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Cloud-enabled prognosis for manufacturing

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ABSTRACT

Advanced manufacturing depends on the timely acquisition, distribution, and utilization of information from machines and processes across spatial boundaries. These activities can improve accuracy and reliability in predicting resource needs and allocation, maintenance scheduling, and remaining service life of equipment. As an emerging infrastructure, cloud computing provides new opportunities to achieve the goals of advanced manufacturing. This paper reviews the historical development of prognosis theories and techniques and projects their future growth enabled by the emerging cloud infrastructure. Techniques for cloud computing are highlighted, as well as the influence of these techniques on the paradigm of cloud-enabled prognosis for manufacturing. Finally, this paper discusses the envisioned architecture and associated challenges of cloud-enabled prognosis for manufacturing.

1. Introduction

Prognosis refers to forecasting the likely outcome of a situation, and typically involves two inherently related steps. First, analytical models are established to summarize the historical evolution of the situation (e.g., variation in stock price, deterioration of machine conditions, or spread of infectious disease) in a quantitative manner. These models are then modified by updated information to predict the future development of the situation. The predicted value is associated with a confidence level, which results from the uncertainty involved in the prediction process.

Prognosis has been investigated for a wide range of applications, including disease [73] and epidemiology prediction [147], weather forecasting [64], and stock market prediction [54] (Fig. 1). In the context of manufacturing, prognosis has been used to identify short-term and long-term actions or decisions to estimate the remaining useful life (RUL) of a tool, machine or system [193,89,219,97,200] based on the conditions monitored and diagnosis obtained [212,27,99]. It provides a scientific and technological basis for maintenance scheduling, asset management, and more reliable system design [160,52].

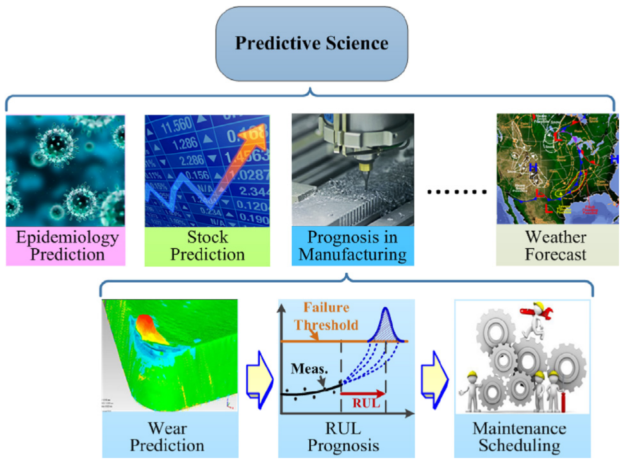

Fig. 1. Predictive science and its application in manufacturing.

1.1. *Benefits of prognosis for manufacturing*

The operational reliability of industrial machines and assets significantly influences the sustainability of manufacturing [132] and competitiveness of the industry. Because the operational reliability of a machine system decreases as the duration of its operation progresses, ensuring reliability during the designed lifecycle of the machine becomes a critical task for maintenance [245,24]. In traditional time-based maintenance, actions (e.g., machine

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inspections) are performed periodically at preset intervals independent of a machine's current operation condition [97]. Although such an approach is effective in reducing equipment failures, it generally does not provide information on the RUL of a machine. Furthermore, time-based maintenance can be a major expense with the increasing complexity of machines and equipment in modern manufacturing.

Addressing this challenge, condition-based maintenance (CBM) has been developed as a maintenance strategy that schedules activities based on the result of condition measurements without interrupting normal machine operations [104,205]. Fault (or defect) diagnosis is a critical part of this process that links the identified abnormal behaviors in a machine to possible root causes [272,50,268]. Maintenance actions may then be performed based on the identified failure type and underlying mechanism [135]. With the advancement of predictive science, prognosis has been increasingly recognized as a valuable complement to CBM in manufacturing. This has led to a more efficient maintenance approach termed intelligent preventive maintenance (IPM), which minimizes the machine down time, maintenance cost, and reliance on human experience for maintenance scheduling.

Failure in a machine progresses through several stages from failure initiation to functional failure. Predictive techniques can help determine how quickly a machine's functional degradation is expected to progress from its current state to its final failure [109,66]. An important element in devising a preventive maintenance strategy is the trade-off analysis [72]. Fig. 2 illustrates the relationship between maintenance cost and reliability of machines [160]. Preventive maintenance can specifically [194]:

- Increase system safety, improve operational reliability, and extend service life of machines
- Increase maintenance effectiveness and optimization of logistic supply chains
- Reduce maintenance costs created by repair-induced failures or unnecessary replacement of components.

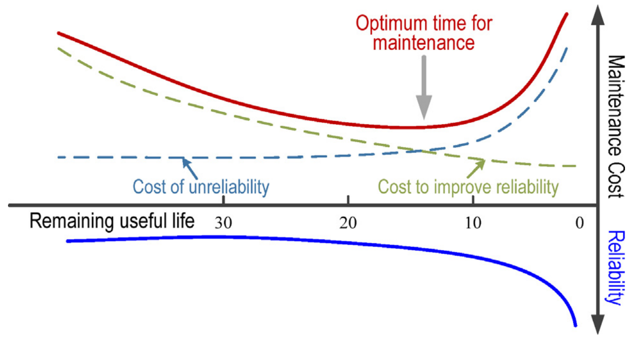

Fig. 2. Relationship between RUL, reliability, and maintenance cost, adapted from [160].

