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Performance evaluation of a manufacturing process under uncertainty using Bayesian networks

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ABSTRACT

This paper proposes a systematic framework using Bayesian networks to aggregate the uncertainty from multiple sources for the purpose of uncertainty quantification (UQ) in the prediction of performance of a manufacturing process. Energy consumption, one of the key metrics of manufacturing process sustainability performance, is used to illustrate the proposed methodology. The prediction of energy consumption is not straightforward due to the presence of uncertainty in many process variables and the models used for prediction. The uncertainty is both aleatory (statistical) and epistemic (lack of knowledge); both sources of uncertainty are considered in the proposed UQ methodology. The uncertainty sources occur at different stages of the manufacturing process and do not combine in a straightforward manner, thus a Bayesian network approach is found to be advantageous in uncertainty aggregation. A dimension reduction approach through variance-based global sensitivity analysis is proposed to reduce the number of variables in the system and facilitate scalability in high-dimensional problems. The proposed methodologies for uncertainty quantification and dimension reduction are demonstrated using two examples – an injection molding process and a welding process.

1. Introduction

In recent years, manufacturing processes and production networks have been rapidly pushing the envelope in building complex, optimized products, by taking advantage of new materials, advanced manufacturing techniques, and digital information technology. Along with such developments, it has become increasingly necessary to estimate the economic, social and environmental consequences of the manufacturing activities. Metrics such as energy consumption (in the larger context of sustainability), agility, and asset utilization are being studied to evaluate manufacturing processes and production networks. With the increasing complexity in modern manufacturing processes and production networks, quantification of performance metrics becomes quite complicated. Also, the presence of variability and uncertainty in different processes and their parameters contributes to significant uncertainty in the overall performance prediction. Therefore, it is essential to develop a systematic and rigorous methodology for quantifying the uncertainties in performance prediction in a complex production network. The errors and uncertainty need to be quantified at multiple levels and stages of the manufacturing supply chain, in order to facilitate resource allocation decisions regarding uncertainty reduction and risk management.

Uncertainty sources in various components of the production network may be broadly classified into three categories: natural variability in the manufacturing processes (aleatory uncertainty), information uncertainty due to inadequate, qualitative, missing, or erroneous data (epistemic uncertainty), and modeling uncertainty induced by assumptions and approximations (epistemic uncertainty). The focus of this paper is to develop a systematic methodology that quantifies the overall uncertainty in the computation of performance metrics as well as the contributions of individual sources of uncertainty to the overall uncertainty in the metrics assessment.

Quantification of uncertainty in manufacturing performance prediction in the manufacturing domain has been previously attempted using fuzzy set theory (Reza et al., 2013) and Monte Carlo simulations (Pehlken et al., 2015; Sonnemann et al., 2003). This paper pursues the Bayesian network approach for this problem. The Bayesian network allows the integration of various types of uncertainty that (a) occur at

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Nomenclature

$\boldsymbol{X}$	a vector of random variables
X	a single random variable
Θ	distribution parameters of a random variable
θ	a realization of distribution parameters of a random variable
Y	a single output random variable
G	a deterministic function connecting input to output variables
$Var()$	Variance operator
$E()$	Expectation operator
D	Observation data
$\boldsymbol{N_{obs}}$	Observed variables in a Bayesian network
$\overline{\boldsymbol{N}}_{\boldsymbol{obs}}$	Unobserved variables in a Bayesian network
Pr()	Probability density function
ABC	Approximate Bayesian Computation
AHP	Analytic Hierarchy Process
BN	Bayesian network
GSA	Global Sensitivity Analysis
MCMC	Markov Chain Monte Carlo
UQ	Uncertainty Quantification

different stages of the life cycle, and (b) combine in different ways (linear, nonlinear, coupled, nested, and iterative) (Sankararaman et al., 2011; Liang and Mahadevan, 2011). Information about various uncertainty contributors is available in heterogeneous formats and fidelity, from multiple sources (e.g., test data, expert opinion, operational data, legacy system data, and model-based simulations). The Bayesian network offers a systematic and rigorous approach for uncertainty integration and management, making use of all available heterogeneous information (Bartram and Mahadevan, 2014). The term "uncertainty integration" here implies the aggregation of uncertainty resulting from multiple sources.

