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Optimization of Dry Electrical Discharge Machining of Stainless Steel using Big Data Analytics

Saman Fattahi[a], AMM Sharif Ullah[b*]

[a]*Graduate School of Engineering, Kitami Institute of Technology, 165 Koen-cho, Kitami 090-8507, Japan*
[b]*Division of Mechanical and Electrical Engineering, Kitami Institute of Technology, 165 Koen-cho, Kitami 090-8507, Japan*

* Corresponding author. Tel./Fax: + 81-157-26-9207. *E-mail address:* ullah@mail.kitami-it.ac.jp

Abstract

Big data (datasets accessible through the Internet) coupled with machine learning arrangements constitute big data analytics, which is heavily resource-depended and creates inequality-only large organizations can sustain or utilize big data analytics, and medium and small organizations fall behind. This article presents a novel inequality-free big data analytics for process planning in medium and small enterprises. Big data, search mechanism, control and evaluation variables relevant datasets, uncertainty quantification using possibility distributions, and decision rules are the components of the proposed analytics. This article reports the characteristics of the analytics applied to optimizing dry electrical discharge machining conditions of stainless steel.

Keywords: Optimization; Big Data Analytics; Electrical Discharge Machining; Uncertainty; Intelligent systems

1. Introduction

The maturity index of Industry 4.0 [1] leads to implementing cyber-physical systems [2] where datasets collected from embedded systems and geographically distributed sources play a vital role. These vast array of datasets result in an information silo called big data [3-4]. This silo evolves with time and consists of unstructured, semi-structured, and structured datasets. While making decisions using this silo, computational arrangements are required. These arrangements are called big data analytics. In most cases, big data analytics offers a wide range of data visualization facilities. Users thus rely on the visualized information to make decisions. In addition to visualization facilities, machine learning and computational intelligence-driven arrangements are often added to big data analytics. This makes the decision-making process more formal. However, adding these computational arrangements makes the analytics computationally heavy and highly resource-depended. As a result, only large organizations can sustain big data analytics, and medium and small organizations fall behind [5]. Thus, big data analytics results in an inequality referred to as big data inequality [5]. Measures are needed to mitigate big data inequality.

Let us focus on issue called process planning. Process planning is a micro-level decision-making activity associated with manufacturing processes. In process planning, computerized systems are used to determine the optimal conditions ensuring desired safety, economy, and quality of the relevant manufacturing process. In most cases, stand-along computerized systems equipped with the necessary knowledge have been used to facilitate the decision-making process during process planning. From the viewpoint of the maturity index of Industry 4.0 [1], these systems must be redesigned. One of the concerns of redesign is whether the process planning systems are compatible with big data, and, thereby, big data analytics.

Many authors have studied big data or big data analytics from the context of real-life manufacturing. For example, Ismail et al. [6] found that data ingestion is a problem in manufacturing when big data is a concern. They identified that new tools to bring the datasets into the decision making

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process. Effective visualization of relevant datasets must be addressed, enabling engineers to use them in decision making. O'Donovan et al. [7] found that the requirements and management of big data analytics from the context of smart manufacturing are significantly different from traditional information systems. They have proposed the big data pipeline facilitating transparent data integration without committing to extensive technology replacement. Oleghe [8] developed a methodology to deal with missing and invalid value correction in process datasets. This is a big data-induced problem in manufacturing. LaCasse et al. [9] developed big data analytics based on a fuzzy inference approach that performs data filtration and feature prioritization in the connected manufacturing enterprise. Ji et al. [10] presented a framework of process planning where big data analytics is incorporated. The analytics is designed in such a way so that it runs using machine learning and computational intelligence-based arrangements. Nevertheless, the big data analytics proposed so far [6-10] may cause big data inequality [5], as described above. Therefore, further research is needed to introduce big data analytics that serves its purpose (makes necessary decisions to optimize a process) without causing big data inequality. This article contributes in this direction.

