6-2016

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Opus Citation
David S. Cochran, D Kinard, and Zhuming M. Bi (2016). *Manufacturing System Design meets Big Data Analytics for Continuous Improvement*. *Procedia CIRP*.50, 647-652. Elsevier.Presented at 26th CIRP Design Conference, Stockholm, Sweden.
http://opus.ipfw.edu/engineer_facpres/211

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 50 (2016) 647 – 652

www.elsevier.com/locate/procedia

26th CIRP Design Conference

Manufacturing System Design meets Big Data Analytics for Continuous Improvement

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Abstract

Desired business results are the direct result of the system design. It is also theorized that the 'thinking' within an organization creates the organization's 'structure' or design, which then drives the system's 'behavior.' Achievement of enduring change in a system's performance must begin with a change in the thinking of all the people in the enterprise, but especially that of leadership. In the absence of such a change in the thinking, the needed structural changes within a system may result in short-lived, point solutions, resulting in localized optimization of sub-systems versus systemic improvement. Axiomatic design, applied to a manufacturing system, is a design methodology to best reflect, understand and control the inherent complexity of large-scale integrated systems. System stability, and ultimately cost and span-time reduction, are the desired objectives of system design. This paper provides an overview of the manufacturing system design decomposition, and discusses the integrated use of data analytics to identify bottlenecks for system-improvement and use of the manufacturing system design decomposition to cost-justify resource allocation decisions for improvement.

Peer-review under responsibility of the organizing committee of the 26th CIRP Design Conference

Keywords: Manufacturing System Design; Data Analytics; Systems Engineering; Enterprise Architecture; Axiomatic Design; Lean

1. Introduction

At the design stage, enterprise architecture is developed based on numerous assumptions such as abundant raw materials, available manufacturing resources and anticipated product variants and throughputs. These assumptions are not always valid. During system operations, to achieve better performance, enterprise architecture must be established and then tuned to reflect the nature of the particular manufacturing system to support system stability. High volume manufacturing system architecture may be different than low volume products and there may be great differences in initial system maturity [1]. Moreover, due to the dynamics and uncertainties of the business environment, enterprise architecture is not static anymore; the performance of a manufacturing system must be evaluated and monitored closely to identify variation and disruptions in many areas of the manufacturing system to facilitate necessary improvement. In such a way, enterprise architecture can be tuned-up as needed to mitigate the impact of changes and uncertainty.

Traditionally, the continuous improvement of a manufacturing system poses some great challenges due to scarce and inaccurate data. The emerging Internet of Things (IoT) allows a manufacturing system to acquire any data at any time about any object, and the big data analytics can then be deployed to identify disruptive variation and bottlenecks in the system operation [2,3].

The importance of big data analytics to manufacturing systems has been well identified. PWC [4], Intel [5], and McKinsey [6] gave some extended discussions on the relationship of IoT and big data analytics within manufacturing industries in the USA and the world. Mo and Li [7] indicated that as a type of traditional industry, the manufacturing sector was influenced significantly by the advent of big data; it was pushing a shift of the system paradigm into Forecasting Manufacturing. Data was the essential lifeblood of manufacturing, big data made it possible to improve productivity, reduce waste, and enable profit gains [8]. In addition, big data analytics facilitated information visibility and elevated the level of automation in design and manufacturing engineering [9].

From the perspective of the return on investment, Nedelcu [10] concluded that big data was growing its influence on manufacturing enterprises even though the application of big data was still experiencing numerous challenges. Barlow [11] regarded big data analytics as a necessary viewpoint in the architecture of emerging systems. To promote the application of big data in manufacturing, Oracle [12] developed the guides to build big data architecture and reference architectures to im-

Peer-review under responsibility of the organizing committee of the 26th CIRP Design Conference
doi:10.1016/j.procir.2016.05.004

prove enterprise performance. Josheph et al. [13] discussed the application of big data analytics to implement machine learning in manufacturing, which includes the activities of 'build data infrastructure, prepare and understand the data, develop right machine learning models, set up the big data platform, test model for continuous improvement, deploy and monitor solution, and prioritize business challenges.' These activities could be generic and applicable to most big data analytics applications.

