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Rahul Singh University of North Carolina at Greensboro

Richard Redmond Virginia Commonwealth University

Victoria Yoon University of Maryland

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DESIGN ARTIFACT TO SUPPORT KNOWLEDGE-DRIVEN PREDICTIVE AND EXPLANATORY DECISION ANALYTICS

Design Science

Rahul Singh

Information Systems and Operations Management The University of North Carolina at Greensboro, Greensboro, NC rahul@uncg.edu **Richard T. Redmond**

Department of Information Systems Virginia Commonwealth University, Richmond, VA <u>Richard.Redmond@vcu.edu</u>

Victoria Y. Yoon Information Systems Department, University of Maryland, Baltimore County, Baltimore yoon@umbc.edu

Abstract

In this paper, we develop a novel design artifact to support knowledge-driven predictive and explanatory decision analytics for a complex business process. Following Design Science research guidelines in Hevner et al, (2004), we show the development of the design artifact and evaluate the artifact's effectiveness in providing intelligent decision support for a complex business process. We present a design artifact that provides predictive and explanatory analytics to support intelligent decision-making. We use a large, automated, continuous manufacturing process as the problem domain where the continual monitoring of the process using knowledgedriven, intelligent tools is useful for process monitoring and quality control problems. This research contributes to design science by explicating a novel artifact with predictive and explanatory features that are useful in intelligent systems design. It provides sophisticated and adaptable intelligent decision support to the problem domain of process control.

Keywords: Design Science, machine learning, decision trees, process control, intelligent decision support.

Introduction

Knowledge is an important organizational asset for sustainable competitive advantage. Organizations are increasingly interested in knowledge-driven decision analytics to improve decision quality and the decision support environment. This requires use of corporate data to develop higher-level knowledge in conjunction with analytical tools to support knowledge-driven analysis of business problems (Ba et al., 1997). Advances in systems support for problem solving and decision-making increasingly use artificial intelligence (AI)-based techniques for knowledge representation (KR) (Whinston, 1997; Goul et al., 1992; Goul and Corral, 2005). KR takes multiple forms including business rules, decision analytics, and business intelligence generated from various machine learning algorithms and data mining techniques. *Intelligence is the ability to act appropriately in an uncertain environment to increase the probability of success and achieve goals* (Albus, 1991). Intelligent decision support systems (IDSS) incorporate intelligence as problem domain knowledge with knowledge representation that informs and supports the decision process to facilitate problem solving and reduce the cognitive load of the decision-maker.

The manufacturing process is a critical business processes for any firm involved in the manufacture of tangible goods and has significant bearing on its competitive advantage. Considerable human and financial resources are involved in manufacturing process control to maintain product quality. Decision-making for quality control is a central activity in manufacturing organizations. Many complex relationships in manufacturing processes have direct bearing on analysis and decisions and have a significant impact on the product quality, process, s and profitability of the organization. These make the quality control problem challenging and a potent candidate for IDSS to support

problem solving for complex quality control problems in manufacturing processes. We propose a design artifact that supports intelligent decision-making and continually learns from process data to maintain accurate decision models. A large, continuous manufacturing process is the problem domain where continual process monitoring using knowledge-driven, intelligent tools has great utility to the quality control problem.

"Design science addresses research through the building and evaluation of artifacts designed to meet the identified business need....The goal of design research is utility" (Hevner et al., 2004). Design science improves the understanding of a problem domain by developing purposeful IT design artifacts that address important organizational problems. These innovations define the ideas and technical capabilities useful for developing systems for the problem domain. The design artifact includes the construct vocabulary and symbols, models that provide abstraction and representations, and methods and prototype instantiations that illustrate proof-of-concept for evaluation (Hevner et al., 2004; March and Smith, 1995). Research in systems makes a contribution by utilizing systems domain knowledge and problem domain knowledge to develop a better artifact for the problem domain, thereby improving the state of the art in the problem domain (Khatri et al., 2006). This, in turn, improves our ability to design better systems (March and Smith, 1995).

In this paper, we develop a novel and useful design science artifact to support knowledge-driven decision-making, including prediction and explanation capabilities, for a complex manufacturing process. We show the constructs and models, illustrate methods to develop the design artifact, and evaluate the artifact's effectiveness as an IDSS for a complex process. We follow design science research guidelines outlined in Hevner et al. (2004) and Vaishnavi and Kuechler (2006) and present a design artifact that provides knowledge-driven decision analytics in the complex problem domain of manufacturing process control. We show the verification and validation of the artifact using descriptive, analytical, and experimental evaluation methods as outlined in Hevner et al. (2004). The artifact developed in this research offers predictive and explanatory support through machine learning techniques that develop knowledge representation to support decision-making in the problem domain. The novel combination of these features provides features heretofore unavailable in the problem domain (Albus 2006). This research contributes to improving the decision analytic capabilities available in the problem domain by providing sophisticated and adaptable prediction of potential errors in the process (Albus, 1993; 2006). It contributes to design science by explicating a novel artifact with features useful to intelligent systems design (Mao and Benbasat, 2000; Ye and Johnson, 1995).

