Dependability and Sustainability Evaluation of Data Center Electrical Architectures

Kádna Camboim*†, João Ferreira‡, Carlos Melo§, Jean Araujo†, and Fernanda Alencar*
*Centro de Tecnologia e Geociências, Universidade Federal de Pernambuco, Recife, Brazil
†Universidade Federal do Agreste de Pernambuco, Garanhuns, Brazil
‡Colégio Agrícola Dom Agostinho Ikas, Universidade Federal Rural de Pernambuco, Recife, Brazil
§Centro de Informática, Universidade Federal de Pernambuco, Recife, Brazil
{kadna.camboim, jean.teixeira}@ufape.edu.br, joao.ferreirasilva@ufrpe.br, casm3@cin.ufpe.br, fernandaalenc@gmail.com

***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_2) 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_2 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_2) into the atmosphere due to burning fossil fuels (such as carbon, gas, and oil) used mainly for energy production. China, United States, India, Russia, and Japan have been leading the ranking of the five countries that emit the most CO_2 [2] for some years, significantly impacting global warming.

The industrial and academic environment has made countless efforts to prevent the CO_2 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_2 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 article, 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_2 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 infrastructure of a data center should generally offer a minimum availability of 99.67% (tier 1), but to support highly reliable systems, the ideal would be that this number should be at least 99.9%, considering the capacity of withstanding failures. Each additional "nine" increases the order of magnitude of availability by a factor of 10. Thus, an increase from 99.99% to 99.999% is quite significant and represents a tenfold cost in investment [5]. 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 [6]–[9].

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) Mean time to failure (MTTF): The mean exposure time between consecutive repairs (or installations) of a component and the next failure of that component. MTTF of a system can be calculated by Equation 1.

$$MTTF = \int_0^{\infty} R(t)dt \tag{1}$$

5) Mean time to repair (MTTR): The mean time to replace or repair a failed component. The logistics time associated with the repair, such as purchasing parts, mobilizing the team, is not included. MTTRs are closely related to the maintenance policy adopted by and can be achieved by Equation 2.

$$MTTR = MTTF \times \frac{UA}{A} \tag{2}$$

Where UA represents system downtime ($UA = 1{-}A$) and A represents system availability (Equation 3).

6) Availability: The ability of an item - under combined aspects of its reliability, maintainability, and maintenance support - to perform its required function at a given time or for a given period. To obtain a system's availability by analysis or simulation of the steady-state, the Equation 3 is used.

$$A = \frac{MTTF}{MTTF + MTTR} \tag{3}$$

7) Reliability: The ability of a component or system to perform the required functions under conditions established for a specified period. Mathematically, the reliability function *R(t)* is the probability that the system will function correctly, without failure, in the time interval from 0 to t, as presented in Equation 4.

$$R(t) = P(T > t), t \geq 0 \tag{4}$$

Where T is a random variable, representing the time to failure.

8) 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, $N_s \cap N_i = N_s \cap N_t = N_i \cap N_t = \oslash$;
- $A \subseteq (N_s \times N_i) \cup (N_i \times N_t) \cup (N_i \times N_i)$ = {(a,b) | 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);
- $f_d : N \rightarrow \begin{cases} \mathbf{R}^+ & \text{if } n \in N_s \cup N_t, \\ 0 & otherwise; \end{cases}$
  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);
- $f_c : N \rightarrow \begin{cases} 0 & \text{if } n \in N_s \cup N_t, \\ \mathbf{R}^+ & otherwise; \end{cases}$
  is a function that assigns each node with the respective maximum energy capacity;
- $f_p : N \rightarrow \begin{cases} 0 & \text{if } n \in N_s \cup N_t, \\ \mathbf{R}^+ & otherwise; \end{cases}$
  is a function that assigns each node (a node represents a component) with its retail price;
- $f_\eta : N \rightarrow \begin{cases} 1 & \text{if } n \in N_s \cup N_t, \\ 0 \leq k \leq 1, k \in \mathbf{R} & otherwise; \end{cases}$
  is a function that assigns each node with the energetic efficiency.

