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Tracing the Interrelationship between Key Performance Indicators and Production Cost using Bayesian Networks

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Abstract

Key performance indicators (KPIs) are used to monitor and improve manufacturing performance. A plethora of manufacturing KPIs are currently in use, with others continually being developed to meet organizational needs. However, obtaining the optimum KPI values at different organizational levels is challenging due to complex interactions between manufacturing decisions, variables, and desired targets. A Bayesian network is developed to characterize the interrelationships between manufacturing decisions, variables, and selected KPIs. For an additive manufacturing case, it is shown that the approach enables appropriate value estimation for decisions and variables for achieving desired KPI values and production cost targets in a manufacturing enterprise.

Keywords: Manufacturing performance indicators; Cost modeling; Bayesian networks; Additive manufacturing

1. Introduction

Manufacturing exists as a cornerstone of modern economic systems. Throughout the history of industrialization, society has progressed towards more efficient resource utilization with the help of technological advancements. Manufacturing enterprises, as they exist today, require transparent and integrated departments, such as sales, marketing, design, manufacturing, and quality control, which communicate from idea conceptualization to final product realization. Such integrated product development processes increase the number of stakeholders associated with each new product and, in turn, increase the number of decisions made across the production enterprise. Decisions on design constraints, choice of raw materials, choice of manufacturing processes, and required manufacturing process parameters are challenging to make and, at times, can be counterintuitive due to unforeseen tradeoffs. Thus, for efficient operation of a manufacturing enterprise, production decision (type of product, type of manufacturing process, manufacturing location and material supplier location, etc.), design decision (part dimensions and shape complexity), and manufacturing decision variables (process parameters) need to be identified, modeled, and compared against key performance indicators (KPIs) and manufacturing targets, such as production cost.

Manufacturing industry and academia have worked towards developing different KPIs to measure and monitor the success of an enterprise based on objectives of performance [1]. KPIs have been identified and developed for measuring performance in various domains, e.g., economic, environmental, social, product design, production, quality, and labour [2]–[4]. To efficiently measure, record, and monitor KPIs, decision makers

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must understand how individual stakeholder actions affect the various KPIs. However, the number of decisions, variables, and their interactions within an enterprise make it difficult to simultaneously observe and control changes in KPIs. Hence, mapping the interrelationships between KPIs, manufacturing decisions, manufacturing variables, and manufacturing targets is required to optimize KPI values and improve overall manufacturing performance. Towards that goal, a Bayesian network (BN) based monitoring strategy is proposed, which is well-suited to characterizing the complex interrelationships between manufacturing decisions, product design variables, manufacturing parameters, KPIs, and manufacturing targets (here, we choose production cost as the target) [5], [6].

A process-based cost model is used in this study [7]. The cost model is translated into a BN to estimate the most favourable manufacturing decisions, manufacturing variables, and process parameters for the chosen process for achieving specific KPI values, including cost targets. The approach is then used to estimate manufacturing variables (e.g., annual production ratio, product build time, and material use efficiency) to optimize specific KPI values. The BN strategy is demonstrated for production of a shell and a tailpipe for a turbine assembly [8], using wire and arc additive manufacturing (WAAM) and electron beam melting (EBM).

The manuscript is organized into several sections. Section 2 provides an overview of Bayesian networks. Section 3 describes the application of the BN methodology for the additive manufacturing case study. Section 4 discusses the results from the developed BN for the case study. Section 5 presents the conclusions of the work. Section 6 discusses limitations of the current model and future development efforts.

