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Implementing self-service business analytics supporting lean manufacturing: A state-of-the-art review

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Abstract: Piloting lean manufacturing projects requires dynamically tailoring suitable sets of metrics. Quick turnaround in implementing such metrics is critical, as the typical duration of a Lean Six Sigma project is 3 to 6 months. Self-service Business Analytics (SSBA) can provide managers with the much-needed flexibility to efficiently design and redesign comprehensive metrics in fragmented information system contexts. A review of state-of-the-art practices for SSBA implementation is performed, which lays down the foundations for an upcoming framework geared towards lean manufacturing. Key SSBA planning and architecture findings are summarized. Practical evaluation of the framework in a complex information system landscape through Design Science Research (DSR) is projected with the Canadian division of an international steel parts manufacturing company

Keywords: Self-service analytics; Implementation; Lean manufacturing; BPMN; Constructive Research;

1. INTRODUCTION

In order to stay competitive, manufacturing companies need to improve their ability to quickly react to fluctuating demand. Execution of production routings through an increasingly global supply chain requires keen awareness of manufacturing capacity, as well as solid inter-departmental communication. Numerous information systems (IS) are available to assist production planners with these challenges. However, investing in powerful off-the-shelf software does not guarantee process improvement. While flagship ERP systems and modules are widely marketed as polyvalent, implementation in specialized manufacturing environments will often require compromise, even with subsequent investments. Managers navigating such environments to drive positive change – Lean initiatives – must adapt to the IS landscape with limited time and resources.

If effectively deployed, ERP neutral self-service tools can help managers bridge the gap between IS-native features and their lean manufacturing requirements. A literature review is conducted, which supports the outline of an upcoming implementation framework. Albeit broad-scoped, this study is geared towards application at a partner company in the steel parts manufacturing industry.

For our partner company, the core business is thermal cutting of parts out of sheet metal. SAP Business One (B1) enhanced by the BX Manufacturing module is adopted as corporate ERP, while the SigmaNEST software package enables programming CNC plate processing machines. From a supply chain perspective, it should be noted that this company also manufactures welded assemblies, and that a portion of orders require outside processing for operations such as bending or machining. Lean manufacturing projects impacted by the upcoming SSBA information system include improving lead time estimation with live update, increasing plasma/oxyfuel cutting torch time percentages by showing sales under-utilized machine capacity, and maximizing on-time delivery by detecting at risk orders.

Fig. 1 below shows current order management processes with the help of Business Process Model and Notation (BPMN) by the Object Management Group (2013). Lead times whiteboard & ad-hoc production impact assessments are central in the pre-SSBA workflow.

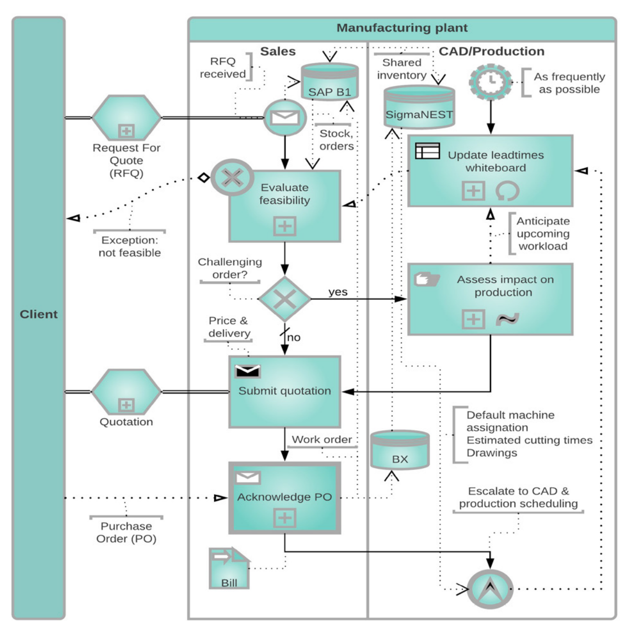

Fig. 1. Partner company current order management BPMN

Fig. 2 represents the projected SSBA integration with the whiteboard superseded. This paper begins with a presentation

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of the background in related fields. Then, selected state-of-the-art literature is further detailed; findings are synthetized in a mental model, and we conclude on a validation roadmap for this projected integrative framework.

