A digital twin model for enhancing performance measurement in assembly lines

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Abstract Dynamic manufacturing processes are characterized by a lack of coordination, complexity and sheer volumes of data. Digital transformation technologies offer the manufacturers the capability to better monitor and control both assets and production. This provides also an ever-improving ability to investigate new products and production concepts in the virtual world while optimizing future production with IoT-captured data form different devices and shop floor machine centres. In this study, a digital twin is presented for an assembly line, where IoT-captured data are fed back into the digital twin enabling manufacturers to interface, analyse and measure the performance in real-time of a manufacturing process. The digital twin concept is then applied to an assembly production plan found in the automotive industry, where actual data is considered to analyse how the digital duplicate can be used to review activities and improve productivity within all production shifts.

Key words: digital twins, performance measurement, assembly lines, automotive industry

1 Introduction

The distribution of products with shortened life cycles, as well as the continuously increasing customer expectations have led manufacturing companies to invest more in technology and product augmentation [1, 25]. Production managers put efforts to reduce production costs significantly while maintaining excellent product quality and high levels of customer services. The globalization of markets together with the elimination of import trade duties and restrictions has also forced manufacturers to look for ways to improve their competitive positions by focusing on Research &

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Development (R&D) [5]. Many companies contemplate that significant (especially long-term) savings can be achieved by managing their manufacturing supply chain more effectively in the midst of investing in technology [32, 24].

Manufacturing systems should be not only designed and operated for high reliability and throughput but also to have the capability to integrate the shop-floor with other departments and sections of the business environment. Production planning in a dynamic business environment should have the capacity of dealing with uncertainty in line with satisfying customer delivery time, low cost and high quality. Therefore, manufacturing plants require a mechanism that monitors production process flow and normalization in the case of production disruption [8].

Manufacturing plants are often characterized by complexity and very often managers experience difficulties to perform in-depth data analysis and decision making. In most cases, efforts are made to evaluate production data and elaborating results by improving the quality of products while reducing manufacturing costs [23]. Production planning in manufacturing involves in most cases the synchronization with the downstream demand and thereby has a strong impact in warehouses of both manufacturers and other participants of supply chains [19]. By the manipulation of the production line, it is hoped that new knowledge about the production process can be obtained without the inconvenience or cost of manipulating the real process itself. Therefore, it becomes indispensable to understand production systems' behaviour and the parameters that affect the performance of production lines [11, 27].

In the past years, manufacturing companies have been able to reduce waste and volatility in their production processes and dramatically improve product quality and yield by applying lean techniques [1]. However, in certain processing environments, extreme swings in variability are still a fact of life, while the complexity of manufacturing systems complicates planning and scheduling for managers and operators. Often, the continuity of the production process is at risk due to the inadequate planning and control in the production systems [17]. Standstills in the manufacturing line - in the event of failure, commissioning, reconfiguration, adaptation or breakdown - apart from the disruption that cause can be very detrimental to the manufacturing company.

Production and manufacturing systems are characterized by a number of different performance measures including flexibility, resource and output measurement [5]. The goals of each of these three measures are different, and therefore, at least one individual goal type that corresponds with the organizations' strategic goals from the three listed measures must be present in a supply chain performance measurement system. According to Simpson *et al.* (2007), flexibility level system reacts to uncertainty and also made a similar observation by proposing a performance measurement system, should be carried out at each node of an extended enterprise [26]. Firms should have key performance indicators in the areas of cost, time, innovation, quality and precision corresponding with the mission and strategy according to stakeholders' perception.

Output measurements are often associated with throughput and average up-times. Thus, most of the manufacturers in order to increase the productivity tend to minimise the unavailability of the lines. As a result, reconfiguration of the manufacturing systems occurs (erroneously) only when essential work has to be done although upgrades of the system are desirable to increase quality, increase throughput or reduce energy consumption. Assessing real-time manufacturing environment involves understanding the dynamics affecting the performance. In a manufacturing environment, a precise performance measurement of supply chain activities is based on quantitative measures which are the utilization of resources and cost, quality and manufacturing flexibility. The related data to the quantitative key performance indicators (KPI) can be retrieved from annual and financial companies' report and company management opinion. Very often manufacturers invest in new machinery and online optimisation after commissioning and installation. In high volume manufacturing and especially in automotive manufacturing a efficiency and good performance heavily depend on reliable and highly available manufacturing and automation systems.

