Decision Support for Smart Manufacturing

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INTRODUCTION

A post-industrial revolution is encouraging the deployment of novel concepts both for designing smart factories and for creating a new generation of monitoring, control and man-machine collaboration systems. In general, companies are embracing an era of smart manufacturing built upon Cyber Physical Systems (CPS), the Internet of Things (IoT), and Cloud and Cognitive computing. Using digital technologies with advanced manufacturing tools can provide opportunities for building smart decision support systems (DSS) to improve manufacturing analysis, monitoring, output, and performance. Despite the potential of improved Decision Support Systems (DSS), the major challenge is successfully adapting smart manufacturing processes to use new digital technologies that can enable the implementation of Intelligent systems and improved DSS.

Additionally, to move towards smart manufacturing, better means are required for technology deployments. The speed of technology implementation should be significantly faster, and machines should have greater accuracy of calibration in comparison to traditional manufacturing. One approach to enhancing deployment is incorporating optimization models into manufacturing systems. This change should provide a design that provides ease of use for operators and decision makers in real-time during the manufacturing process.

This chapter defines requirements for various types of DSS (see Power, 2002 and 2004, for details on the typology of DSS) in a smart manufacturing environment based upon increased use of optimization. It focuses on identifying key barriers which prevent the development and use of enhanced or “smart” DSS in manufacturing and then provides the requirement and architecture for a system engineering design for using optimization and other techniques with advanced computing and manufacturing technologies.

This review aims to promote a standard design or framework that is useful for both the manufacturing and academic communities that can facilitate needed efforts and innovation while stimulating adoption and use of smart manufacturing technologies.

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BACKGROUND

Mathematical models and optimization techniques are the driver for model-driven DSS. With regards to the structure of data and a problem's objective and constraints, many programming tools and mathematical algorithms are available to aid decision-makers in building a DSS with optimal recommendations. The critical step is to know the type of optimization algorithm needed to solve the problem. For more details on a taxonomy of optimization problems, one can refer to a comprehensive collection of optimization resources at https://neos-guide.org/.

Mathematical algorithms support convergence towards optimal solutions. This review classifies optimization problems in terms of traditional and intelligent approaches. The most commonly used intelligent optimization models are search-based (i.e., metaheuristic models), learning-based (i.e., machine learning models), uncertainty-based (i.e., robust optimization; stochastic optimization), simulation-based (i.e., Markov Chain Monte Carlo) and Markov Decision Process (MDP) (see Tao et al., 2016, for a comprehensive review on intelligent optimization).

Although using an intelligent optimization algorithm can gradually adapt a specific model-driven DSS for smart manufacturing, such a DSS requires several other criteria be met to be adequately intelligent. More intelligent DSS are created with a learning algorithm, a knowledge sharing system, and with cognitive computing capabilities. Nevertheless, in a smart manufacturing system, with connectivity among all manufacturing processes, an intelligent, integrated DSS is required to manage a manufacturing system. Features of an integrated, intelligent DSS include expert knowledge, risk management, production control, quality monitoring, marketing and sales management, project management, and supply chain (SC) support. Guo (2016) provides an extensive collection of DSS capabilities and features needed for managerial tasks of smart manufacturing integrated with intelligent optimization algorithms.

There is a gap in the literature on the applications of optimization techniques in DSS for smart manufacturing. Moreover, there is a lack of a comprehensive system design which can cover all types of DSS and managerial decision making (DM). This analysis identifies the requirements of parameter alignment, and conceptual design of an integrated, intelligent DSS for smart manufacturing by considering the core of an optimization procedure.

DECISION SUPPORT CAN AID SMART MANUFACTURING INITIATIVES

Manufacturing in developed nations must incorporate more data capture and decision support to control costs and maintain product quality. Digital transformation of manufacturing means production must be transformed using technologies like robotics, IoT, Intelligent systems, and real-time analytics. Smart manufacturing means all aspects of production are transformed so they are data, computing, and decision support intensive. Smart manufacturing has been defined by i-SCOOP.eu as the "fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs." Various decision support and data-driven capabilities must be incorporated in smart manufacturing systems, including:

Knowledge-Driven DSS

In a smart manufacturing environment, sharing expert domain knowledge at the manager-operator and operator-machine interface level is very important. Recommender systems and opinion mining can

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