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ABSTRACT

More recently, interest in designing products and manufacturing processes with major consideration given to the resources used and waste produced over the entirety of product/process life cycle, viz. sustainable manufacturing has increased. Unlike design and manufacturing process development activities that generally have access to a wealth of material information, sustainability assessment activities are generally made difficult by lack of a centralized source of information to incorporate sustainability knowledge into current manufacturing life cycle strategies. Even though considerable research has been accomplished in sustainable manufacturing domain, its application to real life problems is known to be in the early stages due to complexity in information representation, model compositions, system integrations, and computation. Moreover, isolated activities of process planning within the gate-to-gate life cycle can lead to localized solutions in sustainability assessment. Integrating operation plans and process plans provides globalized sustainable and productive solutions in the manufacturing gate-to-gate life cycle. This thesis, first, presents an attempt to understand these complexities for building material information model by addressing the requirements for defining a high-level material information model for sustainability that can capture this information across different life cycle stages as well as primary stakeholders. Second, the performance of job shop manufacturing is often related to diversified activities that impact sustainability and productivity. Process and operation plans are particularly considered as the main activities that significantly impact different key performance indicators. The research proposed a systematic methodology for supporting manufacturing decision-making regarding sustainability and productivity assessment by integrating these plans.

In the first stage the different ways in which materials and material information influence the decision-making process were analyzed. For this purpose information modeling techniques were employed to generate manufacturing scenarios. Activity models were generated and analyzed to collect and categorize key concepts towards constructing a Materials Information Model for Sustainability. The analysis helped in identifying locations where materials factor into the decision-making process, the key information requirements that help build a material information model for sustainability. In the second stage of this research, a systematic methodology was developed for enabling the sustainability and productivity performance assessment for integrated process and operation plans at the machine cell level of manufacturing systems. Selection of processes and operations is accomplished through building a Multi-Criteria-Decision-Making formulation. This formulation enables the combined assessment of sustainability and productivity in selecting the optimum process and operation plans. Analytical Hierarchical Process (AHP) is employed to address the problem of conflicting key performance indicators during process planning. Discrete event simulation (Arena™) and optimization techniques (heuristic search algorithms in OptQuest) are combined to determine the set of inputs out of a number of possible planning scenarios and their interactions that optimize system sustainability and productivity performances. The possibility of applications of the approach to real-world production is demonstrated through a case study that uses the proposed methodology to analyze and understand manufacturing floor-level scenarios.

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DEDICATION

This work is dedicated to the twelfth Imam Muhammad ibn Hasan al-Mahdi.

CHAPTER 1

INTRODUCTION

Introduction

Sustainability and sustainable manufacturing are becoming increasingly important from social, economic and manufacturing contexts. Though sustainability is a well-researched area, very little work is done in defining a material information model and using that model, and hence the information it provides to arrive at optimal decisions in the manufacturing context. This thesis precisely addresses this gap.

The first part this thesis provides a set of information requirements that support building a centralized material information model, which address variations in the way the material information is used, and provide transparency for viewing material information across the life cycle stages of product. This type of material information model (MIM) will be an important resource in the development and assessment of sustainable products and processes. MIM will also define the interfaces among different stakeholders' activities that are involved in manufacturing life cycle as well as allowing for a better understanding of sustainability tradeoffs for design-time decisions. Centralizing information will be supported through globalized information, which can be shared between different life cycles and stakeholders activities. An interface between different activities within the manufacturing life cycle gate-to-gate (G2G) is, therefore, imperative. A review of literature suggests that process planning and operation planning are the most dominant activities for process planning in their large impact on sustainability and productivity. In the second part, therefore, this thesis addresses a systematic methodology for integrating process and operation planning through simulation and optimization techniques for assessing sustainability and productivity of a manufacturing life cycle.

1.1 Background and motivation

Sustainable manufacturing is now considered a vital feature of global economy and sustainability. According to the World Commission on Environment and Development (WCED), sustainability will be attained when the remaining natural resources of the earth are used in a manner that satisfy the developmental needs of the present generation without compromising the ability of future generations to meet their own needs [1]. Industry efforts were often focused at the enterprise level aimed at large-scale implementation [2]. As sustainability practices have matured, industry has redirected its efforts to address smaller-scale needs particularly in sustainable manufacturing efforts [3] for increasing efficiency and decreasing waste during manufacturing [4]. As the costs of energy, water, and resources increase, sustainability-conscious companies must benchmark sustainability metrics. These include metrics like carbon footprint to facilitate adequate energy, water, and resource reduction strategies to lower operational cost.