Furthermore, existing literature suggests that essential knowledge such as information and advanced technology can enhance supply chain performance [16, 5]. However, there is a limited literature on how this knowledge can be applied in the manufacturing supply chain. Most of the studies in regard to measuring performance management of a manufacturing plant in the automotive industry are restricted in limited locations such as Brazil, India, and Australia. This constitutes a limitation per se because the conclusions can be hardly generalized to other countries [14]. Therefore, it is vital to investigate how knowledge contributes to the automotive industry in another country as performance is subject to location, plant's setting and size among other factors [4].

1.1 Digital twins in manufacturing context

In the last five years, technology and knowledge transfer within an industrial organisation or between manufacturing plants have been reinforced by digital transformation and Internet of Things. Fourth industrial revolution has started to reshape many organisations while digitalization has enabled companies to transform operational effectiveness, improve safety and increase production. However, as both complexity and uncertainty are always present in production lines, industrial organizations should make a further step beyond digitalization and consider a more granular virtual model approach to monitoring, diagnosing and correcting process flaws. This model approach constitutes a form of a digital twin.

Digital twins (DT) have been introduced initially as virtual clones to physical products, in order to improve geometry assurance in early product design phases or to observe and study certain aspects of the products without having to interfere or taking the product out of service [31, 27]. Tuegel *et al.* (2011), propose a DT for predicting the life of aircraft structure and assuring its structural integrity while system dynamics of a product were reinforced by DT for better interpretation of customers' needs [29].

The interest in digital twin technologies is rising as the concept of a smart digital factory and sensor-driven operations have gained the attention of many manufacturing companies [2]. DT enable autonomous objects to imitate the current state of processes and their own behaviour. Also, they can be used as a flexible data-centric communication middleware to develop a reliable advanced driver assistance system in autonomous systems such as self-driving cars [33]. In recent years, there is a focus on digital twin-driven manufacturing cyber-physical system (MCPS) for parallel controlling and simulation of shop floor processes [18, 7]. Thanks to the historical production data, manufacturers can apply computational methods to create a digital model of the manufacturing process whereas the use of real-time data from sensors in may reduce waste, maximize throughput and conduct innovations. Alam and Saddik, (2017), introduced a digital twin architecture reference model to describe the properties of a cloud-based cyber-physical system (CPS) [3]. Modelling and simulation with the aid of DT may offer recommendations, support design tasks or validation of system properties [6].

This work suggests a DT platform, which replicates a complex manufacturing system and predicts future intervention requirements by supporting “ad-hoc” data analytics to maximise the performance of the factory. Apart from the palpable benefits to the manufacturing process, the proposed DT model coupled with the Internet of Things, big data analytics and cloud technologies can be used to drive growth in manufacturing and to open up new business models. Software companies develop DT technology that further builds out IoT capabilities in their enterprise asset management portfolio by allowing customers to leverage IoT data in creating a virtual model of an asset.

2 The digital twin modelling platform

Manufacturing systems require deeper analysis of various data from machine centres and processes. Although manufacturing companies take advantage of state-of-the-art modelling techniques and advanced systems increasing complexity due to the large data arrival can be only addressed using appropriate distributed, interoperable, and high-performance ICT solutions. For that reason DT technology, which is applied in dynamic manufacturing processes, should self-optimize, capturing data from production and, potentially, ambient data from various sensors, as well as data from operators and managers involved in the production process. The data feeds back into the DT, creating a closed loop that enables manufacturers to interface with an actual plant as if it were internet-based software.

An overview of the proposed DT platform within a manufacturing environment is depicted in Figure 1. As it can be inferred, prediction techniques derived via the DT platform are able to forecast the ever-changing needs of plant facilities and to offer the potential of creating new markets. DT platform adopts and leverage (symbiotic) simulation techniques, and, thus, it interacts with the physical system in a mutually beneficial way. Also, the DT platform is highly adaptive, in that the DT platform not only performs what-if experiments that are used to control the physical system but also validates and responds to data from the physical system via actuators. [12].

