

# Chapter 7

## Big Data and Data Modelling for Manufacturing Information Systems

**Norman Gwangwava**

*Tshwane University of Technology, South Africa*

**Khumbulani Mpofu**

*Tshwane University of Technology, South Africa*

**Samson Mhlanga**

*National University of Science and Technology, Zimbabwe*

### ABSTRACT

*The evolving Information and Communication Technologies (ICTs) has not spared the manufacturing industry. Modern ICT based solutions have shown a significant improvement in manufacturing industries' value stream. Paperless manufacturing, evolved due to complete automation of factories. The chapter articulates various Machine-to-Machine (M2M) technologies, big data and data modelling requirements for manufacturing information systems. Manufacturing information systems have unique requirements which distinguish them from conventional Management Information Systems. Various modelling technologies and standards exist for manufacturing information systems. The manufacturing field has unique data that require capturing and processing at various phases of product, service and factory life cycle. Authors review developments in modern ERP/CRM, PDM/PLM, SCM, and MOM/MES systems. Data modelling methods for manufacturing information systems that include STEP/STEP-NC, XML and UML are also covered in the chapter. A case study for a computer aided process planning system for a sheet metal forming company is also presented.*

### INTRODUCTION

The quest to improve the quality of manufactured products, achieve higher efficiency, improve communication, and complete integration of processes has resulted in large data being collected by manufacturers. The current era for large and complex data sets has been termed big data. Big data is difficult to process using traditional data processing applications. In order to achieve better control of

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their processes, manufacturers need to capture, store, search, share, transfer, analyse and visualise data pertaining to their products, machinery, and various stages of raw material conversion. Technologies used to achieve data processing requirements in the manufacturing field are a bit complex compared to conventional database management tools. The complete life cycle of products start as a need from the customer, progresses into CAD model of the interpreted need, raw material conversion into finished product, use by the customer and regular maintenance support and finally disposal or recycling. CAD systems used to model the product store attribute data for the various parts of the product and also use unique file exchange formats. The CAD models are analysed using computer aided engineering (CAE) systems so that optimal designs can be achieved. The manufacturing process is aided by computer aided manufacturing (CAM) systems that interpret the CAD data and generate files for manipulating the raw work-piece into the finished products using appropriate machine tools. As the world population continues to grow, production output and product varieties in many companies continue to grow generating a lot of data that should be processed often. The challenges for the manufacturer are not only centred upon the product and its life cycle but the health of the manufacturing plant (plant maintenance), supply chain integration, and in some instances tracking the product during its usage period. This led to the advent of e-based maintenance systems that track the performance of plant machinery in real time.

Whilst the talk about big data is popular in customer relationship management (CRM), supply chain management (SCM), and social media, there is significant application in in-house manufacturing processes. Some manufactures use big data to leverage their technical capabilities so that they can offer customisation to their customers. The trend has been influenced by the growing trend in mass customisation and reconfigurable manufacturing systems (RMS). The capability of RMS systems to be reconfigured or changed to meet new customer demand enables manufactures to offer customised products. However reconfiguring a manufacturing facility requires highly integrated systems if ramp-up time and optimised set-ups are to be achieved without costly investments. In this instance, big data can be viewed as measuring the finite details in manufacturing plants or factories.

Achieving tightly integrated systems in manufacturing pose challenges to manufacturing system designers and system integrators. The major aspects tackled in the chapter include data modelling, data exchange formats, and systems architecture in order to address the gap in traditional and modern practice. Cooperation with suppliers and customers require neutral data exchange formats in product modelling so that both ends can view the transmitted data across different software platforms.

## **BACKGROUND**

Industry has evolved from traditional factories dominated by mechanical production facilities powered by steam and water, through mass production based on division of labor, to introduction of electronics and IT, and currently cyber-physical systems (CPS). Koren (2010) categorized the industrial revolution into four phases namely industry 1.0, industry 2.0, industry 3.0, and industry 4.0. Industry 4.0 is the current stage which is driven by cyber-physical production systems. Rajkumar, *et al* (2010) defined Cyber-physical systems (CPS) as physical and engineered systems, whose operations are monitored, coordinated, controlled and integrated by a computing and communication core. CPS can be considered to be a confluence of embedded systems, real-time systems, distributed sensor systems and controls. CPS is leading towards smart future factories with a network of intelligent objects linking products and assets with information from the internet, as well as capturing context information.

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