9) 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 [8], [12].

The reliability of n blocks connected in series is obtained through the Equation 5.

$$R_s(t) = \prod_{i=1}^{n} R_i(t) \tag{5}$$

Where $R_i(t)$ corresponds to the reliability of block b_i at time instant t.

The reliability of n blocks connected in parallel is obtained through the Equation 6.

$$R_P = 1 - \prod_{i=1}^{n} (1 - R_i(t)) \tag{6}$$

Where $R_i(t)$ corresponds to the reliability of block b_i at time instant t.

The reliability of $k - out - of - n$ blocks non identical is obtained through Equation 7.

$$R_s = \sum_{r=i}^{n} \left(\begin{array}{c} n \\ r \end{array} \right) R^r (1 - R)^{n-r} \tag{7}$$

Where n is the total number of non-identical blocks, r is the minimum number of units required for system success. R is the reliability of each unit.

10) Parametric Sensitivity Analysis: Sensitivity analysis is adopted to determine the most influential factors over a metric of interest [13]. In this paper, the differential sensitivity analysis is applied, one of the most well known parametric techniques. A sensitivity index characterizes this technique is known as $S_\theta(Y)$, which indicates the impact of a given measure known as Y for a parameter θ.

Equation 8 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 θ over the range of its n possible values of interest.

If $Y(\theta)$ is known to vary monotonically, only the extreme values of θ (i.e., θ_1 and θ_n) may be used to compute $max\{Y(\theta)\}$; $min\{Y(\theta)\}$, and subsequently $S_\theta(Y(\theta))$ [14].

$$S_\theta(Y) = \frac{\max\{Y(\theta)\} - \min\{Y(\theta)\}}{\max\{Y(\theta)\}} \quad (8)$$

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]. The efficiency of a system's energy consumption can be estimated from the exergy used. Consider F as a quality factor represented by the Exergy/Energy ratio so that exergy can be calculated with the Equation 9.

$$\text{Exergy} = Energy \times F \quad (9)$$

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 Equation 10.

$$\text{PUE} = \frac{\text{DC}_{load}}{\text{IT}_{load}} \quad (10)$$

Where DC_{load} is the total load of the data center infrastructure, in kW and IT_{load} is the effective critical load, in kW.

3) Operational Cost: For this work, we consider the acquisition costs of the data center energy infrastructure and its operational cost. The operating cost considers the DC operation period, the energy consumed, energy cost, and the availability (which varies according to the tier classification). Equation 11 denotes the operating cost [17].

$$OP_{Cost} = (P_{input}).(Energy_{Cost}).(T).(A + \alpha(1 - A)) \quad (11)$$

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

4) CO_2 Emission: We also calculate the environmental sustainability impact by quantifying the CO_2 emission produced by the DC operation. Different types of raw materials for energy generation will be considered. Its percentage of use is multiplied by its impact factor. For example, 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 factor of aggression to the environment. Thus, the calculation for CO_2 emission [17], is given by Equation 12.

$$CO_2Emission = \sum_{i=1}^{n}(D_e.P_i.F_i) \quad (12)$$

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.

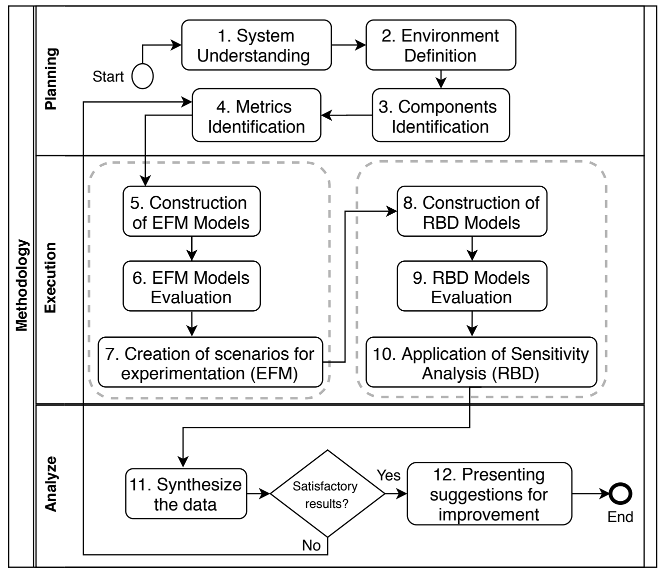

Fig. 1. Phases for conducting this work.