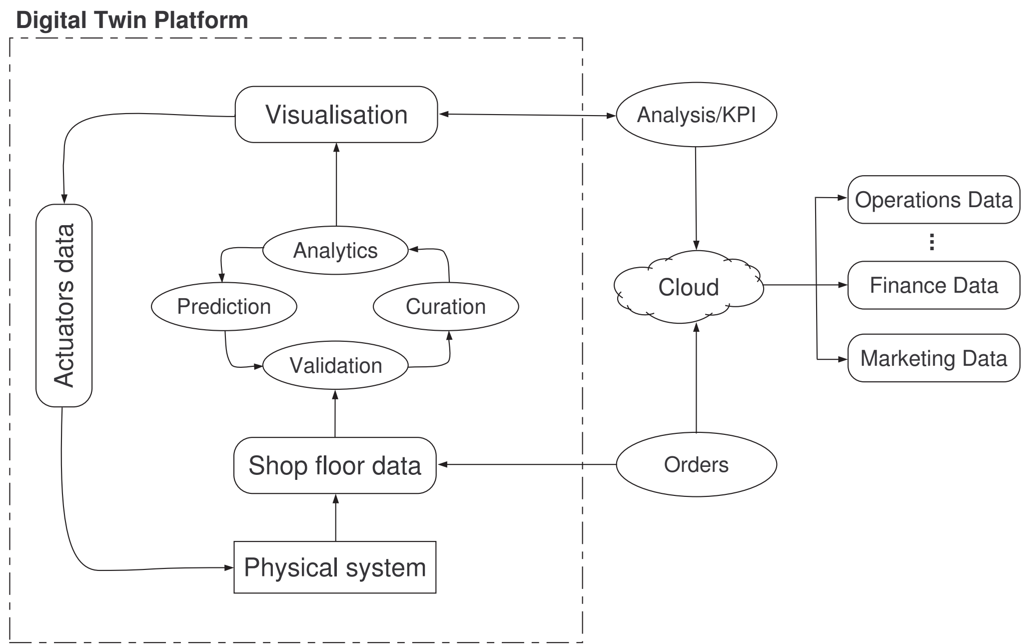

Fig. 1 Digital twin modelling platform

There are still manufacturing companies that fail to exploit valuable big datasets created in process planning while working with quality and environmental standards [20]. Shop-floor data analytics are very important as it is expected that data in manufacturing environments will increase exponentially during the following years. The DT platform can manipulate large amounts of shop floor data accrued from the physical system. The proposed DT platform may work as an enabler to manipulate big data and optimise the physical system by automatic control based on scenario testing of different variables in real-time towards optimisation. It can run in parallel with the manufacturing processes whilst constantly analysing, modelling and visualising relevant data in real-time. As a result, the DT platform may uncover and leverage data that is hidden or unappreciated so as to deliver information capable of transforming processes.

With the aid of big data analytics, the proposed DT platform provides also an integrated approach for advanced modelling, analysis, feedback and visualisation techniques which are helping manufacturing companies to eliminate waste and create value through the design and production of the products. Datasets are analysed against essential KPIs, while with the aid of a cloud this information is propagated to other departments and core activities of the company including marketing and finance. Thus, the DT platform depicted in Figure 1 constitutes an inextricable "business as usual" strategic business module that offers further opportunities including product development acceleration, design methods that minimise production costs and a plethora of products that can be bought at better prices from customers. Moreover, DT platform harnesses consumer insights to reduce development costs through innovative approaches and customized products, which can mark the dawning of the Manufacturing as a Service innovation [9]. Things are already starting to move in that direction with companies such as Adidas with its innovative SpeedFactory facility, which produces semi-custom shoes and Nike, which just acquired computer vision firm Invertex [30].

With the ever-increasing complexity of manufacturing organisation processes and business models, the challenge of linking high performance and quality with cost-effective productivity is always present. Most manufacturing companies in order to cope with downstream demand and new customer requirements follow the traditional three shifts scheme, which often increases in involvement in occupational injury for employees [28]. On the other hand, studies showed that night-shifts operators manage their work-life balance without sacrificing productivity. From management's perspective, the performance for each shift is subject to throughput and shop-floor data. Thus, a DT platform should also provide a transparent user interface of all relevant variables, such as throughput, and raw data derived from shop-floor and especially machinery. In the next section, the purposed DT platform will be utilized to study the performance of a three-shift assembly setup in an automotive industry.