2. Bayesian Networks

Bayes' theorem describes the probability of occurrence of an event based on the prior knowledge of conditions that might have some relation to the event [9]. A BN uses this Bayesian inference to assign and update probabilities for a hypothesis as it is exposed to more evidence or information. A BN is often used as an inference tool, which is capable of using available information from a subset of variables in a system, to predict the behaviour of other parts of the same system [9]. In recent times, BNs have been employed in various disciplines such as engineering, natural sciences, medicine, sports, and economics, largely due to their advantages, as explained by Heckerman [10]: 1) ability to handle incomplete datasets by encoding statistical dependencies between the variables, 2) ability to learn causal relationships between the variables within a system to perform interventions and investigate predicted results, and 3) ability to model domain knowledge and data simultaneously, making it a sophisticated package for data analysis.

A BN uses Directed Acyclic Graphs (DAGs) to represent the dependencies within a system (comprising all the variables and decisions). Each manufacturing variable or decision is represented as a node in the BN. The dependency between variables or decisions are represented by arcs (unidirectional arrows) connecting the respective nodes. Parent nodes feed dependencies into the dependent child nodes, forming a hierarchy of decisions. Based on the dependencies between different variables, their joint probability distribution can be factorized into a set of conditional and marginal probability tables. The network uses these probability tables at each node to make inferences during simulations [11].

The causal relationships between nodes in a BN can be created using empirical data and machine-learning techniques. Alternately, knowing the interactions between variables from expert knowledge or literature, this information can be fed to the network in the form of connections (arcs) between nodes and the probability tables. In this research, cost models for products produced using additive manufacturing are translated into a causal graph using Dimensional Analysis Conceptual Modeling Framework (DACM) [12]. The resultant causal graph is used as a DAG for implementing the BN to provide interaction capabilities. The emphasis given to cause-effect relationships via the use of a causal graph provides an intuitive approach to explicitly evaluate the uncertainties in potential decisions and their outcomes with the use of probability tables. The rationale for implementing cost models in a BN is to leverage its ability of characterizing the impact of intrinsic and extrinsic factors on the different cost categories. Factors such as market forecasts, supply chain uncertainties, and market fluctuations can be modeled into the BN as extrinsic factors under certain boundary conditions. This approach will reduce the effective person-hours and effort required to estimate production costs for possible scenarios.

The different nodes of the BN are connected and their interactions are modeled using mathematical equations and conditional statements. Several cost modeling strategies, such as activity-based costing, product-based costing, process-based costing, bottom up costing, and top-down costing, have been developed for characterizing production cost [5], [13]–[15]. For the current case, a bottom-up, process-based costing method is used to evaluate the two manufacturing choices (WAAM and EBM) [7]. The methodology for translating deterministic cost models into a BN is explained in Section 3 using the additive manufacturing case, but the approach also applies for other processes.

3. Methodology and Case Study

The methodology developed herein facilitates modelling the manufacturing performance metrics for a product during early design by using a BN. The model herein characterizes manufacturing decisions, design and manufacturing variables, and KPIs into quantifiable production cost metrics for additive manufacturing processes. Production cost is modelled using six cost components: facility cost, capital cost, utilities costs, raw material cost, labour cost, and maintenance cost. Consumables cost is not considered in this study. Raw material transportation cost is added to examine the influence of raw material supplier location on production cost. The six cost components are dependent upon factors such as manufacturing location, type of manufacturing process, raw materials used, source of raw materials, and transportation modes, to name a few.

The first step in implementing a BN is to develop a holistic system model in which design and manufacturing variables, constraints, and decisions are defined. As noted above, the case study considers the manufacture of a shell and tailpipe for a turbine assembly using WAAM and EBM. The functionality of the two additive manufacturing technologies have been discussed in prior studies [16]. WAAM uses an electric arc as the heat source and wire as the feedstock. The equipment considered in this study is a collaborative setup consisting of a six-axis ABB robot arm for the welding torch and Fronius welding equipment based on cold metal transfer (CMT) technology. In comparison, EBM is a powder bed fusion process, wherein an electron beam is used as the heat source and metal powder is used as feedstock. The electron beam scans over the powder following a pre-defined toolpath for each layer, heating it to a temperature at which the powder fuses based on tool path and layer profile information.