Background and Motivation

Problems in Process Control

Quality control problems occur when the final product is not within pre-established, acceptable parameters defined for normal operation. In such situations, process engineers and managers need to identify the problem, identify its causes, and select a requisite course of action to solve the problem. In addition, errors in the manufacturing processes need to be corrected as soon as possible to avoid waste of materials and consequent financial losses. *There is a practical temporal bound to decision-making regarding the course of action to take when errors occur in a production line.* An ideal system would incorporate early warning mechanisms to warn operators of imminent failures in the system so that action could be taken to pre-empt such situations.

Statistical process control (SPC) is a common approach for monitoring process quality. SPC examines preestablished measures of quality in the product and their association with critical measures of performance of the manufacturing process. SPC informs the user of the extent of conformity of the process with the established measures of stability by examining measures of central tendency and deviations. Quality control personnel, in conjunction with process engineers and managers, decide how to make changes to the process so that the product can conform to quality requirements. SPC offers no analytical or explanatory support to help decision-makers understand process failures, examine causes, and devise alternative corrective actions.

The use of SPC to examine the results of single measurements of process characteristics is easy to interpret. However, this does not capture the multivariate nature of complex processes. A linear relationship between process characteristics and product quality measures is assumed in SPC. However, there is a natural tendency for data that are collected from physically close sources to be related to one another. Such autocorrelation exists in data collected from the same machine, from the same production shift, or from the same batch of the product. Autocorrelation violates the linearity and independence assumptions of data. With autocorrelation, data on SPC charts may appear to be out of statistical control when the process may be running in a stable manner and producing good quality product. If any corrective action is taken on the process in response to these situations, the operator may run the risk of causing a stable process to become out of control. SPC may identify false positives and false negatives, leading to missing and misleading information in auto-correlated data; thus, it is not an accurate process and quality control technique in this regard.

A commonly used improvement of SPC is multivariate SPC that takes into account the multidimensionality of the data. Multivariate approaches identify the major contributors to variations in the process. Using techniques such as factor analysis and principal component analysis, multivariate SPC reduces the dimensionality of the process and makes it easier to understand the variations in the data. Multivariate statistical process control techniques account for existing relationships in the data. They provide a more suitable method for detecting errors in the production process. Manufacturing environments that produce a lot of correlated data usually have some variables that display a trend, while others follow this trend due to the existing correlation. This data typically has a small number of dimensions and a lot of variables that co-vary with these dimensions. Contribution plots can be used to identify the variable(s) that contribute the most to an out-of-control process. This approach is particularly useful for large and ill-conditioned data sets and provides a more accurate technique for the identification of problems in the manufacturing process (Kourti and McGregor, 1996). One drawback of multivariate control charts is that they do not directly provide the information an operator needs, such as the location of problems in the process and an explanation of its causes. *Multivariate techniques do not offer any analytical support for decision-making, and it is very difficult for users who are not trained in multivariate methods to understand the output of multivariate statistical process control.*

Artificial Intelligence Techniques in Process Control

Expert systems and neural networks are two techniques from AI used to support process control. Expert systems can be used to build system models and provide excellent analytical support for the decision-makers. Their strength lies in their ability to explain the alternatives and the decision choices to the user. Such models, however, are usually rule-based and do not capture all nuances of the system. Expert systems formalize the knowledge of domain experts and make this available to non-experts (Dhar, 1987). *Expert systems are not adaptive, and changes in the problem environment render the system inaccurate. Expert systems by themselves do not make effective process control systems* (Alexander, 1987).

Machine learning uses AI algorithms for machines to learn and exhibit *intelligent* behavior. Machine learning approaches are applied in the design of embedded systems to intelligently control the behavior of sub-components of the manufacturing process (Albus, 2006). This form of solution is usually applied to individual control loops or small pieces of machinery. Neural networks are very effective in developing models for non-linear systems that require the ability to handle noisy data. They are useful for manufacturing process data that is typically noisy and is missing observations due to intermittent failures of data collection devices. Neural networks can be used to provide effective process control with on-line, real-time data. The prediction capabilities of neural networks are used to develop early warning systems. Neural networks can be trained to build accurate, sophisticated, and dynamic models of the system. They are commonly used as embedded intelligent components for control loops of individual pieces of machinery and are rarely used to model the entire manufacturing process (Calabrese, 1991). They provide little support to help the user understand the process and fare poorly in providing analytical support and understandable representation of the system (Dagli, 1994). *Embedded solutions control the process with no human intervention and have no explanatory or interactive component to support managerial and engineering decision-making about the cause of the errors and its consequences to the entire production line.*

A real-time system can perform state transitions bounded in the temporal dimensions of the problem domain (Kratzer, 1992). All systems are required to enact changes of state in the current environment; the additional requirement on a real-time system is the temporal bound: A real-time system is conceptualized as a conventional system that satisfies the temporal bounds and constraints of the problem environment. The violation of temporal constraints may invalidate the operational consistency requirements of the problem domain. Real-time algorithms can then be defined as those that can be guaranteed to execute within a specified response-time window. Real-time systems have greater requirement in terms of speed, interrupt scheduling, and prioritization as compared to a conventional process (Kratzer, 1992). An important and practical need of manufacturing processes is the temporal constraint. With advances in manufacturing technology, more sophisticated methods produce more in less time. Without intervention, a process producing an inferior quality product will continue to do so, leading to more waste and consequently larger losses for the organization. This temporal constraint makes the task of detection and

correction of errors challenging in modern manufacturing environments. The real-time requirement is pragmatic in the context of continuous manufacturing environments where a faster response time can directly translate to a decrease in the number of out-of-specification products produced and a consequent decrease in waste of resources.