3 Case study: The adoption of digital twin platform to leverage the performance of an assembly line

The motivation for this case study is to review the problems encountered within a complex manufacturing plant with respect to the execution of performance valuation within production management, as well as how these problems can be checked, controlled and enhanced within the performance management perspective of production. In accomplishing this motive, this study was centred on the assembly manufacture line of an automotive company situated in the UK. There are 56 machine centres (workstations) across the production line whereas parts are processed in a sequential manner.

The occurrence of machine breakdown is very common and uncertain in assembly production plants and repair times depend on the condition of the machine at each breakdown event. In this study, the overall time of machine breakdowns for all machine centres and for each eight-hour shift in a single day is calculated. As the determination of the exact time of machine breakdown and the duration of the repairs is quite difficult, manufacturing companies fail in achieving an optimal plan of productivity or even due-to-order deliveries of end products under the given time horizon by the client. There are different reasons for machine breakdown varying from poor maintenance, machine deterioration and overruns to weather conditions and operator mistakes. However, there is a limited number of studies on the breakdown events. For example, changeovers may last longer than the work schedule due to operators' own volition or machines' stoppage times can be elicited manually by operators for no certain reasons. Some studies suggest that preventive maintenance may lessen the likelihood of machine breakdown [10], however the emphasis is given more on the reduction of maintenance cost rather than on operational performance and breakdown events [15]. Thus, a DT platform with the aid of an automated data collection system and actuators may restore machines' operation to the desired work levels.

This study opts for the acquisition of quantitative shop-floor data that could assist in determining the impact of machines breakdown in performance by using the proposed DT platform depicted in Figure 1. Furthermore, primary research helped to acquire important data that assisted in obtaining answers to the following questions identified in this study:

- Question 1: *What are the major difficulties and requirements with respect to affecting performance management within production management by utilizing a DT platform?*
- Question 2: *In what way can these difficulties and requirements be observed and addressed by deploying a DT platform in the performance management context?*

3.1 Validation and curation of the shop floor data

Different raw shop-floor annual data (365 days) was gathered and aggregated. This data includes (a) "flag" event data every time a breakdown arises accompanied by information of the date and the ID of the machine centre the breakdown occurred, and two timestamps signifying the start and end of the breakdown; (b) temperature data from the machines centres, collected every second; and, (c) the number and duration of jobs each machine performs in an hour. Due to the fact that all this information comes in raw format, validation helps to confirm the source of data in terms of origin and contain.

Curation of raw data from the shop floor is important in light of the fact that every company has its own methods of data collection. This data is extremely instrumental on the grounds that it helps in comprehending the company's machines behaviour under certain ambient conditions. The accumulation of raw semi-structured data poses the challenge of complexity in terms of analytics given the huge amount of data generated by the shop floor. Thus, this step provides a sustained and consistent form of systematic data curation and error prevention, which can eliminate bias in analysis and misinterpretation of machines behaviour. Validation and curation stage was processed by means of a numerical computing environment and proprietary programming languages.

3.2 Analytics and prediction of the shop floor data

After the data has been validated and curated, analytics can identify certain machine activities and reveal important information (e.g., patterns) about the performance of each machine. In this section, the DT platform is utilized to exploit complex and large data to obtain trend analysis and prediction of breakdowns which is otherwise an extremely complex time-consuming task and very often prone to errors. Most manufacturing organisations currently have systems which capture and store data from all business areas; however, they do not have a technology which provides trend analysis and prediction, but most importantly, they do not run a simulation in real-time which can optimise the physical processes.

The production plant's performance for each shift is measured by throughput rate (TR), which provides the number of finished products at a given time. In a traditional manufacturing, environment throughput is often subject to machines' breakdown times and production yield; which is expressed by the number of non-defective products divided with the total number of manufactured products [28]. By introducing a DT platform, data from compressing sensors measuring temperature changes in all machine centres is also considered to investigate whether temperature levels in addition to key shop-floor data are associated with throughput rates. It should be also noted that data curation and validation of such data with the aid of visualization tools - provided a new set of variables, which constitute a "clean" format of manufacturing ambient data.

