

# Dependability and Sustainability Evaluation of Data Center Electrical Architectures

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**Abstract**—Faced with the demand to maintain the high availability of data centers (DC), companies are being pressured to seek sustainable alternatives, given that these infrastructures consume a total of 1% of all electricity worldwide [1]. In a time of pandemic (COVID-19), when the digital economy has assumed an even greater share of representativeness, DCs and telecommunications companies need to meet the requisitions of “everything-as-a-service”. Linked to this are the large amounts of carbon dioxide (CO<sub>2</sub>) emitted into the atmosphere due to the production and consumption of energy caused by these infrastructures. Given the above, this paper proposes models of energy flow and reliability block diagrams to quantify the environmental impact from different raw materials used to feed the data center loads and computes sustainability and dependability metrics for the entire DC’s power infrastructure. According to the specifications for classifying the tiers, this study’s hybrid modeling is performed to represent four different electrical architectures. From the model evaluations, we compare whether the availability achieved corresponds to the minimum availability suggested for each tier and show the emissions of CO<sub>2</sub> in the atmosphere for each tier over a year. Besides, we apply a parametric sensitivity analysis technique to identify the most critical components for the modeled systems’ availability.

**Index Terms**—Data Center, Energy Efficiency, Energy Flow Model, Dependability, Sustainability, Sensitivity Analysis

## I. INTRODUCTION

One of the biggest dilemmas in recent years has been related to the global emissions of carbon dioxide (CO<sub>2</sub>) into the atmosphere due to burning fossil fuels (such as carbon, gas, and oil) used mainly for energy production. The industrial and academic community has made countless efforts to prevent the CO<sub>2</sub> concentration from reaching 450 ppm (parts per million), a critical limit for heating 2°C. In 2019, the world surpassed the 410 ppm mark [2], and that value approached 415 ppm in CO<sub>2</sub> emissions, according to a survey presented by the Global Monitoring Laboratory [3].

Given this scenario, in which high availability rates must be achieved/provided by data centers, at all times and around the world, it is imperative that the industry truly applies the concepts of sustainability [4] and best practices for the conscious use of energy, ranging from production to consumption.

Therefore, in this paper, we present a hybrid modeling approach to represent electrical architectures for data centers,

given their tier redundancy classification. The main objective is to show how the type of raw material used for energy production can negatively impact environmental sustainability, quantifying CO<sub>2</sub> emissions in tons over a year. Also, we show the importance of components for these architectures’ availability using one of the sensitivity analysis techniques.

The rest of this paper is organized as follows. Section II shows basic concepts on data centers dependability and sustainability. Section III presents the support methodology for the evaluation of the proposed models, which are presented in Section IV. In this last, we also present experimental studies for EFM and RBD modeling. Section V presents the works related to this research. Finally, Section VI presents some final considerations and proposal for future works.

## II. PRELIMINARIES

### A. Dependability

The dependability attributes make it possible to obtain quantitative measures, which are often crucial for analyzing the services offered. Some terms commonly used in systems reliability and dependability analysis are presented for this research, whose definitions can be referenced in several publications [5]–[8].

1) *Component*: A piece of electrical or mechanical equipment viewed as an entity to reliability analysis.

2) *Failure (f)*: The end of the ability of a component or system to perform a necessary function.

3) *System*: A group of components connected or associated in a fixed configuration to perform a specified function.

4) *Reliability*: Consider a random variable  $X(t)$  as the system’s state at the moment of  $t$ .  $X(t) = 1$  represents the system’s state up, which means the system is working properly. On the other hand,  $X(t) = 0$  means that the system is down (i.e., not working). Formally, if we consider a random variable  $T$  representing the necessary time to reach  $X(t) = 0$ , where the system starts in  $X(0) = 1$ , then  $T$  is the time that the system takes to fail ( $T \geq 0$ ).  $F_T(t)$  is its cumulative distribution function [9], where

$$\bullet \quad 0 \leq F_T(t) \leq 1,$$

- $F_T(t)$  is non-decreasing, that is, for any  $a < b$ ,  $F_T(a) < F_T(b)$ ,
- $\lim_{t \rightarrow -\infty} F_T(t) = 0$ , and  $\lim_{t \rightarrow \infty} F_T(t) = 1$ ,
- $P(a < T < b) = F_T(b) - F_T(a)$ .  $F_T(t)$  is continuous over  $t \geq 0$ .

The derivative of cumulative distribution function,  $F_T(t)$ , of continuous random variable  $T$  is called the probability density function (pdf) of  $T$ , which is denoted by  $f_T(t)$ . More formally:

$$f_T(t) = \frac{dF_T(t)}{dt}, \quad (1)$$

where  $f_T(t) \geq 0$  and  $\int_0^\infty f_T(t) dt = 1$ , assuming  $T$  is defined in  $(0, \infty)$ .