The geometries of the shell and tailpipe are predefined. Six KPIs are used to evaluate the performance of the system by considering social performance (labour productivity), environmental performance (energy intensity and percentage of recycled materials in manufacturing), production performance (order-to-delivery lead-time and setup rate), and production quality (scrap ratio) metrics. The different decisions for the system, KPIs, and key manufacturing variables and their values are reported in Table 1. The defined system model and cost models are translated into a DAG (Fig. 1) using DACM, and the BN is implemented using BayesiaLab 8 modelling software [17]. The network represents all variables, decisions, and targets as nodes. The decision nodes (green) are connected to manufacturing variables with arrows, which represent the interactions between each decision and the connected variable. The KPIs (blue) and cost categories (red) represent target nodes. Each manufacturing variable node's interaction with decisions and targets are modelled using system constraints and the deterministic cost models.

The probability tables are obtained using a sampling technique similar to the Monte Carlo method. The governing equations obtained through DACM are used to propagate several samples from the independent variable nodes (parent nodes) to the dependent variable nodes (child nodes). Sampling starts with defining the domain (value range) of the child nodes based on the domain of the parent nodes and the governing equations that determine the relationship between the parent and child nodes. The domains of the parent nodes and child nodes are then divided into multiple states. The user has the freedom to set multiple states and the range of each state can be normalized or set freely. The granularity of the results depends on the number of states and the ranges within these states. Next, a number of random sample values from each defined state of a parent node are obtained and the resultant value for each child node are calculated using the governing equations. A counting method is then used to count the number of samples that lie within each state of the child node. This count is used to calculate the conditional probability that a sample from a specific state of the parent node will result in the value of the child node being in a specific state. For example, we take 1000 samples from the first defined state of the parent node. Then, the corresponding values of the child node are calculated based on the sample values from the parent node and the governing equations.

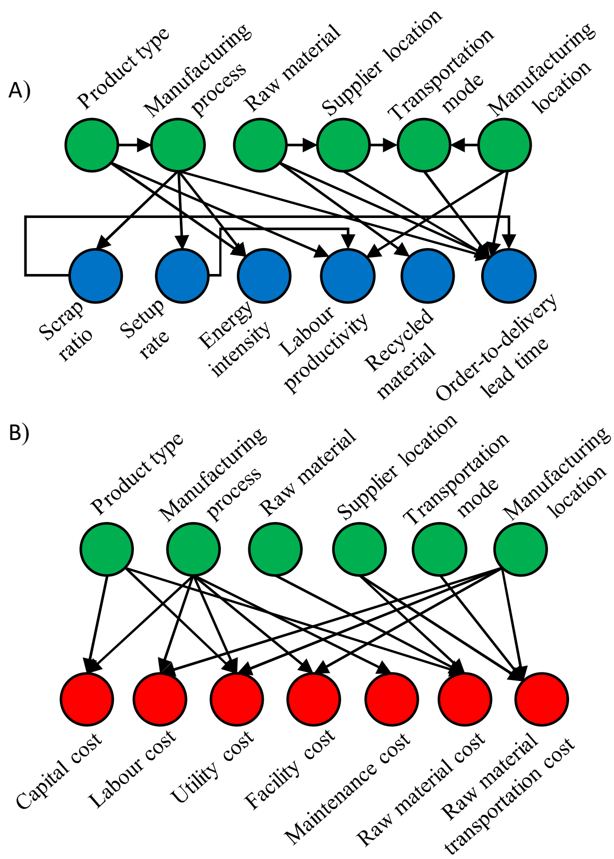

Fig. 1. Directed acyclic graphs (DAGs) with causal relationships between A) manufacturing decisions (green) and KPIs (blue) and B) manufacturing decisions (green) and cost targets (red).

Now, if 800 calculated values for the child node lie within the range of the first state of the child node, then the probability that the calculated value for a child node will be in the first state for a sample taken from the first state of the parent node is 80%. Using this method, conditional probability tables are computed for all the nodes in the network.