However, the question of how to utilize the captured information in a manufacturing system turns into a great challenge. Parker [14] commented that only about 10% of the value potential of the information collected was actually utilized to enhance the level of management productivity. This fact is aligned well with the conclusion of our literature survey: little work has been reported on some actual case studies where big data analytics has been applied to support the design and evolution of manufacturing systems. In this paper, the authors are motivated to integrate the big data analytics with the Manufacturing System Design Decomposition (MSDD) [15] to identify bottlenecks for system-improvement and to cost-justify resource allocation decisions for the continuous improvement and sustainability of manufacturing enterprises.

2. Manufacturing System Design

2.1. Axiomatic Design and Robustness

Axiomatic Design [16] was developed with the main purpose of establishing a scientific basic for design. This science base for design establishes both a natural and mathematical language to facilitate the collective understanding of the relationship between conceptual requirements (called, Functional Requirements) and the details of implementation (called Design Parameters or Physical Solutions). This idea is represented as a transfer function between the physical domain, Design Parameters (DP_j), and the functional domain, Functional Requirements (FR_i), as shown in matrix form by Equation 1.

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ \vdots \\ FR_i \end{Bmatrix} = \begin{bmatrix} A_{11} & A_{12} & A_{13} & \vdots \\ A_{21} & A_{22} & A_{23} & \vdots \\ A_{31} & A_{32} & A_{33} & \vdots \\ \cdots & \cdots & \cdots & A_{ij} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ \vdots \\ DP_j \end{Bmatrix} \tag{1}$$

The application of Axiom 1 of axiomatic design to "maintain the independence of the functional requirements," leads to defining solutions that have only a one-to-one relationship between a physical domain Design Parameter and the achievement of a Functional Requirement in the functional domain. The most acceptable design in accordance with Axiom 1 is an uncoupled design; the matrix A_{ij} is a diagonal matrix.

The second axiom states that a design with the minimum information content has the highest probability of success of the system operating range achieving the design-specification FRs. A design is said to have the least information content and is the most robust when the design range / capability of the design is completely within the system range specified by the designer [16,17].

2.2. Application of Axiomatic Design to Design Manufacturing Systems

The application of Axiomatic Design to manufacturing systems resulted in the logical system design of a manufacturing system called the MSDD [15]. The MSDD is a methodology to qualitatively, and in some specific cases quantitatively, evaluate system requirements and solutions. The resulting system design decomposition (or map) can be used to identify where the system design does not effectively meet a design functional requirement. In addition, the map serves to quantify the cost of not achieving system design requirements and is used to calculate the benefit of improving the solution [18].

The MSDD has been applied to comparing the 'before' and 'after' state of the redesign of a manufacturing systems and cells [19,20]. Direct correlation was identified between achievement of MSDD requirements and improved system performance. Research based on the logical system design as defined by the MSDD also was used to develop and apply an investment and resource allocation methodology to support manufacturing system design implementation [21]. The methodology can be used by a company with constrained investment resources to target and prioritize potential continuous improvement projects to most effectively apply limited resources to ensure the greatest increase in system stability. It can also be used to prioritize those system requirements and solutions that would, per the design have the most impact on system performance. The issue is and was that the ability to determine the quantitative connections between meeting the system requirements and overall system stability and cost is today difficult and involves significant estimation. However, the emergence of data analytics and the ability to dive into the performance data at unprecedented levels offers the opportunity to quantitatively evaluate performance at a system level as well as begin the march toward predictive analytics.

In many cases, data for large manufacturing operations is resident in many IT systems. For large aerospace companies, these include an ERP/SAP financial and parts ordering system, a human resources and training system, a Manufacturing Execution System (MES), an Engineering Product Life-cycle Management (PLM) system, and a Sustainment system. These systems frequently do not interact directly with each other, although there are data streams that are utilized from one system to another on an as required / needed basis. Data Analytics can be seen as connecting these systems in real time and allows the analysis of data which can be used to better evaluate system performance.

2.3. System Design definition of Lean

Functions in organizations such as Engineering, Manufacturing, Quality, Human Resources, etc. may not necessarily recognize or understand their positions within a system design and may not proliferate system thinking within their enterprise. The consequence of organizational stovepipes is that data analytics is frequently driven toward localized, point solutions for specific users / requesters and typically does not attempt to reflect analysis that is based on an overall system design.