The aggregated breakdown times (BT) in seconds, production yield (PY) and average temperature values (TV) in ^{o}C for all 56 machine centres in a single day are used as independent variables in a two-step hierarchical multiple regression model, in order to investigate their effect on the throughput rates. Two-tailed correlations among the variables adopted in the analysis are shown in Table 1. In this study, Shift 1 is the night-shift (22:00-06:00), Shift 2 the early-shift (06:00-14:00) and Shift 3 is the late-shift (14:00-22:00). It should be noted that almost all same types of shop-floor data differ among the three shifts, with breakdown times between Shift 2 and Shift 3 the only exception. Also, the night-shift has the lowest production yield, throughput rate and the longest breakdown times. This signifies that night-shift has the worst performance, which may lead to long cycle times and an increase of control costs in factories [17].

Table 1 Descriptive statistics and correlation among variables

	Mean	Min	Max	TR1	PY1	BT1	TV1	TR2	PY2	BT2	TV2	TR3	PY3	BT3
Throughput, Shift 1 (TR1)	493.904	0.000	860.000	1.000										
Yield, Shift 1 (PY1)	0.371	0.007	0.944	0.247*	1.000									
Breakdown, Shift 1 (BT1)	99932.86	11820.394	379264.342	-0.263*	-0.009	1.000								
Temperature, Shift 1 (TV1)	215.536	50.650	348.870	0.797†	0.133	-0.080	1.000							
Throughput, Shift 2 (TR2)	590.231	0.000	870.000	0.126	0.002	-0.007	0.209	1.000						
Yield, Shift 2 (PY2)	0.653	0.017	0.998	0.082	-0.194	-0.091	0.136	0.276◇	1.000					
Breakdown, Shift 2 (BT2)	97807.606	26940.073	459027.734	0.005	-0.260*	-0.054	-0.038	-0.458†	0.008	1.000				
Temperature, Shift 2 (TV2)	269.282	45.670	383.730	0.168	0.218*	0.005	0.210	0.766†	0.153	-0.599†	1.000			
Throughput, Shift 3 (TR3)	586.519	0.000	830.000	-0.116	-0.055	-0.249*	-0.247*	0.032	-0.105	-0.140	-0.052	1.000		
Yield, Shift 3 (PY3)	0.715	0.075	0.997	0.135	0.039	-0.052	0.141	0.080	0.111	-0.072	0.122	0.150	1.000	
Breakdown, Shift 3 (BT3)	98442.055	24619.447	330000.447	-0.091	-0.093	0.293◇	0.012	0.178	0.219*	0.130	0.044	-0.679†	-0.279◇	1.000
Temperature, Shift 3, (TV3)	296.634	88.100	390.240	-0.211*	-0.197	0.107	-0.101	-0.071	-0.083	-0.141	-0.006	0.473†	-0.062	-0.278◇

† significant at 0.01 level, ◇ significant at 0.05 level, * significant at 0.1 level

To further understand whether key shop-floor data is associated with productivity, hierarchical regression analyses were performed. Estimations based on a two-step hierarchical regression model for each shift are presented in Table 2. Initially, three different models were implemented to examine the linear relationship between the throughput rates with traditional key managerial data Model A1, Model A2 and Model A3 for each shift, respectively. Then, the impact of the proposed digital twin platform was examined by adding the temperature levels for the 56 machine centres leading to Model B1, Model B2 and Model B3 for each shift, respectively. The initial findings suggest a significant direct association between throughput rates and shop-floor data for Shift 1. The addition of temperature levels increases the regression model's R^2 from 0.229 to 0.636. Thus, the inclusion of temperature levels assisted by DT platform explains more than 63% of the variance in throughput rates (Model B1), while the production yield and breakdown times on their own explain 22.9% of the variance in throughput rates (Model A1).

Table 2 Results of Hierarchical Regression Analyses

	Dependent variable: Throughput rate					
	Shift 1		Shift 2		Shift 3	
Independent variables	Model A1	Model B1	Model A2	Model B2	Model A3	Model B3
Constant	589.077†	588.058†	473.062†	383.139†	797.894†	510.333†
Production yield	209.038*	170.030*	164.711	145.477*	-29.387	-1.056
Breakdown times	-.002†	-.001†	-.005	.000	-.002†	-.002†
Temperature levels		2.239†		.417*		.825†
Model F	7.262†	27.902†	2.058	2.125*	21.130†	18.903†
R^2	.229	.636	.077	.117	.463	.542

†significant at 0.01 level, $^{\diamond}$significant at 0.05 level, *significant at 0.1 level