This article presents big data analytics, which is free from big data inequality. It consists of five components: big data, search mechanism, control and performance variables relevant datasets, uncertainty quantification using possibility distributions, and decision rules. This article also reports this framework's characteristics when applied to optimizing dry electrical discharge machining conditions of stainless steel.

2. Proposed Big Data Analytics

This section presents the proposed big data analytics and its general characteristics.

The proposed big data analytics is schematically illustrated in Fig. 1. As shown in Fig. 1, the analytics consists of four modules: 1) Initiation module, 2) *CV-EV* datasets module, 3) uncertainty quantification module, and 4) decision rule module. The initiation module consists of two submodules denoted as big data of scholarly outcomes and process-driven search. *CV-EV* datasets mean datasets consist of Control Variables (*CV*s) and Evaluation Variables (*EV*s). *CV*s are those variables that can be controlled during a manufacturing process. *EV*s are those variables that are used to evaluate the process performances. The uncertainty quantification module quantifies uncertainty using probability-distribution-neutral distributions (e.g., possibility distributions). The decision rule module extracts and represents rules by which one can decide which *CV*s must be used to ensure the optimal level of the respective *EV*s.

The general description of the initiation module is as follows. The open-access scholarly articles can be used as big data of scholarly outcomes. Otherwise, issues related to big data inequality cannot be mitigated. Nowadays, search engines offered by Google™ can be used to search the open access scholarly articles (i.e., the big data of scholarly outcomes). For the search, keywords derived from manufacturing processes must be used. In this case, the names of the manufacturing processes (turning, milling, electric discharge machining, additive manufacturing) can be used. The quantifies limiting the scope of the manufacturing process can be added if needed. For example, "dry" can be used along with "electrical discharge machining" to limit the search. Besides, materials can be used as keywords to make the search more meaningful. The reason is that when a researcher studies a manufacturing process, s/he conducts the study for a specific material (e.g., electric discharge machining for stainless steel). Therefore, keywords can be represented by the following set: keywords = {manufacturing process, process quantifier, materials}.