The final computed network allows the user to compare the impacts of different decisions on KPI values and production cost. For instance, selection of different production processes will result in use of different manufacturing equipment. This will in turn affect the facility cost, capital cost, maintenance cost, utilities costs, labour cost, production performance, and environmental performance of the system. Similarly, each of the other decisions is linked to several or all cost and performance metrics. Hence, it is important to measure, record, and visualize the impact of these decisions on cost and other performance metrics to make better choices. Based on the level of accuracy and granularity that is required for the BN, the production cost targets can be represented as a range or as precise cost estimates.

The usability of the developed method is demonstrated for estimating production cost and the above-mentioned KPIs for different manufacturing decisions. Two scenarios are chosen to evaluate BN performance and estimate target values. The results are presented and discussed in Section 4.

4. Results and Discussion

The developed BN is evaluated under two scenarios to understand how the decisions made (in green), the key performance indicators (in blue), and cost categories (in red) interact with each other. Scenario 1 defines the product type and type of manufacturing process; its impact on the cost and the performance indicators are observed by simulating the network. In the Scenario 2, the user is allowed to set target cost ranges for total production cost and labour cost; fix the range for one manufacturing variable, build time; and fix one KPI, order-to-delivery lead-time. The model responds to Scenario 2 by providing the user with the necessary decisions that should be made in order to attain the desired targets. In both the scenarios, with each decision made, the system computes the joint probability for the whole network based on the likelihood of occurrence of that particular choice. On the condition that evidence is introduced in any of the nodes, the system will then compute the posterior probabilities for all nodes within the network. The extent to which the nodes are affected by changes made to corresponding nodes depends upon the relationship between the nodes.

In the BN, prior to manually making any decisions for the decision nodes, the system autonomously presents an initial probability for choices of the decisions and variable nodes. This initial probability is the result of the probability distributions of the nodes, which propagate through the network. It is dependent on the interactions between the different nodes, the joint probability of the network, and the conditional probability table within each node.

Table 1. Bayesian model decisions, KPIs, and variable descriptions.

Decisions	Choices	
Product	Shell and Tailpipe	
Manufacturing process	WAAM and EBM	
Raw material	Titanium and Aluminium	
Manufacturing location	USA and China	
Raw material supplier location	USA, China, and India	
Transport mode	Rail, Road, and Sea	
KPI	**Description**	
Scrap ratio	Ratio between scrap quantity and processed product quantity	
Setup rate	Ratio between actual unit setup time and actual unit processing time	
Recycled material use	Percentage of materials used that are recycled input materials	
Energy intensity	Ratio of electricity generation and transmission losses (based on locational electricity mix) to the total direct energy required to manufacture the product [7]	
Order-to-delivery lead time	Latency between the initiation and execution of process	
Labour productivity	Ratio between value of monthly product shipped and monthly labour expenditures	
Variable	**Unit**	**Ranges / Discrete values**	
		EBM	**WAAM**
Material processing rate	kilograms/hour	0.2	2.9
Equipment floor space	square meters	4.46	24.15
Setup time	hours	1.3	4

This results in the choice of product as tailpipe (54.42%) compared to shell (45.58%) because the conditional probability that the shape complexity is two (2) corresponds more to the product tailpipe. Similarly, the choice of manufacturing process node favours EBM (54.42%) over WAAM (45.58%) for both products. EBM is capable of producing highly complex parts with better accuracy than WAAM and hence, a higher probability for EBM is calculated by the network for a shape complexity value of two (2) or higher.