The marriage of system design and data analytics offers the opportunity to optimize performance by creating data that is relevant to the overall system. The question is, "are we stable and are we achieving the defined purpose of the system expressed by the Functional Requirements (FRs) of stability as defined by the MSDD at the lowest possible cost?" The authors define "lean" here as the result of achieving effectively all of the FRs of the MSDD; therefore, Lean Manufacturing should be the result of uniting the way that work is done in manufacturing to achieve all of the FRs of the MSDD / system design map.

In many cases, Lean terminology is misunderstood and at best leads to point optimization. Worse still, lean may be incorrectly interpreted as cutting cost, by leaning out or cutting people and programs. Data analytics tools that are integrated with system design enables the design, evaluation and sustainability of systems in a precise and systems-oriented manner since every functional requirement of a system design must be stated and agreed to by team members.

In addition, a system design map that reflects systems thinking should drive a more effective data analytics program and identify which efforts will best reflect on system performance since it would then be based on the relationships and understanding of the impact of the various Design Parameters (DPs), Physical Solutions (PSs) on the Functional Requirements (FRs) of the total system.

3. The Manufacturing System Design Decomposition (MSDD)

Application of Axiomatic design to large manufacturing systems has resulted in the development of logical system design map shown in Figure 1 [22,23]. The priority left to right order of the elements is reflective of the axiomatic design process as a partially coupled, path-dependent design. The MSDD uncouples the elements of the manufacturing system design, and it reflects the interaction and priorities of the system elements. As shown in Figure 2, the decomposition process, for example prioritizes product design, quality, problem solving, and predictable output over delay (i.e., throughput time / span or flow time in system) reduction, which has historically tended to be the focus of traditional "lean" manufacturing implementations. Lean manufacturing tends to treat issues within these elements as pure waste and focuses on span-time / throughput time reduction, wasted motion, and area organization, instead. In contrast, Figure 1 illustrates that Lean is a result of a stable manufacturing system, which is a direct result of satisfying the stability requirements of each branch to minimize variation (σ) in product design(σ_d), process quality (σ_p), identifying and resolving problems (σ_t) and predictable output (σ_t). Figure 1 illustrates that flow time in system ($\bar{X}_t$) is path-dependent on satisfying the elements of the higher priority (items to the left of delay reduction) system design branches affecting stability. A stable manufacturing system enables flow, establishing flow in and of itself does not create a stable system or meet the overall system design requirements.

As shown in Figure 2, the system design is a decomposition of requirements and solutions that enables qualitative evaluation of a system. Figure 3 illustrates a complete analysis [23]. This qualitative evaluation was useful in the sense that it helped focus the "system thinking" of the production team, and it created a common mental model which is critical to enterprise success. In 2002, Cochran and Hendricks took some of the elements of the system design from the full model; it was based on a pain-staking manual analysis to quantify the cost of not achieving each Product Delivery System (PDS) map Requirement. The PDS Map is the extension of the MSDD to include product development [24].

4. Big Data Analytics in Manufacturing System Design

The analysis of the elements identified above was difficult owing to the lack of sufficiently detailed data. However, the objectives of the prior research were limited by the available data and by the structure of available data. The goal of this prior effort was to provide sufficient data to support specific investments in specific solutions and attempted to calculate the cost / benefit of these investments. For example, an industrial engineer sampled part shortages for several months and collected data on the touch and support labor costs. Different types / categories of shortages have different impact on the system and support costs; but is was difficult to calculate an average impact. The goal of the analysis was used to demonstrate that purchasing spare parts produced an acceptable return on investment. In addition, the analysis was used to justify improved mechanic training to reduce non-conformances.

One of the striking results of the analysis was not just the expected impact on touch labor, but the relationship between touch labor disruptions and non-touch or support labor costs. In general, the support labor costs for disruptions was higher than the impact on touch labor costs. If the manufacturing system was interrupted by a disruption, the workforce is assigned other tasks; while the support staff must stop doing other tasks to resolve the disruption. Based on this analysis, management also estimated the contributions of various elements to the overall learning curve (defined as percentage reduction in cost due to improvement) for this particular manufacturing system.

