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# The big potential of Big Data in manufacturing: evidence from emerging economies

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**Abstract.** In the last years, the manufacturing sector of developed economies is going through extensive changes to adopt Industry 4.0 principles. Prior studies investigated key enabling technologies for Industry 4.0 and their applications focusing on developed economies. However, there is a lack of studies covering emerging economies (e.g., Serbia). This research provides an overview of the use of technologies for automatic storing of operational data and the exchange of operational data between different entities from the manufacturing sector. For this purpose, the Serbian dataset of 240 companies from the European Manufacturing Survey gathered in 2018 is used. The empirical results indicate that 43% of manufacturing companies are utilizing the systems that automatically record operational data, 88.3% of manufacturing companies are creating an immense amount of data through ERP systems, and 78.6% of companies are using a digital exchange with suppliers or customers. The results reveal the big potential for the Big Data in the manufacturing sector in emerging economies.

**Keywords:** Industry 4.0, Big Data, Manufacturing.

## 1 Introduction

The transformation of manufacturing systems characterizes Fourth-Industrial Revolution or Industry 4.0 through deeper digitalization [1]. The concept of Industry 4.0 was first declared as a German strategic initiative in 2013 [1]. Industry 4.0 is enabled through the use of technologies like Cyber-Physical Systems (CPS), Internet of Things (IoT), Cloud Computing, Big Data, and Data Science [2]. Prior studies investigated key enabling technologies for Industry 4.0 and their applications focusing on developed economies. However, there is a lack of studies covering emerging economies (e.g., Serbia). In this paper, the analysis will be conducted on how many compa-

nies from the manufacturing sector of the Republic of Serbia automatically record data from their production and examine the potential for the use of Big Data in the manufacturing sector of the Republic of Serbia. Moreover, we investigate which systems are used to record data automatically and in which manufacturing sectors. Our analysis used the Serbian dataset from the European Manufacturing Survey (EMS) conducted in 2018.

The remainder of the paper is structured as follows. A literature review is presented in Section 2. Section 3 describes the research questions and method that has been used in this paper, Section 4 presents the research results and discussion, and Section 5 presents the conclusion of this paper with identified limitations of the study and suggestions for further research.

## 2 Literature review

One of the turning points of human history is the emergence of the First-Industrial Revolution, which dramatically changed human production. The use of water and steam powers introduced mechanized industry systems in the manufacturing sector. Second-Industrial Revolution introduced the use of electrical energy in manufacturing that paved the path to mass production. Third-Industrial Revolution saw further automation in manufacturing through increased use and development of informational technologies. For the implementation of Industry 4.0 in their operation, companies can use various novel technologies that include CPS, automated robotics, Big Data analytics, and cloud computing, etc. [3]. Developed countries formed government strategies, which included Industry 4.0 as guiding principles. Germany created “High Tech Strategy 2020” and “Industry 4.0” [1], the United States “Advanced Manufacturing Partnership” [4], China “Made in China 2025” [5], and the United Kingdom “The Future of Manufacturing: A New Era of Opportunity and Challenge for the U.K.” [6]. Prior studies investigated key enabling technologies for Industry 4.0 and their applications focusing on developed economies [7]. However, there is a lack of studies covering emerging economies (e.g., Serbia). In this paper, we will focus on the connection between CPS, IoT, Big Data, and Data Science regarding Industry 4.0, specifically the manufacturing sector. To respond to constant pressure from the competitors and to improve total production performance, companies in the manufacturing industry are integrating new solutions [8]. CPS presents one of the essential pillars of Industry 4.0 implementation [9]. CPS is defined as processing technologies with the high interconnection between physical assets and computational tools [10]. CPS provides integration of objects from the virtual world with artifacts from the physical world through embedded computing technologies [11]. Regarding manufacturing, every component of CPS will be capable to sense environment, itself and to collect and transmit data and consequently take actions that will be constructed through input from the acquired information [12]. Likewise, one of the critical pillars of industry 4.0 is IoT. IoT will completely change current ways of manufacturing and set-up a path to advanced manufacturing [13], and manufacture will progress from automated to intelligent manufacturing [14]. IoT is defined as a network of interconnected devices,