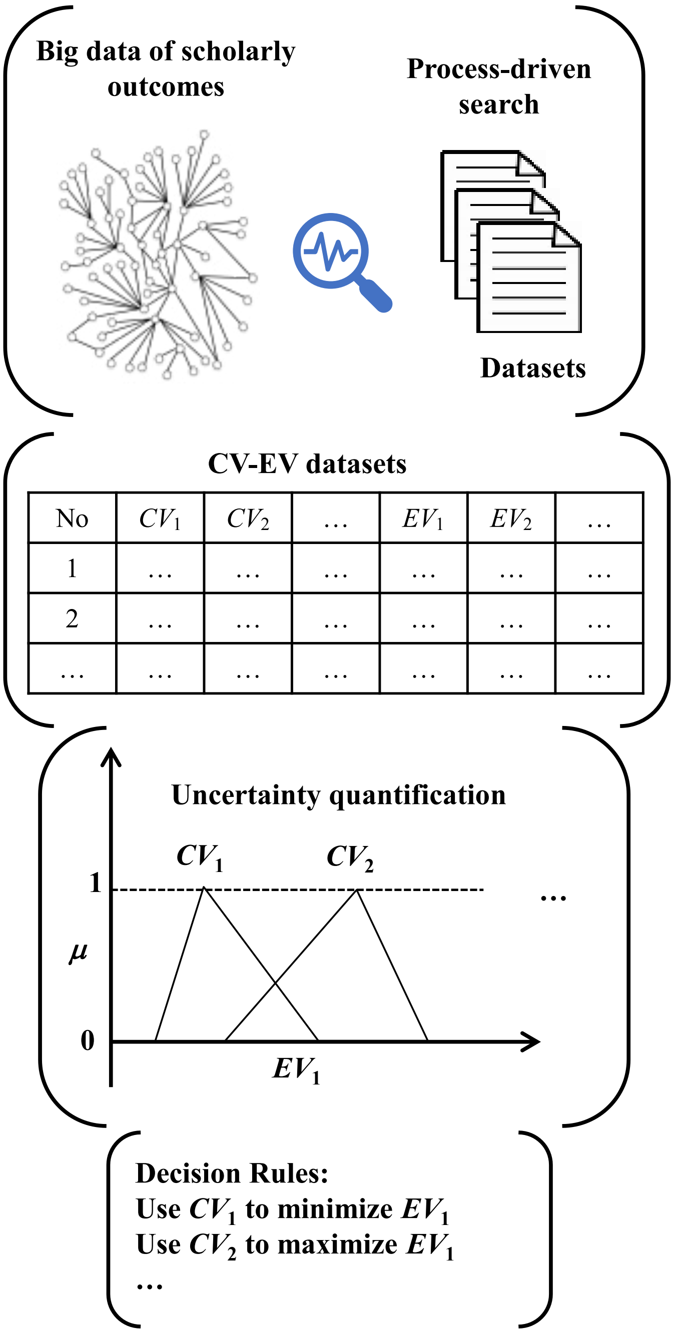

Fig. 1. Big data analytics for manufacturing process optimization.

The general description regarding *CV-EV* datasets module is as follows. Once the process-driven search is completed, different types of contents can be obtained. Contents explicitly

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.

showing *CV-EV* datasets qualify for the analytics. For example, since depth of cut, feed rate, cutting speed, and other variables can be varied to control a machining operation, they become the constituents of *CV*s.

On the other hand, machining time, surface roughness, subsurface damages, environmental burden, tool wear, and other relevant variables can be used to evaluate the performance of the process; thus, they become the contents of *EV*s. When experimental contents qualify as *CV-EV* datasets, it is highly likely that the contents underlie a design of experiments [11,12] scheme. Therefore, the contents where the design of experiments related results are presented qualify for *CV-EV* datasets. The digitization level of the *CV-EV* datasets matters. If the data points are presented by plotting graphs, the plots must be computed to extract numerical data. Thus, data points presented in tabular form and downloadable XML data is perhaps the easiest to handle.

The general description of the uncertainty quantification module is as follows. Only the scholarly outcomes for a specific manufacturing process and materials are allowed for *CV-EV* datasets. Therefore, each dataset is somewhat unique. As far as decision-making is concerned, the datasets are competing datasets. The most trusted dataset can be used to make a decision ignoring others. Alternatively, few selected or all qualified datasets can be used to make a decision. The total number of datasets may vary with time. In this case, additional datasets may or may not affect the decision rule. This means that a limited number of datasets and data points are available for uncertainty quantification. In this case, probability-distribution-free distributions, e.g., possibility distributions, which can be constructed without going through cumbersome statistical data processing, can be constructed to quantify uncertainty. Since fuzzy numbers [13] are possibility distributions, how to contract fuzzy numbers from a selected segment of *CV-EV* datasets is an important issue in this module. The construction process must be user-friendly, less resource-dependent, and not computationally heavy. Otherwise, the analytics suffers big data inequality.

The general description of the last module is as follows. In this module, decision rules are established using the information of the previous module. For example, consider the arbitrary scenario shown in Fig. 1. In this case, two possibility distributions are shown partitioning EV_1. CV_1 guarantees the possibility of securing low values EV_1. On the other hand, the possibility of securing high values of EV_1 is guaranteed by CV_2. This manifests two decision rules: 1) Use CV_1 to minimize EV_1 and 2) Use CV_2 to maximize EV_2.

3. Dry Electrical Discharge Machining

This section describes electrical discharge machining (EDM) and its environmentally friendly variant called dry EDM (DEDM).