Research suggests that the practice of sustainable manufacturing can be scoped to address the creation of sustainable impact at all stages of a product's life cycle, from material extraction to product disposal [5]. As such, recently more efforts are being directed towards understanding product life cycle interactions, and their implications on sustainability. The designs for sustainability, disassembly, and recycling, etc., are the outcome of such efforts. Many, if not most, of these efforts are to bring life cycle analyses into design-time consideration [6]. However, in the context of sustainability, there is still much to learn about the interactions between design-time decisions and their manufacturing implications. In studying these interactions, efforts are prone to rely on available manufacturing process data, such as that available with Life Cycle Inventories (LCIs), and how this data can be used to incorporate sustainability into design considerations. Moreover, the lack of models that could support standardized decision-making activities at their life cycle domains presents a major challenge in this field.

The major activities involved in the manufacturing life cycle (i.e. gate-to-gate life cycle; *henceforth,* G2G life cycle) concentrate on: making the part, identifying the types of machines, identifying stock materials or components to be used, selecting and sequencing the major processes to be performed that include cutting and forming processes, assembly processes, and finishing processes and inspection processes. Material properties may decide what processes can be used, and how these processes should be controlled. Assigning the appropriate materials to the appropriate manufacturing production processes thus becomes rapidly critical for sustainability assessement specially environmental impacts [7]. Consequently in the context of sustainability, material and process selection play a vital part in determining the total life cycle impact.

1.2 Statement of the research problem and discussion

Although support for sustainable decision-making continues to mature, challenges to its standardization and implementation remain. This section elaborates on the research problem and the solutions proposed through this research.

1.2.1: Problem 1: Material information model for sustainable manufacturing

Sustainability assessment activities are generally made difficult by a lack of understanding of the information requirements for determining the sustainability impacts pertaining to both engineering materials and manufacturing processes. This lack of information leads to scenarios where localized and suboptimal solutions may be reached at the cost of exploring more inclusive global alternative options. Moreover, cost savings, customer demands, tightening legal requirements and a building pressure for environmentally friendly products are increasing awareness of sustainability in global industries. Industries are also held accountable for assessing organizational sustainability performance and operational efficiency. To facilitate sustainability assessment, information should be adequately incorporated at the design stage and uniformly represented to the design community in the same location as other information such as material structure and propertie. Moreover, the stakeholders' (decision-makers) activities interactively contribute to manufacturing methods. Knowledge of how each stakeholder relates to a particular stage of the manufacturing life cycle, and knowledge of which criteria/metrics of the sustainability that each stakeholder considers, facilitate sustainability assessment.

Material information offers a solid foundation to support sustainability assessment as materials impact the entire life cycle of a product. However, access to this information is constrained by the many different views through which materials are understood and represented. As a product progresses through the different life cycle stages, the perspectives from which the material is viewed may change. This inconsistency is reflected in the many different ways material information is captured, stored, and presented. In a given scenario, to produce a given design, the manufacturer needs to select a particular material and a particular process from among a set of materials and processes. Each combination contributes to sustainability and productivity differently and the challenge lies in selecting the best combination. For example, water consumption and energy consumption can be considered as two sustainability metrics. Therefore, a stakeholder first requires computing each of these metrics for a given design-material-process combination. However, assessing individual metric values could cause optimizing one metric at the cost of another. Thus, one must define and develop a methodology for aggregating different key indicators for sustainability and productivity.

The basic objective of selecting any manufacturing processes, material removal or additive processes, is to produce a given part blueprint at a minimum cost where the design requirements and master production schedule are met. Yet today, the increasing awareness for sustainability issues is forcing product designers and manufacturers to be conservative in shop floor decisions including process selections and sequencing. Understanding these challenges will help decision-makers to advance not only their sustainability knowledge, but also performance knowledge on productivity, and agility regarding the influences and interrelationship of the manufacturing activities that contribute in fabricating/assembling a given design. A product may also be realized through different activities that typically result in different environmental and productivity impacts. These activities affect resources usage such as of tool, lubricant, energy and cost, and also impact the quality of the product. Additionally, the settings determine how long it takes the product to be processed through the shop floor thereby affecting overall throughput and productivity. If this information regarding sustainability and productivity impacts is available at the design stage, the designer can specify the product and associated processes with combined minimal impact.