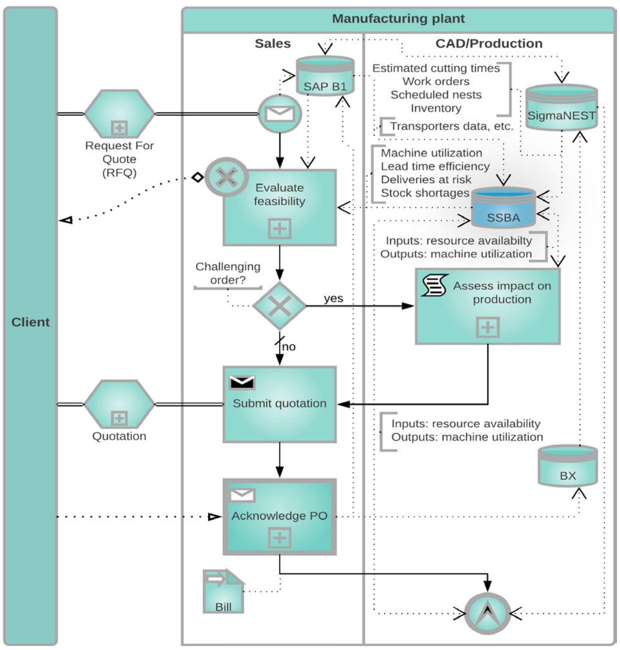

Fig. 2. Partner company projected order management BPMN

2. LITERATURE REVIEW

2.1 Background

A fundamental principle in Lean is that we need to measure if we are to improve. The more mature the lean organization, the harder the bottlenecks are to find and improve (Sims and Wan, 2017), and doing so will more often than not require gathering data. As in any science, data quality must be considered – cleansing big data is a major challenge today's organizations face (Sadiq, 2013). Still, data by itself is not enough to drive improvement, as it needs significance. Business Analytics (BA) address turning valid data into valuable insight for managers (Unver, 2012); this discipline adds the past and future dimensions (Calfa et al., 2015) to Business Intelligence (BI), which tracks real-time status (Unver, 2012).

The impact of Lean management initiatives (e.g. standard work) on key performance indicators (KPI) such as Overall Equipment Effectiveness (OEE) can then be tracked (Unver, 2012). With recent advances in the internet of things (IoT) yielding tools such as Worximity (2017), data acquisition (DAQ) can be performed from virtually any industrial equipment. Still, care must be taken to avoid pitfalls in defining KPIs, for instance setting the bar too low to make ourselves look good (Hammer et al., 2007).

On the other hand, analytic tools such as Bayesian networks can assist decision makers by effectively processing highly complex datasets to forecast Engineer-to-Order (ETO) project workloads (Eickemeyer et al., 2014), helping reduce bottom-line uncertainty (Kogan and Tell, 2009). Analytics can also interface with Enterprise Resources Planning (ERP) systems, modulating sales-production interactions, which in turn correlate with higher customer satisfaction (Parente et al., 2002, de Vries and Boonstra, 2012), all the while enabling dynamic pricing strategies (Özer and Uncu, 2015).

A new, disruptive trend in Business Analytics is self-service. Over the last decade, an increasing number of companies have opted for software such as Tableau, Microsoft Power BI, and IBM Watson Analytics (Dinsmore, 2016, Alpar and Schulz, 2016). Microsoft is positioned as the leader in this field for "ability to execute" and "completeness of vision" according to the Gartner (2018a) Magic Quadrant. Although less powerful than leading data science solutions like RapidMiner (Gartner, 2018b), these tools target end users instead of experts (Dinsmore, 2016).