In regard to Shift 2, the results in Table suggest that for Model A2 the regression equation is not significant (F=2.058). The addition of temperature levels in Model B2 improved significance (F=2.125, $p < 0.1$), but only temperature levels variable is significant (β = 2.125, $p < 0.1$). The R^2 has slightly increased from Model A2 (0.077) to Model B2 (0.117), indicating a small contribution to the throughput rates for the Shift 2 by utilizing the DT platform. In contrast, the results for Shift 3 show that production yield is not significant to the throughput rates. This means that production yield numbers derived for Shift 3 do not provide a clear picture of the production performance. However, Model A3 and Model B3 suggest that the breakdown have a negative impact on throughput rates (β=-0.002, p <0.01. The inclusion of a DT platform in our analysis resulted to a highly significant model (Model B3) with R^2=0.542, as more than 50% of the variation in throughput rates can be explained by breakdown times and temperature levels. The analyses reveal that the insertion of a DT platform has a statistically significant positive relationship with the performance of the production plant. Note that temperature levels variable has the largest and highly significant coefficient in all 6 models, indicating that it is the most important factor, statistically, that could affect the performance by the means of throughput rates.

Results in Table 2 show that although a direct significant association exists between production's performance and breakdown times, the proposed DT platform helps to explain the influence of the machine centres' temperature values far more precisely and meaningfully. Note, that the results for Shift 3 indicate that problematic shifts in terms of throughput and can be linearly explained with the aid of breakdown times, production yield and temperature values. It is also clear that the proposed DT platform reinforces the initial results derived by the means of Model A1, as more than 63% of the variation in throughput rates can be explained by all independent variables in Model B1. Last, in order to ascertain the multicollinearity does not comprise an issue in shop-floor data, the variance inflation factor (VIF) was derived for all models. The largest VIF score found was 5.67 (Model B3), which is below the maximum level of 10 that multicollinearity could cause unstable regression coefficients [22].

4 Managerial implications

Even in complex manufacturing environments, continuous improvement and adoption of advanced technology to attain manufacturing excellence are often essential. Large investments at all of the products' life-cycle from designing to re-engineering, involve decisions pertaining to technology and innovation management. The adoption of the proposed DT platform indicates that a manufacturer, as the recipient of knowledge, investor and decision-maker, should actively seek how digital twins can be provisioned, realized and utilized within the manufacturing environment. As assembly lines consist of many workstations and may become very complex especially with large product variety [21], the beneficial role of a DT platform should be emphasized and encouraged.

As the vast majority of manufacturing companies rely on key performance indicators to assess the production performance versus operational costs and compliance (e.g., strict environmental laws and regulations) the interconnection of objects and processes via open virtual platforms becomes essential. The integration of computation with physical processes is not new as cyber-physical, socio-technical systems and symbiotic simulation offer a plethora of advantages, however, manufacturers should be also able to monitor the behavior of the physical asset in real life and embed technology seamlessly into core business processes. Thus, as throughput rates relate also with ambient data derived from machinery, DT platforms can enhance machine-to-machine communication to save energy and prevent machines precocious deterioration, and thus, minimise breakdown times and occurrences. The evaluation of data and information provides also the benefit of improving human-machine interaction (e.g., by introducing new technologies that promote the use of immersive data), which cultivates personnel' skills, performance and working conditions.

Managers from manufacturing companies should recognize that DT platforms are very important in order to simulate operations under different performances and predict key performance indicators with the actual behaviour of existing machinery. Visualization techniques can help also managers to understand whether a particular machine is reliable and switch from preventive maintenance to predictive maintenance. The findings of this study suggest that DT platforms give prominence to powerful simulation models that increase the accuracy and reliability of machines and controls within assembly production facilities. This is very important as the dependability on planned production sequence in assembly lines is very high [13].

5 Limitations and future directions

The proposed DT platform can assist manufacturing companies to become more competitive and generate the income that is required to cover labour costs and overheads of knowledge workers and to invest in environmentally friendly and worker-friendly factories. However, as sophisticated as a given DT technology might be initially, further studies should be undertaken to anticipate the sheer number of variables that can affect production, whether it is humidity, temperature, the intensity of use of a given machine and so on.

