A Conceptual Reference Model for Smart Factory Production Data

Giulia Boniotti[1], Paola Cocca[2](✉), Filippo Marciano[2], Alessandro Marini[1], Elena Stefana[2], and Federico Vernuccio[2]

[1] Quantra S.r.l., BS 25068 Sarezzo, Italy
[2] University of Brescia, 25123 Brescia, BS, Italy
paola.cocca@unibs.it

Abstract. As a consequence of the fourth industrial revolution, the data produced by companies' day-by-day activities and the rate at which the transactions occur are growing exponentially. In order to extract business value from those data, they need to be organised under a reference conceptual model facilitating data analysis and decision making. Since no sound reference model for organising digital factory production data has been proposed in the literature, this paper aims at developing and testing a conceptual multidimensional model to support a broad range of data analytics activities for the management and optimisation of production in a smart factory. The testing of the model in a case study company of the printing sector provides insights into the applicability of the model and the connected benefits.

Keywords: Industry 4.0 · Big data · Multi-dimensional modelling · Analytics

1 Introduction

The fourth industrial revolution is fostering the adoption of technological innovations to enhance production processes through the integration of multiple automation, control, and information technologies [1]. As a consequence, the data produced by companies' day-by-day activities and the rate at which the transactions occur are growing exponentially [2]. On one side, this creates the opportunity to shift today's manufacturing paradigm to smart manufacturing [3]. Smart manufacturing (also known as intelligent manufacturing) is a fully integrated, collaborative manufacturing system that responds in real time to meet changing conditions in the factory and in the supply network, and customer needs using advanced information and manufacturing technologies [4, 5]. On the other side, the massive volume of data creates unprecedented challenges in data collection, storage, processing, and analysis [1]. In order to extract business value from those data, they need to be organised under a global unified schema that facilitates data analysis and supports decision making [6]. This reference schema should offer an integrated view of all data sources [7].

The concept of multidimensional data modelling originates from the information system domain [7]. In a data model, the axes are called "dimensions" and represent

Published by Springer Nature Switzerland AG 2021
A. Dolgui et al. (Eds.): APMS 2021, IFIP AICT 633, pp. 110–118, 2021.
https://doi.org/10.1007/978-3-030-85910-7_12

the different ways of analysing the data [7]. Each dimension corresponds to a business perspective under which facts can be fruitfully analysed and could be organised in a hierarchy of levels [8]. Although a variety of multidimensional data models have recently been proposed by both academic and industrial communities, a consensus on formalism or even a common terminology has not yet emerged [8]. In the information system domain, data models have been primarily intended to support the design of a data warehouse in an implementation-independent way, but based on the needs of the specific context. However, to assure flexibility and re-usability, a model should be specified on a conceptual level, i.e. representing information in an abstract and company-independent way [7, 8].

Despite the importance of the topic, no sound reference firm-independent model for organising and analysing the massive volume of production-related data generated and collected in a smart factory has been proposed in the literature. To overcome this gap, this paper aims at developing and testing a conceptual multidimensional model to support a broad range of data analytics activities for the management and optimisation of production in a smart factory. The model is not developed adopting an information system perspective and does not conform to technical formalisms, because it is not intended to directly support data warehouse design. Neither it is intended to develop an ontology, since the focus is not on knowledge representation or semantic data integration [9]. Rather it is qualitative in nature, because it adopts a managerial point of view and aims at facilitating performance assessment and decision making by plant, process, and production managers.

The remainder of the paper is organised as follows. Section 2 describes the methodology adopted. Section 3 presents the proposed conceptual multidimensional model. An implementation case study is presented and discussed in Sect. 4. Conclusions and possible developments of the present research are outlined in the last section.

2 Methodology

The model has been developed on the basis of literature review and experts' opinions.

The literature review had the objective to identify the types of production-related data generated, collected, and elaborated in a smart factory. First, Web of Science, ScienceDirect, Scopus, and Emerald have been selected as the electronic databases of scientific publications most relevant for the topic under investigation. Then, relevant keywords, e.g. "smart factory data", "industry 4.0 data", "digital factory data", have been used to interrogate those databases. Finally, relevant papers have been analysed to identify possible data dimensions to include in the initial version of the model.

