DEVELOPMENT OF PLATFORM FOR HARD DISK DRIVE FAILURE PREDICTION

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Abstract – In the operation of the Multifunctional Information and Computing Complex (MICC) of the Meshcheryakov Laboratory of Information Technologies (MLIT) at the Joint Institute for Nuclear Research (JINR), a large volume of server equipment is utilized, which provides computational resources to manyscientific groups and experiments. Some components of this equipment (primary hard drives, as well as CPUs and memory modules) are subject to wear and must be replaced in a timely manner to ensure the uninterrupted operation of the computing complex. For the replacement of failing equipment, MICC maintains a spare parts warehouse that requires replenishment. This paper presents a system and tools for collecting, storing, and processing information about hard disk drives for future predictions of HDD failures and improving spare parts inventory planning. As an example, a statistical method based on Weibull distribution was used on a collected data to provide basic estimations of HDD failures depending on their working time. The developed solution is built on freely distributed components and can be used in similar infrastructures. Integration into the inventorysystem of the JINR Cloud infrastructure is also planned.

INTRODUCTION

Today, many large-scale experiments in various fields of science require significant computational resources. To perform these computations, a large amount of server equipment is utilized. The Multifunctional Information and Computing Complex (MICC) of the Joint Institute for Nuclear Research (JINR) has an extensive computer infrastructure that provides computing resources and data storage for scientific research. Such computing centers can reach considerable sizes and involve very large volumes of equipment. For example, currentlyat CERN, the data center consists of over 10,000 servers, offering approximately 450,000 processor cores and more than 1024 petabytes of disk space [1]. While JINR's MICC may not be as big as CERN's data center, it still includes more than 30,000 of computing cores and over 35 petabytes of storage, enabling the processing and analysis of data for various scientific experiments [2].

The components of these systems are subject to wear and may require periodic replacement. Rapid failure prediction and proactive maintenance expedite repair processes, especially since these systems are often used beyond the warranty period. Consequently,

developing a software tool based on statistical analysis methods to predict equipment failures has become a relevant task that could aid in this effort.
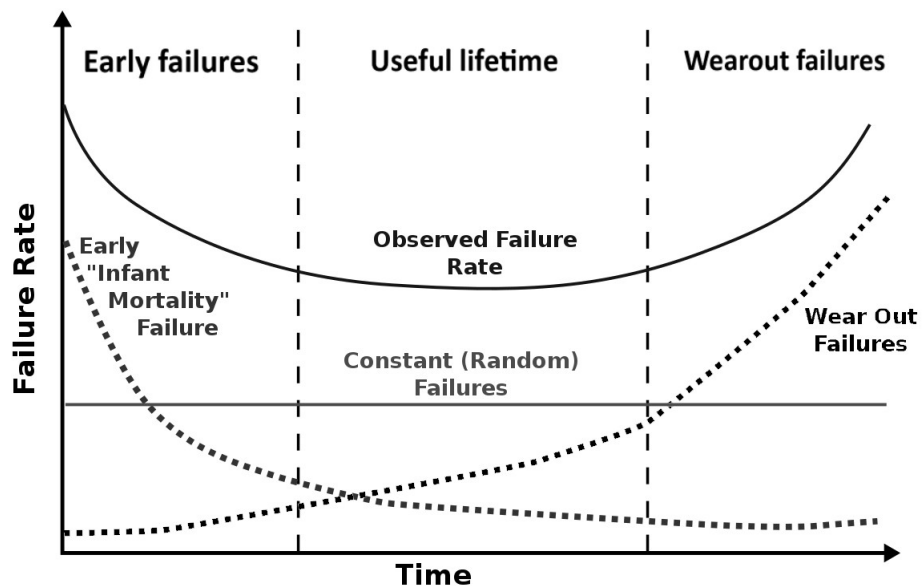

Fig 1. "Bathtub curve": failure rate graph of equipment at different stages of the lifecycle

Failure rates of hardware equipment throughout their life cycle are often schematically represented using the bathtub curve [Figure 1]. In this work, the focus is on the 'Wear-Out Failures' part of the curve, where the probability of failure begins to rise due to increasing wear of equipment during operation.

Although existing methods for hardware failure predictions are applicable to many other components subject to wear, this work focuses on hard disk drives (HDDs) on the development stage of a platform. They are emphasized initially because they are consumables, fail most frequently, and are more numerous than othercomponents. Also, hard drives are equipped with SMART controllers, which store extensive information about each drive's operational history that can be used to predict failures. Continuous collection and storage of SMART data enable the creation of a dataset that can be leveraged by various methods for HDD failure prediction.