The complementary cumulative distribution function  $F_T^c(t)$  is defined by

$$F_T^c(t) = 1 - F_T(t) = 1 - P(T < t) = P(T > t). \quad (2)$$

As  $T$  is the time to fail,  $F_T^c(t) = R(t)$  is the system reliability. Hence,

$$R(t) = F_T^c(t) = 1 - F_T(t) = P(T > t) \quad (3)$$

and

$$R(0) = 1 \text{ and } \lim_{t \rightarrow \infty} R(t) = 0. \quad (4)$$

The hazard function,  $\lambda(t)$ , is defined as

$$\lambda(t) = -\frac{dR(t)}{dt} \times \frac{1}{R(t)}. \quad (5)$$

Hence, the reliability is also represented by

$$R(t) = e^{-\int_0^t \lambda(t) \times dt} = e^{-H(t)}, \quad (6)$$

where

$$H(t) = -\ln R(t) dt = \int_0^t \lambda(t) \times dt \quad (7)$$

is the cumulative hazard rate function. If the failure rate function is constant, then the reliability is

$$R(t) = e^{-\lambda t}, \quad t \geq 0, \quad (8)$$

where  $\lambda$  is the failure rate and the mean time to fail is

$$MTTF = \frac{1}{\lambda}. \quad (9)$$

5) *Steady-State Availability*: The steady-state availability of a system is defined by Equation 10, where *up* is the system uptime, and *down* is the system downtime. It also can be represented as the association between the mean time to failure (MTTF) and the mean time to restore or repair (MTTR) [9].

$$A = \frac{E(up)}{E(up) + E(down)}, \quad (10)$$

As the  $E(up) = MTTF$  and  $E(down) = MTTR$ , then

$$A = \frac{MTTF}{MTTF + MTTR}. \quad (11)$$

The MTTR required to achieve steady-state availability may be estimated by

$$MTTR = MTTF \times \frac{1 - A}{A}. \quad (12)$$

If the time to failure and the time to restore are exponentially distributed with rates  $\lambda$  and  $\mu$ , respectively, then the steady-state availability may also be represented by

$$A = \frac{\mu}{\lambda + \mu}. \quad (13)$$

The availability can also be represented by the number of nines (#9s), which is estimated by

$$\#9s = -\log(1 - A). \quad (14)$$

6) *Energy Flow Model (EFM)*: It is proposed to estimate costs, exergy, the necessary electrical demand, and other sustainability metrics for data centers, respecting the restrictions of use and efficiency of the components. This is done with algorithms that run through EFM and calculate these metrics. The EFM is a directed acyclic graph defined in [10], [11] as follows.

$G = (N, A, w, f_d, f_c, f_p, f_\eta)$ , where:

- $N = N_s \cup N_i \cup N_t$  represents the set of nodes (i.e., the components), in which  $N_s$  is the set of source nodes,  $N_t$  is the set of target nodes, and  $N_i$  denotes the set of internal nodes,  $N_s \cap N_i = N_s \cap N_t = N_i \cap N_t = \emptyset$ ;
- $A \subseteq (N_s \times N_i) \cup (N_i \times N_t) \cup (N_i \times N_i) = \{(a,b) \mid a \neq b\}$  denotes the set of edges (i.e., the component connections).
- $w : A \rightarrow \mathbf{R}^+$  is a function that assigns weights to the edges (the value assigned to the edge  $(j, k)$  is adopted for distributing the energy assigned to the node,  $j$ , to the node,  $k$ , according to the ratio,  $w(j,k)/\sum_{i \in j^\bullet} w(j, i)$ , where  $j^\bullet$  is the set of output nodes of  $j$ );

- $f_d : N \rightarrow \begin{cases} \mathbf{R}^+ & \text{if } n \in N_s \cup N_t, \\ 0 & \text{otherwise;} \end{cases}$

is a function that assigns to each node the heat to be extracted (considering cooling models) or the energy to be supplied (regarding power models);

- $f_c : N \rightarrow \begin{cases} 0 & \text{if } n \in N_s \cup N_t, \\ \mathbf{R}^+ & \text{otherwise;} \end{cases}$

is a function that assigns each node with the respective maximum energy capacity;

- $f_p : N \rightarrow \begin{cases} 0 & \text{if } n \in N_s \cup N_t, \\ \mathbf{R}^+ & \text{otherwise;} \end{cases}$

is a function that assigns each node (a node represents a component) with its retail price;

- $f_\eta : N \rightarrow \begin{cases} 1 & \text{if } n \in N_s \cup N_t, \\ 0 \leq k \leq 1, k \in \mathbf{R} & \text{otherwise;} \end{cases}$

is a function that assigns each node with the energetic efficiency.