Initially, we classified three phases for conducting the specified activities, as described below.

Planning - In this phase, we perform the activities that correspond to the general understanding of the system to define which architectures and components to be represented, in addition to identifying and finding the metrics that serve as input parameters of the models.

Execution - At this stage, we execute the modeling. For this research, it was done in a hybrid way to design the EFM and RBDs models, representing four data center power architectures with different redundancy levels. For each type of model, we carry out different experiments. For EFMs models, we create scenarios based on a load of data centers tiers 1 to 4 to represent the use of different types of raw materials used in energy production and thus quantify CO_2 emissions and other sustainability metrics. From the RBD models, we created scripts to perform the sensitivity analysis to identify the most critical components for the modeled architectures' availability and identify dependability metrics.

Analysis - In this phase, we carry out the synthesis of the data to understand and identify whether the results correspond to the objectives of the research and then present suggestions to contribute to environmental sustainability and to improve the availability.

We use the graphical interfaces for EFM and RBD in version 4.8 of this work's Mercury tool. We also use the scripting language to perform the sensitivity analysis. Mercury is software for supporting performance, dependability, and energy flow modeling quickly and powerfully. The tool provides graphical interfaces for creating and evaluating EFMs, RBDs, Stochastic Petri Nets (SPNs), Continuous-Time Markov Chains (CTMCs), Discrete-Time Markov Chains (DTMCs), and Fault Trees (FTs) [18].

IV. Modeling

A. Input Parameters

To create the energy flow models, we consider a certain number of 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. We also contemplate the cooling system and battery loads, lighting, and space for future growth, as suggested in [5]. Thus, we perform the electrical demand estimates in a more realistic way for the four data center architectures, according to the redundancy specifications for tiers 1, 2, 3, and 4. 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^2)	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 [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 metrics as input 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%, that is, between 4 and 12 hours. MTTFs were obtained from [19], [11]. Only the junction box component suffered a reduction of 0.8, considering the MTTF value. Due to the manufacturer's original value, this reduction can be applied at a 95% confidence level, as [20]. Table III shows the components' MTTF and the variation of the value to -50% to +50%, to be used in the sensitivity analysis.

B. Proposed Models

This paper 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 that represents the total load of the data center project, whose values are presented in Table I (last line). The $SourcePoint$ component does not receive an input value since this value is estimated after evaluating the model.

Figure 2 presents the electrical architecture of a tier 1 data center. This model has the minimum necessary to be considered a DC electrical system. 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, in addition to the central UPS ($UPS1$), there is a redundant module ($UPS2$), which assumes the IT critical load in case of failure of the main one. In this case, the

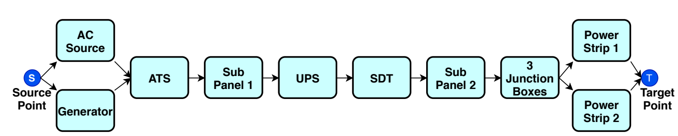

Fig. 2. EFM for tier 1 data center.

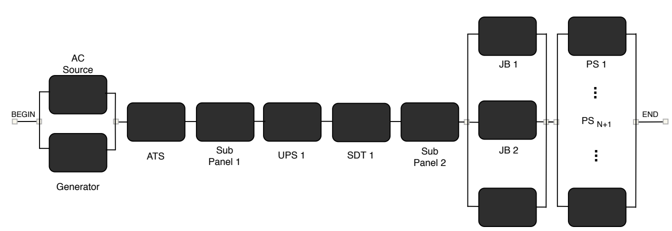

Fig. 3. RBD for EFM Tier 1.

TABLE II
INPUT PARAMETERS OF EFM MODELS.

Components	Eficiency (%)	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
$Generator_{redundant}$	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
$UPS_{redundant}$	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 RBD MODELS.