A MIMS thus needs to focus on the identification of core information requirements at the design time throughout the life cycle of the product, and supporting the information needs of different decision-makers at different stages of the product life cycle. Supporting these information needs requires the understanding of decision-time criteria from sets of globally dispersed information from across the life cycle.

1.2.2: Problem 2: Integrated optimization and simulation modeling framework for sustainable manufacturing

With a unified MIMS for sustainability all the information that will be mapped for designing a specific process plan will be based on the sustainability objective such as selecting processes that has less environmental impact or selecting process settings that are more productive. However, besides sustainability, productivity and agility also play a significant role in how the manufacturing system performs, or how it complements the design systems. One of these problems is selecting processes and process settings that are sustainable and productive. Conventional process and operation plans have been sequential activities within the process-planning framework. With the help of MIMS these can be integrated. The second part of this research, therefore, examines the candidate process and operation plans for a given design that has less impact on sustainability, and which improves productivity among other different candidates. This methodology thus can also help in two ways: in the first phase it proposes process and operation plans that are more sustainable and productive; and in the second phase, it utilizes the information to modify a given design for sustainability and productivity.

Traditionally, process planing and operation planning have been two sequential activities within the overall process planning framework. These activities are often performed by different stakeholders in the production organization. Process planning activities such as machine tool and tool assignment, determining process sequence, and defining tool paths are created by a processing engineer [8],[9]. On the other hand, operation planning activities are usually formed by production engineers who evaluate current production activities and make recommendations for improvements, develop best practices to improve production capacity, quality and reliability, and develop operating instructions and equipment specifications for production activities [10],[11]. Production engineers, thus, are not involved at the decision-making stage for establishing a sequence of manufacturing operations that are based on examining the engineering drawing of the part and enterprise strategic planned goals. The process sequence is decided at early stages in process planning and is later provided to secondary levels for process settings. Various manufacturing technologies such as main shape generating processes, joining techniques, assembly systems and surface engineering processes require that selection is based on the factors appropriate to that specific technology [12].

The need for more flexible process planning in which information can be shared and integrated to better support product fabrication with respect to sustainable, profitable, productive, and technical concerns has underscored the importance of combining different decision-makers at machining operation planning. The research goal is to build a stepwise novel reasoning information model at the machine level of the manufacturing system that systematically models process planning information. To ensure that machined part sustainability and productivity criteria satisfy the required specification, simulating the manufacturing system will provide meaningful and practical plans. Quantitative determination of energy, cost and time associated with manufacturing operations will enable quantitative evaluation of optimal plans based on pre-defined goals. The proposed methodology has been applied in a job shop framework. The simulation model establishes feasible manufacturing process sequences and searches for optimal plans abased on the respective goals from various stakeholders.

To assist in planning for the manufacturing processes, methods and tools are required for assessing the sustainability and productivity impacts in the early stages of product and process design and planning. Process planning is influenced by production requirements for each job and available technology. The effective utilization of resources (e.g., machines and workforce) has to satisfy both the strategic and operational goals. Therefore, to properly address, describe, analyze, and optimize the performance indicators for these manufacturing activities, a systematic methodology for building a multi-criteria optimization model for evaluating alternate process plans is presented in this research. The solution is generated with the use of discrete-event simulation.

Simulation enables decision-makers to represent a system in a virtual environment, and to test and evaluate the system's performance under different operating conditions. Moreover, making decisions from the large number of possible alternatives requires combining simulation with optimization methods.

Brady and Yellig [9] proposed two approaches for integrating simulation and optimization. The first one is to construct an external optimization framework around the simulation model. The second one is the internal approach, to investigate the relationship between input variables based on the dynamics of their interaction within the simulation model. This methodology builds on the second approach to optimize the simulated process planning scenarios and in cases where aggregated indicators are required to be simultaneously optimized, a multi-criteria decision making (MCDM) was utilized. The overall methodology is designed to provide decision-makers with guidance for selecting the best sustainable and productive scenario in relation to resources, processes, machines, tools, materials, and auxiliary materials selections for manufacturing a given part design. To test this methodology, different machining shop floor scenarios are developed as simulation inputs to predict system sustainability and productivity performance.