Decision Trees and Explanatory Decision Support

Models of decision problem domains provide analytical support to the decision-maker, enhance understanding of the problem domain, and allow the decision-maker to assess the utility of alternative decision paths for the decision problem (Goul and Corral, 2005). Decision trees are a popular modeling technique with wide applicability to a variety of business problems (Sung et al., 1999). The performance of a particular method in modeling human decisions is dependent on the conformance of the method with the decision-makers' mental model of the decision problem (Kim et al., 1997). The simplicity of model representation is particularly relevant if the discovered explicit models are to be internalized by decision-makers (Mao and Benbasat, 2000) Decision trees represent a natural choice for IDSS, whose goal is to generate decision paths that are easy to understand, explain, and convert to natural language (Sung et al., 1999). The choice of decision trees are among the most commonly used inductive learning techniques to learn patterns from data (Kudoh and Haraguchi, 2003; Takimoto and Maruoka, 2003). The ID3, C4.5, and SEE5 algorithms provide a formal method to create and model decision rules from categorical and continuous data (Takimoto and Maruoka, 2003; Kudoh and Haraguchi, 2003). Kiang (2003) compared multiple machine learning techniques and found that the decision tree technique had the most interpretive power. They suggest the use of multiple methods in systems for effective intelligent decision support.

The explanatory power afforded by decision trees comes from generation of understandable rules, clear identification of fields that are most important for prediction and classification, and the incorporation of explanation facility. Explanation is essential to the interaction between users and knowledge-based systems (KBS) describing what a system does, how it works, and why its actions are appropriate (Mao and Benbasat, 2000). Explanation can make KBS conclusions more acceptable (Ye and Johnson, 1995) and build trust in a system (Swartout, 1983). Decision trees lend themselves to automatic generation of structured queries for extracting pertinent data from organizational data repositories making, them particularly useful in providing insights and explanations for the non-technical user (Apte and Weiss, 1997). Decision trees are especially suitable for decision problems that require generation of human, understandable decision rules based on a mix of classification of categorical and continuous data (Quinlan, 1996). They clearly indicate the importance of individual data fields to the decision problem and reduce the cognitive burden of the decision-maker (Mao and Benbasat, 2000). Decision trees represent a powerful and easily interpretable technique for modeling business decisions that can be reduced to a rule-based form.

Design: Goals, Utility, and Requirements

Design is the use of scientific principles, technical information and imagination in the definition of a system to perform pre-specified functions with maximum efficiency. Information systems design is a goal-oriented activity (Simon, 1996; March and Smith, 1995). The design artifact includes *construct vocabulary, symbols, and models* for abstraction and representations, and *methods* and *prototypes* that illustrate proof-of-concept for evaluation (Hevner et al., 2004; March and Smith, 1995). Hevner et al., (2004) note the similarity between a *design artifact* and *IS Design Theory* (Walls et al., 1992). Design Science research develops artifacts useful in the application domain. Theories of *IS Domain knowledge* provide representations and techniques that form the basis for artifact development; while *Application Domain knowledge* organizes and structures constructs in the application domain (Venable, 2006). IS problem solving applies the IS domain knowledge and concepts to the theories of the application domain.

For the process control problem, a system has to intelligently process data in a timely manner, identify and react to subtle changes in process characteristics, evaluate their impact, and offer support to analyze interventions that mitigate these problems. Design requirements in this problem domain include:

- 1. Take a proactive role in identifying possible failures in sub-components of the process and indicate the possibility of their occurrence.
- 2. React to process anomalies in a responsive manner and suggest possible causes and reasons for their occurrence.
- 3. Use knowledge from process models to provide explanatory reasoning that supports decision-making, including process information, information about normal operations, and probable causes of error.

4. Use accurate and adaptive process models to analyze all aspects of the process. Models of the process must constantly adapt to changes in the process.

The techniques used to create sophisticated models depend on the data mining technique employed and the nature of the data used to create these models. It is the designer's responsibility to use appropriate technologies that fit the task at hand. For example, the use of artificial neural networks will create a complex, multi-level model that is very accurate in terms of predictions and learning the nature of the data sets. However, models created using neural networks are not very easy for humans to understand, and hence effort needs to be expended in terms of explaining the results that these models generate. On the other hand, decision trees offer a mechanism for creating models of the data that is easy to understand. However, the level of accuracy and extent of conformity with actual data using this approach is not as high as that obtained by using neural networks.