For Scenario 1, we set the product type as *tailpipe* and the type of manufacturing process to be *WAAM* by providing evidence to the BN that the probability is 100% for *tailpipe* and *WAAM*. This evidence is provided solely for the sake of simulation. Users may make other similar choices, depending on their needs and the type of analysis required. Based on the provided evidence, we can see that the values for facility cost, capital cost, labour cost, and maintenance cost increase (Fig. 2). The increase in facility cost, capital cost, and maintenance cost is due to the larger equipment floor space and high equipment cost associated with the WAAM machine. The major change was seen in the medium (M) state range for capital cost ($1,900-$3,800) and maintenance cost ($400-$800) with increases in likelihood of occurrence of the medium state for the two cost components from the original values of 21.71% and 23.13% to 34.59% and 37.75%, respectively.

Manufacturing process selection is followed by the choice of raw material, which is chosen to be aluminium due to its low cost. Lack of granularity in the defined state ranges for the cost of raw materials node, however, prevents users from making inferences related to the raw material cost. It is prematurely set to be in the low (L) state range due to the prior decisions (product type and manufacturing process).

Nevertheless, based on the model, the unit price of the raw materials is low for aluminium, which is priced at an average of $56.60/kg, compared to titanium with an average of $410.00/kg. Hence, with better granularity in the states, the effect of raw material unit cost would be visible on the total raw material cost for the product.

The next decision is regarding the raw material supplier location and the manufacturing location. The choices with the highest probability are USA for the raw material supplier location and China for manufacturing location. For these two choices, the constraint nodes in the network ensure that the transport mode chosen is by sea. The immediate effect (Fig. 3) was observed in the increase in transportation time (736 hours or 30 days) and the cost of raw material transportation, which now lies in the high (H) state range ($40-$90 per product). In addition, choosing the manufacturing location as China reduces the labour cost significantly; the hourly labour rate for skilled labour in China is $3.22 versus $16.60 in the USA [18].

The total cost of manufacturing the goods in China with raw materials sourced from the USA has a likelihood occurrence of 87.95% in the low (L) state range (up to $21,897) and a mean value of $13,647. The alternative of having the manufacturing facility in the USA, sourcing materials from within the USA, and having the transport mode as rail results in an increased mean value for overall total cost ($13,835) (Fig. 4). This change is again due to the higher labour rates in the USA compared to China. Therefore, the savings in transportation cost are dominated by increased labour costs, for this case.

In Scenario 2, an inverse evaluation is conducted to evaluate the effect of fixed cost targets and KPIs on the available choices for decisions. By defining the total cost of manufacturing to lie in the medium (M) state range ($21,897-$43,795), a significant change in the probabilities of certain decision choices is observed. The likelihood of manufacturing the shell using titanium as the raw material sees an increased probability (an increase of 38.13% for the shell and 37.43% for titanium). Next, setting the build time to the high (H) state range (227-342 hours) further confirms the manufacturing decisions of producing the shell using titanium, but also provides new information regarding which manufacturing process to consider. The analysis strongly suggests (100% likelihood) that EBM should be used for manufacturing the shell; EBM has a lower material processing rate (0.2 kg/hr) than WAAM (2.9 kg/hr) and thus, a high build time, but higher quality.

Another change observed is that labour cost has an increased tendency to lie in the high (H) state range ($3,900-$5,700) due to the longer build time. Setting the labour cost to the high state range, the model informs us that the manufacturing location should be in the USA. Lastly, the manufacturing facility should abide to strict delivery policies requiring low order-to-delivery lead times. This means that the setup time, build time, and transport time must be low. Therefore, we see an increase in the likelihood of the raw material supplier to be located in the USA and the transportation mode to be rail or road.

From the foregoing, it can be seen that using the BN model would enable industrial decisions makers to understand the consequences of the various decision choices on production performance metrics and cost targets. It is worth noting that the percentages for low, medium, and high ranges do not add up to 100% in some cases, due to presence of another range, called the filtered state. As the name suggests, the values in filtered states are outliers, which cannot physically exist in the real world.