The initial model was then evaluated and improved iteratively based on two expert user review sessions. The experts were a group of 30 people, being entrepreneurs, managers, researchers, or consultants, who were involved in a research project on the topic of factory digitalisation. During the first session the initial model was presented and experts were asked for critical analysis and improvement suggestions. After the first session the improvements identified were introduced, and during the second session the refined model was presented to the experts. Some additional inputs were collected that led to the final version of the model.

The applicability of the conceptual model was then tested in a case study company. Two of the authors of this paper acted as consultants supporting the company over a six-month period in the implementation of the model, specifically with the aim to change the currently adopted cost accounting approach.

3 The Conceptual Model

The multidimensional model proposed in this paper is shown in Fig. 1.

The model comprises of five axes, namely: production, plant hierarchy, process, context, and resources. Each axis is a dimension, i.e. a business perspective under which factory data could be organised and analysed.

In the following a description of each dimension is provided:

- *Production* dimension gathers those data dealing with production management that are usually stored in the Enterprise Resource Planning system (ERP) (e.g. production orders, bills of materials, production cycles, hourly output, production batches) or provided by other manufacturing information systems (e.g. Manufacturing Execution System (MES), Customer Relationship Management (CRM), Supply Chain Management (SCM), and Product Data Management (PDM)). ERP systems still represent the central core of enterprise systems and are considered the backbone for the Industry 4.0 [10, 11].
- *Process* dimension identifies the process data collected by Industrial Internet of Things (IIoT) technologies, which are related to a machine/component functioning state (e.g. real-time performance, operating conditions, rotation speed of a rotor) or specific data detected by sensors monitoring a production process (e.g. pressure, temperature) [3].
- *Plant hierarchy* dimension represents the different hierarchical levels of a factory, adapted from the Reference Architecture Model for Industrie 4.0 (RAMI4.0) [12, 13]: component, station, machinery, work centre, plant. They correspond to the different levels at which factory data could be aggregated. This dimension collects data also on the maintenance history of production equipment (e.g. anomalies, breakdowns, malfunctions, and their causes, occurring to each of the components at the various hierarchical levels in the factory).
- *Context* dimension gathers data related to the external conditions in which machinery operates: environmental conditions in terms of, for example, air temperature, relative humidity, and pressure; and the more general context conditions, for example the personnel on duty in the plant (e.g. in terms of skills, training). Indeed, there is evidence in the literature regarding the relevance of environmental [14–16] and general [17–19] conditions in influencing production. This calls for inclusion of this dimension in the conceptual model.
- *Resources* dimension collects data related to the consumption of resources during production, both in terms of utilities (e.g. electrical energy, methane gas, water) and materials. Indeed, resource consumption monitoring is interesting both from a sustainability point of view, and because the identification of production abnormities can be often anticipated by anomalous material and energy consumption patterns [3, 20, 21].

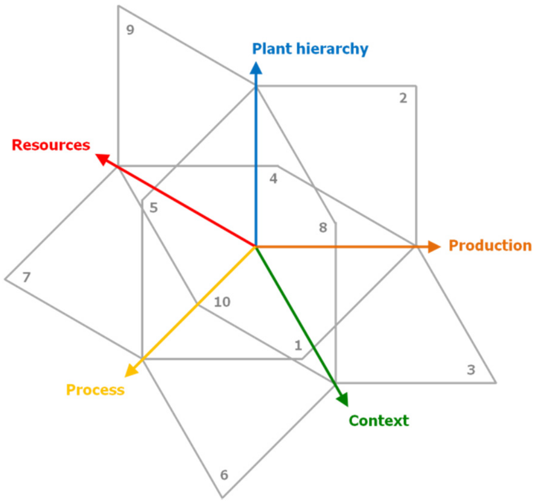

Fig. 1. The conceptual reference model

Two or more axes identify multidimensional spaces interesting for data analysis and performance assessment. Bidimensional spaces (plans) are shown in Fig. 1. Some examples of significant analyses suggested by each plan are described in the following:

1. *Impact of the process on production.* The plan enables analysing the direct impact that process data (e.g. temperature and pressure) have on process compliance, with reference to given production data (e.g. production order, hourly output); this plan can be used, for example, to identify which changes in process conditions have led to the production of a non-conforming batch, or a reduction in production rates.
2. *Impact of the state of production equipment on production.* This plan makes it possible to track the product during the production cycle, with reference to the machinery involved in the various stages of processing, and link all machinery-related events (e.g. anomalies, breakdowns, malfunction) to production orders and all other production-related data.
3. *Impact of context on production.* The plan analyses the direct impact that context data (e.g. environmental conditions, personnel) have on production, with reference to given production data (e.g. production order, hourly output); this plan can be used, for example, to analyse which changes in context conditions have led to the production of a non-conforming batch, or a reduction in production rates.
4. *Resource consumption by production.* This plan enables analysing the specific consumption of different type of resources (e.g. utilities and materials) by each production item (e.g. single product, batch, production order).
5. *Impact of the state of the production equipment on process.* This plan makes it possible to link all the events related to machinery (e.g. anomalies, breakdowns, malfunction) to production process parameters. For example, it allows analysing possible correlations between changes in process parameters and equipment faults in order to implement predictive maintenances approaches.

6. *Impact of context on process*. This plan enables monitoring the quality of production processes in relation to the personnel involved and environmental conditions; it can be useful for detecting, for example, the role of personnel in determining variations in the process.
7. *Impact of process on resource consumption.* This plan makes it possible to associate resource consumption levels to production process parameters. For example, by cross-referencing energy consumption data with data related to production process, it is possible to carry out effective energy monitoring, which is the basis for energy management, i.e. the management and optimisation of energy consumption.
8. *Impact of context on the state of production equipment*. This plan makes it possible to link all the events related to machinery (e.g. anomalies, breakdowns, malfunction) to context parameters. For example, it allows analysing possible correlations between changes in context parameters and equipment faults in order to implement predictive maintenances approaches.
9. *Resource consumption hierarchy.* This plan allows to make each level of the factory accountable for its resource consumption.
10. *Impact of context on resource consumption.* This plan makes it possible link resource consumption levels to context parameters. For example, it enables analysing the energy impact of ensuring certain operating conditions, particularly in environmental terms.

    In order to complement the analyses described above with an economic quantification, an additional axis related to the economic-financial dimension, called *Cost* axis, can be introduced. In this way, five further plans are identified, as shown in Fig. 2:
11. *Production cost*. The plan analyses the costs of production items such as products, production orders, batches.
12. *Process cost.* This plan analyses the cost of each activity carried out to complete the production process.
13. *Cost of plant equipment.* This plan analyses machinery rate, i.e. it includes the cost for machinery ownership (e.g. depreciation) and the operating costs (e.g. fuel, lubrication, maintenance). The costs could be aggregated at different hierarchical levels (e.g. work centre, plant).
14. *Context cost.* This plan analyses the value attributed to the environmental factors affecting the production, and the labour cost.
15. *Cost of resources*. This plan analyses the cost of materials and utilities.

More than two axes identify further multidimensional spaces interesting for data analysis and performance assessment. As an example, the axes Process, Cost, and Resources create a space that makes it possible to analyse the influence of certain process parameters (e.g. processing pressures and temperatures) on the final resource cost of the factory. This allows a precise calculation of the resource costs as a function of process parameters.

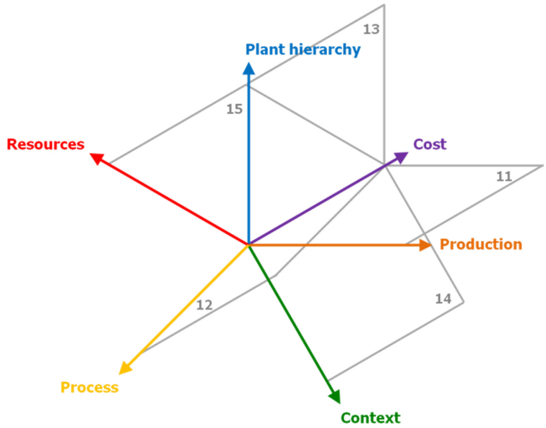

Fig. 2. The conceptual reference model with the cost axis

4 The Case Study

The conceptual model presented in the previous section has been tested in a case study company. The company is an Italian small enterprise operating in the printing sector. The most important piece of equipment in the factory is a Heidelberg printing machine, which is equipped with advanced functionalities that allow the real time collection of data related to operators, jobs, production parameters (e.g. speed, time, energy consumption), productivity, and quality of products. In addition, it is interconnected with the company's information system, allowing the integration of all the data collected by the machine with other information coming from the other interconnected elements of the company.

