BaNHFaP: A Bayesian Network based Failure Prediction Approach for Hard Disk Drives

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***Abstract*—A Hard Disk Drive (HDD) failure may lead to serious consequences for users and companies. Hence, predicting failures in HDDs became a topic that attracted much attention in recent years. Monitoring a HDD status can provide information about its degradation, so as to let the user or a system manager know about a failure before it happens, preventing loss of information. In this paper, we propose a failure prediction method using a Bayesian Network. Our method uses the deterioration over time of a HDD, calculated via SMART (Self-Monitoring Analysis and Reporting Technology) attributes, for predicting eventual failures. To demonstrate practical usefulness, this method was applied to a dataset consisting of 49,056 hard drives from Backblaze's data centers. The proposed method has improved the mean and median quadratic errors in 28.3% and 17.6% respectively in comparison with a baseline model.**

I. Introduction

Condition monitoring of electronic equipments have attracted much interest in recent years due to its valuable benefits [1]. Particularly for Hard Disk Drives (HDD), the number of papers on condition monitoring was boosted by the increasing amount of data available nowadays. Being able to detect, in advance, a HDD failure may both prevent data losses from happening and reduce service down-time.

According to Vachtsevnos *et al.* [2], the task of condition monitoring can be split into two sub-tasks: fault detection and failure prediction. Fault detection consists of identifying anomalous behaviors of an equipment. Such situation may indicate that, although the equipment is still working, an incipient failure (fault) occurred. It is worth noting that the output of a fault detection algorithm is the early detection of a failure that will occur in a near future. The task of predicting the amount of time until a failure is addressed by failure prediction methods. Failure prediction can be defined as the task of estimating the Remaining Useful Life (RUL) of a given system or component [3].

In the literature, the papers of [4], [5] and [6] exhibit the most promising results. In [4], [5] the authors design distance based fault detection methods using attributes extracted from SMART (Self-Monitoring, Analysis and Reporting Technology). SMART is a monitoring system that collects performance parameters that can be used to infer the actual condition of an HDD [7]. The same set of attributes is used in [6] alongside with a Support Vector Machine (SVM) classifier [8].

It is worth noticing that previous works are focused on fault detection and no effort towards the direction of failure prediction is done. In this work, we develop a failure prediction method for HDDs based on SMART attributes.

Concerning previous works on failure prediction in other components, several methods were used. Neural Networks [9], Nonlinear filters and Bayesian Networks (BN) [10] are among the most common approaches. In this work, a BN model is designed. BN is a method that incorporates concepts of graph theory and probability to reason under uncertain input variables [11]. In our model, the RUL is estimated using the amount of working hours of each HDD and the values of a subset of the SMART attributes.

Our approach is tested using real HDD data and is compared to the standard reliability based failure prediction [12]. The standard method makes its predictions using only historical data and the working hours of each HDD. Results show that our model significantly improves the accuracy of failure predictions when compared to this baseline model.

The remainder of this paper is structured as follows. Section II discusses the theoretical background that supports our contribution. Section III presents our failure prediction method. Section IV shows the results achieved with our method and compares it with the baseline model. Finally, Section V concludes this paper and exposes some possible future works.

II. Theoretical Background

A. Recursive Feature Elimination

Recursive Feature Elimination (RFE) [13] is a technique that tries to eliminate irrelevant or redundant features, leading to a smaller but more representative data. The method consists of recursively removing attributes, assigning weights to features using an external estimator and removing the least relevant ones. This procedure is repeated until the desired number of features is reached.

Small changes in the set of features may lead to major differences in the weights generated by an external estimator [13]. RFE captures effectively this property thanks to its method of assessing the impact caused by the removal of every subset of features.

RFE has applications ranging from genetic [13], [14], agro-industrial problems [15], [16] and brain-computer interfaces [17], [18]. Most of the research using RFE also works with

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Support Vector Machines (SVM) [8] as estimator. Nevertheless, in this paper we chose Random Forest (RF) [15] since it has also achieved good results with faster execution.

