Sustainability and Dependability Evaluation on Data Center Architectures

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***Abstract*—Business service through the Internet, particularly the cloud computing paradigm, have demanded more computational resources from data centers to provide high-availability services. As consequence, issues such as operational costs and sustainability increase, mainly, due to the redundant infrastructures needed to support the data center operation. However, data center designers have slightly information on the sustainability impact, operational cost and availability of data center architectures. In this context, models are important to support data center designers to estimate the environmental impact, dependability as well as the cost associated to the infrastructure before implementing it. This paper presents a set of formal models for estimating sustainability impact and dependability metrics, supported by an integrated environment, namely, ASTRO.**

***Index Terms*—Petri Net, Reliability Block Diagrams, Sustainable Data Center, Dependability.**

I. Introduction

Sustainability has received great attention by the scientific community, due to concerns for meeting current needs of energy without compromising, for instance, non-renewable resources for future generations. In addition, as a result of stringent availability constraints, dependability plays a prominent role in the infrastructure that supports business service through the Internet, particularly, the growth of cloud computing paradigm. Thus, there has been a tremendous growth in the number, size and power densities of data centers.

A data center is not only composed of IT equipments, but also the power and cooling infrastructures, which incur considerable energy consumption. Besides that, considering the increase in energy costs as well as the global attention focused on sustainability, the energy management and environment impacts of data centers are critical. Indeed, data centers consume about 2 % of the U.S. power generation [1], and, so, they also significantly contribute to the global carbon emissions.

Efforts have been conducted to address sustainability in data centers, in which energy consumption management techniques and the adoption of clean energy sources are fundamental for reducing the energy consumption and environmental impacts. In this context, sustainable data centers are those that are built using the least amount of the appropriate materials and consume the least amount of appropriate sources of energy throughout their lifetime [2].

At present stage, data center designers do not have many mechanisms to support sustainability and dependability evaluation. For instance, two different data center architectures with similar availability may have very different sustainability impact. Additionally, a growing concern of data center designers is related to the identification of components that may cause system failure as well as systems parts that must be improved before implementing the architecture.

In this work, we estimate sustainability impact, total cost of ownership (TCO) and dependability metrics for datacenter infrastructures. The adopted approach evaluates sustainability impact based on lifecycle assessment (LCA) [3] in terms of lifetime exergy (available energy) consumption [4]. Besides, the methodology adopts a hybrid modeling technique that considers the advantages of both stochastic Petri nets (SPN) [5] and reliability block diagrams (RBD) [6] to evaluate system dependability. ASTRO [7] has been extended with new functionalities, which are described in this work. More specifically, a sustainability model, an energetic model as well as TCO evaluation.

This paper is organized as follows. Section II presents related works. Section III introduces basic concepts on data center infrastructures, dependability, sustainability and TCO. Section IV describes the adopted methodology. Section V presents the sustainability, dependability and energetic models. Section VI presents a real-world case study and Section VII concludes the paper as well as presents future works.

II. Related Works

In the last few years, some works have been developed to evaluate the infrastructure of data centers and a subset has also considered the impact on sustainability. [8] proposes a risk anatomy to detect single point of failure in data center power distribution systems as well as a mechanism for improving investments concerning the risk acceptance level. In [9], the authors propose a platform for evaluation of smart data centers taking into account cooling, power and IT components. Wiboonrat [10] adopts an approach based on reliability block diagrams and Monte Carlo simulation to compare data center topologies.

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In [11], the authors propose an approach for reliability evaluation and risk analysis of dynamic process systems using stochastic Petri nets. [12] describes opportunities for energy integration in the context of combined cooling, heating and power systems. The authors demonstrate that dependability attributes, such as reliability, are benefited from an integrated approach. In [13], the authors demonstrate that other issues, in addition to energy efficiency, should be considered to the quantification of data center environmental impacts. Additional impacts may stem from the production, transportation, maintenance of each data center device.