SYSTEM ARCHITECTURE

The proposed system architecture is schematically illustrated in Figure 2. It consists of the following main components: SMART reports collector, intermediate SMART report storage, aggregated SMART reports storage and visualization system, inventory system.
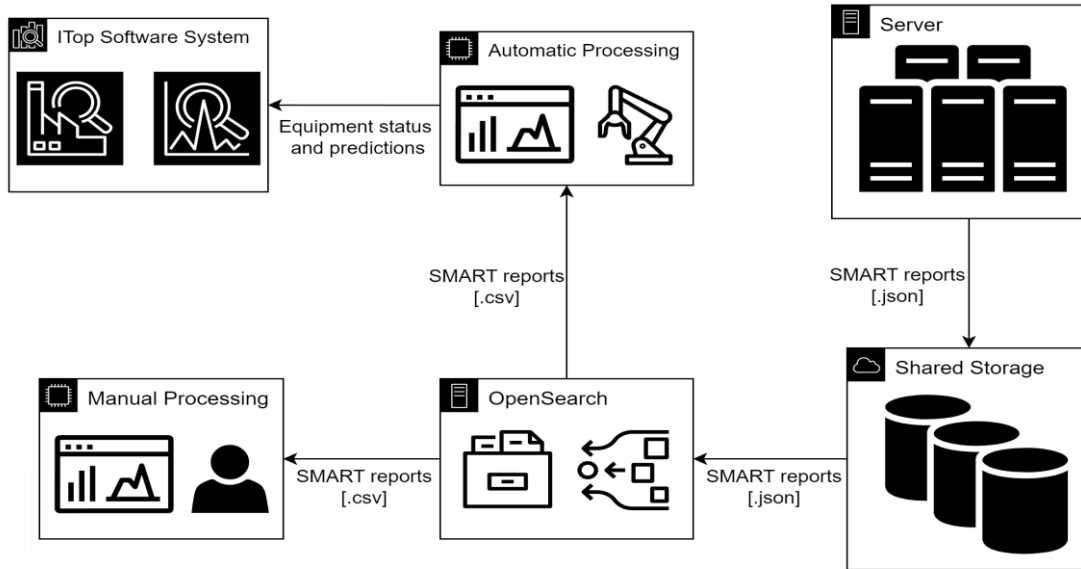
Fig. 2. System architecture for equipment failure prediction

To perform data analysis using statistical methods, it is essential to establish a system for collecting, storing, and visualizing data. Special bash script was developed to collect the data. Its task is to identify all disks presentin a server, generate full SMART reports, and send these reports to a centralized storage. The script can be run on a schedule determined by the infrastructure administrator, for example once a day, thereby accumulating data over time.

OpenSearch, which was already used at JINR [3], was chosen as the data aggregation and storage system due to its extensive visualization capabilities and the ability to use pipelines for preliminary data processing. The latter is an important feature for handling hard drive reports where the same fields can be named differently: when examining SMART reports from different disks, certain attributes may have inconsistent names despite representing the same parameter. For instance, the attribute for reallocated sectors might appear as *Reallocated_Sector_Ct* on one disk and as *Reallocated_Sector_Count* on another. Similarly, other attributes like *Power_On_Hours* may have slight variations in naming. These discrepancies highlight the need for datapreprocessing to standardize attribute names before analysis can be performed.

In the final version of the developed system the analysis results are planned to be automatically sent to the iTop system as recommendations for stocking spare parts. iTop is an open-source IT service management system used as the inventory and configuration management at the JINR Cloud.

Different analysis methods may be sensitive to the volume of available data, and analysis methods are sensitive to the amount of data available for analysis, and larger datasets may provide more accurate results. During the testing stage of the development only a small fraction of MICC is monitored — 150 hard drives — which is a small number for a statistical analysis.

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It is possible to incorporate additional datasets from open-access sources such as Backblaze into the JINR dataset in order to increase the volume of available statistical data. Backblaze operates large-scale data centers and provides online backup services for personal and enterprise use. The company is widely recognized in hard drive reliability analysis for regularly publishing detailed hard drivereliability statistics based on the drives used in their data centers [4]. One of the project's tasks is to organize the collection of data from JINR infrastructure, combine it with data from Backblaze and update it regularly.

DATA ANALYSIS

The proposed system allows for the collection and storage of data on the operational usage of hard drives. By augmenting these data with information from open-access sources, such as Backblaze, the dataset can be expanded and enriched for further analysis.

For the initial phase of this project, while we were working out technical solutions and tools, the Weibull distribution was used to model our data because it is well studied and widely used inmodeling equipment wear and reliability [5]. It can represent different failure patterns depending on its parameters and it is versatile enough to describe different shapes of the data. Despiteits versatility, Weibull distribution may not be the best one and selecting a more appropriate statistical model requires separate research, which is beyond the scope of this paper.

In this project,the Python library called Reliability [6] was utilized to determine the parameters of Weibull distribution. This library provides a comprehensive set of tools for reliability analysis, facilitating the fitting of the best model based on the provided data and it is used to fit the Weibull distribution and determine its parameters.

After fitting the distribution of hard drives failure times and determining its parameters, the model based on Weibull distribution can be used for predictive analysis [5]. For instance, by inputting the total number of hard drives, one can get the expected number of failures over a specific time interval or the probability of a single disk failing by a certain point in time as shown in Table 1.

Table 1. **Probability of Failure for a Single Hard Drive Based on Power-On Hours**

Power on hours	10,000	20,000	30,000	40,000	50,000	60,000	70,000	80,000
Probability of failure (one disk)	1.399%	3.183%	5.123%	7.155%	9.244%	11.369%	13.512%	15.663%

These predictions can then assist in improving maintenance planning and spare parts inventory management, contributing to reduced downtime caused by hardware failures.

CONCLUSION

The system proposed for collecting SMART reports is being developed to analyze the MICC complex at JINR with the aim of maintaining its uninterrupted operation. By collecting and analyzing SMART data, the system currently utilizes only operating time as a primary metric during the development stage, but it is intended to incorporate additional parameters from SMART data. The system is not limited to HDD failure prediction and is planned to be used for other components such as RAM or processors in the future. To verify system's functioning, the Weibull distribution was employed as an example due to its versatility in modeling failure rates. However, the Weibull distribution is not the only available option, and other statistical distributions may be selected; choosing the most appropriate model requires a separate study due to its complexity. One of the objectives is to aid inventory management by integrating the system into the existing inventory platform of the MICC. By using appropriate methods and being built on freely available components, the system could be adopted by similar infrastructures to enhance reliability and efficiency in computational resource management.

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