- Operator learning (25%)
- Improvement projects (25%)
- Disruptions (Quality and Parts) (50%)

As mentioned earlier, although a discrete quantitative analysis was performed based on an extension of the MSDD called the Product Delivery System (PDS) map; the data were suspect because it was based on sampling and estimating the cost of the disruptions (quality, engineering, material, etc.). Although it was sufficient for the particular goals of the selected study, the data collection methodology did not lend itself to general applications to other systems. It was a type of point solution-analysis for specific disruptions. To make continuous improvements in a system, one needs to understand the quantitative relationships between the requirements and solutions. In other words, system designers and managers need to understand the coefficients of the requirements (FR) / solutions (PS) matrix such as:

$$\begin{Bmatrix} FR_1 \\ FR_2 \end{Bmatrix} = \begin{bmatrix} X & 0 \\ X & X \end{bmatrix} \begin{Bmatrix} PS_1 \\ PS_2 \end{Bmatrix} \quad (2)$$

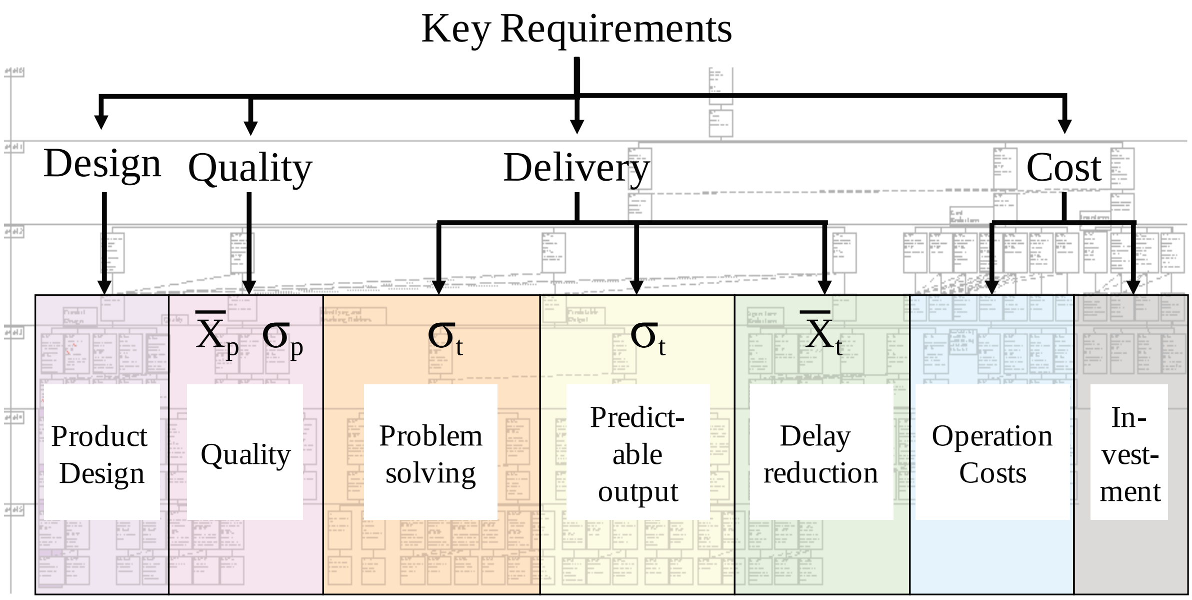

Fig. 1. Key requirements and design precedence of a path dependent manufacturing system