EDM is a non-conventional machining process. In EDM, an electrode (cathode) is placed near the workpiece (anode), maintaining a stipulated gap. A part of the electrode and the whole workpiece are submerged into the dielectric liquid. When a rapidly recurring current is passed, electrical discharges (sparks) occur. This increases the energy concentration of the workpiece near the electrode. As a result, material removal takes place. The remarkable thing is that EDM can machine difficult-to-cut materials [14]. Thus, many manufacturers in the mold and die industry have been using this process for manufacturing complex structures made of difficult-to-cut (e.g., tungsten carbide) [15]. There are some limitations of conventional EDM, which are caused by the oil-based dielectric liquids. This type of dielectric liquids creates non-recyclable toxic wastes with fire hazards [16]. I In addition, the oil-based dielectric liquid may deposit carbon, causing damage to the workpiece surface. Instead of an oil-based dielectric liquid, deionized water can be used. This is more sustainable but could lead to defects in the workpiece like surface cracks and corrosion [17]. Therefore, more environmentally friendly EDM has been developed, referred to as DEDM. DEDM uses dielectric gas, not liquid. In its initiation, it could machine small cavities only. Research has been carried out to make DEDM suitable for larger objects [17].

Nevertheless, the first generation DEDM supplies oxygen in the gaseous form into the discharge gap in the presence of water-based dielectric substance [18]. Kunieda et al. [5] found that using this type of DEDM can increase the material removal rate (MRR) and discharge frequency compared to the conventional EDM. Later, oxygen gas is used as the dielectric substance DEDM to increase the MRR [19].

Figure 2 schematically illustrates the setup of DEDM [19]. As seen in Fig. 2, high-velocity gas (mainly air, oxygen, argon and/or their mixture) works as the dielectric jet, passing through a thin-walled tubular electrode. The electrode rotates while machining. This arrangement stabilizes the plasma channel of electric dischage. At the same time, the low viscosity of gas dielectric enhances the flushing conditions [19]. This is not the case in conventional EDM. However, how to achieve a better surface finish, high dimensional accuracy, less subsurface damage, low residual stress, thin white-layer, and small heat-affected zone have been the challenges of DEDM, along with MRR [20].

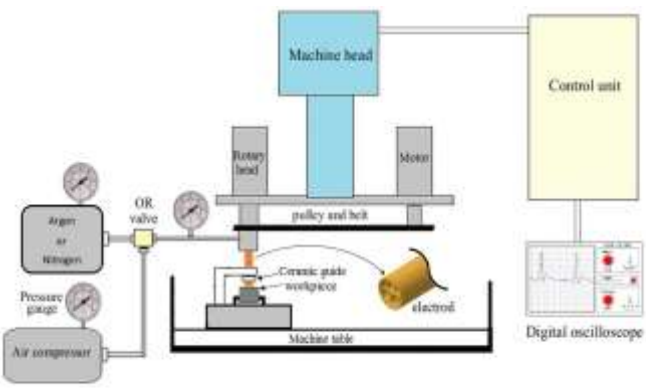

Fig. 2. Setup of DEDM. [16]

In this regard, innovative ideas have been applied. For example, a DEDM setup is developed by adding a piezoelectric actuator for achieving better performance [21]. Air/argon mixture is used as the dielectric substance better to optimize the process performance of DEDM [16]. A pulsating magnetic field applied tangential to the electric field, which increases the movement of electrons and degree of ionization in the plasma, is used to enhance the process performances of DEDM [22]. The cryogenic arrangement is added to cool the workpiece surface, which results in better MRR [23]. Furthermore, it is shown that ultrasonic vibrations applied to the workpiece can improve the performance [24, 25]. The list continues. As far as the optimization of process performance is concerned, some parameters become Control Variables (*CV*s). These variables are fine-tuned to achieve better performance. On the other hand, the process performance is evaluated by the variables denoted as Evaluation Variables (*EV*s). Thus, in an optimization process, *EV*s are brought to their optimal levels by adjusting *CV*s to certain levels. For, DEDM, the variables listed in Table 1 are considered *CV*s and *EV*s, repectively. The *CV*s are as follows: Current (*I*), Voltage (*V*), Pulse Off-time (T_{off}), Pulse On-time (T_{on}), Duty Factor (*D*), Gas Pressure (*P*), and Spindle Speed (*N*). On the other hand, *EV*s are as follows: Material Removal Rate (*MRR*), Surface Roughness (*SR*), Radial Overcut (*ROC*), and Tool Wear Rate (*TWR*).