B. Bayesian Network

A Bayesian Network (BN) [19] is a probabilistic graphical model that represents a set of random variables and their conditional dependencies. Given a rich set of observations of an object, Bayesian Networks are able to infer information about it. Formally, a BN is a structure $B = \langle G, \Theta \rangle$, where G is a Directed Acyclic Graph (DAG) whose set of vertexes is composed by the random variables $X_1, \ldots, X_n$ and the edges are used to model conditional dependencies between the random variables. These dependencies are represented by a set of probability functions Θ. This set contains the parameter $\theta_{x_i|\pi_i} = P(x_i|\pi_i)$ for each $x_i \in X_i$ conditioned by π_i, that is the set of parameters for X_i. The following equation presents the joint distribution defined by a BN over the set of random variables:

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(x_i|\pi_i) \tag{1}$$

In its basic formulation, the BN is built upon probabilities estimated over discrete variables. However, in various applications only continuous variables are available. In such situations it is possible to use any discretization method such as the variant of the Minimum Description Length Principle (MDLP), proposed in [20], that considers a discretization based on a minimization heuristic entropy. The proposed algorithm uses the entropy of the labels of classes to select a separation threshold of attributes, minimizing the entropy. The algorithm is then recursively applied to both fragments resulting from the separation.

III. The BaNHFaP Method

In this section, we will present a method for RUL estimation of HDDs. The proposed method is named as Bayesian Network based HDD Failure Prediction (BaNHFaP). The inputs of our method are the set of observations, like SMARTs attributes, and the output is a probability distribution, that represents when the HDD is expected to fail.

BaNHFaP contains the following modules: preprocessing, which implements feature selection and binning process, that discretizes continuous SMART attributes; estimation of parameters, to calculate the conditional probability distributions for each node in the network. Figure 1 shows a graphical representation of the method. The rest of this section describes the aforementioned modules in detail.

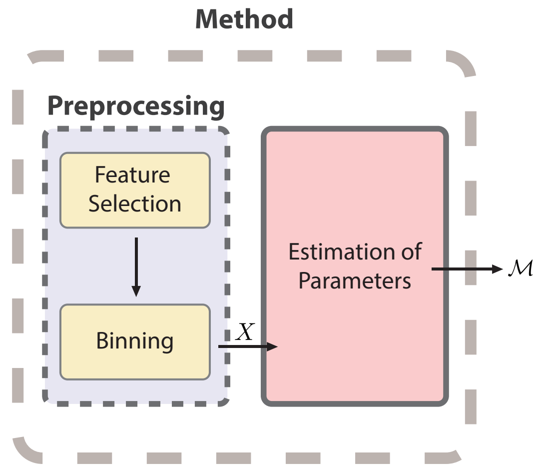


Fig. 1: Workflow of the BaNHFaP method.

A. Preprocessing

The preprocessing phase is divided into two steps: feature selection and binning process.

The feature selection procedure finds a subset of SMART attributes, which well describes the data. So, the most important features are selected using RFE method, as shown in II-A. In our approach we chose Random Forest [21] as the predictor. The influence of the attributes might be determined through the entropy function. Therefore, the optimal subset of features is chosen by this predictor together with RFE.

After that, the selected attributes are discretized using MDLP, as explained in II-B. The process, frequently called binning process, partitions continuous values into a number of bins, which can be seen as categories. The features that represent time, like Power On Hours (POH), are discretized by an equal width interval binning, such that it is possible to perform inferences over RUL.

After the POH discretization, we are capable of generating the RUL attribute for each instance of the dataset. This can be easily performed with the complete time series of an HDD. The calculation consists of the last registered POH minus the current POH of a given HDD.

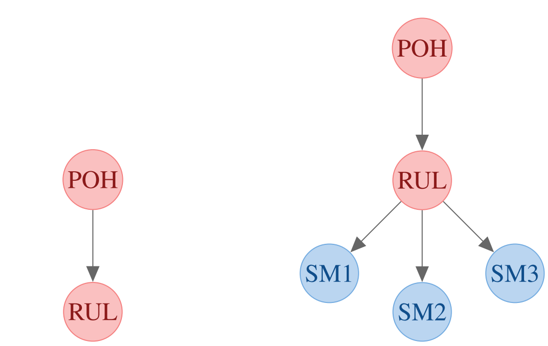
B. Estimation of Parameters

The estimation procedure finds parameters, depicted by Θ, of a Bayesian Network denoted by $\mathcal{M}$. The BN has structure $\langle G, \Theta \rangle$, as shown in II-B. The model G represents the behavior of the network.