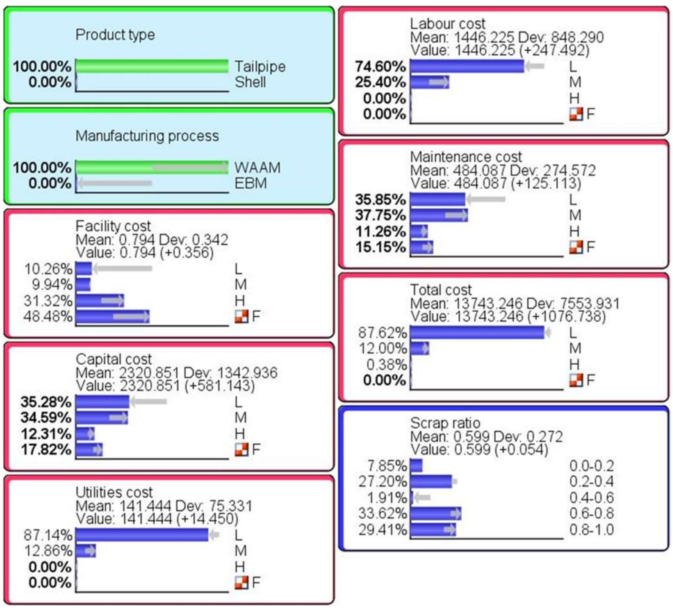

Fig. 2. Simulated results for fixed product (tailpipe) and manufacturing process (WAAM) in Scenario 1.

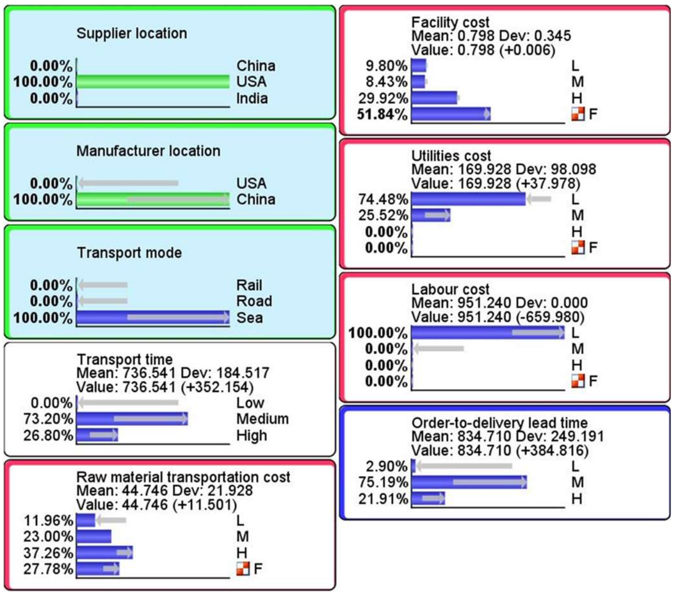

Fig. 3. Simulated results for fixed supplier location (USA) and manufacturing location (China) in Scenario 1.

For each parent node and its corresponding child nodes, the software computes values for all combination of numbers that fall in the ranges of the parent nodes, resulting in unfiltered ranges in computed values for the child nodes. These unfiltered values propagate throughout the model, and as the complexity and number of nodes increases in the model, the unfiltered ranges also compound. To reduce compounding we introduce filtered states to perform filtering.