Numerous applications of statistical process control have dealt with variability and quality control in manufacturing, by monitoring the variance of product features or manufacturing process parameters. The advantage with a Bayesian network (BN) approach is that it allows for multiple analyses such as sensitivity analysis, dimension reduction, resource allocation, model calibration, and forward uncertainty propagation, by fusing heterogeneous information. The methodology in this paper seeks to exploit these features of the BN for manufacturing applications.

Probabilistic graphical models such as Bayesian networks have shown much effectiveness in the aggregation of uncertainty information across complex networks in many application domains, such as information retrieval, data fusion and engineering decision-making (Dahll, 2000), safety assessment of software-based systems (De Campos et al., 2004), computational biology and bioinformatics (Friedman et al., 2004; Jiang et al., 2011), epidemiology (Jiang and Cooper, 2010), and civil infrastructure networks (Bensi and Der Kiureghian, 2010). Discrete probabilities have been considered in many applications of BN to risk analysis and decision-making (Castillo et al., 1999; Mahadevan et al., 2001), whereas recent work is expanding the BN approach to uncertainty quantification, diagnosis and prognosis using both discrete and continuous probabilities. The use of a BN for uncertainty aggregation across multiple physics and scales, and using experimental data at multiple levels, has been illustrated for mechanical systems (Urbina et al., 2012) and microelectromechanical systems (MEMS) devices (Ling and Mahadevan, 2013). Recent work has also extended the use of BN towards resource allocation decision making, in selecting the optimum combination of tests needed to meet the target uncertainty level in model prediction (Sankararaman et al., 2013).

The above research has focused mostly on the analysis of physical systems, not manufacturing environments involving multiple processes. So far, Bayesian networks have been used in the manufacturing domain for fault diagnosis (McNaught and Chan, 2011; Rodrigues et al., 2000) and discrete-event reliability modeling (Weber and Jouffe, 2006), but the focus in this paper is on information fusion, calibration of uncertain parameters, uncertainty reduction and handling of both discrete and continuous variables for performance prediction. Note that fault diagnostics and monitoring are focused on measurement and inference about the current state. Prediction involves forward uncertainty propagation, which has to include the contributions of both aleatory and epistemic variables. The BN framework accommodates both measurement and prediction as discussed in Section 2.

The Bayesian network enables analyses in two directions: (1) forward and (2) inverse. Forward propagation through the Bayesian network aggregates information from all available sources (e.g., models, data, expert opinion) to quantify the uncertainty in the overall performance metric of the manufacturing process, such as cost, material or energy consumption, CO_2 emission etc. Several types of inverse problem are of interest: data analytics, model calibration, fault diagnosis, process and quality control, resource allocation, and performance optimization; all these are enabled by the Bayesian network (Sankararaman, 2012).

Along with Bayesian network construction, variance-based global sensitivity analysis (explained in Section 2.C) can be carried out to identify the dominant variables affecting the uncertainty in the output; the variables (either input variables or model parameters) with low sensitivity indices can be assumed to be deterministic at their nominal or most probable values. In addition, the contributions of aleatory and epistemic uncertainty sources can be individually distinguished, using global sensitivity analysis. Sankararaman and Mahadevan (2013) assessed the contributions of aleatory and epistemic sources of uncertainty within a single random variable and illustrated the method with two simple mathematical examples. In this paper, that approach is extended for networks with multiple models and variables (some aleatory, some epistemic and some variables with both aleatory and epistemic uncertainty). Distinguishing the aleatory and epistemic contributions guides resource allocation towards uncertainty reduction, since only epistemic uncertainty is reducible.

The main contributions of this paper can be summarized as follows – (1) Development of an uncertainty quantification framework using Bayesian networks for the performance evaluation of manufacturing processes; (2) Development of a dimension reduction technique using variance-based global sensitivity analysis, clearly distinguishing the contributions of aleatory and epistemic uncertainty sources; and (3) Illustration of the developed techniques for two manufacturing processes – injection molding and welding.

The remainder of this paper is organized as follows. Section 2 provides an introduction to epistemic sources of uncertainty, Bayesian networks and sensitivity analysis. Section 3 describes the methodology for characterizing the uncertainty in manufacturing performance metrics using Bayesian networks, and Section 4 discusses dimension reduction using sensitivity analysis. In Section 5, two examples are provided to demonstrate the proposed methodologies in energy consumption in welding and injection molding. Concluding remarks are provided in Section 6.

2. Background

This section provides brief introductions to epistemic uncertainty representation due to data and modeling sources, Bayesian