In BaNHFaP model, shown in Figure 2b, uses information about the SMART parameter through time and the POH of each HDD to estimate the RUL. The POH is a random variable that quantifies the amount of time which the HDD has run and the RUL is an indicative of leftover life time, so the older the HDD is, the less remaining lifetime it has. Thus, the random variable RUL is probabilistic dependent on POH. Thereby, we modeled the RUL node as a child of the POH node.

It is known that the SMART attributes represent an HDD state, so in order to model a state time series and, consequently achieve the progressive deterioration model, that describes the common behavior, we modeled those attributes nodes as children of RUL node in the model G.

It is important to notice that the BaNHFaP model differs from the standard failure prediction model (baseline model)



(a) Baseline Model (b) BaNHFaP Model

Fig. 2: Comparison between the baseline and proposed prediction models for HDD failures based on SMART features.

[12]. BaNHFaP makes use of SMART attributes, while a standard reliability based model uses only lifetime to estimate the RUL. Figure 2 depicts the difference between baseline model and proposed model.

Since we have the model G of BN, the parameter Θ must be calculated. For that, we must obtain a running tally of the frequency with each evidence from the dataset. The tally is a sum of occurrences. Consequently, after normalizing the tally, we acquire the probabilities distributions using the features. In other words, the relative frequency of the times that the node has each value defines its posterior probability distribution.

To better distribute the posterior probability we will use the Additive Smoothing Technique [22]. The probabilities estimation needs satisfactory amount of data to precisely estimate the values. In case of insufficient data, we propose a smoothing method in order to make the distribution of probabilities more uniform.

$$\hat{\theta}_i = \frac{x_i + \alpha}{N + \alpha d} \quad (2)$$

In Additive Smoothing or Laplace Smoothing, as we can see in equation 2, the occurrence frequency of each feature x_i is increased by α, called as smoothing parameter, and divided by $N + \alpha d$, where N is the length of distribution and d is the number of observations.

Thereby, the graph G and the probability functions Θ were built, and, consequently, the BaNHFaP construction process is completed.

IV. Experimental Results

The implementation of BaNHFaP was written in Python, using SciPy 0.17 [23] and scikit-learn 0.17 [24] packages for RFE. In addition, we adopted Discretization-MDLPC tool as implementation of MDLP and libpgm 1.1 package to build Bayesian Network model and evaluation process.

A. Dataset

The data used in this paper was provided by Backblaze company [25]. The dataset has 49,056 real hard drives spread across 26 different models, varying from 1.0TB to 8.0TB in size. Each entry of the data is a daily snapshot of the HDD status. The dataset has 29,747,966 records and unhealthy disks represent 4.81% of the total. A hard drive labeled as unhealthy denotes that its SMART status self test has failed, though that all records are labeled as healthy, except the last one.

Each data sample has serial number, model, capacity, label and 90 performance-monitoring attributes, that are the raw and normalized values for 45 different SMART stats reported by the driver. Most drives do not report values for all SMART attributes, so there are blank fields in every record. Also, different drives may report different statistics based on their model and manufacturer.

Before the preprocessing module, the data must be handled in order to remove attributes that have few records and discard samples with blank fields. In this process, 19,453,812 samples and 17 columns were removed.

The feature selection process, described in III-A, attempts to remove unnecessary attributes. The RFE method was applied in the data, except on the SMART 9 RAW, with Random Forest estimator using 3-fold cross validation and the forest consisting of 10 trees. The technique returned 8 features: SMART 187 RAW, SMART 240 RAW, SMART 5 RAW, SMART 184 RAW, SMART 190 RAW, SMART 7 RAW, SMART 188 RAW, SMART 197 RAW. Table I represents the importance of the features that were returned by RFE. Higher importance values have a significant impact on the result of the model. The SMART 9 RAW was only added to the data, since it represents the POH.

Most features obtained from the RFE method are consistent with the Backblaze's list of features that indicates impending disk drive failure. The SMART attributes selected (187, 240, 5, 184, 190, 7, 188 and 197) can be defined respectively as: Reported Uncorrectable Errors, Head Flying Hours, Reallocated Sectors Count, End-to-End error, Temperature Difference from 100, Seek Error Rate, Command Timeout and Current Pending Sector Count.