In the literature, many articles can be found where authors report experimental or theoretical results showing the interplay of the abovementioned *CV*s and *EV*s. These articles become the source of knowledge regading DEDM. The knowledge extraction process can be assisted by the big data analytics presented in the previous section.

Table 1. *CV*s and *EV*s of DEDM

Control Variables (*CV*s)	Evaluation Variables (*EV*s)
Current (*I*)	Material Removal Rate (*MRR*)
Voltage (*V*)	Surface Roughness (*SR*)
Pulse Off-time (T_{off})	Radial Overcut (*ROC*)
Pulse On-time (T_{on})	Tool Wear Rate (*TWR*)
Duty Factor (*D*)	
Gas Pressure (*P*)	
Spindle Speed (*N*)	

4. Results and Discussions

In the literature of DEDM, many articles can be found where the authors report their experimental or theoretical studies showing the interplay of the abovementioned *CV*s and *EV*s. These articles become the source of knowledge regarding DEDM. The knowledge extraction process can be assisted by the big data analytics presented in the previous section. This section presents some of the remarkable results found when big data analytics (Section 2) is applied to optimize DEDM. The results regarding the initiation module, *CV-EV* datasets module, uncertainty quantification module, and decision rule module are presented separately. The implications of the results are also described whenever necessary.

4.1. Initiation module

This module consists of two submodules denoted as big data of scholarly outcomes and process-driven search.

First, consider the submodule defined as big data of scholarly outcomes. Nowadays, many sources of big data of scholarly outcomes exist. The big data sources of scholarly outcomes can be divided into primary big data and secondary big data. The primary big data is single publisher-managed big data. The secondary big data aggregates datasets from multiple primary big data sources. ScienceDirect, SpringerLink, MDPI, and Wiley Online Library are four examples of primary big data offered by Elsevier, Springer Nature, Multidisciplinary Digital Publishing Institute, and John Wiley & Sons, respectively. Among these, MDPI offers fully open access contents, and others offer partially open access contents. Google Scholar, J-STAGE, ResearchGate, and repository of different academic institutes worldwide are examples of secondary big data sources. These sources provide content collected from different publishers and authors. Some of the contents are open access, and some others are not. In most cases, the contents are provided in Portable Document Format (PDF). In some cases, numerical datasets are provided in XML format, making it suitable for big data analytics to handle—for example, the contents provided by MDPI. However, in this study, the secondary big data called Google Scholar is considered.

Consider the other submodule—process-driven search. The process-driven search is defined in Section 2. In this type of search, the keywords set consists of “manufacturing process,” “process quantifier,” and “materials.” When the keywords “Dry EDM,” which is consists of a manufacturing process (EDM) and a quantifier (Dry), is used to search the secondary big data called Google Scholar. This search results in 242 articles with PDF documents. Out of these articles, only 21 articles are relevant to the “design of experiment” (DoE). These articles are useful for the proposed big data analytics because when DoE is used to collect numerical data regarding a manufacturing process, the datasets relevant to *CV-EV* can be identified easily. Otherwise, a great deal of effort must be given to identify the datasets relevant to *CV-EV*, which is not desirable. Finally, the keyword relevant to “materials” is used. This time, the materials called “Stainless Steel (300 Series)” is considered. This results in only four articles [26-29] out of the 21 articles.