Data from dynamic processes is inherently dynamic. This implies that the relationships in the data are subject to change. Therefore, any system that supports decision-making based on these models should dynamically update the models to reflect current states of the process in light of changes in the operating environment. Otherwise, users run the risk of making decisions on information that does not hold true in the current environment. In the proposed system, the data mining component responsible for maintenance of the explanatory models of the system must constantly evaluate these models based on new data. This process will keep process models up-to-date with current data from the production process. This must be done in parallel to, and separate from, the active, on-line components of the system.

These goals guide the development of the following required features of the design artifact:

- a. <u>Proactive Analysis</u>: to analyze current data and check for conformity with system process models. If the current data conforms to known failure patterns, the system provides warning to avoid potential losses from process failure.
- b. **Interactive Analysis:** to interact with process models and decision-makers about the current process states based on explanatory models of the systems using current and historical data. This component should explain causes of potential failures and provide information on successful measures that have averted these failures in the past. In addition, this component should provide "what-if" and sensitivity analysis on the process and its sub-components.
- c. <u>Accurate models</u>: derived from process data to explain the relationships in the process data. The models should provide proactive and interactive analysis features of the artifact.
- d. <u>Model Updating</u>: to continually evaluate and re-generate process models to preserve their accuracy and synchronicity with current process states. This component is decoupled with current models and asynchronously trains itself and learns from new process data.

In this research, we develop a model that integrates the predictive capabilities of neural networks and decision trees and the analytical support offered by decision trees and on-line analytical processing technologies to support intelligent decision-making for real-time process control. Data mining is used to discover knowledge from process data and used in making intelligent decisions about the environment. An evolutionary approach is suggested in which the models are constantly reviewed as new data is gathered. This data is organized and presented for decisionmaking using OLAP to allow multidimensional views of the data. This integrated approach can be used to analyze incoming real-time data to locate and explain possible error conditions. An improvement on existing approaches, the integrated approach offers explanatory and predictive capabilities based on accurate and adaptive models of the process and provides early warning of imminent failures.

Design Artifact: Model and Instantiation

Here we discuss the design artifact of the intelligent DSS and its components. The conceptual model of the artifact is shown below in Figure 1.



Figure 1. Model of an Integrated System

The following sections provide an overview of the primary components of the artifact.

Manufacturing Process

The problem domain is an automated, continuous manufacturing process where data collecting equipment periodically collects various pre-established performance measures and deposits them in a repository. While manufacturing processes are usually continuous processes, data is typically collected at discrete time intervals depending on the sampling frequency of the data collection instruments. This data is used by process monitoring systems to monitor the process state using established process stability measures. Process control systems are event-driven systems. If critical variables are outside their established range, ad-hoc intervention is required for problem investigation. In current systems, the characteristics of such events are typically identified by expert opinion.

We used 41 process variables from a critical sub-part of the complete manufacturing process responsible for the final processing of raw materials to the final product. This sub-process was identified by the process experts as an error-prone and critical manufacturing process component. Therefore, it is a suitable target application area. An observation set representing normal process operation with known errors in the final output was used to train the knowledge discover components. Another set of observations that produced known errors in the output was used to test the effectiveness. For the prototype described here, the training set contained 10,000 observations of input and output variables, while the test set contained 1500 observations.

Process Data Repository

The manufacturing data repository stores multitudes of data from all parts of the process. The different data collection units from the process automatically store this data in the data repository. For most firms, this data is critical process data that is collected to monitor and control the manufacturing process. The data is typically time-

indexed to facilitate easy retrieval and processing. As discussed earlier, much of this data is usually not used by SPC systems. The ailment that these systems suffer from is not lack of data but rather too much data and not enough information, which creates low data utilization.

Knowledge Discovery Component

In the context of a real-time process control system, data mining can be used to extract meaningful relationships between the various data items in the production data. The application of machine learning and knowledge discovery techniques is a set of models of the steady-state process and conditions of departure from steady-state. The objective of the data mining process is to create a "model base" that describes the correct and incorrect operation of the production process in terms of process variables. They are tested and validated on historical data before being deployed in the system. The integrated system was implemented as an object-oriented system using the C++ programming language. The model base is mechanically updated on a regular basis. If known changes are made to the process parameters, the model base is regenerated by human intervention. The knowledge discovery component provides *proactive analysis* to monitor conformance of the process state in real-time and *explanatory analysis* models that support reasoning and drill-down analysis of process failures.

Predictive Process Analysis

Predictive models predict the future departure from steady-state from current process information. A primary requirement of such models is to identify imminent failures of the system and provide early warning. Machine learning algorithms learn historical patterns that have historically led to failure by using data mining techniques.