7) *Reliability Block Diagram (RBD)*: Are adopted to represent a system through blocks of subsystems or components connected according to their functions or a trust relationship between them, making possible the analysis of systems reliability [7], [12]. The reliability and the instantaneous availability of  $n$  blocks connected in series are obtained through of

$$P_s(t) = \prod_{i=1}^n P_i(t), \quad (15)$$

where  $P_i(t)$  corresponds to the reliability ( $R_i(t)$ ) of block  $b_i$  or its availability ( $A_i(t)$ ) at time instant  $t$ .

The reliability and the instantaneous availability of  $n$  blocks connected in parallel are obtained through of

$$P_P(t) = 1 - \prod_{i=1}^n (1 - P_i(t)), \quad (16)$$

where  $P_i(t)$  corresponds to the reliability ( $R_i(t)$ ) of block  $b_i$  or its availability ( $A_i(t)$ ) at time instant  $t$ .

The reliability and the instantaneous availability of  $k-out-of-n$  blocks nonidentical are obtained through of

$$P_{KooN}(t) = \sum_{r=i}^n \binom{n}{r} P_i(t)^r (1 - P_i(t))^{n-r}, \quad (17)$$

where  $n$  is the total number of non-identical blocks,  $r$  is the minimum number of units required for system success, and  $P_i(t)$  corresponds to the reliability ( $R_i(t)$ ) of block  $b_i$  or its availability ( $A_i(t)$ ) at time instant  $t$ .

The steady-state availability are obtained by the respective non-time-dependent functions:

$$A_s = \prod_{i=1}^n A_i, \quad (18)$$

$$A_P = 1 - \prod_{i=1}^n (1 - A_i), \quad (19)$$

and

$$A_{KooN} = \sum_{r=i}^n \binom{n}{r} A_i^r (1 - A_i)^{n-r}, \quad (20)$$

where  $A_i$  is the steady-state availability ( $A_i$ ) of block  $b_i$ .

8) *Parametric Sensitivity Analysis*: Sensitivity analysis is adopted to determine the most influential factors over a metric of interest [13]. In this paper, differential sensitivity analysis is applied, one of the most well-known parametric techniques. A sensitivity index that characterizes this technique is  $S_\theta(Y)$ , which indicates the impact of a given measure known as  $Y$  for a parameter  $\theta$ . Equation 21 shows how the percentage difference index is calculated for a metric  $Y(\theta)$ , where  $\max\{Y(\theta)\}$  and  $\min\{Y(\theta)\}$  are the maximum and minimum output values, respectively, computed when varying the parameter  $\theta$  over the range of its  $n$  possible values of interest. If  $Y(\theta)$  is known to vary monotonically, only the extreme values of

$\theta$  (i.e.,  $\theta_1$  and  $\theta_n$ ) may be used to compute  $\max\{Y(\theta)\}$ ;  $\min\{Y(\theta)\}$ , and subsequently  $S_\theta(Y(\theta))$  [14].

$$S_\theta(Y) = \frac{\max\{Y(\theta)\} - \min\{Y(\theta)\}}{\max\{Y(\theta)\}} \quad (21)$$

Each  $S_\theta(Y)$  is calculated by fixing the other parameters' values. The respective impact is computed for each of the input parameters, and then the most significant impact is found based on rank [14].

## B. Energy Efficiency and Sustainability

Next, we describe some metrics used to quantify sustainability in data centers regarding energy efficiency, costs, and  $CO_2$  emissions.

1) *Exergy*: It is a thermodynamic metric that represents the maximum amount of energy present in a system that is available to be converted into useful work [10], [15]. Consider  $F$  as a quality factor represented by the Exergy/Energy ratio so that exergy can be calculated with the Equation 22.

$$\text{Exergy} = \text{Energy} \times F \quad (22)$$

2) *Power Usage Effectiveness (PUE)*: It is one of the metrics established to assess the energy efficiency of data centers [16]. PUE is defined as the total data center load divided by the useful critical load, according to

$$\text{PUE} = \frac{\text{DC}_{load}}{\text{IT}_{load}}, \quad (23)$$

where  $\text{DC}_{load}$  is the total load of the data center infrastructure, in kW and  $\text{IT}_{load}$  is the effective critical load, in kW.

3) *Operational Cost*: Considers the DC operation period, the energy consumed, energy cost, and the availability (according to the tier classification). Equation 24 denotes the operating cost [17].

$$OP_{Cost} = (P_{input}) \cdot (\text{EnergyCost}) \cdot (T) \cdot (A + \alpha(1 - A)) \quad (24)$$

Where  $P_{input}$  is the power supply input,  $\text{EnergyCost}$  is the energy cost per unit of energy,  $T$  is the period considered,  $A$  is the system availability,  $\alpha$  is the percentage of energy that continues to be consumed when the system fails.

