Developing Big Data Analytics to Optimize Cutting Conditions of Machining Operations

Kitami Institute of Technology, ○Saman Fattahi, Sharifu Ura, and Angkush Kumar Ghosh

Abstract

This study presents analytics to optimize manufacturing processes (case study of dry electric discharge machining (DEDM)) using datasets available in huge information silos or big data. The proposed analytics correlates process variables and performances using quantitatively different datasets available in the big data. At the same time, it quantifies the uncertainty associated with the correlations among process variables and performances.

1. Introduction

Big data is a term used to describe huge information silos where the many sensor-laden digitized datasets are organized in networks [1]. It is one of the key concepts of Industry 4.0 [2] or smart manufacturing [3]. However, big data entails two critical issues. The first one is how to prepare datasets from past research and operational activities, as well as from online operational activities, so that the contents become useful for the stakeholders: cyber-physical systems, digital twins, IIoT, digital manufacturing commons, and human users. For example, datasets of surface roughness must be preprocessed considering the structure of a digital twin before incorporating them (datasets) into a big data of smart manufacturing. The other issue is how to construct big data analytics. Here, "analytics" means a computational arrangement for logical or statistical data analysis. In other words, big data analytics logically or statistically analyzes relevant datasets retrieved from big data to decide the right course of action. In some cases, data visualization results (e.g., two-dimensional scatter plots) are used by the analytics rather than numerical data [4]. In some other cases, numerical datasets retrieved from big data are directly used by the analytics [5]. This article considers the latter option. In particular, trend analysis and uncertainty quantification are considered. For showing the efficacy, maximization of material removal rate of dry electric discharge machining (dry EDM) is considered.

2. Proposed Big Data Analytics

Figure 1 schematically illustrates the proposed framework of big data analytics using an arbitrary case. As seen in Figure 1, the analytics entails eight elements: documents, big data, search, data acquisition, representation, trend, uncertainty, and conclusion. The transformation among these elements takes place in sequential order. Six systems denoted as Systems A,…,F perform the transformation. Thus, to realize the proposed big data analytics, Systems A,…,F must be built, and before building the systems, the systems requirements must be elucidated.
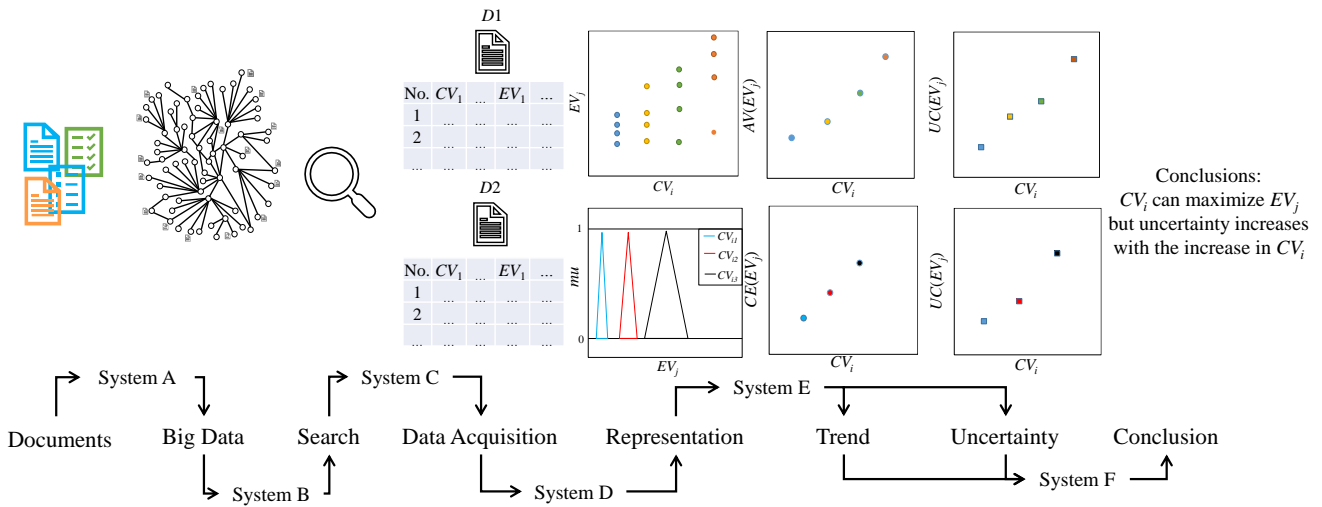

Figure 1. Proposed big data analytics.