As a result of the shorter design cycles these decision support tools facilitate, time-sensitive decision making can be improved (Mayer et al., 2015). Managers quickly get actionable intel – the edge to effectively adapt in fast-changing environments (Monostori et al., 2015, Balogun and Tetteh, 2014). Visual analytics can now be updated real-time (Selvaraju and Peterson, 2017), and multi-database query mashups modified in a few clicks – minimal "data-wrangling" (Lohr, 2014) is required. Another benefit of self-service BA is it requires managers to frame their requirements. Traditionally, resorting to Business Intelligence specialists without sufficient attention to requirements engineering (RE) could induce delays of weeks (Dinsmore, 2016), impacting long-term usability in notorious cases (Schlesinger and Rahman, 2016). Self-service attempts – even failed – can help mitigate such risks, as requirements are better framed should there be need for experts.

TABLE 1. Systematic literature review summary [b]

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<tr><td>Business Intel* OR BI</td><td>Business Anal* OR BA</td><td>Manufact* Intel* OR MI</td><td>Decision Support OR DS</td></tr>
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[b.] Strategy executed 31/07/17 in Scopus, Engineering Village, and Web of Science
[c.] No hits if the "Lean" keyword is included

There is limited research on the relatively new topic of self-service analytics, particularly regarding the implementation dimension. In fact, the only two relevant hits in our systematic literature review at TABLE 1 (Olavson and Fry, 2008, Schuff et al., 2016) are not directly related to manufacturing. Since end-user software is involved, some improvisation is expected, which may explain in part why such implementations have been scarcely documented. This seems particularly true for the case of make-to-order (MTO) dominant manufacturing sites, where weak matrix project management support structures are frequent (Project Management Institute Inc, 2013). Nevertheless, a need is to be addressed for implementation guidelines to maximize results and minimize delays with respect to the project manager's triple constraint (see Fig. 3).

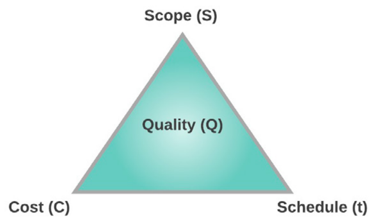

Fig. 3. Project management triangle (Project Management Institute Inc, 2013)

While project management best practices drive project team overall effectiveness to implement traditional ERP systems in manufacturing environments (Boykin, 2014), overemphasis on traditional project planning techniques may actually burden self-service BA implementations. This is analogous to the plan-centric and agile approach dichotomy in software development (van Waardenburg and van Vliet, 2013). Some implementations of self-service business analytics can also be seen as form of corporate entrepreneurship (intrapreneurship) initiative, for which autonomy and organizational ambiguity tolerance are key enablers – maturity factors (Elia et al., 2016). Furthermore, corporate culture factors such as workplace attitude and commitment should be taken into account in the implementation strategy, as they bear strong influence on long-term sustainability (Glover et al., 2011). Guidelines such as the MIT Lean Enterprise Self-Assessment Tool (LESAT) enable characterization of current versus desired states, as well as a Lean transformation roadmap (Lean Advancement Initiative, 2012).

Our aimed contribution to the body of knowledge (BOK) is through development of a structured methodology to implement SSBA in lean manufacturing environments with regard to current IS, sales and operations planning (SOP), and workplace culture. This state-of-the-art review constitutes the foundations for this upcoming framework, for which a first draft is discussed in form of a mental model in Fig. 6. This framework will be backed by lessons learned throughout SSBA implementation in the steel industry.

Related state-of-the-art literature addresses several problems associated with design and implementation of intelligent systems supporting lean improvement programs in multiple industries. Selvaraju and Peterson (2017) present critical socio-technical factors of success for analytics in a lean context. Unver (2012) introduces a manufacturing intelligence (MI) system assisting lean continuous improvement by contextualizing shop floor data. Saha et al. (2016) develop an expert system to help prioritize customer orders. Urabe et al. (2016) attempt to solve KPI conflicts between sales and production by means of better communication with the help of an inter-departmental cockpit – improved SOP. Dresch et al. (2015) produce a comprehensive guide to Design Science Research (DSR) in management and engineering, effectively synthetizing key advances such as those from Peffers et al. (2006) in information systems (IS) research.