4.2. CV-EV datasets module

In the four articles [26-29], the authors considered five *CV*s (Current (*I*), Voltage (*V*), Pulse Off-time (T_{off}), Gas Pressure (*P*), and Spindle Speed (*N*)) and two *EV*s (Material Removal Rate (*MRR*) and Tool Wear Rate (*TWR*)). The *DoE* related information regarding these four articles is summarized in Table 2. As listed in Table 2, the first article [26] shows 15 experimental results where four levels of *V*, *I*, T_{off}, *P*, and *N* are considered. The second article [27] shows 27 experimental results where three levels of *V*, *I*, T_{off}, *P*, and *N* are considered. The third article shows 31 experimental results where five levels of *V*, *I*, T_{off}, *P*, and *N* are considered. The last article shows 31 experimental results where two levels of V, I, T_{off}, P, and N are considered. Thus, heterogeneous datasets are available to extract knowledge.

Table 2. *CV-EV* states in the selected four articles.

Article Number	Number of Experiments	Control Variables (Number of Levels)
1 [26]	15	V (4), I (4), T_{off} (4), P (4), N (4)
2 [27]	27	V (3), I (3), T_{off} (3), P (3), N (3)
3 [28]	31	V (5), I (5), T_{off} (5), P (5), N (5)
4 [29]	8	V (2), I (2), T_{off} (2), P (2), N (2)

4.3. Uncertainty quantification module

The uncertainty quantification module represents the uncertainty associated with the datasets using the possibility distributions (fuzzy number). Figure 3 shows the computing tool developed to induce possibility distribution from a given dataset. This tool imports the relevant dataset and converts it to a possibility distribution and triangular fuzzy number, according to the procedure defined in [13].

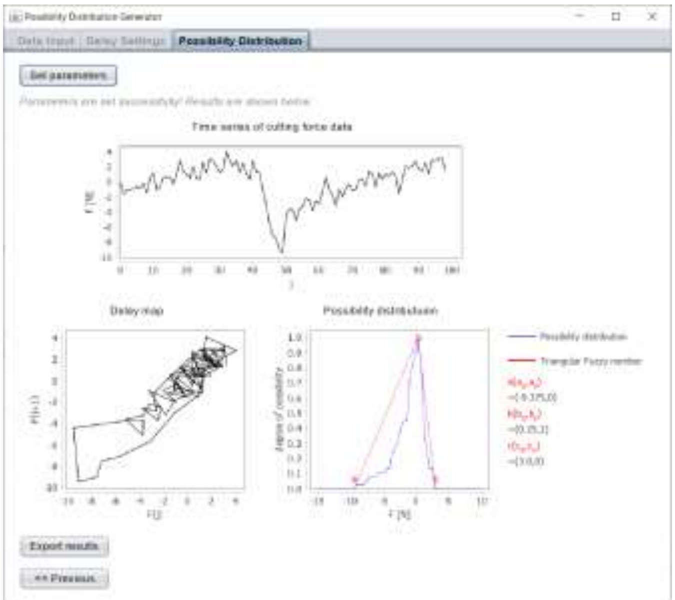

Fig. 3. Possibility distribution generator.

The datasets in [27] are used to quantify the uncertainty. Figure 4 shows one of the examples. In Fig. 4, three triangular fuzzy numbers shown by three different colors quantify the uncertainty associated with CV = Current (I) while relating it with EV = MRR. Since there are three states of Current, I = 12A, 15A, and 18A, three triangular fuzzy numbers are constructed, respectively, using the computing tool shown in Fig. 3.

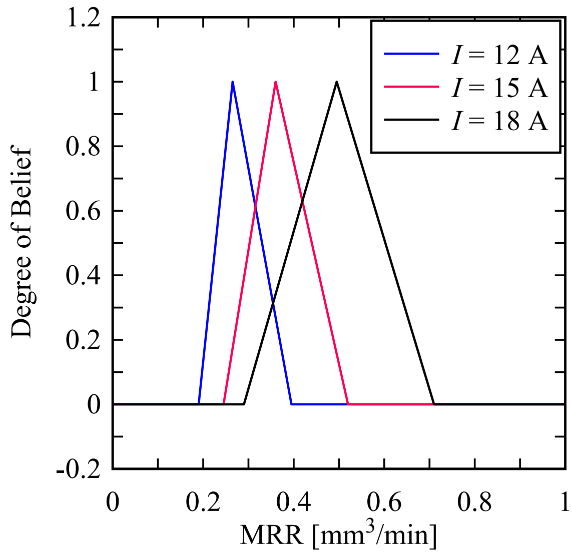

Fig. 4. Relationship between Current and MRR based on datasets in [27].