1.3 Research objectives

From the above discussions and evaluation, the following research objectives are defined:

(1) To analyze the requirements for material information model for sustainability

(2) To build a data model that captures the parameters needed for determining targeted sustainability and productivity metrics

(3) To map the sources of data for the sustainability and productivity assessments

(4) To build a multi-criteria decision model to aggregate productivity and sustainability indicators for evaluating process planning scenarios, and

(5) To use optimization and simulation models to integrate process and operation planning activities for evaluating their performances under different realistic scenarios.

1.4 Innovations and contributions

In this thesis a material information model based on activity modeling is developed. Specifically, G2G manufacturing is addressed through the use of activity models. By analyzing these activity models, the research collects and categorizes the key concepts towards constructing MIMS. The requirement analysis provides the context for the sustainability decision criteria that must be supported to facilitate decision-making, driving the information requirements of a MIMS.

Selection of process and operation is accomplished through building a multi-criteria-decision-making model formulation. This formulation enabled the combined assessment of sustainability and productivity in selecting the optimum process and operation plans. This thesis formulates an Analytical Hierarchical Process (AHP). The analyses addressed the problem of conflicting key performance indicators that affect one another during process planning – for example, the improvement of one performance indicator (e.g., energy consumption) may be at the cost of the others (e.g., tool usage).

To evaluate alternative scenarios and to generate outputs for optimization-based modeling, this thesis builds a simulation platform using a discrete event simulation package (Arena^{TM}) and optimization algorithms embedded in OptQuest. The synthesis of optimization and simulation in capturing the complexities and dynamics of the manufacturing system are novel in this thesis.The systematic methodology employs the search algorithm embedded in the OptQuest optimization to perform a non-monotonic search. The successively generated inputs produce comparable evaluations. Although, not all of the solutions (output) improve the scope of the analysis, over time they provide a highly efficient trajectory to offer solutions. The process continues until the termination amount criterion is satisfied. This is usually based on the decision-maker's preference for the time to be devoted to the search, which has been exemplified through a case study.

In this thesis, life cycle stages and stakeholders' perspectives are represented using activity models. Analyzing these activity models with respect to the needs of stakeholders and information model helped in providing the key requirements on which a MIMS can be designed. Based on this idea a methodological approach was constructed to select the optimum process and operation plans in gate-to-gate life cycle for assessing sustainability and productivity. The methodology comprised of building a data model that captured the parameters required in determining the sustainability and productivity metrics (i.e. energy, time, cost, and carbon emission).

1.5 Outline of the thesis

In Chapter 2, requirements to establish sustainability material information model is analyzed in terms of life cycle stages and their significant stakeholders. Chapter 3 describes the new systematic methodology that is developed in this research. Chapter 4 illustrates a case study that demonstrates the methodology. Chapter 5 concludes and summarizes this dissertation. And Chapter 6 discusses the directions for future research.

The Appendices include a description of the types of database and the summaries of Arena models.

CHAPTER 2

INFORMATION MODELING REQUIREMENTS TO SUPPORT SUSTAINABLE MANUFACTURING

In chapter 1, we have defined two problems addressed in this research. In this chapter, we elaborate on problem one, which is to identify the core information requirements at the design time throughout the life cycle of the product, and supporting the information requirements of different decision-makers at different stages of the product life cycle.

2.1 Background

To support manufacturing for sustainability, the impacts of material choice need to be considered early in the product design phase, when resources are being committed. Materials provide a path for studying interactions between design and manufacturing, promising to offer valuable insight into the sustainability consequences of a manufactured product. Many different factors determine the sustainability of a product and its associated processes, and these factors need to be made explicit when it is time to make a decision. In this chapter, the different ways in which materials, and material information, influence decision-making processes are analyzed. This research analyzes these scenarios and identifies locations where materials factor into the decision-making process. Moreover, key information requirements factoring in to the development of a Material Information Model for Sustainability (MIMS) are identified. Based on these investigations, a set of core information requirements that will aid the development of an adaptable material information model to support decision-making in sustainable manufacturing are proposed.[1]

Researchers at the National Institute of Standards and Technology (NIST) have proposed the development of a material information model for sustainability (MIMS) to facilitate sustainability-driven decisions across the life cycle [14], [15], [16]. Starting with design time and throughout the life cycle of a product, a MIMS focuses on the identification of core information requirements to support material information from across the life cycle. While the synthesis of such material information is a daunting task in itself, one of the foremost challenges is supporting the information needs of different decision-makers at different times. This requires the understanding of decision-time criteria from sets of globally dispersed information from across the life cycle. To this end, the work detailed in this chapter investigates the role of material information in sustainability-driven decision-making across a life cycle, and particularly in manufacturing.