So far, the production cost used for defining the price, and thus determining the profit margin of the product, was a rough standard cost. It was estimated once a year based on standard values of energy consumption by each work centre and allocation of all the other costs based on the forecasts of total annual operating hours of each centre. Therefore, the company was uncertain about the goodness of such standard cost and needed more reliable cost figures to be able to modulate the price offered based on the strategic importance of each customer or order.

In order to support the organisation of the huge amount of data available and the selection of those data needed to improve cost accounting, and specifically the calculation of the actual hourly production cost, the multidimensional model proposed by this paper was used. The data available were first classified according to the six dimensions of the model. Then, two multidimensional spaces relevant for the analysis have been selected.

The first space is defined by the Cost, Resources, Process, and Production axes. This allows calculating the real time energy consumption for each production order, and thus its specific contribution to the total energy cost. In addition, it allows analysing the relationship between process parameters and energy consumption, thus enabling the optimisation of process parameters for each type of product in order to minimise the consumption.

A second space of analysis is provided by the axes Cost, Context, and Production. Within this space it is possible to integrate information about the influence that different operators and environmental conditions have on the printing process, monitoring the working time, the production speed, the quantity of pieces produced for each production order and their quality. This makes it possible to calculate the performance of operators and to allocate costs based on contextual factors.

All these analyses enabled the calculation of the actual cost of production of a specific product under specific process and context conditions. For example, with reference to one of the most relevant products of the company, it emerged that, based on the actual price, the profit margin determined by the standard costs was 25%, while taking into consideration the actual average product cost, the margin was 37%. The availability of a more accurate product cost enables more informed decisions during the tendering stage. Indeed, the company now knows the maximum reduction of price that still allows covering production cost and could decide for significant discounts in order to win a specific order or to get a new customer.

The company was extremely satisfied of this result. They reported that the multidimensional model has been effective in helping with classification of the huge amount of data available into dimensions, thus transforming raw data into useful information. In addition, the model suggested relevant perspectives for the analysis of those data that have provided new insights into cost accounting.

5 Conclusions

A conceptual reference model for organising and analysing the "big data" related to production available in a smart factory has been proposed in this paper. The testing of the model in a case study company of the printing sector has provided insights on the applicability of the model in real contexts and on the connected benefits. In the specific case, the model has proven useful in increasing the accuracy of product cost calculation, thus facilitating the implementation of data-driven strategies for order winning.

We believe that this paper has both theoretical and practical implications.

From the theoretical point of view, it fills a gap in the literature since it proposes the first multidimensional model for smart production data analysis adopting a managerial point of view. In addition, it could provide useful inputs also to researchers interested in developing a multidimensional model for smart factory data adopting an information system perspective.

From a practical point of view, it could represent a valuable tool to support production-related data analysis and decision making in the complex environment of a smart factory. The use of the model could help managers in the difficult task of organising and exploiting the huge amount of data available in digitalised companies in order to enable data-informed decisions. In addition, it could provide the developers of Information Technology tools for data analytics with useful insights into the multitude of multidimensional spaces relevant for data analysis and performance assessment.

The main limitation of this study concerns the generalisability of results, since only one case study is considered. Further case studies are required for a refinement and full validation of the model.

Acknowledgments. This work was supported by Regione Lombardia (POR FESR 2014–2020), under Grant 236789.