2.2 Critical factors of success for analytics in a lean context

The first step in Selvaraju and Perterson's research is developing a framework to assess the organization's maturity for technology-supported Lean (Selvaraju and Peterson, 2017). A second goal of the authors is defining technology-supported business problem solving best practices. Thirdly, the authors wish to use analytics to monitor the lean transformation, as well as technology adoption rates. The framework aligns with Balanced Scorecard metrics: "Customer value, Financial excellence, Culture growth, and process excellence" (Selvaraju and Peterson, 2017).

The developed methodological artefact is based on existing state of the art models. First of all, an Organizational Culture Inventory (Human Synergistics International) is employed to characterize the organization's culture for key behavioral styles such as Constructive or Passive/Defensive. Secondly, this analysis is combined with a lean technology and process maturity assessment. The technology and process assessments are out of the article's scope. Then, BA are integrated in a decision-making methodology throughout the lean transformation. Here, BA enable managers to quickly identify improvement opportunities from dynamic performance measurements. The visual analytics process feedback loop enables continuous improvement of problem solving and decision-making processes.

Application of this methodology yields an "Information Delivery Management Tool". The resulting dashboard-based application is designed to gauge the effectiveness of organizational lean measures. The dashboard is deployed online with the help of IBM supply chain manufacturing. Selvaraju and Peterson (2017) conclude that the framework has been successfully validated for implementation in a complex manufacturing environment. Authors foresee application of the framework to other fields.

2.3 Contextualization of shop floor data with ERP systems

Unver (2012) aims to develop a framework for business analytics in the form of a manufacturing operations center (MOC) following guidelines of the International Society of Automation's ISA-95 standard. Another requirement for the framework is to support implementation of the Lean philosophy, namely measures such as total productive maintenance (TPM) (Unver, 2012). As a major improvement over current tools and techniques, the author wishes to address the disconnection problem between shop floor systems and corporate-level ERP.

The author's methodological approach is mainly one of software architecture. He is part of a team of developers at Oracle. The software architecture team starts by assessing the shortcomings of current ERP-integrated production support systems. Design requirements are outlined; for instance, the possibility for the system to bring relevant KPIs to both plant managers and cross-plant vice-presidents. An ERP-agnostic concept is then developed with numerous industry partners to support shop floor integration. The neutral design, bound by the ISA-95 standard, is meant to be sufficiently generic to harness components from various industries. Two use cases are presented, which are examples of lean transformations where the software helps.

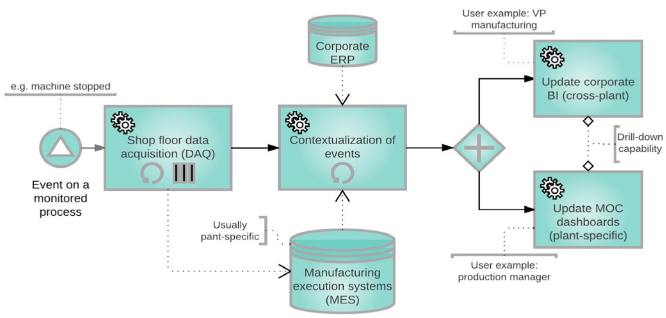

Fig. 4. BPMN for the MOC from Unver (2012)

Unver's research yields a MOC (see Fig. 4) which works by converting real-time data from shop floor equipment into business events, aggregating these events with context data acquired from ERP systems, and then generating relevant KPIs. A cornerstone of the system is hierarchical drill-down capability, which enables corporate-level managers to investigate otherwise superficial plant KPI components – disaggregate performance metrics down to problematic machine shifts to outline possible root causes. Use cases include TPM (i.e. OEE), as well as live production line status dashboards to improve incident response delays. The Oracle MOC offering is Oracle BI Enterprise Edition (OBIEE). Future work includes adding other important metrics such as work in progress (WIP) and manufacturing lead times.

2.4 An expert system to help prioritize work orders

Saha et al. (2016) endeavor developing an End-to-End (E2E) Customer Order Management System (COMS) constituted of three integrated tools and a real-time dashboard. The problem researchers mean to tackle is quantification of strategic and operational impacts of expert system assisted order prioritization decisions. Authors wish to assist the prioritization decisions, but also track order progression and late delivery risk.