2.2 Understanding Life Cycle and Stakeholder Perspectives

Sustainability is a distributed, life cycle-driven problem, but decision-making is often constrained by available information and may result in localized solutions. To evaluate, and predict the sustainability impact of a product, it is critical for decision criteria to provide insight into its overall bearing, from product design, to production, to use and end of life impacts. In practice, decision-makers are often asked to focus on a

[1] Qais Hatim, Paul Witherell, KC Morris, Sudarsan Rachuri, Christopher Saldana, and Soundar Kumara Requirement Analysis for a Material Information Model to Enable Sustainability Assessment – submitted to *Information Systems Frontiers* and in NIST peer review process (Editorial Review Board ERB)
Al-Khazraji, Qais.Y., Saldana, C., Sudarsan, R., Kumara, S. (2013). Material Information Model across Product Life Cycle for Sustainability Assessment. Appeared in *20th CIRP Conference on Life Cycle Engineering LCE 2013*
Al-Khazraji, Qais.Y., Saldana, C., Donghuan, T., and Kumara, S. (2013). Information Modeling to Incorporate Sustainability into Production Plans. Appeared in *9th 2013 IEEE International Conference on Automation Science and Engineering* (CASE 2013)

single, localized stage of the life cycle, such as design for remanufacture at end of life, or lean manufacturing during production. One might focus on product composition, such as with the use of recycle materials. These decisions are often made in the context of the life cycle stage. The decision criteria are often presented in a limited context, overlooking the possible incorporation of inputs from across the life cycle. A goal for MIMS, a crosscutting, globalized approach, is to support the incorporation of distributed life cycle impacts through material-related information. The value of material information when making decisions regarding sustainability is greatly influenced by how the information is represented, and how it can be interpreted. The challenge is to provide the right information at the right time, to help make an informed decision. This context requires understanding 1) what life cycle stage(s) are providing the context that sustainability with which information is being associated (beginning of life, end of life, overall impact), and 2) to whom the information is being provided.

2.2.1 Sustainability Information by Life Cycle Stages

Materials can play significantly different roles in sustainability impact depending on the life cycle stage with which the information is associated or at which decision is being made. For example, material density may affect sustainability impact at the usage stage while melting point may affect sustainability impact during the manufacturing stage. In addition, it is important to realize the challenges that can be created by different information representations associated with different stages. The ability of a MIMS to support inputs from across life cycle stages is crucial as it (1) provides decision-makers with a holistic view of a problem, (2) supports decision-making based solutions in the context of stakeholders’ objectives and constraints, and (3) provides a unified communication structure among stakeholders at different life cycle stages to facilitate information sharing and exchange.

Design and planning stages: At the early stages of the product life cycle, information requirements focus mostly on design details. These may be the most critical stages, as the early stages of the product life cycle have been shown to determine about 70% of the overall costs [17], [18], [19]. This cost commitment reflects the significant amount of resource utilization determined in the early design stages, when it is important to make as much sustainability-related information as possible. Material information at the earliest stages of the product life cycle traditionally focuses on the metrics needed to meet performance, quality, and cost requirements. Material representation at the design stage varies in detail depending on the application. Material information is, however, different at the manufacturing and end-of-life cycle stages. For instance, at the manufacturing stage, it will include attributes of density, strength, and cost resistance to corrosion. Also any product design requests a certain profile of the material attributes. There are conflicting objectives that engineers and designers have to optimize in choosing the optimum material for specified applications within G2G. These objectives can be from selection of a cheaper material for more economic benefits to lighter material for reducing energy consumption (e.g., fuel) and carbon footprint emission. While at the end-of-life cycle stage, the value of a product is determined by whether it is disposed, recycled, remanufactured or is handled in some other way within the retrieval infrastructure. Work at NIST on the Core Product Model (CPM) [20] and later the Semantic Product Meta Model (SPMM) [21] focused on developing core representations of product information, providing placeholders for material without defining many specifics. Standards such as ISO 10303 (e.g., STEP) [22] and ISO 13584 [23] have been developed to support product requirements, but also offer some material support.