References

1. Santos, M.Y., et al.: A Big Data system supporting Bosch Braga Industry 4.0 strategy. Int. J. Inf. Manage. **37**(6), 750–760 (2017)
2. Niesen, T., Houy, C., Fettke, P., Loos, P.: Towards an integrative Big Data analysis framework for data-driven risk management in Industry 4.0. In: Proceedings of 49th Hawaii International Conference on System Sciences, 5–8 January, Koloa, pp. 5065–5074 (2016)
3. Tao, F., Qi, Q., Liu, A., Kusiak, A.: Data-driven smart manufacturing. J. Manuf. Syst. **48**, 157–169 (2018)
4. Zhong, R.Y., Xu, X., Klotz, E., Newman, S.T.: Intelligent manufacturing in the context of Industry 4.0: a review. Engineering **3**(5), 616–630 (2017)
5. Kusiak, A.: Smart manufacturing. Int. J. Prod. Res. **56**(1–2), 508–517 (2018)
6. Cavalheiro, J., Carreira, P.: A multidimensional data model design for building energy management. Adv. Eng. Inform. **30**, 619–632 (2016)
7. Sapia, C., Blaschka, M., Höfling, G., Dinter, B.: Extending the E/R model for the multidimensional paradigm. In: Kambayashi, Y., Lee, D.-L., Lim, E., Mohania, M., Masunaga, Y. (eds.) ER 1998. LNCS, vol. 1552, pp. 105–116. Springer, Heidelberg (1999). https://doi.org/10.1007/978-3-540-49121-7_9
8. Torlone, R.: Conceptual multidimensional models. In: Rafanelli, M. (ed.) Multidimensional Databases: Problems and Solutions, pp. 69–90. IGI Global, Hershey (2003)
9. Modoni, G.E., Doukas, M., Terkaj, W., Sacco, M., Mourtzis, D.: Enhancing factory data integration through the development of an ontology: from the reference models reuse to the semantic conversion of the legacy models. Int. J. Comput. Integr. Manuf. **30**(10), 1043–1059 (2017)
10. Haddaraab, M., Elragala, A.: The readiness of ERP systems for the factory of the future. Procedia Comput. Sci. **64**, 721–728 (2015)
11. Cocca, P., Marciano, F., Rossi, D., Alberti, M.: Business software offer for Industry 4.0: the SAP case. In: Proceedings of 16th IFAC Symposium on Information Control Problems in Manufacturing (INCOM 2018), Bergamo, Italy, 11–13 Jun (2018)
12. Rojko, A.: Industry 4.0 concept: background and overview. Int. J. Interact. Mobile Technol. **11**(5), 77–90 (2017)
13. Reference Architecture Model Industrie 4.0 (RAMI4.0) (2015). https://www.zvei.org/fileadmin/user_upload/Presse_und_Medien/Publikationen/2016/januar/GMA_Status_Report__Reference_Archtitecture_Model_Industrie_4.0__RAMI_4.0_/GMA-Status-Report-RAMI-40-July-2015.pdf. Accessed 15 June 2021
14. Ye, X., Chen, H., Lian, Z.: Thermal environment and productivity in the factory. ASHRAE Trans. **116**(1), 590–599 (2010)
15. Somanthan, E., Somanthan, R., Sudarshan, A., Tewari, M.: The impact of temperature on productivity and labor supply: evidence from Indian manufacturing. Working paper 244, Centre for Development Economics, Delhi School of Economics (2015)
16. Zhang, P., Deschenes, O., Meng, K., Zhang, J.: Temperature effects on productivity and factor reallocation: evidence from a half million Chinese manufacturing plants. J. Environ. Econ. Manag. **88**, 1–17 (2018)
17. Corvers, F.: The impact of human capital on labour productivity in manufacturing sectors of the European Union. J. Appl. Econ. **29**(8), 975–987 (1997)

18. Syverson, C.: What determines productivity? J. Econ. Literature **49**(2), 326–365 (2011)
19. Backman, M.: Human capital in firms and regions: impact of firm productivity. Pap. Reg. Sci. **93**(3), 557–575 (2014)
20. Mourtzis, D., Vlachou, E., Milas, N., Dimitrakopoulos, G.: Energy consumption estimation for machining processes based on real-time shop floor monitoring via wireless sensor networks. Procedia CIRP **57**, 637–642 (2016)
21. Zuo, Y., Tao, F., Nee, A.Y.C.: An Internet of Things and cloud-based approach for energy consumption evaluation and analysis for a product. Int. J. Comput. Integr. Manuf. **31**(4–5), 337–348 (2018)