The methodological approach employed by Saha et al. starts by a characterization of the system for which a COMS will be developed, and performing a diagnosis of areas where decision support is most needed. A set of assumptions is derived from the supply chain assessment, and the three-module decision support system is designed. The order prioritization tool relies on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as a multi-criteria decision-making model. Then, an order fulfillment progress projection tool (OFPPT) is developed. It utilizes a Mamdani Style Fuzzy Inference System (MSFIS) to simulate subject matter expert (SME) judgement. Finally, a risk mitigation tool (RMT) is developed to draw a risk criticality matrix by aggregation of order parameters and context into the Integrated Risk Likelihood (IRL) and Total Impact (TI) variables. Interactions between these systems and work in progress (WIP) are represented in Fig. 5.

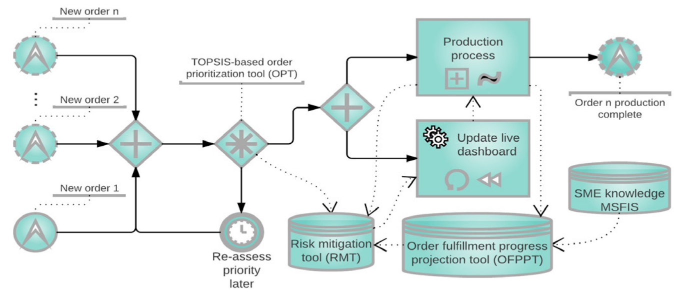

Fig. 5. BPMN for the expert system from Saha et al. (2016)

Evaluation of the system is possible with an application at a server manufacturer. An order management dashboard is implemented. The result is expressive, effective, suitable, comprehensible, coherent, complete, and efficient (Saha et al., 2016). The RMT could be improved by incorporating very low likelihood yet massive impact risks like terrorism.

2.5 Dashboards to help solving departmental KPI conflicts

Urabe et al. (2016) wish to address the problem where some departments will jeopardize other departments KPI to maximize their own. Low synergy and chronic finger-pointing are ultimately detrimental to the company's bottom line. The authors wish to develop a strategy to better manage this issue, and then implement it through an automated tool.

From a methodological standpoint, authors start by highlighting the issues with traditional methods for supply-demand planning. KPI conflict patterns are outlined. Then, a visualization system is developed in order to provide a communication-based solution.

In their diagnostic, authors emphasize a recurring KPI conflict pattern: if sales focus on fast-selling products to catch up on their KPI goals rather than to try selling overstocked items, not only will the overstock be detrimental to supply chain management (SCM), which is penalized by excess inventory, but the sales surge will also force the production department to utilize more resources than initially allocated to maintain on-time delivery rates. This is the production sales and inventory (PSI) problem. A communication-based strategy is then prescribed to help overcome the issue. It integrates the three departments affected by the diagnosed pattern: production, sales, and SCM. Where PSI problem-solving used to be done by individual departments – often neglecting the systemic perspective –, it should now be accomplished through inter-departmental cooperation. To implement a PSI-Cockpit supporting this strategy, two main features are selected: drill-down and alert. Drill-down enables involved departments to quickly identify item-level parameters which cause KPI conflicts, modify these in a tabular interface, all the while simulating the impact on KPIs real-time. The alert feature displays a notification when a departmental KPI reaches a critical threshold. Problem solving following an alert is performed through what-if analysis with the simulation feature. Future research will evaluate the impact of this tool on the manufacturing ecosystem.

2.6 *Producing and presenting information systems research*

Dresch et al. (2015) perceive a lack of systematization and consolidation of the concepts of DSR in current literature, particularly for application in management and engineering. To address this, authors wish to contextualize the foundations of Design Science, DSR, and synthetize a method for DSR.