4)  *$CO_2$  Emission*: Suppose that  $D_e$  represents the DC energy demand,  $i$  represents the energy source used,  $P_i$  represents the percentage of the energy source, and  $F_i$  represents the aggression factor to the environment. Thus, the calculation for  $CO_2$  emission [17], is given by Equation 25.

$$CO_2\text{Emission} = \sum_{i=1}^n (D_e \cdot P_i \cdot F_i) \quad (25)$$

### III. METHODOLOGY

The methodology used in this work's conception considers some steps presented in a generic way to describe the activities to obtain the results. The steps for carrying out this research are shown in Figure 1. We used the graphical interfaces of the Mercury [18] tool in version 4.8 to create the EFMs and RBDs of this work. We also used the scripting language to perform the sensitivity analysis.

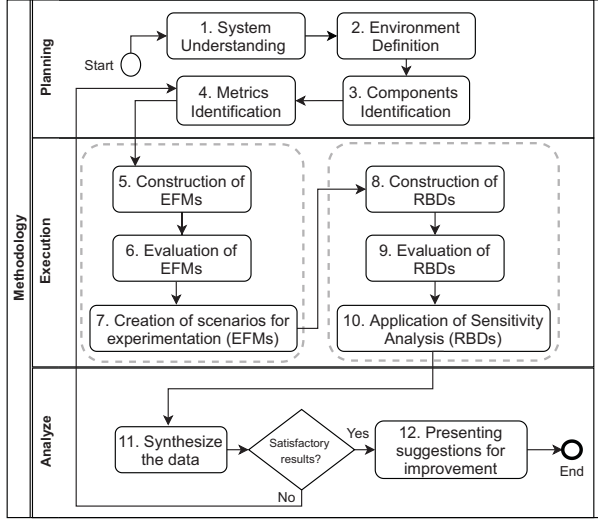


Fig. 1. Phases for conducting this work.

### IV. MODELING

#### A. Input Parameters

To create the energy flow models (EFM), we consider specific components to represent the IT critical load. We consider that each rack consists of five-blade center chassis and consumes an average of 14,125 kW/h [16]. Table I shows the number of chassis and racks, the total area, and the electrical demand for the data centers represented in this study.

TABLE I

AMOUNTS OF CHASSIS, RACKS, TOTAL AREA, AND ELECTRICAL DEMAND BY DC TIER.

Data	Tier 1	Tier 2	Tier 3	Tier 4
Chassis	75	150	300	600
Racks	15	30	60	120
Total area (m <sup>2</sup> )	400	600	800	1000
Electric demand (kWh)	662.27	1,326.18	2,649.07	5,286.58

The electric demand for each DC tier will serve as an input parameter for the energy flow models. From these values, we will receive the total electrical demand based on the components' efficiency. From the graphical interface of the Mercury, tool [18] the user can choose among the various components available for EFM to those that best represent the desired architecture. Besides, for each component, we can use the default values or change them as needed. For this study, we changed the maximum energy capacity and the price of

all components, leaving the default values of efficiency and embedded energy. Component prices have been updated to the most current reality. The parameters of efficiency, embedded energy, and price are the same for the different tiers, differently from the maximum energy with distinct values for each tier. Each component's maximum energy capacity was calculated based on the electrical demand (See Table I). The input parameters for each component are shown in Table II.

To perform the dependability analysis of electrical architectures, we had to implement RBD modeling. We try to be faithful to EFM models, but some possible differences between the components' connections can be noticed due to each modeling technique's nature. Unlike EFM, for RBDs models, we only need to inform two input metrics for the components, MTTF and MTTR. For all components, in all tiers, we consider the 8-hour MTTR. For the sensitivity analysis, we varied this value from -50% to +50%. MTTFs were obtained from [19], [11]. Only the junction box component suffered a reduction of 0.8, considering the manufacturer's original MTTF value [20]. Table III shows the components' MTTF and their variation of -50% to +50% (for the sensitivity analysis).

#### B. Proposed Models

We modeled four architectures to represent the energy models for data centers tiers 1, 2, 3, and 4. The *TargetPoint* and *SourcePoint* (See Figure 2) components represent the IT power demand and the power supply, respectively. According to the tier classification, *TargetPoint* receives the value representing the data center project's total load, whose values are presented in Table I (last line).

Figure 2 presents the electrical architecture of a tier 1 data center. Under normal operating conditions, the electrical system is supplied by the local utility. The energy flow leaves the source/concessionaire (*ACSource*), passing through the low voltage panel (*Subpanel1*), through the uninterruptible power supply (UPS), through the power distribution units – composed of a transformer (SDT) and a subpanel, through junction boxes, power strips and arrives at the power distribution units for the IT devices (Chassis Racks). For this architecture, we consider three junction boxes, each connected to two power strips. In the absence of power supply by the concessionaire, the generator takes over the load and, during the switching period (when ATS starts the generator), the UPS system keeps the IT critical load in operation. Next, Figure 3 presents the RBD model for this electrical architecture. Note that for EFM, for simplicity, we represent each junction box connected to two power strips, while in the RBD model, we represent this by parallel blocks.