Different from previous works, this paper proposes a set of formal models to quantify sustainability impact, dependability metrics and TCO in the context of data center design. Furthermore, the adopted approach for the quantification of those values takes into account a hybrid modeling technic, which utilizes RBD and SPN whenever they are best suited.

III. Preliminaries

This section presents a summary of the concepts needed for a better understanding of this work. Initially, an overview of data center infrastructures is performed. Next, dependability and sustainability concepts are presented.

A. Data Center Infrastructure

This work considers a generic data center system, which essentially consists of the following subsystems, in addition to the building facility: (i) IT infrastructure; (ii) cooling infrastructure; and (iii) power infrastructure.

The IT infrastructure consists of three main components - servers, networking and storage devices. Cooling infrastructures are basically comprised of computer room air conditioning (CRAC) units, chillers and cooling towers. The cooling infrastructure may account around 40% of the total power consumption of the data center [14].

Heat dissipated from IT equipment is extracted by CRAC units and transferred to the chilled water distribution system. Chillers extract heat from the chilled water system and reject it to the environment through cooling towers. Water is lost by evaporation to the ambient environment during this process of heat rejection.

The power infrastructure is responsible for providing uninterrupted, conditioned power at the correct voltage and frequency to the IT equipment hosted in data center racks. From the electric utility, the power typically, goes through step down transformers, transfer switches, Uninterruptible Power Supplies (UPS), Power Distribution Units (PDU), and finally to rack power strips.

B. Dependability

The dependability [6] of a system can be understood as the ability to deliver a set of services that can be justifiably trusted. Indeed, dependability is related to disciplines such as fault tolerance and reliability. Reliability is the probability that the system will deliver a set of services for a given period of time, whereas a system is fault tolerant when it does not fail even when there are faulty components. Availability is also another important concept, which quantifies the mixed effect of both failure and repair process in a system. If one is interested in calculating the availability (A) of a given device or system, he/she might need either the uptime and downtime or the time to failure (TTF) and time to repair (TTR). Considering that the uptime and downtime are not available, the later option is the mean. If the evaluator needs only the mean value, the metrics commonly adopted are Mean Time to Failure ($MTTF$) and Mean Time To Repair ($MTTR$). For more details, the reader should refer to [6], which also provides the equations for estimating dependability metrics.

Dependability metrics might be calculated either by using RBD or SPN (to mention only the models adopted in this work). RBDs allow to one represent component networks and provide closed form equations. Nevertheless, when faced with representing dependent activities, some drawbacks may limit the model. On the other hand, state-based methods can easily consider those dependencies. However, they suffer from the state-space explosion. Some of those formalism allow both numerical analysis and stochastic simulation, and SPN is one of the most prominent models of such class.

C. Sustainability

Life-cycle assessment (LCA) [3] is a common approach to quantify environmental sustainability. In this work, an LCA-based approach is adopted to estimate the sustainability impact of an equipment in terms of its lifetime exergy (available energy) consumption. It should be noted that while the proposed approach is applied to analysis of the data center power and cooling infrastructures, the model is sufficiently general to be applied to any component of a data center infrastructure.

The approach essentially divides the life-cycle into two phases: (1) embedded phase, which involves all impacts related to product design decisions (including material extraction, manufacturing and supply chain impacts, as well as end-of-life); and, (2) operational phase, which involves all impacts related to decisions during product use (such as operational and maintenance cycles). For the embedded phase, an LCA model is developed that quantifies the environmental impacts in terms of average sectoral compositions as a function of cross-sectoral economic activity. For the operational phase, a detailed operational model is constructed that takes into account the individual device efficiencies, uptime (i.e., availability), and runtime power consumption.

IV. Methodology

The methodology's first step concerns understanding the system, its components, their interfaces and interactions. This phase should also provide the set of metrics (e.g. availability, reliability, sustainability indicators and economic losses). The next broad phase aims at grouping components in order to generate subsystems, which are adopted to mitigate the complexity of the final system model evaluation. For each subsystem, the dependability metrics are computed. These metrics might be calculated either by using RBD or SPN (to mention only the models adopted in this work). After obtaining the subsystem models, the next step will be composing the subsystem models. Lastly, the system model is evaluated to obtain the metrics of interests. Due to space constraints, the reader should refer to [7] for more details.