Research on prognostic technologies has grown and provides the basis for prognosis-centered maintenance. Jardine et al. [97] summarized technologies for diagnosis and prognosis that implement CBM. Peng et al. [160] and An et al. [8] reviewed typical prognostic techniques and presented a strengths-and-weaknesses analysis of the candidate techniques. Si [183] discussed statistical approaches. Sikorska et al. [186] compared different modeling options for RUL estimation, from the perspective of industry and business applications. Baraldi [16] investigated the capabilities of prognostic approaches to deal with various sources of uncertainty in RUL prediction, focusing on particle filtering (PF) and bootstrap-centered techniques. Heng et al. [72] and Sun et al. [194] discussed the potential benefits, challenges, and opportunities associated with rotating machinery prognosis.

Depending on the types of data and information needed to characterize the systems of interest and predict its future behavior, prognosis techniques can be classified into three categories: physics-based, data-driven, and model-based (see Fig. 3). Physics-based techniques describe the system behavior with empirical formulae, for

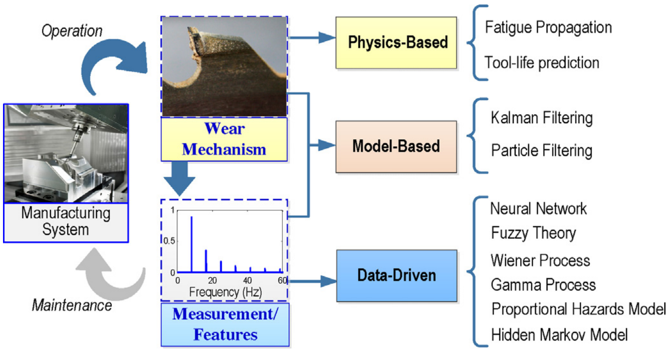

Fig. 3. Classification of prognosis methods.

which the related parameters are determined experimentally. In comparison, data-driven methods rely exclusively on historical data, and numerically establish the relationship between a machine's current damage state and future health state. Data-driven methods can be further divided into artificial intelligence-based (AI) and statistical methods. In contrast to AI-based methods, the relationship between current and future states in statistical methods is presumed to be specific probability distributions, for which the parameters are obtained through regression or maximum probability distribution algorithms. Model-based prognostic techniques combine the above-mentioned two methods to improve the prediction accuracy and robustness. In addition to this classification scheme, prognosis techniques can also be specified by how uncertainty is handled in the prediction process, in terms of deterministic or probabilistic properties. Compared to deterministic methods, probabilistic methods regard machine health states and observations as probability distributions instead of a defined value. Accordingly, damage degradation can be modeled as evolution of the distributions. Furthermore, the results of prognosis, such as future state or RUL, are also presented as probability distributions, with which confidence intervals for evaluation of prognosis results can be obtained.

1.2. Cloud-enabled prognosis and cloud manufacturing

Motivated by the potential of cloud computing [264,10] and cloud manufacturing [171,119,247,222], cloud-enabled prognosis represents a new type of service-oriented technology to support multiple enterprises in deploying and managing prognostic service over the Internet. The architecture of cloud-enabled prognosis is illustrated in Fig. 4. First, machine condition monitoring realized by sensors and data acquisition systems gather data remotely and dynamically on the shop floor. Based on these measurements, remote data analysis and degradation root-cause diagnosis and

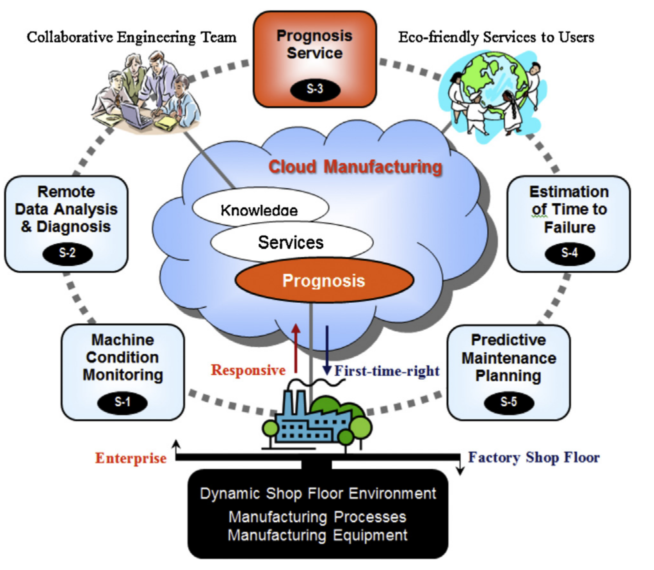

Fig. 4. Architecture of cloud-enabled prognosis.