The requirements of System A are elucidated using the case of surface roughness, where it is shown that the requirements depend on digital twins, particularly phenomena twins [4]. The requirement of System B depends on a process-based search where search keywords are constructed from a manufacturing process (dry EDM), an engineering material (stainless steel), and an experiment-relevant concept (design of experiment) [5]. Since big data regarding manufacturing processes is still unavailable, scholarly articles stored in Google Scholar (https://scholar.google.com/) can be used as an alternative. If so, System B results in scholarly articles denoted as D1, D2,…. The articles most likely present experimental datasets regarding the relevant manufacturing process. Nevertheless, the articles showing the numerical datasets regarding Control Variables (CVs) and Evaluation Variables (EVs) are the most useful. The CVs are varied while performing a manufacturing process, and EVs evaluate the performance of a manufacturing process. As a result, the main requirement of System C is to acquire CV-EV datasets from D1, D2,…. The other systems, Systems D, E, and F, transform CV-EV datasets into a set of rules in three steps. In the first step, System D represents the datasets using scatter plots or possibility distributions, as appropriate, for all combinations

of *CV*s and *EV*s. In the second step, System E establishes correlations among *CV*s and *EV*s. In addition, it determines uncertainty in the correlations. Finally, System F concludes, aggregating all possible correlations and uncertainties for each combination of *CV* and *EV*. In other words, System F finds a set of rules for maximizing or minimizing the performances given by the *EV*s.

3. Results

The authors have been researching how to build Systems A,…,F. This section reports results regarding Systems D and E, only, for a manufacturing process called dry EDM [5-7]. According to the previous work of the authors [3], dry EDM entails five *CV*s: current (I), voltage (V), pulse off-time (T_{off}), gas pressure (P), and spindle speed (N). In addition, it entails two *EV*s: material removal rate (*MRR*) and tool wear rate (*TWR*). Assume that *MRR* must be maximized. In this regard, which *CV* out of the five should be used is a question. Figure 2 shows the outputs of System D from the *CV–EV* datasets presented in. This time the representation is done using two scatter plots, one for *MRR* versus I (Figure 2(*a*)) and the other is *MRR* versus T_{off} (Figure 2(*b*)). Figure 3 shows the outputs of System D from the *CV–EV* datasets presented in. This time the representation results in possibility distributions (fuzzy numbers). As seen in Figures 3(*a*)–(*b*), three possibility distributions show the variability in *MRR* for the three levels of I and T_{off}, respectively. System E operates on the outputs shown in Figures 2–3. It first determines the trend using the average of the datasets of each level of I and T_{off} when the datasets are represented by scatter plots. For possibility distributions, the centroid of each distribution determines the trend. The standard deviation or area of the possibility distribution is used to calculate the uncertainty. Figure 4 shows the results of System E. The upper four plots in Figure 4 show the trends. The lower four plots in Figure 4 show the uncertainty. Both studies confirm that I can help increase *MRR* whereas T_{off} is ineffective in increasing *MRR*. There is a tendency for uncertainty to increase with the increase in I or *MRR*, whereas uncertainty may or may not increase (decrease) with the increase in T_{off}.
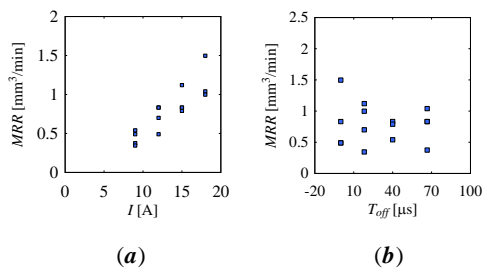
Figure 4. Output of System E.

4. Concluding Remarks
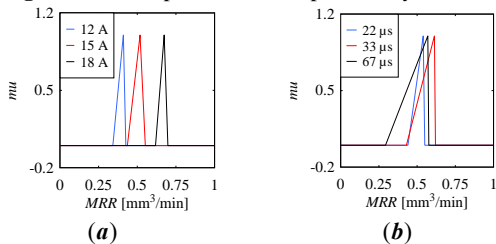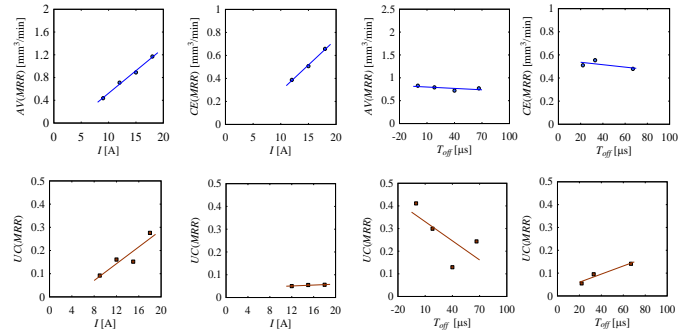
The concept of big data has been introduced under the umbrella of Industry 4.0 or smart manufacturing. As this study shows, a set of systems is needed to materialize big data and big data analytics. The authors have been studying these systems and made remarkable progress. However, still, works need to be done. In the next phase of the study, System F will be considered so that conclusions can be made in natural language as if a human is interpreting the trend and uncertainty diagrams.

References

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(*a*)   (*b*)

Figure 2. Examples of the outputs of System D [6].

(*a*)   (*b*)

Figure 3. Examples of the outputs of System D [7].