V. MODELS

This section presents the models adopted for quantifying system dependability and sustainability. Initially, the energetic model, which verifies the energy flow between the system components, is presented. Next, the sustainability model is detailed. Finally, the dependability models are described, which are represented by RBD and SPN models.

A. Energetic Model

The system under evaluation can be correctly arranged, in the sense that the required components are properly connected, but they may not be able to meet system demand for electrical energy or thermal load. For instance, consider the cooling infrastructure depicted in Figure 1 (a). Assume that the amount of heat that should be extract from the data center room corresponds to 10kJ (Figure 1 (b)), and the maximum cooling capacity of the adopted CRACs and Chiller are 8kJ and 18kJ, respectively. Figure 1 (c) depicts a possible energetic flow, which extracts heat using both CRACs (with a load of 5 kJ in each component) that transfer the heat to the Chiller (10 kJ). Considering another example, in which instead of adopting two CRACs, only one is considered in the infrastructure. As shown in Figure 1 (d), the system will be able to extract 8kJ of heat. Thus, the system will not be able to satisfy the required thermal load.

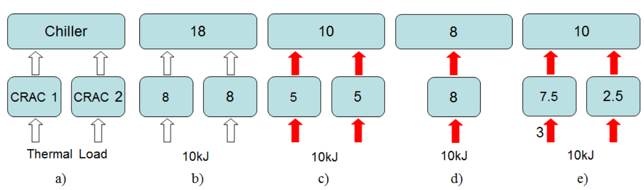

Fig. 1. a) System example; b) Maximum Cooling Capacity; c) Successful Energetic Flow; d) Failed Energetic Flow; e) Representation with Weight.

To perform such an evaluation, an infrastructure model is converted into a graph, in which the components are represented by nodes and the respective connections are modeled by edges. The edges have weights that are adopted to compute the amount of energetic flow directed to a component. For instance, consider Figure 1 (e) in which a weight of 3 unit is defined for one edge and 1 unit for the other edge. In this case, CRAC1 component extracts 3 times more heat than CRAC2. Next, an algorithm traverses the graph, checking the component capacities to meet the load for electrical energy or heat extraction.

Let $G = (N, V, w, f_p, s, t)$ be a graph which represents the energetic model in which:

- N represents the set of nodes (i.e., the components);

```
1  verify(G, D_a, a) {
2    O = {n | (a,n) ∈ V};
3    if(O = ∅) return TRUE;
4    ws = Σ_{n∈O} w(a,n);
5    ∀n ∈ O, if (f_p(n) < (D_a × w(a,n)/ws + n.c)) {
6     return FALSE;
7    } else {
8     n.c = n.c + D_a × w(a,n)/ws;
9    }
10    ∀n ∈ O, return verify(G, out(n, D_a × w(a,n)/ws));
11 }
```

Fig. 2. Energetic Algorithm

- $V \subseteq (N \times N)$ denotes the set of edges (i.e., the component connections);
- $w : V \rightarrow \mathbf{R}$ the weights of the edges (i.e., the value adopted for computing the amount of energetic flow directed to a component);
- $f_p : N \rightarrow \mathbf{R}^+$ represents the function that relates each node with its corresponding maximum power;
- $s \in N$ is the source or root node (i.e., an abstract component that represents the initial node of the infrastructure);
- $t \in N$ is the target node (i.e., an abstract component that represents the final node of the infrastructure);

Besides, G has also the following properties: (i) acyclic, assuming no cycles and (ii) directed, assuming directed edges which represents the energetic flow. Each node n has also an attribute c ($n.c$), which represents the current capacity utilized by the component. Initially, the current capacities of all nodes are set to 0. The algorithm is depicted in Figure 2, which adopts a depth-first approach to traverse the graph.