We utilize a back propagation-based neural network that is rigorously trained on failure and steady-state process data to create a prototype for the predictive models of process state. An artificial neural network (ANN) based on the back propagation algorithm is developed and trained on the actual data from the manufacturing process. The ANN is implemented with input nodes for process variables and output nodes for outcome variables. The two outputs represent the variables that have been identified by process experts to be critical measures of process stability. The ANN was trained on normalized data using the model means and standard deviations for the production process. A standard learning rate of 5% was used to train the network to within a 10% acceptable range of error using training data that represents the normal operation of the manufacturing process. After training, the ANN was validated against three regions representing test data for acceptable and unacceptable products. Table 1 below lists the "Hit Rate" for the ANN, a ratio measure of its prediction performance over the sample of data for three different product types produced by the manufacturing process. The prediction results of the neural network conformed to the acceptable error rate commonly used for ANNs in data mining literature and other manufacturing processes. Table 1 shows the accuracy of verification results for the ANN as a hit rate (the percentage difference between predicted and observed values). A product region denotes a particular product type produced by the manufacturing process. This ANN is used to examine data from the system and predict whether the critical variables are within their established ranges.

Product Type	Hit Rate
Product Region 1	96.6 %
Product Region 2	91.8 %
Product Region 3	94.2 %

Table 1. Neural Network Training Results.

The resultant trained ANN detects if a process stability measure is within acceptable, pre-established limits of operation. Information regarding the predicted values of these variables, obtained from the ANN, will be used to predict failure in the manufacturing process. *This differentiates our approach from other methods of error detection in that the prediction is obtained from non-linear models of the system that incorporates the autocorrelation and inter-relationships among process variables.*

Explanatory Process Analysis

Explanations from the design artifact support decision-making and knowledge-based search for data analytics using data queries based on process knowledge. Rule-based inductive learning algorithms, including decision trees, use

process data to create models with decision paths for process outputs using inputs to the process. The root node of a decision tree has the largest discriminating power to differentiate between states of the process. Each subsequent node of the decision tree is an input variable of the manufacturing process. The number of children for each node of the decision tree is based on the number of categories that the variable exhibits in the training data set. Training a decision tree generates "if-then" rules that classify each output value of the system based on the observed ranges of input values.

We used a modified ID3/C 4.5 algorithm (Quinlan, 1996) to develop rule-induction-based decision trees that explain deviations in critical process variables. The output variables are categorized based on the acceptable control limits as set by the manufacturing process experts. Every leaf node of the decision tree is a boolean outcome representing whether the path from the root to a leaf node results in an acceptable value of the output. Once the training set is adapted into categorized values, the decision tree algorithm uses these categorized values to create the decision tree that creates branches at each node based on these values.



Classifying the output shows whether an output variable is within or outside acceptable control limits. Each decision tree path is a set of input variables, their respective value ranges, and a state of the system represented by the value of the output. This creates "if-then" rules that specify conditions for the process stability. For example, Figure 2 represents a decision tree with input and output variables, each with two categories that represent the variable being within or outside control limits. The decision tree of Figure 2 can be interpreted into rules based on the values shown using depth-first traversal. For example, the first depth-first traversal path of the decision tree of Figure 2 generates the following rule:

If Input 1 is in category 1 and Input 2 is in its category 1, then the output is out of specifications.

Rules are created for every depth-first traversal of the decision tree. All rules are examined for error conditions that have occurred in certain output variables. Each decision tree node stores the number of examples in the training data that follow each possible branch disseminating from a node. The number of examples along a path provides a measure of the strength of the path of the decision tree. The result of training the decision tree component of the integrated system is a set of trained decision trees from which a set of "if-then" rules for each output variable is extracted. Each branch of a decision node is created based on the ranges of values, which are incorporated in the explanations offered by the integrated system.

Knowledge-Driven Analysis Component

Knowledge Driven Analysis (KDA) is a key component of the design artifact and required for the utility of the artifact in the problem domain. We utilize multi-dimensional analytical tools to provide this functionality in the design artifact. Online Analytical Processing (OLAP) is a class of technologies that provide, s multidimensional views of data supported by multidimensional database technology. This technology is suitable for multidimensional data with a temporal component, such as manufacturing process data. The KDA component accepts event trigger

data from the multiple data collecting devices of the process and analyzes using the ANN predictive models for the likelihood of a process error condition. When an event trigger detected by the KDA component identifies an imminent problem in the process, action is required. The KDA component flags the process as leaving the normal operating range and informs users of an imminent problem in the process. This is done by a comparison of predictions from the ANN and normal operating range means of the critical variables of the process, and thenrefined and verified by actual process data.

The KDA component retrieves decision tree models of relationships between the critical variables and creates data for all variables that help explain the errors based on the decision tree paths for the output variables under analysis. The data are defined by the model of the effect of the critical out-of-control variable, or variables, and the set of process characteristics it is known to affect. If sufficient evidence of process error is not discernible from the event triggers, then the KDA component passes the variables under consideration to the data mining component and new associations must be derived for those data items as relationships develop between the critical variables and the process variables under consideration. Depending on the observed data and the extent of system information, the KDA component queries the process models for data on developing error conditions. If this query returns a positive result, it is passed to the user interface with explanations of emergent errors and a prognosis for variables to examine. In addition, a set of output and input variables are provided to the knowledge discovery component to search for associations. A set of variables along the decision tree path are the artifact's best estimate of causes for the error under consideration. This set of variables is passed to the KDA component as dimensions along with the trends in the process for decision analysis. This information is incorporated into the views of the system developed for the user analyzing the process. The user can analyze trends in the key variables that are causes of error over time. For instance, the user may view standard deviations outside control limits, note deviations of key variables, and create additional customized views. These dimensions may include variables organized by physical proximity in the manufacturing process, historically error-prone parts of the process, and additional dimensions. These machine learning. AI-based components of the artifact capture and model existing relationships and are used to support the knowledge-driven explanatory analysis of process errors to meet design requirements of the artifact.