TABLE I: Importance of the features returned by RFE

Feature	**Importance**
SMART 187	0.67363818
SMART 5	0.34882314
SMART 184	0.24467154
SMART 7	0.23996446
SMART 240	0.21005881
SMART 190	0.15997393
SMART 188	0.12123306
SMART 197	0.08403013

After the features selection, we discretize them using MDLP, described in section III-A. The cut points, that represent the bins, obtained by the application of the method are shown in Table II.

The SMART 9, or POH, was discretized by means of an equal width binning process. The width of each bin represents a quarter of year, thus we are capable of predicting in which quarter the HDD will fail with some certainty.

TABLE II: MDLP-generated cut points of the features

Feature	Cut Points
SMART 187	0.5, 30.5
SMART 5	1.5, 1540.0
SMART 184	1.5
SMART 7	258588813.5, 858525788.5, 1422218768.5, 3707446036.5, 10685231764
SMART 240	16464
SMART 190	18.5
SMART 188	0.5, 15032614946
SMART 197	0.5, 33.5

B. Performance Evaluation

We define our model following the section III-B. First, we built the graph G out of the SMART attributes originated from the preprocessing module. The graph G is represented by Figure 3:

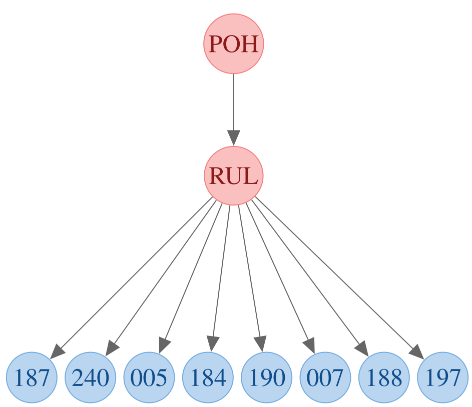


Fig. 3: Representation of the graph generated by the preprocessing module of the BaNHFaP model.

We completed the construction of our method by determining the probabilistic functions, depicted by Θ. The process was made in accordance with model. We used the technique explained in III-B to calculate the tally. Thereby, we have the complete BaNHFaP method ($\langle G, \Theta \rangle$), and now we are capable of making predictions.

To evaluate the prediction we compared the expected value from the predicted distribution with the value of real RUL. In this case for each sample of the dataset (an HDD at a given time instant) was calculated the quadratic error between the predicted value and ground truth RUL. The Figure 4 presents the distributions of the quadratic errors for baseline (Figure 2a) and BaNHFaP models (Figure 3).

Observing Figure 4 it is possible to verify that, for both models, the majority of the predictions are close to the real RUL, because the quadratic error density is concentrated around the value 1. Thereby, most of the quadratic errors are small. However, our method, if compared to the baseline, has a lower density of high quadratic errors, as we can see by comparing the tails of the distributions. This phenomenon can also be observed when calculating the means and medians of both distributions. These values are shown in Table III.

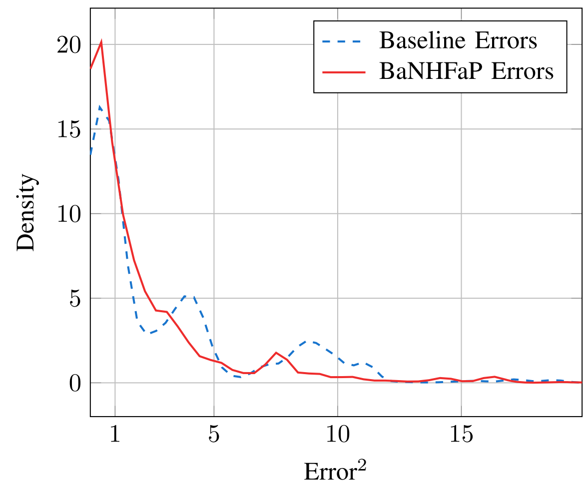


Fig. 4: Comparison of the quadratic errors versus the density of these errors between the baseline and BaNHFaP methods.