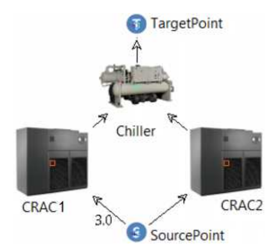

Fig. 3. An energetic model example.

As an example, Figure 3 depicts the ASTRO's graph representation for the energetic model of the Figure 1 (e). Initially, the source node (a=s) is the first node to be visited in G. The respective set of output nodes (O) are obtained (line 2) and verified if it is empty. This verification is not TRUE (line 3), since the node a has two output edges. Next, the sum of its output edge weights (ws) is calculated to estimate the amount of energy that can be transferred to (in the case of electricity) or extracted from a (when concerning heat).

For each $n \in O$ (line 5), the algorithm verifies if the output node still has any capacity to meet the required demand. Function $f_p : N \rightarrow \mathbf{R}^+$ represents the maximum cooling or power capacity of a component (which are informed by the designer); D_a represents the required (electrical or thermal) energy that must be transferred to (e.g, electricity) or extract (e.g., heat) from the node a; $w(a,n)/ws$ is the ratio of energy that needs to be transferred/extracted. Thus, $(f_p(n) < Da \times (w(a,n)/ws) + n.c)$ evaluates the capacity of n to support an additional demand from a node a. If the evaluated value is greater than the maximum capacity, the algorithm terminates. Otherwise, node n is updated (line 8).

Afterwards, the verification is recursively performed for each output node n in order to search for any inconsistence in the energetic model. The demanded energy for a node n is computed by function out, which is based on the equipment's efficiency.

B. Sustainability Model

In this work, environmental impact is computed in terms of the thermodynamic metric of exergy (also called usable available energy). The following paragraphs presents the equations adopted.

1) Embedded Exergy.: The embedded exergy, which involves impacts related to product design decisions, is obtained as follows:

$$Ex_{emb} = E_{man} \times [\eta_{man} + (1 - \eta_{man}) \times (1 - C_{reuse})] \quad (1)$$

where E_{man} is the energy required for manufacturing all equipments adopted in the infrastructure (see Equation 2); η_{man} is the manufacturing efficiency related to the second-law of thermodynamics; and C_{reuse} (coefficient of waste recovered) is the exergy reused in other processes.

$$E_{man} = \sum_{i=1}^{n} E_{eq_i} \quad (2)$$

In the particular case of electrical energy, all energy can be theoretically converted into work, thus, the variable E_{man} in Equation 2 means the total exergy made accessible during the manufacturing phase. A fraction of E_{man} is consumed. The complementary fraction (1-E_{man}) can be reused in other processes (C_{reuse}) or destroyed (1-C_{reuse}).

In this work, the energy required for manufacturing each equipment (E_{eq_i}) has been obtained from [15].

2) Operational Exergy.: The operational exergy consumption can be understood as the fraction of the heat dissipated by each equipment that cannot be theoretically converted into useful work. The following equation represents the operational exergy.

$$Ex_{op} = \sum_{i=1}^{n} Ex_{op_i} \times T_{life} \times A \quad (3)$$

where Ex_{op_i} is the operational exergy of each device (e.g., for electrical devices $Ex_{op_i} = P_{in} \times (1 - \eta)$); P_{in} is the total input power; η is the delivery efficiency; T_{life} is the lifetime (i.e., the period of analysis); and A is the system availability.

3) Lifetime Exergy (LTE): is the sum of the embedded and operational exergies.

C. Dependability Models

This section presents the models adopted for quantifying system dependability and sustainability. Initially, RBD models are presented. Next, SPN models are described.

1) RBD Models: Reliability Block Diagram (RBD) is a combinatorial model that was initially proposed as a technique for calculating reliability on large and complex systems using intuitive block diagrams. Such a technique has also been extended to calculate other dependability metrics, such as availability and maintainability. The blocks (e.g., components) are usually arranged using the following composition mechanisms: series, parallel, bridge, k-out-of-n blocks, or, even, a combination of previous approaches. The reader should refer to [6] for examples as well as the closed-form equations.