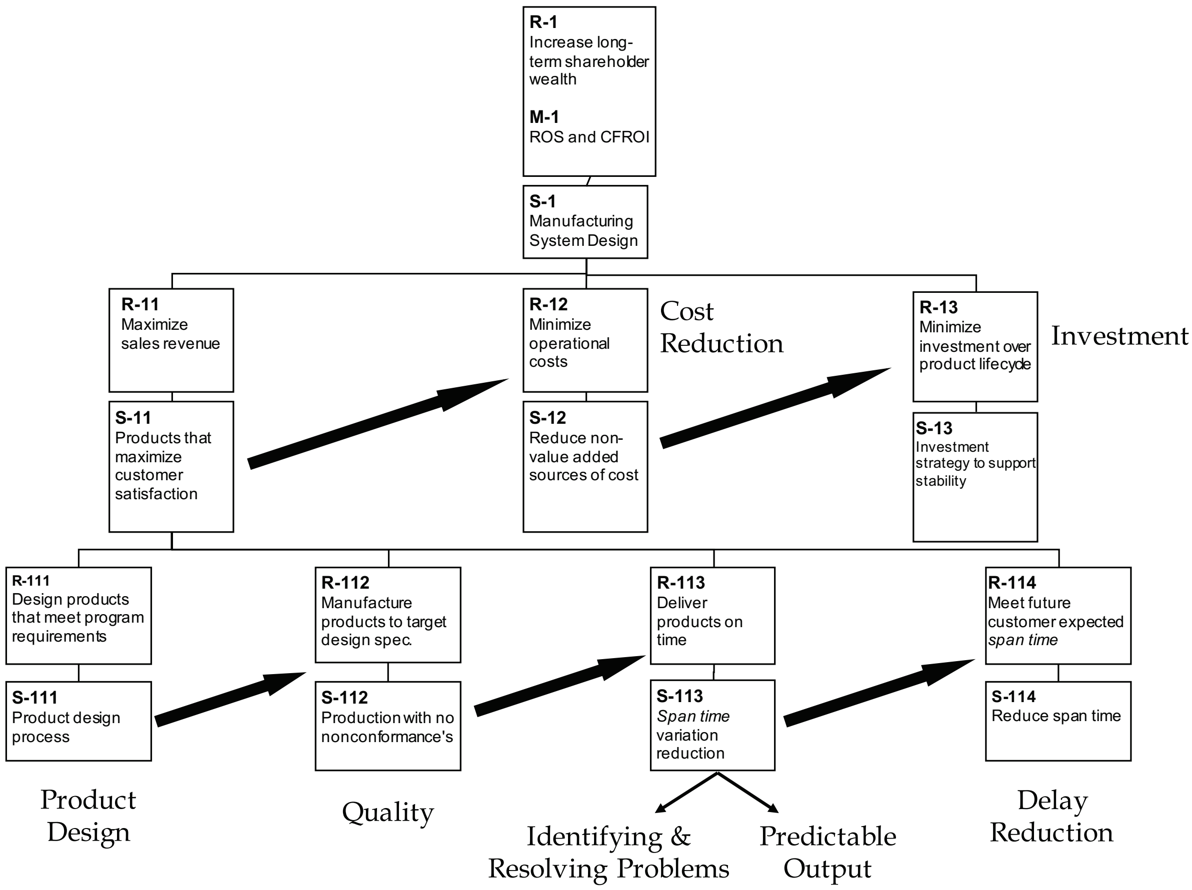

Fig. 2. Detailed decomposition of requirements to evaluate manufacturing system performance