Figure 4 shows the electrical model for a tier 2 data center, characterized by the presence of redundant components. In this model, besides the central UPS (*UPS1*), there is a redundant module (*UPS2*). This module tackles the IT critical load in case of failure of the principal module. In this case, the electric flow will go through the redundant PDU (*SDT2* and *Subpanel2*). We consider four junction boxes, each connected to eight power strips, to support the IT load in the face of *UPS1*



TABLE II  
INPUT PARAMETERS OF EFM.

Components	Efficiency (%)	Embedded Energy (GJ)	Price (US\$)	Max. Power (kW)			
				Tier 1	Tier 2	Tier 3	Tier 4
ACSource	95.3	111.000	8,250.00	3,774.92	7,559.24	15,099.68	30,133.52
Generator	25.0	97.700	36,300.00	50,332.26	100,789.92	201,229.04	401,780.28
Generator <sub>redundant</sub>	25.0	9.700	3,300.00	—	—	201,229.04	401,780.28
ATS	99.5	0.799	440.00	993.40	1,989.27	3,973.60	7,929.87
Subpanel	99.9	0.428	110.00	728.49	1,458.80	2,913.97	5,815.24
UPS	95.3	61.040	33,000.00	3,774.92	7,559.24	15,099.68	30,133.52
UPS <sub>redundant</sub>	95.3	3.139	1,980.00	—	7,559.24	15,099.68	30,133.52
SDTransformer	98.5	0.359	302.50	1,655.67	3,315.46	6,622.67	13,216.46
JunctionBox	99.9	0.267	30.00	728.49	1,458.80	2,913.97	5,815.24
PowerStrip	99.5	0.356	40.00	993.40	1,989.27	3,973.60	7,929.87

TABLE III  
INPUT PARAMETERS OF RBDs.

Components	MTTF (h)	MTTF variation (h)	
		-50%	+50%
ACSource	4,380	2,190	6,570
Generator	2,500	1,250	3,750
ATS	24,038	12,019	36,057
Subpanel	152,000	76,000	228,000
UPS	50,000	25,000	75,000
SDT	141,290	70,645	211,935
JunctionBox (JB)	522,400	261,200	783,600
PowerStrip (PS)	215,111	107,556	322,667

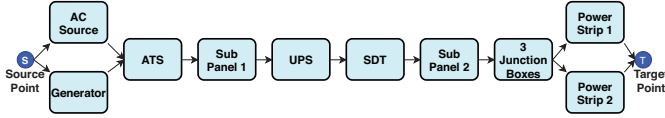


Fig. 2. EFM for tier 1 data center.

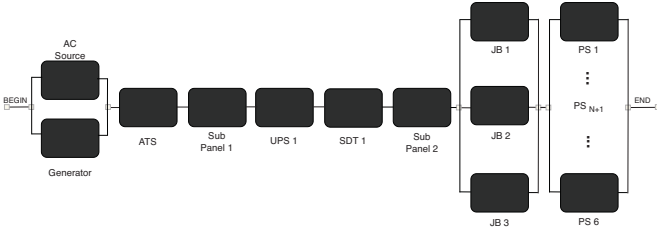


Fig. 3. RBD for EFM Tier 1.

failure. For the other components, the same explanation of the tier 1 model is valid. Figure 5 presents the RBD model for this architecture.

Figure 6 shows the electrical architecture for a tier 3 data center, characterized by the presence of an alternative distribution path. So, maintenance services are carried out without interrupting the operation. In this model, each path has automatic transfer switches (ATS) capable of switching the critical load to any distribution paths and any sources and generators. In addition to the main generator (*Generator1*), there is a redundant module (*Generator2*). The main path (*ATS1*) has a redundant module for UPS (*UPS2*), transformer (*SDT2*),

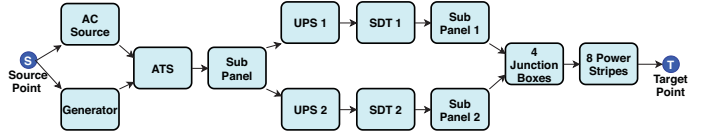


Fig. 4. EFM for tier 2 data center.

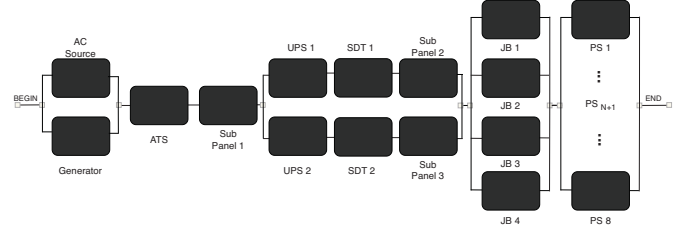


Fig. 5. RBD for EFM Tier 2.

and subpanel (*Subpanel2*). In normal operation, the critical load is fed through the main path (*ATS1*) by the local utility (*ACsource*). However, in the absence of *ACsource* supply, the synchronized switches *ATS1* and *ATS2* switch the main path to the generators to feed the IT critical load. We consider six junction boxes for this architecture, each connected to ten line filters, to support the IT load. Figure 7 presents the RBD model for EFM Tier 3.