2) SPN Models: This work adopts a particular Petri net extension, namely, Stochastic Petri Nets (SPN) [5], which allows the association of probabilistic delays to transitions using the exponential distribution, and the respective state space is isomorphic to continuous time Markov chains (CTMC) [5]. Besides, SPN allows the adoption of simulation techniques for obtaining dependability metrics, as an alternative to the Markov chain generation. Next section briefly present the proposed SPN building block for obtaining dependability metrics. For more details, the reader should refer to [7].

Simple Component. The simple component has two states: functioning or failed. To compute its availability, TTF and TTR should be represented. Figure 4 shows the SPN model of the "simple component", which has two parameters (not depicted in the figure), namely X_MTTF and X_MTTR, representing the delays associated to the transitions $X\_Failure$ and X_Repair, respectively.

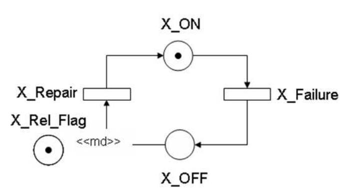

Fig. 4. Simple component model

Places X_ON and X_OFF are the model component's activity and inactivity states, respectively. The simple component also includes an arc from X_OFF to X_Repair with multiplicity depending on place marking. The multiplicity is defined through the expression IF($\#X\_Rel\_Flag$ = 1) 2 ELSE 1, where place X_Rel_Flag models the evaluation of reliability/availability. Hence, if condition $\#X\_Rel\_Flag = 1$ is false (no token in place X_Rel_Flag), then the evaluation refers to availability. Otherwise, the evaluation concerns reliability.

A component is operational if the number of tokens ($\#$) in place X_ON is greater than 0 and in a failure state, otherwise. Hence, if $\#X\_Rel\_Flag = 1$, $P\{\#X\_ON > 0\}$

means the component's availability (steady-state evaluation). If $\#X\_Rel\_Flag = 0$, then $P\{\#X\_OFF > 0\}$ allows computing the component's reliability, if transient evaluation is carried out and the initial marking is $\#X\_ON = 1$ and $\#X\_OFF = 0$.

For such a simple model, the obvious evaluation of the SPN model is through analysis, that, is the generation of the trivial CTMC and then the computation of its availability and reliability. The operational exergy is represented by Equation 3. Since the availability of the simple component adopting the SPN formalism is represented by $P\{\#X\_ON > 0\}$ (if $\#X\_Rel\_Flag = 0$), then the operational exergy is computed by $Ex_{op} = \sum_{i=1}^{n} Ex_{op_i} \times T_{life} \times P\{\#X\_ON > 0\}$.

Besides, although simple component model has been presented using the exponential distribution, other expolinomial distribution that best fits the $MTTF$ and $MTTR$ may be adopted utilizing the techniques presented in [5].

Without loss of generality, the subsystems are combined by serial, parallel, (non) series-parallel, and hierarchical compositions.

VI. Case Study

This section presents a case study in order to illustrate the application of those models (Section V) considering ASTRO to evaluate data center architectures. The case study considers five power and cooling architectures which are analyzed adopting the methodology in order to estimate: (i) availability; (ii) the sustainability impact and (iii) the total cost ownership. The following sections detail those five data center architectures adopted as well as present the results.

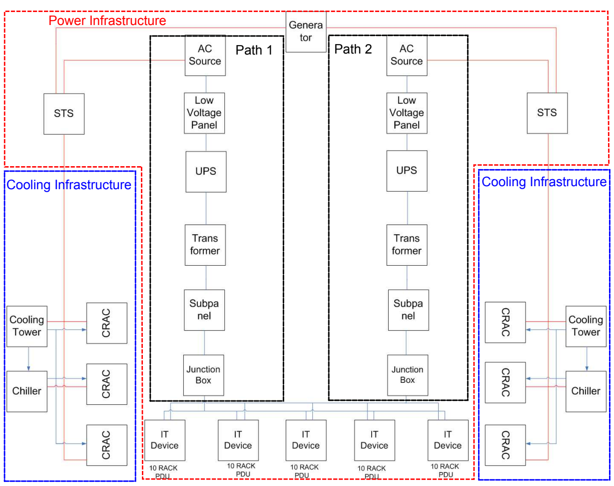

Fig. 5. Architecture 1.

