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# A Computational Framework for Cloud-Based Machine Prognosis

Peng Wang<sup>a</sup>, Robert X. Gao<sup>a,\*</sup>, Dazhong Wu<sup>b</sup>, and Janis Terpenny<sup>b</sup>

<sup>a</sup>Department of Mechanical and Aerospace Engineering, Case Western Reserve University, Cleveland, OH 44016, USA <sup>b</sup>Department of Industrial and Manufacturing Engineering, Pennsylvania State University, University Park, PA 16802, USA

\* Tel.: +1-216-368-6045; fax: +1-216-368-6445; E-mail address: Robert.Gao@case.edu

#### Abstract

Prognosis of machine degradation and failure propagation is essential to preventative maintenance scheduling and sustainable manufacturing. Emerging technologies such as Internet of Things (IoT) and cloud computing offer new opportunities for scaling up computing performance and capacity for machine monitoring and prognosis. This paper addresses challenges in machine prognosis due to high-speed data streaming from real-time sensing by leveraging parallel computing on the cloud. A framework for cloud-based prognosis is then presented to model the relationships between hidden machine states and sensor measurements under varying operating conditions and maintenance actions. To account for uncertainties associated with model representation and/or measurement quality, each relationship is modeled as a probability distribution and estimated through either model-based (e.g. particle filtering) or data-driven algorithms (e.g. support vector machine), according to the available physical/mathematical description of the relationship. A complete prognostic model of the machine is then constructed by merging the individual probability distributions. The computational process is implemented on the MapReduce-based cloud computing platform. Prognosis of the entire machine is accomplished by aggregating prognosis results of the individual components, through a separate parallel computing process. The proposed framework is experimentally demonstrated using tool data collected from CNC machines.

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## 1. Introduction

The operational reliability of industrial machines and assets significantly influences the sustainability of manufacturing and competitiveness of the industry. Hence, ensuring reliability during the designed lifecycle of the machine becomes a critical task for maintenance. Compared to traditional scheduled maintenance condition-based maintenance, predictive maintenance that integrate condition monitoring with reliable prognostic techniques can minimize the machine downtime, maintenance cost and reliance on human experience for maintenance scheduling. Specifically, prognostic techniques can help quickly determine a machine's functional deterioration, predict its remaining useful life (RUL), and identify the appropriate short-term and long-term maintenance actions [1].

Generally, prognostic techniques can be classified into three categories: physics-based, data-driven, and modelbased, according to the required information and the type of prediction results [2]. Physics-based techniques model the degradation of physical quantity of interest (e.g. crack, wear) with physical and/or empirical formulae, where related parameters/coefficients are then determined through regression based on a large mount of experimental data. Datadriven methods numerically train a black-box model that characterizes the relationship between a machine's current damage state (represented by sensor data or extracted features) and future health state. Since no prior physical knowledge is needed in the modeling process, data-driven methods are especially preferable for monitoring and prediction of complex cyber-physical system in practice. Model-based prognostic techniques combine the abovementioned two methods to improve the prediction accuracy

and robustness. It physically/mathematically models the system degradation process, which is then embedded in a filtering method to infer the physical quantity of interest (system state) based on sensor data (measurement). One advantage of model-based prognostic methods is that it is capable of accounting for the stochasticity of degradation process and noise affecting measurements [3]. Kalman filter (KF) and particle filter (PF) are two representatives in model-based approach. Compared to KF, PF has more capability to characterize non-linear and non-Gaussian system and process. Therefore, PF is mainly investigated in this paper [4].

Motivated by the potential of cloud computing and cloud manufacturing [5-6], cloud-based prognosis represents a new type of service-oriented technology. Condition monitoring data [7] collected in shop floor are remotely transferred to the cloud platform, in which diagnostic and prognostic analysis are preformed and expertise on predictive maintenance planning are provided to customers. Cloud-based prognosis has three characteristics [1]:

- Improved accessibility and robustness: By offering an integrated solution to on-demand and configurable prognostic services, cloud can increase the robustness of prognosis of manufacturing processes. In addition, customers can access the service whenever and wherever through Internet connected products.
- Improved computational efficiency and data storage:
  Cloud computing provides enhanced computational power for complex calculations, enabled by elastic data storage and efficient parallel computing mode.
- <u>Collaboration and distribution</u>: The cloud enables treating machine prognosis as a remote and pay-asyou-go service instead of a local, centralized capability. Through information and data sharing realized by crowdsourcing, cloud also provides more effective and efficient selection of prognostic models as well as data interpretation.

This paper mainly focuses on the computational efficiency of prognosis leveraged by cloud computing. Specifically, execution of prognosis on cloud based on parallel computing can be classified into two modes:

- Parallel prognostic modeling: After remotely and dynamically transferred to cloud platform, uploaded condition monitoring and process data are partitioned and stored in multiple storage devices, corresponding to different machines/components. Then individual machine/component's data can be processed individually by one selected prognostic technique, according to the specific data types and physics of the monitored machines/components.
- Parallel program execution: Similar to data partition, single prognostic program can also be partitioned and executed by parallel computing, especially for those algorithms that require large amount of computational load, such as particle filter based on Monte Carlo sampling. But this requires the algorithm is partitionable. PF is a appropriate candidate for this computation mode, since particles in PF independently perform the state prediction and weight update.

#### 2. Data processing in cloud manufacturing

# 2.1. Infrastructure of cloud manufacturing and prognosis

Motivated by cloud computing, cloud manufacturing can be regarded as an integrated cyber-physical system that can provide on-demand manufacturing services digitally and physically to best utilize manufacturing resources [8-9]. Machine prognosis, as one part in manufacturing, can also be leveraged by cloud computing and provide resilient and payas-you-go service. Process and condition monitoring data collected from shop floor are dynamically and remotely uploaded to cloud, where data are processed with enhanced computing capability. The obtained diagnostic and prognostic results are then interpreted by experts, and expertise are provided to customers on maintenance planning and inventory management [10]. The structure of cloud-based prognosis is shown in Fig. 1.

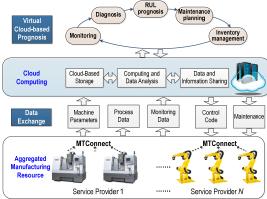


Fig. 1 Infrastructure of cloud based prognosis

### 2.2. Data streaming and parallel computing

The supporting techniques for cloud manufacturing and cloud-based prognosis include Internet of Thins (IoT) and MTConnect [11]. While IoT integrates physical assets into one information network, MTConnect enables machine-to-machine communication via a standard communication protocol. Through a unified interface between different data sources and types (e.g. Ethernet, RS-232, serial port and USB), MTConnect improves the interoperability of collected data and reduce the processing complexity on cloud.

One major advantage of cloud computing benefit on manufacturing and prognosis is its enhanced data storage and processing capability. The uploaded data are dynamically and resiliently allocated to distributed storage devices, which are managed by a hypervisor. Data from different storage devices can then be routed to different devices to perform specific functions in parallel. The invoking of data, allocation of processors and results fusion are all controlled by a programming model, such as MapReduce [12]. The distributed data storage and parallel computing enables parallel prognostic modeling and program execution, which will be discussed in detail in Section 4.

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