systems, and services through Internet infrastructure. IoT enables mutual communication between connected devices, systems, services and objects and provides deeper integration and joint relations among the virtual and physical world [15]. Implementation of IoT in production will inevitably be followed by the creation of massive amounts of data from manufacturing processes and the stacking of data from various devices will create Big Data [16]. Prediction from Cisco and Ericsson is that by 2020 there will be 50 billion devices connected to the internet and Machine Research predicted that the total number of M2M connections would grow from 5 billion in 2014 to 27 billion in 2024 [17]. There can be found a lot of various predictions about the number of connected devices in the future. Still, all of the projections are united in the conclusion that the number will grow substantially. Big Data is defined as dynamic information that is generated in complex systems that is characterized by three V's, by volume represented in enormous amount of the acquired data, by velocity represented in pace of data processing and by variety represented in data coming from highly diverse sources [18]. Permanent acquiring, storing and exchanging of data from different devices from miscellaneous sources and systems will form Big Data. The manufacturing sector generates and stores a larger amount of data than any other sector [19]. Only one particular device, from production, could generate thousands of records within a second, which would amount to several trillion records in a year. Beside large amount of data that is generated from the companies internally, also horizontal integration through value networks that includes processes and data flows between customers, suppliers and various external partners, will produce enormous quantities of data [1] [20] [21]. Trough processing and analysis of data provided by the implementation and use of IoT in the manufacturing sector, valuable information can be extracted that could provide useful knowledge to companies to face the business challenges and to recognize opportunities and form competitive advantages [22]. Gaining insight from data is achieved through the use of artificial intelligence technologies, like Data Science, Data Mining, and Machine Learning [23]. Using Data Mining or Machine Learning algorithms to analyze and study collected data can significantly improve the efficiency of companies' operations in a very efficient manner [24]. In the manufacturing sector Data Science can facilitate better production rates, supply chain innovations, reduction in malfunction rates, improved decision making, development of new business models, etc. [25] [26].

### 3 Research questions and method

Based on the literature review, the following research questions were proposed to increase the available knowledge about the potential for the use of Big Data in the manufacturing sector in developing countries:

- **RQ1:** What is the utilization of the systems that automatically record operational data in the manufacturing sectors of an emerging economy?
- **RQ2:** Which systems for automatic recording of operational data are used and which are the most common?

- **RQ3:** Is it and to what extent Electronic Data Interchange between manufacturers, suppliers, and customers is represented?

Our analysis used the Serbian dataset from the European Manufacturing Survey (EMS) conducted in 2018. EMS investigates technological and non-technological innovation in the European manufacturing sector [27]. The survey is carried out on a triennial basis and targets a random sample of manufacturing companies with more than 20 employees (NACE Rev 2 codes from 10 to 33). The dataset includes 240 companies. Concerning descriptive statistics, the sampled companies report, on average, a company size of 124 employees ( $SD = 207$ ). In total, 110 companies are small firms (fewer than 50 employees), 103 companies are medium-sized (between 50 and 249 employees), and 27 companies are large enterprises (more than 250 employees).

## 4 Research results and discussion

This section presents the results of the research and discusses the results. The presentation of results follows the order of the research questions introduced in the previous section.

### 4.1 Automatically recording operating data

To provide the answer on RQ1 (i.e., What is the utilization of the systems that automatically record operational data in the manufacturing sectors of an emerging economy), we used the data gathered through the following question:

*Do you use machines or systems in your production that automatically store operating data?*

We found that a large number of manufacturing companies (103 or 43%) already in their operations use systems that automatically record operational data.

Table 1 depicts an overview of companies that automatically record operating data by manufacturing industries. Most of the companies are manufacturers of fabricated metal products, except machinery and equipment, manufacturers of rubber and plastic products and manufacturers of food products.

**Table 1.** companies automatically recoding data by industries

| NACE | Manufacturing industry                                    | Nb. of companies | % of companies |
|------|---|------------------|----------------|
| 25   | fabricated metal products, except machinery and equipment | 21               | 20.1           |
| 22   | rubber and plastic products                               | 15               | 14.6           |
| 10   | food products   | 15               | 14.6           |
| 28   | machinery and equipment                                   | 7                | 6.8            |

Since the largest number of the all companies that were included in the survey are NACE 10, 22, 25 and 28, it is logical that most companies which already automatically record data are coming from specified manufacturing sectors. No significant deviations have been established by manufacturing sectors.