A. Architectures

Five architectures for the power infrastructure have been considered with different configurations, which include redundant components and/or different arrangements. The baseline architecture (A1) is depicted in Figure 5, in which the power infrastructure is delineated by red dashed lines and the cooling infrastructure is represented by blue dashed rectangles. From the utility feed (i.e., AC Source), typically, the power goes through voltage panels, uninterruptible power supply (UPS) units, power distribution units (PDUs) (composed of transformers and electrical subpanels), junction boxes, and, finally, to rack PDUs (rack power distribution units). The power infrastructure fails (and, thus, the system) whenever both paths depicted in Figure 5 are not able to provide power to the IT components (50 racks). The reader should assumes a path as a set of redundant interconnected components inside the power infrastructure. Besides a generator is available for the cooling infrastructure, when an AC source is not operational.

The cooling infrastructure is basically comprised of computer room air conditioning (CRAC) units, chillers and cooling towers. The cooling infrastructure fails (and, so, the system) when any of the cooling components fail.

Architecture A2 (Figure 6 (a)) provides replicated transformers in each path, and, in architecture A3 (Figure 6(b)), the AC sources may be switched whenever one fails. Architecture A4 (Figure 6(c)) considers the generator as a cold standby component inside the power infrastructure via a STS. Architecture A5 (Figure 6(d)) is similar to A4, but without an AC source.

B. Results

Initially, the results are presented considering the power and the cooling infrastructure separately, as the latter is not varied in the experiments. Next, the results are demonstrated serially combining each power infrastructure architecture (A1..A5) with the cooling infrastructure.

TABLE I
Summary results.

Architec	Avail(%) (9's)	EMB(GJ)	OPER(GJ)	LTE(GJ)	TCO(USD)
A1	99.99961 (5.41)	374.21	91042.81	91417.02	803734.97
A2	99.99965 (5.46)	374.89	91042.82	91417.71	804835.20
A3	99.99966 (5.48)	376.41	91132.10	91508.51	809163.43
A4	99.97944 (3.69)	270.96	46650.82	46921.78	790541.14
A5	99.99999 (7.11)	376.41	91132.11	91508.52	809165.21
Cooling	98.95687 (1.98)	26.57	35892.04	35918.61	1058350.90

Table I summarizes the results separately for each infrastructure, in which: *Architec* represents the architecture evaluated; *Avail(%) (9's)* is the availability level (A) with the respective number of nines (-*log*[1 - A/100]); *EMB(GJ)* is the embedded exergy in gigajoule; *OPER(GJ)* is the operational exergy in gigajoule; *LTE(GJ)* is the lifetime exergy consumption (*EMB(GJ)* + *OPER(GJ)*); and *TCO(USD)* is the total cost of ownership in U.S. dollars. In this case study, TCO takes into account the cost to build the system and the cost to maintain the system in the operational mode over a period of 1 year.

As expected, the availability increases when redundancy improves in the power infrastructure architectures. For instance, since architecture A4 considers less redundant devices, the respective availability level is the lowest between the assumed architectures. However, A4 provides the best sustainability impact, as the lifetime exergy consumption is the smallest comparing with A2 to A5. Besides, note that the availability improvement considering redundant transformers (A2) is not

