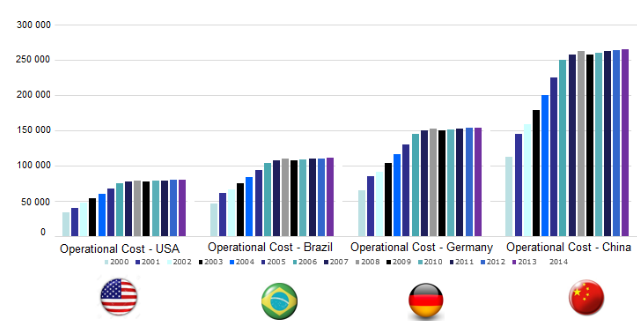

Fig. 4: Op. cost by years: US, Brazil, Germany and China

C. ANN Forecast

The main goal of this subsection is to present the forecasts made using the Mercury tool with the multi-layer perceptron (MLP), and the R tool using autoregressive integrated moving average (ARIMA), considering the energy consumption history of a data center between 2000 and 2014. The autocorrelation option of the R tool was used and the filters chosen were the ARIMA (3,2,2), where 3 represents the size of the regressive factor, 2 a quantity of difference for the objective and 2, the moving average, respectively.

Figure 5 depicts a comparison between the real consumption and that forecast by the learning of ANN. This achieved error (1.58×10^{-4}) may be verified through the graph presented in the figure, which corresponds to a very small difference and, therefore, it may be considered that the ANN demonstrated a good learning.

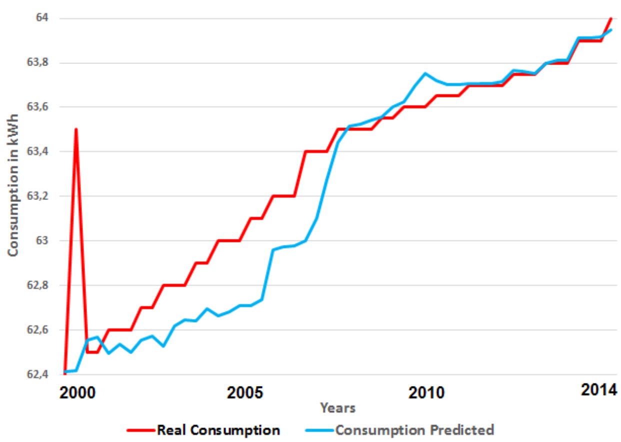

Fig. 5: Real Consumption x Consumption Predicted

With the aforementioned energy consumption values, we forecasted the energy consumption for the coming months using the MLP (Fig. 6).

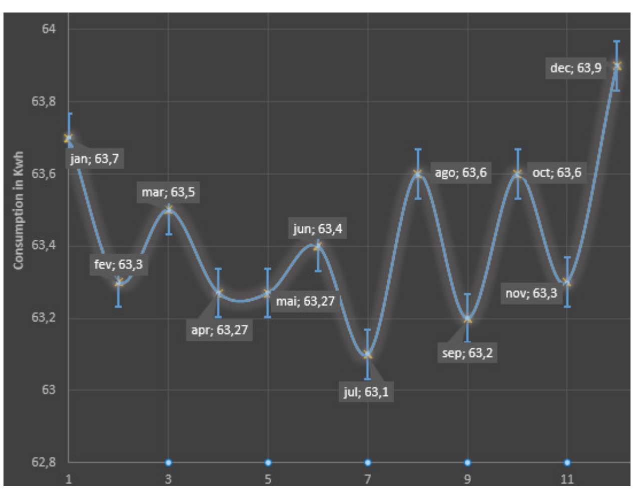

Fig. 6: Predictions to 12 months using MLP

Considering a 90% confidence interval for ARIMA, the energy consumption may decrease by 1.32 or increase by 2.21 percent. Using the standard mean error in multilayer perceptron neural network, the changes in the energy consumption would be between a decrease of 1.25% and an increase of 1.40%.

V. Conclusion

This paper proposed an integrated strategy to evaluate the availability, operational costs and estimate the environmental impacts of data centers, considering different energy sources. We conducted experiments with this strategy and interesting results were achieved. China's energy mix presents the highest levels of CO_2 emissions and Brazil the lowest. The US presented the lowest operating costs per kWh/year, while China presented the highest. Furthermore, we adopted the MLP to forecast energy consumption over the next 12 months and the results are between a decrease of 1.25% and an increase of 1.40%, per year. Thus, this paper has demonstrated that our proposal is effective and is useful.

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