The authors build upon pioneering work from Peffers et al. (2006) for DSR adapted to IS. Peffers et al. addressed a shortcoming in DSR (Dresch et al., 2015) methodological guidelines as to application to information systems research. Although DSR had existed for over a decade, very little research had been published following this method which effectively bridges the gap between rigorous research and prescriptive applications. Indeed, action research and case studies seldom focus on rigorous science fundamentals such as experimental repeatability and hypothesis falsifiability. Emphasis is put on designing artifacts which are consistent with current literature, and building upon those to expand the body of knowledge.

Design Science research in IS involves (Peffers et al., 2006):

- Identifying the problem and the research motivation, and defining objectives for a solution;
- Designing and developing an artefact;
- Demonstrating effectiveness of the artefact in problem-solving along with thorough evaluation, documenting lessons learned from the demonstration, and
- Communicating results.

As the development of DSR guidelines was done following the DSR methodology, the author's recommendations will be validated by upcoming Design Science Research papers which are successful with application of the methodology.

3. DISCUSSION

Key SSBA architecture findings can be summarized:

- Hierarchical drill-down capability can facilitate PSI problem investigations, SOP, and helps scalability;
- An alert feature can be integrated in order to notify stakeholders that a problem is to be addressed, especially in cases where timely action is needed;
- Simulation can improve the decision-making process. Predictive analytics leveraging statistics or machine learning can ultimately help modulate KPI outcomes;
- Tracked KPIs must be chosen carefully, as people will attempt to improve those if they are compensated to do so, even if the outcome is unproductive.

Implementation methodology has additionally been reviewed. Assuming sufficient stakeholder strategic involvement, best practices are split between the phases of planning and execution in the MIT LESAT. Best practice highlights as to planning are the following:

- Assess available information systems, data accessibility;
- Determine areas of possible improvement in current processes, preferably with a structured approach such as process mapping. Establish current versus desired;
- Evaluate data quality, for instance the standard times used to estimate production throughput;
- Adapt to corporate culture factors such as openness to change and inter-departmental power dynamics;

The mental model presented in Fig. 6 integrates these literature review findings into a high-level implementation workflow. A framework will be derived from the added lessons learned through application of the DSR methodology throughout SSBA implementation with our industrial partner. This resulting artefact will aim to fill the gap as to comprehensive SSBA implementation guidelines adapted to lean manufacturing. While current literature can most certainly provide guidance for each of the steps shown in Fig. 6, we wish to tackle the challenge of lean manufacturing SSBA deployment with a holistic perspective.

4. CONCLUSION AND FUTURE WORK

State of the art self-service business analytics architecture & implementation practices have been reviewed. A mental model was derived to define an implementation workflow adapted to lean manufacturing. This model is set to evolve into an integrative framework through application of the DSR methodology to the implementation case of our industrial partner scheduled 2017-2018.

Current and desired states were documented for this industrial partner. The initial SSBA software selected is the Microsoft Power Query Excel add-in, as it has a minimal learning curve for experienced Excel users, can scale into Power BI, and is already packaged by the company's IT department. A link with MES (SigmaNEST) and ERP (SAP B1) was successfully established, and a first draft of visual analytics have been deployed to stimulate interactions at the sales-production interface. Preliminary observations include faster identification of upcoming bottlenecks, enabling timely use of contingencies such as subcontracting.

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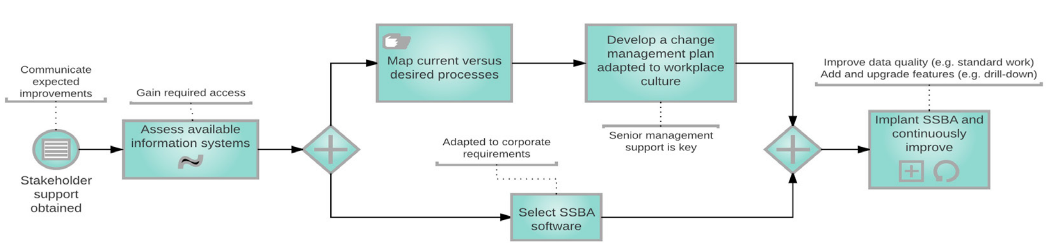

Fig. 6. Lean manufacturing SSBA implementation workflow

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