Design Artifact Evaluation

Here, we provide a two-step approach for validating the design artifact following the research evaluation guidelines from Hevner et al. (2004).

- a. *Analytical and Descriptive*: We provide descriptive and analytical evaluation by examining the structure of the artifact for its qualities. We show how the artifact and its components provide functionality that is beyond the capability of the existing methodologies and meets the needs of the problem domain in a manner that the extant methods cannot. This speaks to the intrinsic components and features of the artifact and their utility for the problem domain.
- b. *Experimental*: We provide the results of a controlled experiment and test the hypothesis that the artifact is functionally able to expose the same errors that a traditional SPC systems does, while providing functionality that other systems are not capable of.

Analytical and Descriptive Evaluation of Design Research

We extract key dimensions of process control to gauge the effectiveness of any solution in the problem domain. The integrated system is compared with SPC based on their effectiveness to identify process control problems. Their respective strengths and weaknesses on some key dimensions of the process control problem and on the overall system effectiveness are evaluated. We discuss why the integrated system is expected to perform better than SPC using arguments grounded in the benefits of the two approaches as they apply to the process control problem domain.

The comparison between the two approaches is made on dimensions relevant to the process control problem including:

- 1. The ability to <u>detect and explain errors</u> in the process,
- 2. The <u>flexibility and adaptability</u> of the approach with respect to changes in the product type and changes in standards for individual products and environmental conditions,
- 3. Access to summary information about the product and process characteristics, and

4. The <u>ability to predict errors</u> in the outputs from examination of system inputs.

Detection and Explanation of Errors

A primary functional requirement of an effective approach to process control is to detect errors in the process by examining the process data. A process error is defined as a condition where one or more output variables are outside normal operating parameters. The purpose of the design artifact is to identify the error and its causes to provide better knowledge-driven decision analytics. The proposed artifact offers explanations of the causes of the error so the decision-maker can decide on a requisite course of action to correct the error. These explanations are the primary contribution of the artifact to the existing state of the art in process control. The ability of the artifact to detect and explain errors comes from the combination of knowledge discovery and knowledge-driven analysis. This assists the usability of the artifact for the novice user while maintaining a high level of sophistication in the decision analytics used to develop the process models. The artifact detects the errors in the process, offers causes for these errors, and provides information related to these causes to allow the user to make an informed decision regarding the cause and subsequent correction of the error. This relies on the availability of a decision tree path created through sufficient training examples so that the knowledge reflects most types of errors. The artifact may not be able to explain all instances of process errors without retraining the data-mining--ased components of the integrated system. Specifically, the artifact will not detect or explain errors that are novel because they were not part of the training set. This limitation is true of all machine learning-based solutions and is overcome by a continual evaluation of process models and re-training based on changes in the problem environment.

Flexibility and Adaptivity

A process control approach should be flexible enough to incorporate changes in the manufacturing environment. Changes in product types, and corresponding changes in process specifications, are frequent occurrences in modern manufacturing processes with high levels of automation and flexible manufacturing environments. The design of process control systems must take into consideration the changes in standards as production shifts from one product type to another. Process control systems should be flexible enough to accommodate changes in the values of the control limits as required by production changes from one type of product to another. The stability of a process is measured by the degree of conformance of process characteristics to established standards. These standards are routinely revised due to changes in manufacturing technology or product characteristics. Changes in standards for a process cause a change in the acceptable control limits of the process control system. A process control system must be able to adapt to changes in the operating environment (Albus, 2006). AI systems adapt to their operating environment through training. This often time-consuming yet critical task is essential for the system models to accurately reflect the environment. Training requires model training data selection with both good and bad examples for the system to learn the intricacies of each. A trained system can identify the different states of the environment that it models. Effective modeling of dynamic environments is a very challenging task. For an AI-based system to be adaptive to changes in conditions of the environment, the system must include a retraining component in the process of the development of the artifact. New models that reflect changes in the environment allow the system to adapt.

Access to Summary Snformation

The system must support KDA to provide the user with summary information regarding the various process and product characteristics to support decision-making regarding the process. The system responds to queries for summary information and provides process critical information on a regular basis as an indication of process stability at any given point in time. The presentation and content of this information should be done to facilitate making decisions regarding the process. The artifact incorporates all benefits of OLAP and provides a mechanism for flexible analysis. The primary contribution of the artifact here is that it generates the summary information based on the dimensions that are identified by the machine learning components. Hence, the integrated approach can provide efficient access to summary information on the dimensions identified in process models in addition to those identified by users' queries.