Components	MTTF (h)	MTTF variation	
		-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

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 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 ($SDT2$), 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 paths of electrical distribution 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. In the absence of one or both

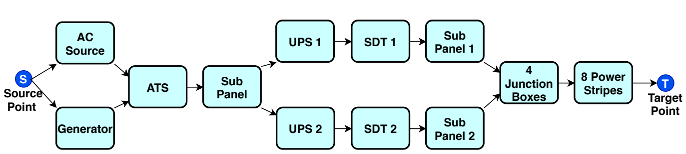

Fig. 4. EFM for tier 2 data center.

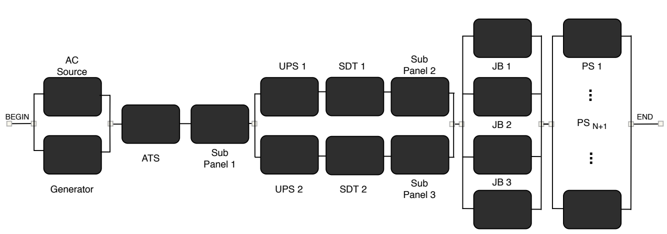

Fig. 5. RBD for EFM Tier 2.

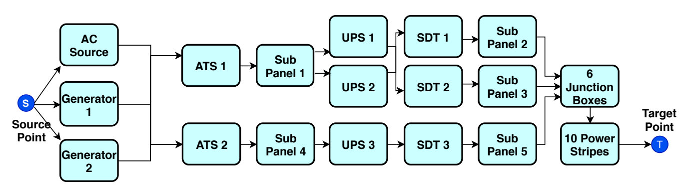

Fig. 6. EFM for tier 3 data center.

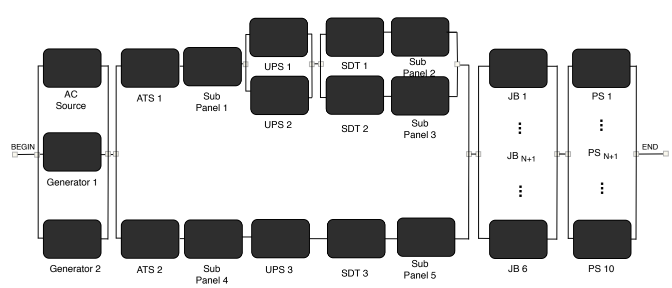

Fig. 7. RBD for EFM Tier 3.

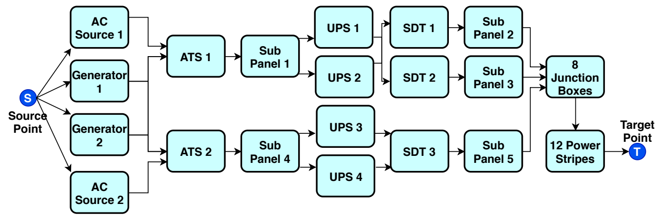

Fig. 8. EFM for tier 4 data center.

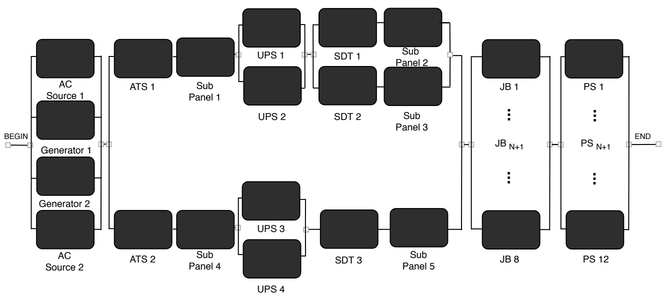

Fig. 9. RBD for EFM Tier 4.

sources, the generators are activated, and the loads remain in operation by either (or both) of the distribution branches. 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, which can be understood as the fraction of the heat dissipated by each item of equipment that cannot be theoretically converted into useful 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 11. 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. This value corresponds to the source's minimum load, including the energy losses suffered by the components, according to their efficiency specification. 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 emission of CO_2, we use Equation 12. 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. 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 2 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 1075.66 kg/kWh and will have emitted **0.00942** tons of CO_2 over a year. The data center tier 3, has an energy demand almost five times greater than the data center tier 1 and still emits less CO_2 than tier 1. This is the same as saying that a single data center, 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. Thus, we can highlight the importance of using cleaner energy sources, that is, 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 level of redundancy 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 that there is 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 is one that will have little or no influence on 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.