This study derives results from an automotive assembly line without investigating how the proposed DT platform may also reinforce machine-to-machine (M2M) communication by allowing cloud connectivity and integration resulting to speeding up manufacturing processes and optimal productivity. M2M technology helps to cope with the challenges of distributed devices and high data capacity by leveraging cloud infrastructures to enable assets spread across distributed manufacturing plants, which would be very helpful in complex assembly lines.

Last, the proposed DT platform should be tested in terms of supporting transmission status and exception information being processed on-the-fly by persistency engines and rendered on workstations through dedicated protocols. A further data analytics could reveal useful insights on how DT technology can provide state-of-the-art solutions for energy-efficient product life cycles and ECO-usage for multi-modal visualisation and interaction technologies. In addition, it should be investigated in the future how the proposed DT platform can facilitate better automation/self-assembly technologies for conventional workforce tasks (e.g., joining processes in a vehicle assembly line or mechanical fastening).

The proposed DT platform can be used as the bedrock to implement the next generation core virtual autonomous platform, which can be used by managers to gain insights into the manufacturing plant and strengthen the company's competitiveness. The exploration and analysis of diverse types of data can assist decision-making and add value to previously unexploited data streams, and, thus, reduce the costs associated with data even involving personnel with less IT skills.

Manufacturing systems integration requires intelligent tools that will have the ability to monitor the plant floor assets, and predict the variation and performance loss. Digital twins can offer dynamic rescheduling of production and maintenance operations, and synchronize with other related business actions to achieve a complete integration between manufacturing systems and upper-level enterprise application. It is expected that the proposed DT platform will reshape industrial production and service design in the name of future outcome-based value creation, mass customization and smarter cities, where citizens' demands and their consuming behavior will become an integral part of the manufacturing process.

6 Conclusion

As many manufacturing companies still suffer from data transparency and shop-floor complexity this study proposes a sophisticated DT platform that can act as the beacon for manufacturing companies to put their big data insights into real-time action and not only map but also optimize their entire plant lifecycle. An actual assembly line and real shop-floor data have been used to associate and predict the production performance initially with breakdown times and production yield. The analysis throughout three different manufacturing shifts did not reveal initially safe deductions. Then, the results from the adoption of a DT platform and the inclusion of machines' temperature levels indicated that digital twins' technologies provide a better understanding on the relationships between shop-floor data and production performance by the means of throughput levels.

References

1. Agus, A., Hajinoor, M.S.: Lean production supply chain management as driver towards enhancing product quality and business performance: Case study of manufacturing companies in malaysia. International Journal of Quality & Reliability Management **29**(1), 92–121 (2012)
2. Alaei, N., Rouvinen, A., Mikkola, A., Nikkilä, R.: Product processes based on digital twin. In: Commercial Vehicle Technology 2018, pp. 187–194. Springer (2018)
3. Alam, K.M., El Saddik, A.: C2ps: A digital twin architecture reference model for the cloud-based cyber-physical systems. IEEE Access **5**, 2050–2062 (2017)
4. Barnes, J., Morris, M.: Staying alive in the global automotive industry: what can developing economies learn from south africa about linking into global automotive value chains? The European journal of development research **20**(1), 31–55 (2008)
5. Beamon, B.M.: Supply chain design and analysis: Models and methods. International Journal of Production Economics **55**(3), 281294 (1998)
6. Boschert, S., Rosen, R.: Digital twinthe simulation aspect. In: Mechatronic Futures, pp. 59–74. Springer (2016)
7. Brenner, B., Hummel, V.: Digital twin as enabler for an innovative digital shopfloor management system in the esb logistics learning factory at reutlingen-university. Procedia Manufacturing **9**, 198–205 (2017)
8. Bunse, K., Vodicka, M., Schönsleben, P., Brülhart, M., Ernst, F.O.: Integrating energy efficiency performance in production management–gap analysis between industrial needs and scientific literature. Journal of Cleaner Production **19**(6-7), 667–679 (2011)