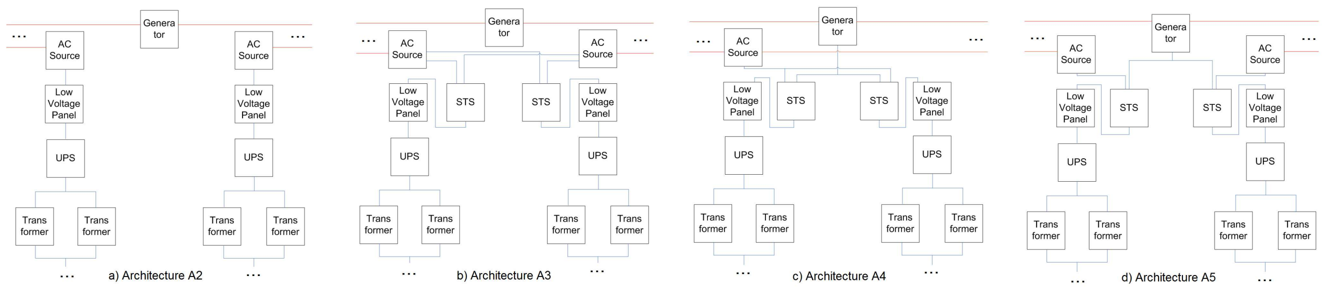

Fig. 6. a)Architecture A2; b)Architecture A3; c)Architecture A4; d)Architecture A5;

significant. Similar result was obtained in architecture A3, in which STS devices are adopted to allow AC sources be switched whenever one fails in a path. A5 corresponds to the architecture with the highest availability level. In this architecture, the generator is adopted as an alternative energy source for the power system as well as the cooling system.

For a better visualization, Figure 7 depicts a graphical comparison between the availability, the total cost of ownership and the lifetime exergy for each power infrastructure architecture.The baseline corresponds to the architecture A1. As the reader should note, architecture A5 is an interesting option, since it is 2% more expensive than the baseline and provides the highest availability (over 30% higher than A1). Besides, the lifetime exergy consumption is similar to architectures A1 to A3. However, considering the sustainability impact, A4 produces the best result.

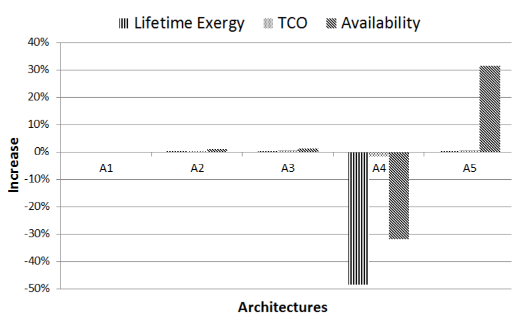

Fig. 7. Power results: comparing Exergy, Availability and TCO.

Figure 8 presents the results take into account each power infrastructure architecture combined serially (via RBD) with the cooling infrastructure. Due to the series relation between the infrastructures, the availability of the whole system is considerably reduced. Thus, in this case, an interesting architecture corresponds to A4, which has the smallest lifetime exergy consumption and the same availability as the other architectures.

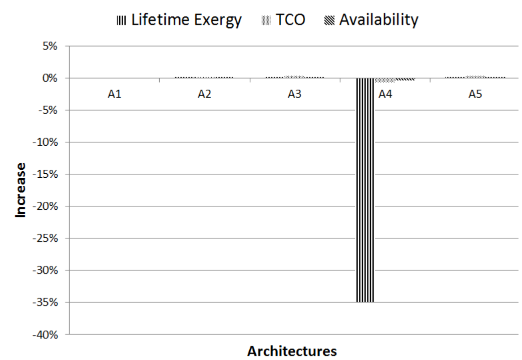

Fig. 8. Power and Cooling results: comparing Exergy, Availability and TCO.

VII. Conclusion

This work presented a set of formal models which is supported by the developed environment, ASTRO, to analyze data center infrastructures. The approach considers that systems should be evaluated piecewisely to allow the composition of simpler models representing a data center infrastructure appropriately. Moreover, experiments demonstrate the feasibility of the models and environment, in which different architectures for a data center power infrastructure have been adopted. Furthermore, the models as well as the environment are generic enough to allow one to evaluate different systems. As a future work, we intend to analyze the IT data center infrastructures.

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