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
RESULTS OF THE EFM EXPERIMENTAL STUDY.

Parameters	CO_2 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			
CO2 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

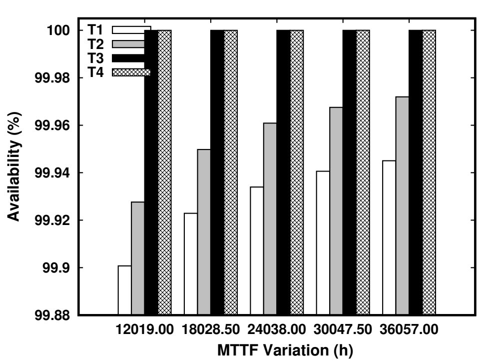

Fig. 10. Availability of ATS components.

TABLE VII
RESULTS OF THE RBD EXPERIMENTAL STUDY - SENSITIVITY RANKING.

Tier	Component	Rank	Value	Reboot
1	mttf_ATS	1st	4.4E-04	mttr_Jb$_i$
	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$_i$
	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$_i$
	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$_i$
	mttf_ATS2	2nd	1.7E-07	
	mttr_ATS1	3rd	1.6E-07	
	mttr_ATS2	4th	1.3E-07	
	mttf_SubP1	5th	3.5E-08	

V. RELATED WORKS

Many works have been conducted with the themes of this study. Below are a few that have a more significant correlation to this research. In [17], the authors carry out electrical architecture evaluations of a tier 3 data center to estimate costs and CO_2 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. Additionally, an artificial neural network is used to forecast energy consumption for the following months. 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 in 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 propose a framework for scheduling tasks in the data center to compute the workload classifications of energy consumption and propose energy-saving strategies based on the consumption of CPU-bound applications. Although these surveys focus on energy efficiency for data centers, they differ from ours in that they do not represent electrical infrastructure. Furthermore, it is not the authors' objective to present data on emissions of CO_2.

In [25], the authors perform a sensitivity analysis on a computer network with redundancy mechanisms to find the system availability bottlenecks. They use Markov chains for the analytical assessment of scenarios. This paper presents dependability metrics and sensitivity analysis techniques, which are common in our research. However, 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 emissions of CO_2 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 emissions of CO_2 based on possible real scenario resources and identify that the proposed electrical architectures can reach the minimum level of availability 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 classifications of layers. 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.

References

[1] Y. Sverdlik, "Study: Data centers responsible for 1 percent of all electricity consumed worldwide," in *Data Center Knoledge*, 2020. [Online]. Available: https://www.datacenterknowledge.com/energy/study-data-centers-responsible-1-percent-all-electricity-consumed-worldwide

[2] V. Quaschning. (2020) Specific carbon dioxide emissions of various fuels. [Online]. Available: https://www.volker-quaschning.de/datserv/CO2-spez/indexe.php

[3] G. M. Laboratory. (2020) Annual greenhouse gas index (aggi). [Online]. Available: https://www.esrl.noaa.gov/gmd/aggi/aggi.html

[4] S. Murugesan, "Harnessing green it: Principles and practices," *IT professional*, vol. 10, no. 1, 2008.

[5] P. S. Marin, "Data centers-desvendando cada passo: conceitos, projeto, infraestrutura física e eficiência energética," *São Paulo: Érica*, 2011.

[6] C. Heising *et al.*, "Ieee recommended practice for the design of reliable industrial and commercial power systems," *IEEE Inc., New York*, 2007.

[7] K. Trivedi, D. S. Kim, A. Roy, and D. Medhi, "Dependability and security models," in *Design of Reliable Communication Networks, 2009. DRCN 2009. 7th International Workshop on*, oct. 2009, pp. 11 –20.

