Convex Nonparametric Least Squares for Predictive Maintenance

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INTRODUCTION

With the industrial Internet of Things (IoT) sensors, predictive maintenance (PdM) becomes viable to identify maintenance issues in real-time by predicting the next error of the system. To develop the prediction model for PdM, a certain number of researchers employed machine learning (ML) methods. From the literature, Random Forests (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and *k*-means are the popular ML methods. On the other hand, regression-based methods are considered inappropriate due to their pre-defined function forms and the non-linear nature of the PdM models. However, the convex nonparametric least squares (CNLS) method can overcome the above shortcomings of the regression-based methods. This chapter discusses the use of CNLS for PdM, which can be an alternative method for PdM.

In the Background section, brief descriptions of predictive maintenance, IoT, and machine learning are given. Then, in the Solutions and Recommendations section, after introducing the CNLS method in detail with two simple examples, the application of energy consumption of production systems or equipment is provided with consideration of using IoT devices. Then, how to use the CNLS to develop the predictive model with the energy consumption is discussed for having PdM of production systems. No method is perfect. In the Future Research Directions section, future developments of the CNLS method are given based on its limitations.

BACKGROUND

Predictive Maintenance and IoT

Conventional preventive maintenance (PvM) is schedule-based maintenance with the same time interval for reducing the likelihood of equipment failure. The PvM assumes the likelihood of failure increases with the usage and age of the equipment. Hence, Malik (1979) proposed the "Proportional Age Reduction" model that, for a piece of equipment with age t, its post-maintenance age can be reduced from *t* to t/β , where β =(1, ∞). Age may not be a good indicator, and the PvM approach may result in the unnecessary replacement of some equipment components after a predetermined period. On the other hand, if the equipment runs with abnormal energy consumption, speed, or temperature before replacement, PvM cannot provide the replacement decision.

To address the above shortcomings of PvM, Predictive maintenance (PdM) enabled by the industrial Internet of Things (IoT) sensors is proposed by which we can identify maintenance issues in real-time. The PdM approach is prediction-based maintenance. The equipment is continuously monitored by various sensors (IoT sensors), which generate data in real-time to predict the next error. PdM can then be conducted before the failure occurs. In particular, PdM is invaluable if the equipment and the corresponding processes are too expensive to have any critical damages.

Predictive Maintenance and ML

Since PdM comes with high potential in reducing maintenance costs, it has recently attracted a certain number of researchers applying machine learning methods to PdM, such as Samatas et al. (2021), Ayvaz and Alpay (2021), Florian et al. (2021), Chen et al. (2020), Çınar et al. (2020), Sahal et al. (2020), Ruiz-Sarmiento et al. (2020), Wan et al. (2017), Susto et al. (2014), and Susto et al. (2012).

According to the review paper of Carvalho et al. (2019), the popular machine learning methods for PdM are Random Forests (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and k-means. They also concluded that "there is no preference for an equipment to perform PdM strategies, and vibration signals are the most common data used to design PdM models, there is a preference for real data to build PdM models."

Ayvaz and Alpay (2021) developed a predictive maintenance model for personal care goods production lines, such as baby care, feminine hygiene, and home care products, in Turkey. They evaluated six algorithms, four ensembles (Random Forest, XGBoost, Gradient Boosting, and AdaBoost), and two constituent machine learning algorithms (Neural Network and Support Vector Regression), developing a model consisting of one dependent output and 47 independent inputs. They also explored the performance of Multiple Regression, Lasso Regression, and Ridge Regression. Due to the non-linear nature of the problem, these three regression-based methods could not capture any variance in the data.

FOCUS OF THE ARTICLE

In this chapter, we would like to introduce a non-parametric regression method, Convex Nonparametric Least Square (CNLS), as an ML approach. A case application is used to discusses how CNLS is used in energy consumption (or efficiency) and PdM.

SOLUTIONS AND RECOMMENDATIONS

Introduction of CNLS

CNLS is a nonparametric regression method shown below.

$$y = f(x) + \varepsilon^{CNLS}$$

where f(x) is a function with shape restrictions, y is the dependent output variable, x is a vector of input variables, and εC^{NLS} is a random variable satisfying $E(\varepsilon CN^{LS|x})=0$. See (Afriat, 1972; Hildreth, 1954) for

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