TABLE III: Mean and Median of the quadratic errors returned by the baseline and proposed methods

	Baseline Model	BaNHFaP Model
Mean	2.9325	2.1024
Median	1.1642	0.9593

As we can see in Table III, the proposed method has improved the results in 28.3% and 17.6% of the mean and median of the quadratic errors respectively.

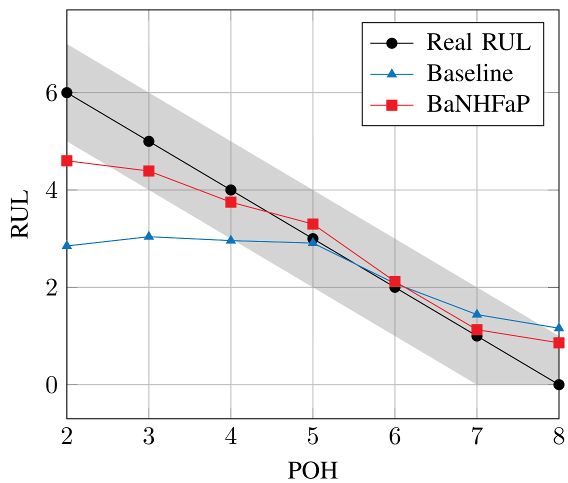
In failure prediction methods, besides the accuracy, the realized predictions should have a rapid convergence. This property can be verified through the Prognostic Horizon (PH) metric [26]. This metric defines an error bound (α_{PH}) around the true RUL and the predictions should enter as soon as possible in error bound. PH is based on the assumption that early accurate predictions give more time to decision-making.

Figure 5 shows the rapid convergence of our method for 6 HDDs. The α_{PH} utilized in the examples are equal to 1. The figure aforementioned represents typical behavior of the HDDs from the dataset.

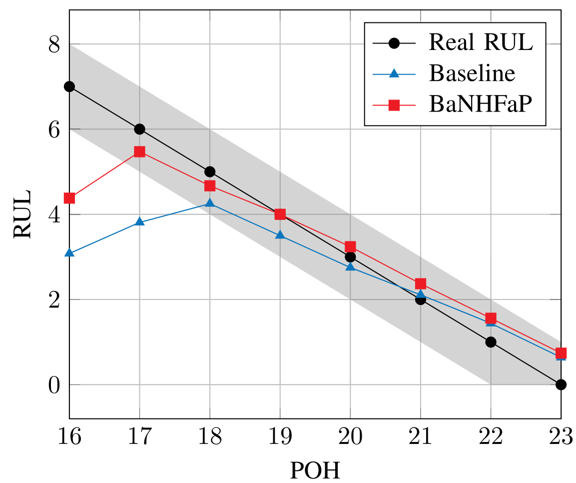
It is possible to verify that the predictions generated by our method gets into the bound before the baseline method for all HDDs. In other words, BaNHFaP model has earlier accurate predictions than the baseline model.

V. Conclusion and Future Work

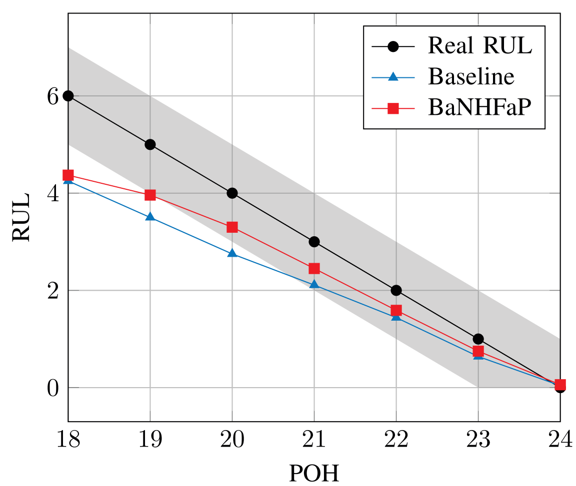
A method for failure prediction in hard disk drives utilizing Bayesian Networks was presented in this paper. This method consists of two phases: preprocessing and estimation