[8] W. Kuo and M. J. Zuo, *Optimal reliability modeling: principles and applications*. John Wiley & Sons, 2003.

[9] P. Maciel, K. Trivedi, R. Mathias, and D. Kim, *Dependability Modeling In: Performance and Dependability in Service Computing: Concepts, Techniques and Research Directions*. Pennsylvania, USA.: Ed. Hershey: IGI Global, 2010.

[10] G. Callou, P. Maciel, D. Tutsch, J. Ferreira, J. Araújo, and R. Souza, "Estimating sustainability impact of high dependable data centers: a comparative study between brazilian and us energy mixes," *Computing*, vol. 95, no. 12, pp. 1137–1170, 2013.

[11] J. Ferreira, G. Callou, P. Maciel, and D. Tutsch, "An algorithm to optimise the energy distribution of data centre electrical infrastructures," *International Journal of Grid and Utility Computing*, vol. 11, no. 3, pp. 419–433, 2020.

[12] K. Trivedi and M. Malhotra, "Reliability and performability techniques and tools: A survey," in *Messung, Modellierung und Bewertung von Rechenund Kommunikation ssystemen*, 1993, pp. 27 – 48.

[13] P. M. Frank and M. Eslami, "Introduction to system sensitivity theory," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 10, no. 6, pp. 337–338, 1980.

[14] R. Matos, J. Araujo, D. Oliveira, P. Maciel, and K. Trivedi, "Sensitivity analysis of a hierarchical model of mobile cloud computing," *Simulation Modelling Practice and Theory*, vol. 50, pp. 151–164, 2015.

[15] I. Dincer and M. A. Rosen, *Exergy: energy, environment and sustainable development*. Newnes, 2012.

[16] G. Schulz, *The green and virtual data center*. CRC Press, 2016.

[17] J. Ferreira, G. Callou, A. Josua, and P. Maciel, "Estimating the environmental impact of data centers," in *2018 IEEE 17th International Symposium on Network Computing and Applications (NCA)*. IEEE, 2018, pp. 1–4.

[18] P. Maciel, R. Matos, B. Silva, J. Figueiredo, D. Oliveira, I. Fé, R. Maciel, and J. Dantas, "Mercury: Performance and dependability evaluation of systems with exponential, expolynomial, and general distributions," in *2017 IEEE 22nd Pacific Rim international symposium on dependable computing (PRDC)*. IEEE, 2017, pp. 50–57.

[19] G. Callou, J. Ferreira, P. Maciel, D. Tutsch, and R. Souza, "An integrated modeling approach to evaluate and optimize data center sustainability, dependability and cost," *Energies*, vol. 7, no. 1, pp. 238–277, 2014.

[20] D. J. Smith, *Reliability, maintainability and risk: practical methods for engineers*. Butterworth-Heinemann, 2017.

[21] V. Quaschning, "Specific carbon dioxide emissions of various fuels," 2020. [Online]. Available: https://www.volker-quaschning.de/datserv/CO2-spez/index_e.php

[22] G. Callou, J. Ferreira, P. Maciel, D. Tutsch, and R. Souza, "An integrated modeling approach to evaluate and optimize data center sustainability, dependability and cost," *Energies*, vol. 7, no. 1, pp. 238–277, 2014.

[23] E. Borba, E. Tavares, P. Maciel, V. Lira, and C. G. Araújo, "Performance and energy consumption evaluation of hybrid storage systems," in *2020 IEEE International Systems Conference (SysCon)*, 2020, pp. 1–6.

[24] L. Ismail and A. A. Fardoun, "Towards energy-aware task scheduling (eats) framework for divisible-load applications in cloud computing infrastructure," in *2017 Annual IEEE International Systems Conference (SysCon)*, 2017, pp. 1–6.

[25] R. d. S. M. Júnior, A. P. Guimaraes, K. M. Camboim, P. R. Maciel, and K. S. Trivedi, "Sensitivity analysis of availability of redundancy in computer networks," *CTRQ 2011*, p. 122, 2011.