Figure 8 shows the electrical architecture for a tier 4 data center, characterized by the ability to recover from faults automatically. The main difference between this power diagram and that of a tier 3 data center is that two electrical distribution paths are simultaneously active, which are provided from different sources. All components are powered, and IT critical loads have dual sources (at least), each connected to a different distribution path. When no external power source is available, the generators are activated. Figure 9 presents the RBD model for tier 4 architecture.

### C. Result Analysis and Experimental Studies

After modeling, we performed model evaluations for 720 hours (one month) and 8760 hours (one year). Table IV shows the embedded exergy results; consumption of operational exergy can be understood as the fraction of the heat

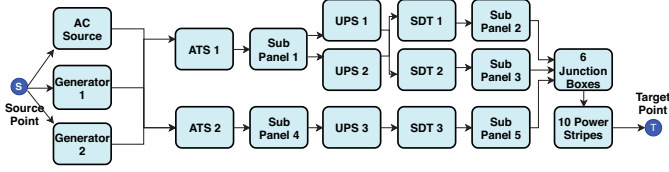


Fig. 6. EFM for tier 3 data center.

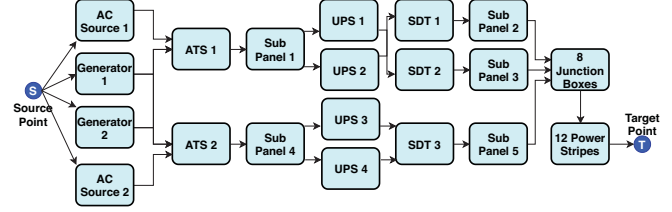


Fig. 8. EFM for tier 4 data center.

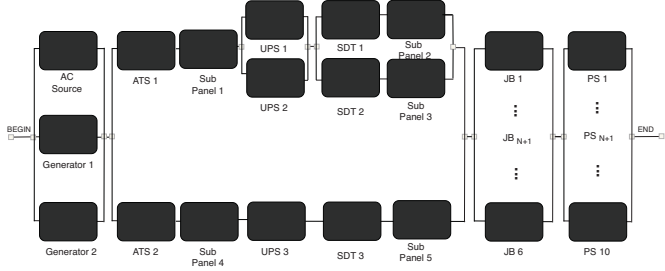


Fig. 7. RBD for EFM Tier 3.

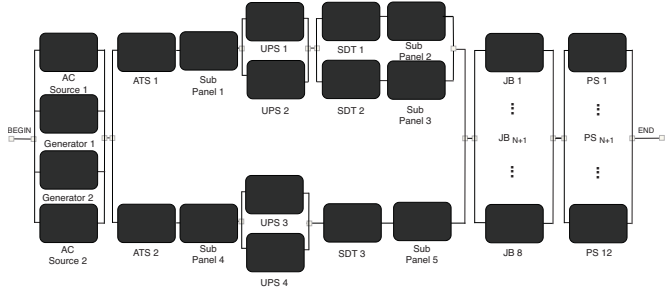


Fig. 9. RBD for EFM Tier 4.

dissipated by each item of equipment cannot be theoretically converted into valuable work. Acquisition costs, operating costs, and total costs are also shown. The energy cost for all tiers in this work was \$0.133. The operating cost was calculated according to Equation 24. The second column shows the minimum availability, which must be achieved in each tier. The penultimate column shows the minimum recommended demand after evaluating the models. According to their efficiency specification, this value corresponds to the source's minimum load, including the energy losses suffered by the components. The last column shows the efficiency of the system. Note that the greater the redundancy, the less efficient the system is.

To execute these research experiments, we decided to create some scenarios based on real information. Table V indicates the modeled scenarios. We chose some primary sources used in energy production, considering that they are used in various parts of the world. For example, Lignite is a type of brown coal, quite common in Australia and Texas, to be used in energy production. To calculate the  $CO_2$  emission, we use Equation 25. The first column shows the type of material used for power generation; the second column shows how many grams of  $CO_2$  are emitted per kilowatt-hour for a given material (aggression factor). We consider two sources of cleaner energy, with greater representation on the planet (wind and hydroelectric), whose aggression factors were obtained from [10], [17]. For other sources, the aggression factors are from [21]. We defined the input power used for the calculation due to the models' evaluation (second line in the table). Within the (minimum) availability that must be achieved by tier (third line), part of the availability is represented using the primary source and the other part using generators. Specifically, for tiers 1 and 2, which only have one generator in their architecture, we consider that they are used 20% and fueled by gasoline (columns 3 and 4, line 7). For tiers 3 and 4,

which have two generators, we consider that each one is used 10% of the availability and is fueled by gasoline and diesel (penultimate and last columns, lines 7 and 8). Tier 4 is the only one that has two primary energy sources.