9. Coullon, H., Noyé, J.: Reconsidering the Relationship Between Cloud Computing and Cloud Manufacturing, pp. 217–228. Springer International Publishing, Cham (2018)
10. Daneshkhah, A., Hosseinian-Far, A., Chatrabgoun, O.: Sustainable Maintenance Strategy Under Uncertainty in the Lifetime Distribution of Deteriorating Assets, pp. 29–50. Springer International Publishing, Cham (2017)
11. Ding, S.H., Kamaruddin, S.: Maintenance policy optimization—literature review and directions. The International Journal of Advanced Manufacturing Technology **76**(5), 1263–1283 (2014)
12. Fujimoto, R., Lunceford, D., Page, E., Uhrmacher, A.M.: Grand challenges for modeling and simulation. Schloss Dagstuhl (350) (2002)
13. Golinska, P., Pawlewski, P., Fertsch, M.: Monitoring the operations management performance in automotive industry. In: Automation Congress, 2006. WAC'06. World, pp. 1–6. IEEE (2006)
14. Humphrey, J.: Globalization and supply chain networks: the auto industry in brazil and india. Global Networks **3**(2), 121–141 (2003)
15. Ji, M., He, Y., Cheng, T.E.: Single-machine scheduling with periodic maintenance to minimize makespan. Computers & operations research **34**(6), 1764–1770 (2007)
16. Koperberg, S.: The information flows and supporting technology in the automotive supply chain: a suppliers focus. In: 6th Twente Student Conference on IT (2007)
17. Kren, L., Tyson, T.: Using cycle time to measure performance and control costs in focused factories. Journal of cost management **16**(6), 18–23 (2002)
18. Leng, J., Zhang, H., Yan, D., Liu, Q., Chen, X., Zhang, D.: Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop. Journal of Ambient Intelligence and Humanized Computing pp. 1–12 (2018)
19. Li, S., Yu, Z., Dong, M.: Construct the stable vendor managed inventory partnership through a profit-sharing approach. International Journal of Systems Science **46**(2), 271–283 (2015)
20. Lundgren, M., Hedlind, M., Kjellberg, T.: Model driven manufacturing process design and managing quality. Procedia CIRP **50**, 299–304 (2016)
21. Make, M.R.A., Rashid, M.F.F.A., Razali, M.M.: A review of two-sided assembly line balancing problem. The International Journal of Advanced Manufacturing Technology **89**(5-8), 1743–1763 (2017)
22. Marquaridt, D.W.: Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. Technometrics **12**(3), 591–612 (1970)
23. Norek, C.D., Pohlen, T.L.: Cost knowledge: a foundation for improving supply chain relationships. The International Journal of Logistics Management **12**(1), 37–51 (2001)
24. Patel, P.C., Chrisman, J.J.: Risk abatement as a strategy for R&D investments in family firms. Strategic Management Journal **35**(4), 617–627 (2014)
25. Sanchez, A.M., Perez, M.P.: Supply chain flexibility and firm performance: a conceptual model and empirical study in the automotive industry. International Journal of Operations & Production Management **25**(7), 681–700 (2005)
26. Simpson, D., Power, D., Samson, D.: Greening the automotive supply chain: a relationship perspective. International Journal of Operations & Production Management **27**(1), 28–48 (2007)
27. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F.: Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology **94**(9-12), 3563–3576 (2018)
28. Trzcielinski, S., Karwowski, W.: Advances in the ergonomics in manufacturing: Managing the enterprise of the future. AHFE Conference (2014)
29. Tuegel, E.J., Ingraffea, A.R., Eason, T.G., Spottswood, S.M.: Reengineering aircraft structural life prediction using a digital twin. International Journal of Aerospace Engineering **2011** (2011)
30. Wang, L., Wang, X.V.: Latest Advancement in Cloud Technologies, pp. 3–31. Springer International Publishing, Cham (2018)

31. Wärmefjord, K., Söderberg, R., Lindkvist, L., Lindau, B., Carlson, J.S.: Inspection data to support a digital twin for geometry assurance. In: ASME 2017 International Mechanical Engineering Congress and Exposition, pp. V002T02A101–V002T02A101. American Society of Mechanical Engineers (2017)
32. Wen, K., Lin, Z.: The strategic evolution of foreign R&D investment in china. In: Engineering Management Conference, 2005. Proceedings. 2005 IEEE International, vol. 1, pp. 119–123 (2005)
33. Yun, S., Park, J.H., Kim, W.T.: Data-centric middleware based digital twin platform for dependable cyber-physical systems. In: Ubiquitous and Future Networks (ICUFN), 2017 Ninth International Conference on, pp. 922–926. IEEE (2017)