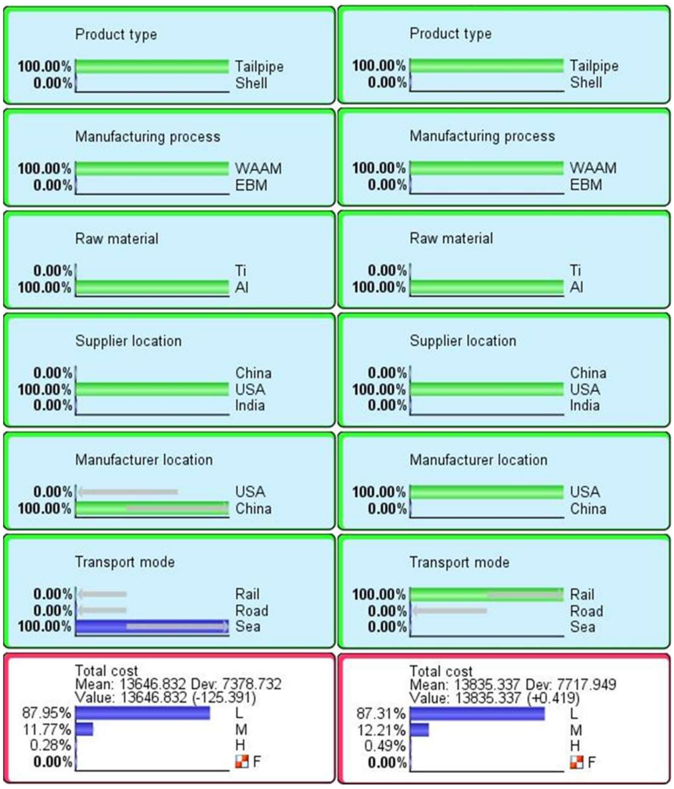

Fig. 4. Comparison of total production cost for set supplier location (USA) and manufacturing location (left - China, right – USA).

5. Conclusions

A Bayesian network (BN) as an interactive multi-criteria decision-making tool in manufacturing performance analysis was developed and demonstrated for an additive manufacturing case to characterize the influence of manufacturing decisions, variables, and constraints on manufacturing KPIs and targets. This method enables a decision maker to observe the effect of their decisions on target performance variables, and vice versa, to obtain information about the most probable variable values and decision choices. The interactive nature of the model makes it an effective tool for stakeholders at different levels of the enterprise to visualize the cause-effect relationships between their choices for performance targets, design constraints, and manufacturing variables.

The DACM framework enables integration of different forms of knowledge (e.g., expert opinion, qualitative models, and deterministic models) into a causal graph for developing the BN. This paper proposes using the DACM framework as a basis to systematically establish causal graphs and governing equations among the influencing variables. The BN is then established as a means to integrate decisions into the casual model and provide interactive analysis to the model. The simulated production cost and KPI values reported herein are not exact; rather, the model provides estimated ranges in which the costs are likely to lie. Hence, system-modelling using a BN offers a preliminary screening method to eliminate combinations of bad decisions. After narrowing down to a select combination of good decisions, real costs and KPI values can be estimated using deterministic methods. The methodology developed is generic and can be applied to any multi-criteria decision making problem supporting multiple types of decision processes.

6. Limitations and Future Work

Causal graphs of the production system, implemented in Bayesian networks (BNs), offer a powerful tool to characterize a complex system at different levels of detail and granularity. It is interesting to note that all nodes in a BN are linked to one another either directly or indirectly for computing the joint probability of the modelled system. During simulation, a marginal probability distribution of the states of the nodes can be displayed. The display shows the mean value for the state of a node where the probability of occurrence is maximum. The value displayed represents the mean of the entire range of a state in a node, and should not be considered to be exact.

Future research will leverage the ability of a combined DACM and BN approach to integrate different forms of knowledge/data. With growing concerns of industrial sustainability, such efforts can enable translation of sustainability reports of different corporations belonging to different types of industries into BN graphs (cause-effect graphs). The value for such research lies in the ability to understand, through visualization (graphs), the sustainability performance measures affecting variables specific to an industry, those specific to individual departments within an enterprise, and those variables with commonalities across different industries or departments. Such evaluations can help industry implement selective measures that target the impactful practices at each level of an organization as well as to implement measures that improve the overall sustainability performance across industries. It is essential for researchers, along with industry partners, to perform inference studies to understand which managerial decisions have a positive impact towards reaching the goals of the manufacturing enterprise. Insights from such inference studies will help in sustainability performance-based future sight and decision-making.

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