Prediction Capability

The ability of a system to accurately predict the conformance of the quality of the product to standards by examination of the process characteristics is a desirable feature of a process control system. Most current process control methods *do not* have the capability of predicting future product quality by examining current process characteristics. This prediction capability is different from looking at current process characteristics to indicate current product quality, which is the principle of statistical process control methods. Hence, this capability adds to the functionality of existing methods. The ANN component of the artifact has predictive capabilities to determine future values of outputs based on the current values of the inputs. The neural network can be trained on inputs in the present to predict outputs at a later point in time.

Experimental Evaluation of Design Research

Errors identified by process experts to be representative of common errors that occur frequently in the manufacturing process were used as a basis for evaluating the effectiveness of the design artifact. Process experts described measures that were taken to correct these errors and parts of the process that were identified as causes. We wanted to see if the design artifact would identify variables from the same process. Through these successful corrective measures, it is possible to identify the variations in the input variables that would explain why these errors took place, according to the experts. The data from the manufacturing process containing these errors was analyzed using SPC by process experts and the design artifact. The set of variables identified by these groups to be the cause of the errors was recorded and compared with the set of variables identified by the artifact. The schematic of Figure 3 represents the comparisons to be made.



Figure 3. Comparisons to Generate Hypotheses.

Process experts are used as the control group in this test. We are interested to see if the artifact provides any information that is misleading by identifying causes that were not identified by the process experts such that V(IS) - V(E) is not null. We are also interested to see if the artifact missed information provided by the experts, such that V(E) - V(IS) is not null. While addition tests against the efficacy of the artifact are possible, since the artifact incorporates all elements of SPC, we do not explicitly test them in this paper. In addition, since the set difference between the variables identified here represents ordinal data, we are not able apply statistical tests to the hypothesis and have to rely on ordinal comparisons. This does reduce the power of the comparative tests of the hypothesis presented here.

Hypothesis:

H1:
$$\{V(IS) - V(E)\} = \Phi$$

This hypothesis states that the set difference between the set of variables identified by the integrated system and the set of variables identified by the manufacturing process experts is the null set. This implies that the integrated system also identifies the variables that are identified by manufacturing process experts to be the cause of errors. The set difference between the set of variables identified by the integrated system and the set of variables identified by the manufacturing process experts to be the cause of errors. The set difference between the set of variables identified by the integrated system and the set of variables identified by the manufacturing process experts represents misleading information provided by the integrated system. If this hypothesis is true, then this difference must be a null set, which implies that the integrated system does not offer any misleading information about the errors that occur in the manufacturing process.

H2: $\{V(E) - V(IS)\} = \Phi$

This hypothesis states that the set difference between the set of variables identified by the manufacturing process experts and the set of variables identified by integrated system approaches a null set. This implies that the manufacturing process experts also identify the variables that are identified by the integrated system approach to be the cause of errors in the manufacturing process. The set difference between the set of variables identified by the manufacturing process experts and the set of variables identified by the integrated system represents information about causes of error missing from the explanations offered by the integrated system. If this hypothesis is true, then this set must be a null set, which implies that manufacturing process experts do not offer any information that is missing from the explanations offered by the integrated system approach about the errors that occur in the manufacturing process.

Experiment

The complete data set consists of 10,000 observations. Each observation contains 42 input variables and two output variables collected from a critical part of the process. Output variables are identified by process experts to be critical measures of the stability of the part of the manufacturing process under consideration. The input variables are all variables that are collected from the part of the manufacturing process under consideration.

For each product region type, the artifact was trained on the training set for that output region, and the models for that region are obtained in the form of a trained neural network and decision trees for each output variable. The trained models are applied to the verification data for that output region, and the variables that are outside prespecified control limits are identified. This set of variables is compared with the set of outputs obtained from manufacturing process experts.

Each error observation was given to the decision tree component of the artifact to retrieve a decision path with the set of variables as the cause of the error. The decision tree also generated a range of values for each variable on its path. This set of variables and their respective value ranges were then formatted to generate natural language explanations for the cause to explain errors to users.

Error Observation Sets	Variables Identified by Integrated System: V(IS)	Variables identified by Experts: V(E)
Error Set 1	6, 41	
Error Set 2	6, 41	6 25 27 20 41
Error Set 3	6, 41	0, 33, 37, 39, 41
Error Set 4	6	
Error Set 5	3, 4, 6	6, 35, 37, 39, 41

The following summarizes the variables identified as causes for errors in the manufacturing process.

Table 2. Summary of Verification Output Values

Errors in a manufacturing process usually exist for a few minutes. During this time, the process stabilizes and the process parameters return to the normal conditions of operation due to corrective action taken by operators. Occasionally the process re-establishes without any corrective action. In the data used for this research, this time period for error typically spans multiple observations. In fact, typical errors span multiple observations, while single observation errors are usually incorrect readings or "spikes" that are essentially outliers that have a negligible effect on the quality of the product. Hence, groups of error observations that occur in continuous blocks of time are of greater concern than individual errors that are occur in single observations.

H1: $\{V(IS) - V(E)\} = \Phi$ Fail to reject this hypothesis.