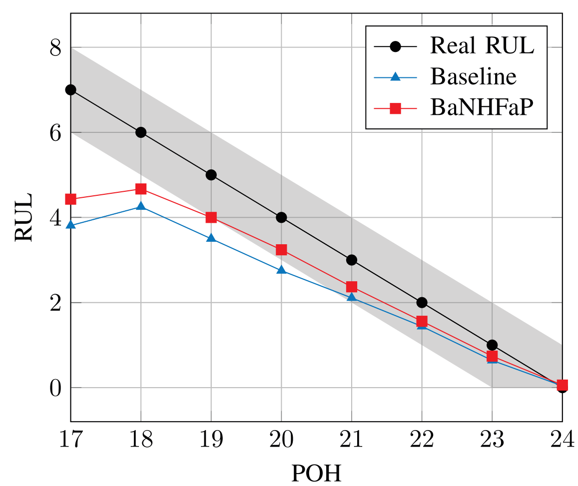
(a) HDD W300KL20



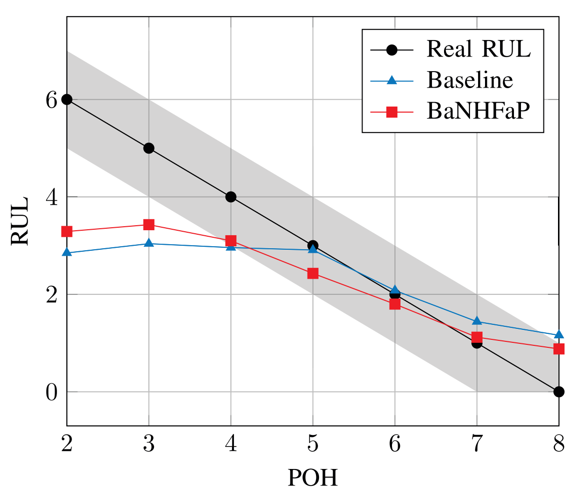
(b) HDD 5XW00F5X



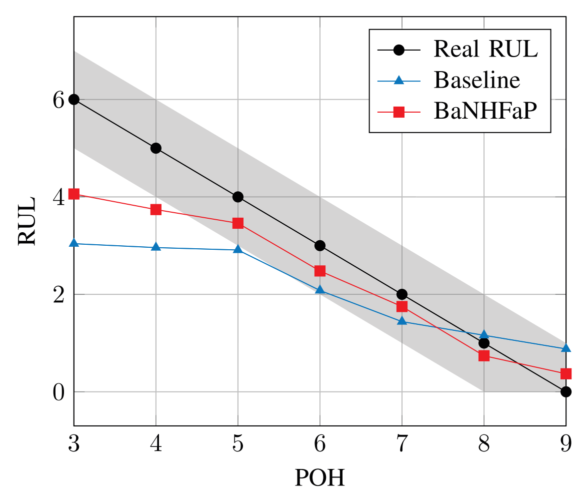
(c) HDD 6XW044NZ



(d) HDD 5XW03ENJ



(e) HDD Z300H2EN



(f) HDD Z300GZ32

Fig. 5: Comparison between the baseline and proposed models using the Prognostic Horizon metric. The graphics show that the proposed method gets into the bounds before the baseline for different HDDs. In Figures 5a and 5b the BaNHFaP has entered in the bound on quarter before than baseline, and the Figures 5c and 5d our method has entered in the α-band on two quarters before the baseline. In Figures 5e and 5f our method has came into the bound on same quarter of the baseline.

of parameters. The preprocessing module is responsible for the data treatment, since the input of the estimation of parameters module must be an optimal set of discrete features. The estimation of parameters module builds the model behavior that assists the failure prediction.

The data preparation by preprocessing module is done using RFE for selecting the optimal subset of features. After the feature selection, data goes on through the discretization process made by MDLP algorithm.

The estimation of parameters module presents the prediction model using Bayesian Networks. This module performs the running tally of probabilities and shows the intuition behind the model through graphical representation of the HDD behavior.

In the evaluation process of BaNHFaP we obtained better results than the baseline model for both mean and median metrics of quadratic errors. It is worth mentioning that, utilizing the Prognostic Horizon technique we obtained graphical representations of the BaNHFaP rapid convergence.

Future works may include models separated by manufacturer, accumulative and gradient features. Other possibility is to apply different width to discretize POH.

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