Thus, we have that Tier 1 produces 607.79 kg/kWh and will have emitted **0.00532** tons of  $CO_2$  into the atmosphere over a year. Tier 2 produces 872.30 kg/kWh and will have emitted **0.00764** tons of  $CO_2$  over a year. Tier 3 produces 586.41 kg/kWh and will have emitted **0.00513** tons of  $CO_2$  over a year. Tier 4 produces 1,075.66 kg/kWh and will have emitted **0.00942** tons of  $CO_2$  over a year. The tier 3 data center has an energy demand almost five times greater than the tier 1 DC and still emits less  $CO_2$  than tier 1. This is the same as saying that a single DC, which makes a wrong choice for its power source, issues the amount of  $CO_2$  that five data centers use cleaner energy source, in this case, the hydroelectric. Hence, we can highlight the importance of using cleaner energy sources, those that produce less  $CO_2$ .

The dependability results achieved with the RBD models' evaluation scripts are presented in Table VI, whose metrics presented are availability, reliability, and MTTF. Observing the availability achieved (See Table VI) and comparing the minimum suggested availability for each tier (See Table IV), we can conclude that all electrical architectures have a satisfactory redundancy level to achieve the suggested availability. Regarding reliability and MTTF, we can see that as the redundancy increases, these metrics also increase. This is due to a more redundant tier to better support component failures, considering an alternative to still maintaining the operating system.

Table VII shows the rank for the sensitivity analysis of the first five most important components for each tier. The sensitivity value and the reboot component are also displayed. The reboot component will have little or no influence on

TABLE IV  
RESULTS OF EVALUATIONS OF THE EFMS.

Tier	Availability (%)	Evaluation Period (h)	Embedded Exergy (kW)	Operational Exergy (kW)	Total Exergy (kW)	Acquisition Cost (US\$)	Operational Cost (US\$)	Total Cost (US\$)	Input Power (kW)	System Efficiency (%)
1	99.671	720	260.96	1,214,690.25	1,214,951.21	45,842.5	17,223,315.37	17,269,157.87	1,804.53	36.70
		8760		14,778,731.42	14,778,992.38		209,550,337.03	209,596,179.53		
2	99.749	720	265.61	2,434,310.38	2,434,575.99	81,345.0	34,516,532.30	34,597,877.30	3,613.55	36.70
		8760		29,617,442.96	29,617,708.57		419,951,143.03	420,032,488.03		
3	99.982	720	280.91	6,468,242.85	6,468,523.76	87,727.5	82,569,873.59	82,657,601.09	8,624.14	30.72
		8760		78,696,954.64	78,697,235.55		1,004,600,128.64	1,004,687,856.14		
4	99.995	720	445.53	12,909,962.36	12,910,407.89	129,117.5	164,801,165.57	164,930,283.07	17,210.67	30.72
		8760		157,071,208.75	157,071,654.28		2,005,080,847.73	2,005,209,965.23		

TABLE V  
EFMS EXPERIMENTAL STUDY.

Parameters	CO <sub>2</sub> Emission (g/kWh)	Tier 1	Tier 2	Tier 3	Tier 4
Input Power (kW)	–	1,804.53	3,613.55	8,624.14	17,210.67
Availability (%)	–	99.671	99.749	99.982	99.995
Wind (g/kW)	10				0.49995
Hydroelectric (g/kW)	20			0.79982	0.3
Refinery gas (g/kW)	240		0.79749		
Gasoline (g/kW)	250	0.2	0.2	0.1	0.1
Diesel (g/kW)	270			0.1	0.1
Lignite (g/kW)	360	0.79671			
CO <sub>2</sub> Emission (kg/kWh)	–	607.79	872.30	586.41	1,075.66

TABLE VI  
RESULTS OF EVALUATIONS OF THE RBDs.

Tier	Evaluation Period (8760 h)		
	Availability (%)	Reliability (%)	MTTF System (h)
1	99.93398	7.88	3,891.37
2	99.96088	9.87	4,275.98
3	99.99996	15.13	5,452.59
4	99.99998	24.90	6,806.54

overall availability. Figure 10 shows the availability achieved according to the ATS components' MTTF variation. The highest sensitivity for tiers 1 and 2 is related to the MTTF variation of the ATS component, and for tiers 3 and 4, it is the MTTF of ATS1 (changing only the nomenclature due to the addition of redundancy). The lower the MTTF value of these components, the greater the system downtime. Thus, we can conclude that this component is the most important for the availability of the four architectures and, in this sense, we can request more attention regarding maintenance and repair and instruct the need for redundancy of these.

