

Review on Reliability and Energy–Efficiency Issues in Cloud Computing

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INTRODUCTION

Cloud computing is an ongoing revolution in ICT that employs virtualization technologies to deliver a powerful and flexible computing environment.

Gartner predicts Public Cloud Services Market will reach \$397.4B by 2022 (Columbus, 2021). Because of the size and complexity of cloud data centers, dependability and energy efficiency are two major concerns that must be addressed. Cloud computing system (CCS) reliability can be defined in terms of security or in terms of resource and service failures.

On the other hand, the energy required to operate the cloud infrastructure is also increasing in proportion to the operational costs. According to Gartner, the electricity consumption by cloud-based data centers has increased to 1012.02 Billion kwh by 2020 (Columbus, 2021).

Each year, data centers in the United States release 100 million metric tonnes of carbon dioxide, which will rise to 1034 metric tones by 2020 (Cook & Horn, 2011). Researchers are under pressure to find innovative strategies to reduce energy usage since huge computing infrastructures' energy consumption, heat output, and carbon footprint have increased. Researchers and designers have spent the previous few decades focusing on improving the system's performance in terms of speed, space, and efficiency. However, the main concern should be energy use.

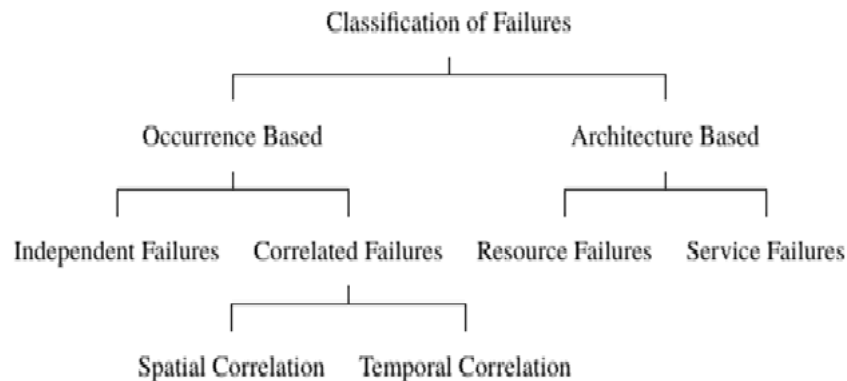
Amazon announced the construction of a 150 MW wind farm in January 2015, which will generate approximately 500,000 MW of wind energy. The energy generated by the wind farm will be utilized to power AWS (Amazon Web Services) data centers, both existing and future.

Google, IBM, and other cloud vendors are also attempting to make cloud services and data centers more energy-efficient and environmentally friendly.

CLASSIFICATION OF FAILURES

The occurrence-based classification is related to the sequence among the failures i.e whether the occurrence of one failure leads to the occurrence of another or not in the system. **Occurrence-based failures** are again categorized into **independent and correlated failures**. Independent failures occur discretely. This type of occurrence is hypothetical because the literature has demonstrated that there is a correlation between failures (Fu & Xu, 2007) [4] (Yigitbasi et al., 2010) [6]. **In correlated failures**, the occurrence

Figure 1. Classification of failures



of a subsequent failure is correlated to each other. The correlated failures could be a spatial correlation and temporal correlation.

The failures are further separated into two types in the architecture-based classification: Resource Failure and Service Failure. Resource failure, as the name implies, is caused by the loss of certain physical resources, such as a system failure, a network or power outage, or a software error. The majority of the literature on failure tolerance has focused on resource failures (Fu, 2010) [8] (Vishwanath & Nagappan, 2010).

CAUSES OF FAILURES

It is important to identify the causes of failures in Cloud Computing Services (CCS) to make them more reliable and available at all times. Various causes of cloud computing problems are depicted in Fig. 2.

Software Failure

Failure in software causes much loss in business and revenue. In October 2013, Knight Capital's⁷ suffer from a loss of \$440 million due to 45 min of software downtime. Another major service outage had seen in January 2015 for 20 min, in which Yahoo Inc. and Microsoft's search engine, Bing, went down during the code update.

Hardware Failure

Hardware failure accounts for around 4% of all failures in cloud-based data centers. Hard disc drives account for 78 percent of all hardware failures/replacements (Vishwanath & Nagappan, 2010). In 2007, the two most popular hardware components delivered to Google for repair were hard disc drives and memory modules (Barroso et al., 2013).

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