This hypothesis states that the set difference between the set of variables identified by the integrated system and the set of variables identified by the manufacturing process experts is the null set. Failure to reject this hypothesis implies that the integrated system also identifies the set of variables identified by manufacturing process experts to be the cause of errors and does not offer misleading information in the verification data about the errors in the manufacturing process.

H2: $\{V(E) - V(IS)\} = \Phi$ Reject this hypothesis.

This hypothesis states that the set difference between the set of variables identified by the manufacturing process experts and the set of variables identified by integrated system approaches a null set. Failure to reject this hypothesis would imply that the manufacturing process experts also identify the variables that are identified by the integrated system approach to be the cause of errors in the manufacturing process. Accepting this hypothesis would imply that the manufacturing process experts do not offer any information that is missing from the explanations already offered by the integrated system about the errors in the manufacturing process that occur in the verification data.

Discussion

H1 cannot be rejected based on the results in the table above. The set of variables identified by the integrated system to be the causes of error in the data sets considered include the variables that are identified by the manufacturing process experts. From the results, there is not sufficient evidence in the data to reject this hypothesis. The integrated system also identifies those variables as causes of errors that the manufacturing process experts do. Failure to reject this hypothesis implies that for the data under consideration, the integrated system does not offer misleading explanations in the verification data about errors in the manufacturing process.

H2 is rejected based on the results. In each output region, for all identified sets of error, the set of variables identified by the integrated system approach is consistently different from those identified by the manufacturing process experts. The variables identified by the manufacturing process experts are not also identified by the integrated system. The integrated system approach provides explanations that are consistently missing some of the variables identified by the manufacturing process experts to be the causes of error. There is sufficient evidence in the data to reject this hypothesis.

The artifact can be used to analyze incoming real-time data to predict, identify, and explain possible error conditions in the process. As an improvement on existing approaches, this approach offers explanatory and predictive capabilities based on accurate and adaptive models of the process and offers early warning of imminent failures. Once an error occurs, the system identifies this by comparing the incoming data with the models of the process. If the error is confirmed, then the current parameters of the process are used to generate explanations for why the error has occurred. These explanations are provided to the user in the form of easy-to-understand if-then rules with information on current values of the system parameters. The system identifies the process variables and reports values that are causes of error. This information is intended to be a set of alternatives with which the user can investigate in the physical process in order to solve problems with the current manufacturing process.

Conclusions

This research presents a design artifact that provides predictive and explanatory decision analytics to support intelligent, knowledge-driven decision-making for complex manufacturing processes. The artifact builds accurate and dynamic models of the process and provides knowledge-driven, analytical views of the data to support intelligent decision-making in this environment. The solution is tested by comparing the results obtained by the proposed system with those obtained from standard process control methods. Results are validated using manufacturing process experts for controlled comparison. Results show that the artifact identifies and explain errors in the process data. It also offers explanations that provide information for decision-making about the environment. The integrated approach offers content-knowledge-based explanations about the nature of the errors and their causes and supports analysis of cause. The integrated approach also provides additional information about these causes of error using decision tree models that supply information about the output variable in question and the input values associated with the output. These explanations take the form of natural language explanations of the output variables' states due to values of the inputs. These explanations can also take the form of queries used to materialize multi-dimensional views of the data from actual operation of the system. This information is knowledge-based and multi-dimensional, and it concerns the operations of the problem domain. Therefore, the artifact can provide valuable information to support the decision-making process and meet the requirements of the complex process analysis in the problem domain.

The proposed artifact provides means for knowledge-driven analysis of large volumes of data by combining methods for developing analytical models of data with means for analysis of large volumes of multi-dimensional data at multiple levels of abstraction to be useful in the problem domain. This approach needs to be tested on other environments and problem contexts in order to address generalizability. This research focuses on data mining the environment to develop explanatory and predictive models to provide appropriate, multidimensional views of the data. Little has been done to develop methods to integrate data mining and OLAP to provide a systematic method for decision-making that allows users to examine multiple views of the data that are generated using knowledge about the environment and the decision problem. Our current and ongoing research looks at the application of an artifact with predictive and decision analytic capabilities in more traditional business processes.

We have followed the process of design science research and guidelines outlined in Hevner et al. (2004) and presented a design artifact with clear utility in the problem domain. We use advances in machine learning and decision analytic techniques to meet the requirements of the problem domain. This is verified and validated through a simple experiment that shows that the results from the artifact are similar to those offered by process experts and

no worse than the current state of the art in the problem domain. In addition, the artifact offers predictive and explanatory models that are pertinent to the problem domain and are well beyond the capabilities of the current state of the art. In this respect, the design artifact presented makes a systems contribution to improving the capabilities of current process control models and advances the level of decision analytic capabilities available in the problem domain. It makes a contribution to design science by outlining an artifact with predictive and explanatory features that have shown to be useful in IS literature (Mao and Benbasat, 2000). Knowledge-based systems and knowledge-driven decision analytics that reduce the cognitive burden of the decision-maker are desirable design artifacts. Our future work addresses the ability to develop design artifacts with these capabilities to a variety of business problems, leading to the development of design theory for incorporating predictive and explanatory knowledge-driven analysis in systems.

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