As seen in Fig. 4, a change in I causes a shift in the corresponding triangular fuzzy in the universe of discourse of *MRR*. The shift follows an order¾the more the Current, the more the *MRR*. Other datasets are also referred to the similar relationship. For example, consider the datasets shown in [28]. The datasets of *MRR* corresponding to five different levels of I = 9A, 12A, 15A, and 18A, as shown in Fig. 5. This time, instead of constructing fuzzy numbers, the datasets are visualized using a scatter plot. The reason for doing this is that the number of data points is inadequate to the induce fuzzy number as required by the method [13]. This plot underlies a trend in *MRR* with respect to I, which is similar to that of the previous case. Therefore, the uncertainty quantification module results in a consistent conclusion regarding the relationship between I and *MRR* in DEDM of Stainless Steel materials.

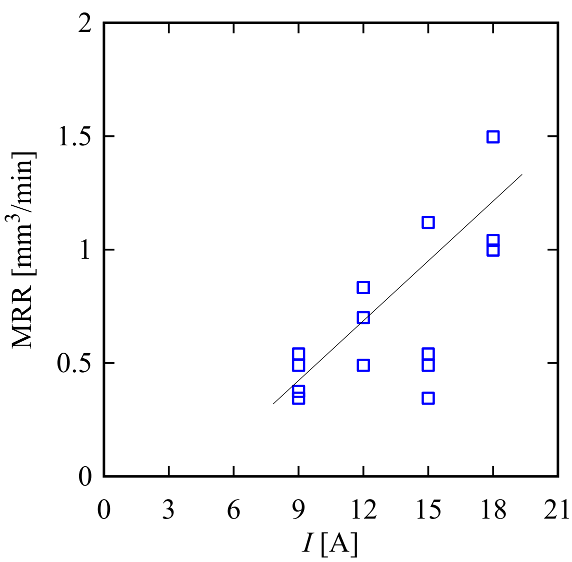

Fig. 5. Relationship between Current and MRR based datasets in [28].

4.4. Decision rule module

This is the last module of the proposed big data analytics. In this module, decision rules are constructed using the results of the previous module. For constructing the decision rules, both informal and formal induction [30] can be used. In this study, informal induction is used. This means that the results shown in Figs. 3-4 becomes the justifications of the decision rules expressed by some simple sentences. As such, the following sentences can be constructed.

Rule 1: Maximize Current to Maximize MRR

Rule 2: Minimize Current to Minimize MRR

The above rules can be used to control the DEDM. Similar rule can be constructed for other *CV*s, if needed.

Thus, the presented big data analytics effectively makes decisions even though a great deal of uncertainty persists in the big data. This experience can be utilized to develop a more formal computing tool to implement the presented big data analytics.

5. Concluding Remarks

Big data analytics offers a wide range of data visualization facilities. It is also equipped with machine learning and computational intelligence-driven arrangements. This makes the decision-making process more formal. However, adding these computational arrangements makes the analytics computationally heavy and highly resource-depended. As a result, only large organizations can sustain big data analytics, and medium and small organizations fall behind. Thus, big data analytics results in an inequality referred to as big data inequality. Measures are needed to mitigate big data inequality. This study offers a novel big data analytics that helps manifest decision rules using a simple but effective machine learning technique. The technique is neither computationally heavy nor highly resource-depended. Thus, it can be sustained by medium and small organizations that need big data inequality-free analytics to support process planning activities within the framework of smart manufacturing.

This study considers process planning of DEDM only. The same big data analytics can be extended to other manufacturing processes. This issue remains open for further investigation.

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