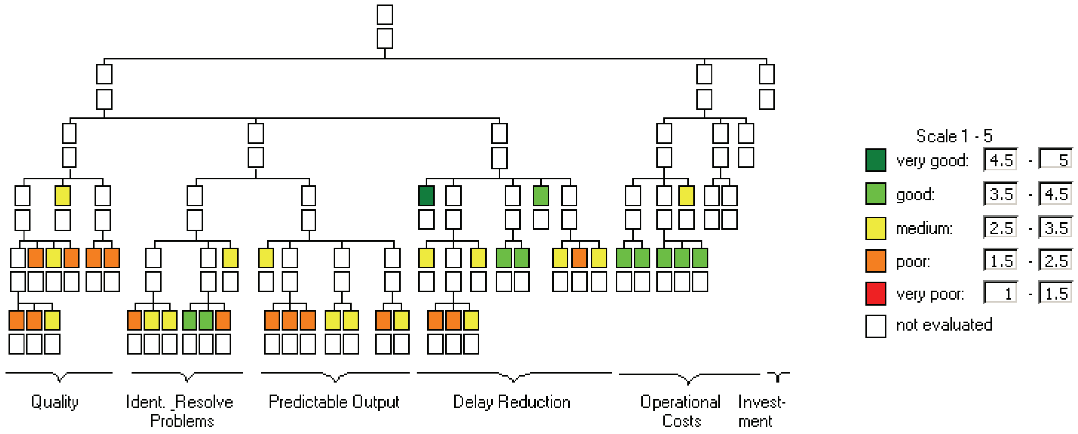

Fig. 3. Example of requirements evaluation based on the MSDD

Data analytics is now seen as the vehicle to provide the relationships between the solutions and requirements, moreover, the system design map could be used to define what data analytics are required to understand the system performance. Currently, data analytics is commonly requested by management to understand specific, point solution-relationships in performance data. The PDS map, has not been applied systematically to understand the interrelationships between all system solutions relative to requirements. For example, it is theorized that part shortages result in non-conformances due to out-of-station and out-of-sequence tasking. Today, part shortages and non-conformances are separate elements that are analyzed using individual metrics. Mechanic availability and experience with certain tasks is theorized to relate to span time, labor hours, non-conformances, and overall cost. However, there is no quantitative data to support this hypothesis. The use of data analytics could validate this hypothesis and determine the X coefficient in Eq. 2. The consequence of validation is that management could rely on the MSDD / PDS (i.e., an enterprise system design map as the general case) to make reliable resource-allocation decisions.

Data analytics technology today will support detailed analysis of variation within a manufacturing system, identify the cause of the variation (parts, people, quality, etc.), which will allow practitioners to fully understand their roles in the overall system design and operation, contribute to continuous improvement, and foster system thinking throughout the enterprise leading to increased system stability and reduced cost.

5. Conclusions

Today, big data analytics makes it possible to model the connections among various enterprise IT systems. This capability enables the study of variation in work performance on specific tasks or in particular areas with unprecedented insight. In other words, one can monitor the manufacturing system from the enterprise level down to the leaf or task level for the system design map defining the design of the enterprise of interest. The ultimate goal of the data analytics is to be able to predict the performance of the system over a period of time based on given criteria, understand the impact of disruptions and variation within a system, and thus make the leap from a descriptive to a predictive system performance model. Big data analytics integrated with manufacturing system design should also provide insight into how a system could be improved under a what if analysis that particular system requirements are satisfied. In addition, it helps to improve the simulation for a well-characterized manufacturing system where the impact of certain changes can be estimated.

In this paper, the authors provide an overview of the theory and methodology of the Manufacturing System Design Decomposition (MSDD); the results from the MSDD express sequence and path-dependencies, which may be evolved to accommodate predicted and unpredicted changes that occur to the manufacturing system. Big data analytics is a promising way to acquire data and to establish the cause-effect model of system-design relationships. An example of how big data analytics was applied to identify bottlenecks in operations from the perspective of quantitative performance evaluation was provided.

The next steps are to investigate data analytics use cases to upgrade the system design model based on the MSDD, and to develop a system architecture that structures data collection for predictive analysis necessary to make effective investment decisions that integrates with the MSDD [21]. Prof. Suh notes that determining the best Physical Solution / Design Parameter requires a data base. The data base can be large or small; however, the existence of a data base and data analytics tool sets does not necessarily ensure that data analytics leads to a better design [25]. For this reason, the paper proposes that system design results may be improved when data analytics tool sets are paired with the MSDD. Ultimately, the selection of the Functional Requirement and Physical Solution / Design Parameter relationship is a human endeavor that requires collective understanding and agreement [26].

The MSDD provides a pedagogy in which to use Data Analytics tool sets. The goal of this research is to be able to accomplish two things: first, to provide people in complex systems with a framework to communicate design intention and proposed solutions with each other and secondly, to focus analytics on system objectives and solutions of merit. Causality can always be found with sophisticated tools; however, the question, “are we able to provide a methodology to focus the tools being used to address relevant system concerns?” is the issue that should be addressed with the advent of Big Data Analytics tool sets [27].

Acknowledgments

The analysis illustrated in Figure 3 was funded under grant between Lockheed Martin and Prof. Cochran's Production System Design (PSD) Lab at MIT. This paper was made possible by agreement between the IPFW Center of Excellence in Systems Engineering, the Purdue University Sponsored Research Program and Lockheed Martin Aeronautics (no proprietary information was divulged in this paper).

Special thanks go to Prof. Joseph T. Foley, Reykjavík University, for assistance in LaTeX document preparation.

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