## V. RELATED WORKS

Many works have been conducted with the themes of this study. In sequence are a few that have a more significant correlation to this research. In [17], the authors carry out

TABLE VII  
RBDs EXPERIMENTAL STUDY - SENSITIVITY RANKING.

Tier	Component	Rank	Value	Reboot
1	mttf_ATS	1st	4.4E-04	mttr_Jb <sub>i</sub>
	mttr_ATS	2nd	3.3E-04	
	mttf_UPS1	3rd	2.1E-04	
	mttr_UPS1	4th	1.6E-04	
	mttf_SDT1	5th	7.5E-05	
2	mttf_ATS	1st	4.4E-04	mttr_PS <sub>i</sub>
	mttr_ATS	2nd	3.3E-04	
	mttf_SubP1	3rd	7.0E-05	
	mttr_SubP1	4th	5.3E-05	
	mttf_ACS	5th	7.7E-06	
3	mttf_ATS1	1st	2.9E-07	mttr_Jb <sub>i</sub>
	mttr_ATS1	2nd	2.2E-07	
	mttf_ATS2	3rd	1.7E-07	
	mttr_ATS2	4th	1.3E-07	
	mttf_UPS3	5th	8.2E-08	
4	mttf_ATS1	1st	2.2E-07	mttr_PS <sub>i</sub>
	mttf_ATS2	2nd	1.7E-07	
	mttr_ATS1	3rd	1.6E-07	
	mttr_ATS2	4th	1.3E-07	
	mttf_SubP1	5th	3.5E-08	

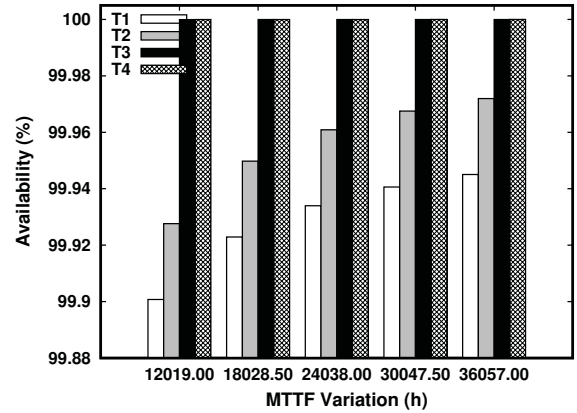


Fig. 10. Availability of ATS components.

electrical architecture evaluations of a tier 3 data center to estimate costs and CO<sub>2</sub> emissions. They also present an energy matrix according to the energy costs from different primary sources for countries like China, Germany, the United States, and Brazil. Our research differs from that mentioned

in several points. Next, we mention the main ones: 1) We present the costs and sustainability metrics for four DC electrical architectures, ranging from tier 1 to 4. 2) We use different materials to quantify  $CO_2$  emissions in contrast to those presented. 3) We present RBDs models to perform a sensitivity analysis of the architectural components. This objective was not presented by the work mentioned. In [22] the authors consider a methodology to support the modeling, evaluation, and optimization processes in data center energy systems using Mercury tool [18] for the construction of RBD, SPN, and Energy Flow Model (EFM). The authors present different architectures, but they are not classified considering the redundancy levels classified for the tiers. Our research differs from this by representing the modeled architectures and points 2 and 3 cited for the work mentioned before. In [23], the authors present an assessment of performance and energy consumption of storage devices and hybrid mechanisms of the data center to provide insights about the benefits of each technology. In [24], the authors perform a sensitivity analysis on a computer network with redundancy mechanisms to find the system availability bottlenecks, but the approach, the assessment environment, and the models presented are different from ours.

## VI. FINAL REMARKS

The higher the tier classification for data centers, the lower the energy efficiency, and the higher the costs and energy consumption. This is due to the redundancy of components for alternative paths. However, the type of raw material for energy production that powers these dense architectures is essential and can significantly reduce the environmental impact in the face of  $CO_2$  emissions into the atmosphere. We have the EFM and RBD modeling for four different electrical data center architectures as contributions to this work. From which we present, as a result, several metrics of sustainability and dependability. We compute the  $CO_2$  emissions based on possible real scenario resources and identify that the proposed electrical architectures can reach the minimum availability level suggested, given the classification by tier. We have also identified the most critical components for the availability of modeled architectures based on the parametric sensitivity analysis technique. Thus, we suggest some proposals that can reduce downtime. As the first limitation of this work, we can say that we try to be faithful to the MTTF values found for real components, but these values can differ significantly due to the manufacturers' variety of brands. Thus, our results do not represent this plurality. A second limitation is the minimum number of components required to fit the tier classifications. However, for many real infrastructures, more resources can be used. As proposals for future work, we intend to perform the modeling and sensitivity analysis for the data center network's critical components, identifying the electrical costs based on the type of raw material chosen to feed the IT load.

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