#### 4.2 Technologies used for automatic storage of operational data

To provide the answer on RQ2 (i.e., Which systems for automatic recording of operational data are used and which are the most common), we used the data gathered through the following questions:

*Which of the following technologies are currently used in your factory?*

- *Software for production planning and scheduling (e.g., ERP system)*
- *Near real-time production control system (e.g., Systems of centralized operating and machine data acquisition, MES – Manufacturing Execution System)*
- *Systems for automation and management of internal logistics (e.g., Warehouse management systems, RFID)*
- *Product-Lifecycle-Management Systems (PLM) or Product/Process Data Management*
- *Which of the specified technologies do you plan to use by 2021?*

The results in Table 2 show that most of the companies use ERP and MES systems. Also, we can see that a certain number of companies plan to implement and use specified systems in their production by the year 2021.

| <b>Table 2. technologies used/planned to be used for automatic data storage</b> |                          |                     |
|---|--------------------------|---------------------|
|   | Companies using 2018 [%] | Planned use by 2021 |
| ERP   | 91 [88.3]                | 24                  |
| MES   | 66 [64.0]                | 32                  |
| WMS   | 38 [36.9]                | 33                  |
| PLM   | 29 [28.2]                | 23                  |

Results are in line with the findings from studies covering developed countries, in which most common systems used are ERP and MES [28]. So, there is no deviation regarding systems used for automatic data storage. Thus, already in the manufacturing sector of the Republic of Serbia, we have a lot of operational data recorded and stored through various specified systems. Also, we can conclude that the number of companies that automatically store operational data will rise in the future.

### 4.3 Electronic Data Interchange

To provide the answer on RQ3 (i.e., Is it and to what extent Electronic Data Interchange between manufacturers, suppliers, and customers is represented), we used the data gathered through the following questions:

*Do you use digital exchange of product/process data with suppliers / customers (Electronic Data Interchange – EDI)?*

*Do you plan to use digital exchange of product/process data with suppliers / customers (Electronic Data Interchange – EDI) by the year 2021?*

The results in Table 3 show that 81 companies use EDI, and 21 companies plan to implement EDI by the year 2021.

**Table 3.** overview of companies using/planning to use EDI

| Technology | Companies using EDI 2018 [%] | Planned use EDI by 2021 |
|------------|------------------------------|-------------------------|
| EDI        | 81 [78.6]                    | 24                      |

The substantial number of companies exchange their data with other companies, suppliers, and customers, thus creating additional quantities of different operational data across the manufacturing sector of the Republic of Serbia. These results indicate the existence of a reasonable basis for the use of Data Science, Data Mining, and Machine Learning to extract hidden knowledge from Big Data.

## 5 Conclusion

This paper focuses on determining the potential for the use of Big Data in the manufacturing sector of the Republic of Serbia. The empirical results indicate that 43% of manufacturing companies are utilizing the systems that automatically record operational data. Our results show that 88.3% of manufacturing companies are creating an immense amount of data through ERP systems. Moreover, 78.6% of companies are using a digital exchange of product/process data with suppliers/customers. These findings indicate actionable insights for managers of manufacturing firms to expand their understanding of how to use various systems to collect data and provide a proper application for the use of Big Data analysis. Furthermore, there are significant quantities of operational data that are recorded and stored, which represents an appropriate basis for the use of Big Data in the manufacturing sector in emerging economies.

Through this research, we have shown that companies from emerging economies, to some extent, already use technologies for automatic recording of operational data. We have shown that a certain number of companies, from the manufacturing sectors, exchange operational data with suppliers and customers. Moreover we have determined that part of the companies also plan to implement technologies that automatically record operational data and to exchange data with other entities. Furthermore,

this research contributes to the existing literature by showing the potential for the creation of Big Data and the possibilities for further use in emerging economies. This research is limited to the dataset from the manufacturing sector of the single country. There are other emerging economies and companies from their manufacturing sector that could be included in future research. Also, future research could include the potential for the use of Big Data covered through different manufacturing sectors, company sizes, regions, etc.

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