Manufacturing stages and systems: The manufacturing stages emphasize the processing and production aspects of products. Material information may include details on process materials, tooling materials, or the raw material being processed (i.e., inventory or storage requirements). The material information represented at this stage may be leveraged to reflect how the processing of different components will affect a product's sustainability impacts. The information representations employed during manufacturing may depend on the type of manufacturing (i.e., discrete, batch, continuous). For instance, ISA88 [24] is a standard for batch control applied to production processes, while ISA95 [25] or IEC 62264 [26] integrate production processes with the supply chain at the enterprise level. Some standards used during the manufacturing stages are not specific to manufacturing, but to systems in general. One such standard came with the development of GEIA-927 [27]. Primarily based on ISO/TS 18876 [28] and ISO 15926-2 [29], GEIA-927 [30] builds on and integrates several existing standards for product information.

Use to end-of-life stages: Details specific to the end-of-life product representations may include metrics such as recyclability or amount of material recoverable, and remanufacturing. Additionally, material information can play an important role in determining the sustainability impact of a product on human health and ecosystem quality. End of Life (EoL) strategies and standards often aim to evaluate which "EoL process" would be most cost-effective for an enterprise [31]. Information related to the material impact of EoL strategies prompted the development of several sustainability standards such as Restriction of Hazardous Substances (RoHS) [32]. These standards require information to assess environmental performance at a product's end of life.

2.2.2 Sustainability Information by Stakeholder

A decision-maker, the stakeholder's perspective will also influence decision criteria. For example, material designers are primarily interested in structure (e.g., chemical composition, microstructure) and property data (e.g., yield strength, conductivity, and transformation temperatures). Product designers may also be interested in functional performance data (e.g., fatigue characteristics, creep resistance). Manufacturing engineers may be interested in accessing data that describes effective parameters for materials processing. Decision criteria can be strongly driven by the perspective from which a decision is being made. A manufacturing engineer may be primarily interested in a sustainable metric (e.g., embodied energy) for the production activities that occur solely within his/her facility. In contrast, a manager may evaluate the sustainability of an entire production sequence, including the intermediate manufacturing operations that are outsourced.

2.3 Material Information Modeling Requirements

Given the diverse set of stakeholders faced with decisions, and the documented challenges presented by sustainability decision-making, a methodological approach is necessary to develop a MIMS. Stakeholder needs must drive the requirements of an information model, as it is their decisions that require support. At the same time, information modeling requirements must be satisfied to effectively manage and communicate decision criteria. To analyze different scenarios, and begin to understand the decision support requirements of a material information model, a list of stakeholder needs as shown in Table 2.1 and derived from [16] is adopted. When representing material information to support decision-making, a conceptual material data model should meet necessities such as completeness, generality, extensibility, flexibility, reusability, and must consist of a minimum number of necessary concepts [33], [34]. Table 2.1 also identifies four information modeling requirements that should be considered in development of a MIMS: 1) Explicit metrics and decision criteria [35], (2) Transparent information flow and traceability [36], (3) Information accessibility [37], and (4) Transparent domain interactions and interoperability [38]. It is with these stakeholders and modeling needs that the information requirements of a MIMS will be recognized. To support sustainability-driven decisions in manufacturing decision criteria diversified by individual stakeholders as well as life cycle stages must be fulfilled, thereby requiring the synthesis of multiple scenarios. Figure 2.1 depicts how views of material information may differ by stakeholder, and by usage.

Table 2.1 Organizing Stakeholder and Modeling Needs

Stakeholder Needs	*Modeling Needs*
• Allow material selection based on customer performance requirements • Allow material selection based on recycling/remanufacturing ratio • Account for effect of material choice on product lifespan • Provide material metrics to processes in Gate-to-Gate operations to predict efficiency	EXPLICIT METRICS AND DECISION CRITERIA
• Bring manufacturing process information into design • Depict dependency, independency, interdependency, and conditionality of information flow between stakeholders • Provide supply chain traceability for sustainability metrics	TRANSPARENT INFORMATION FLOW AND TRACEABILITY
• Account for material information in different phases (material phase change) during manufacturing processes to predict efficiency • Analyze/support information flow within and between decision makers • Provide material sample information after processing • Identifying opportunities for improvement stakeholder requirement	INFORMATION ACCESSIBILITY
• Account for effect of material/process choice through product lifespan • Investigating system behavior and performance	Transparent domain interactions and interoperability

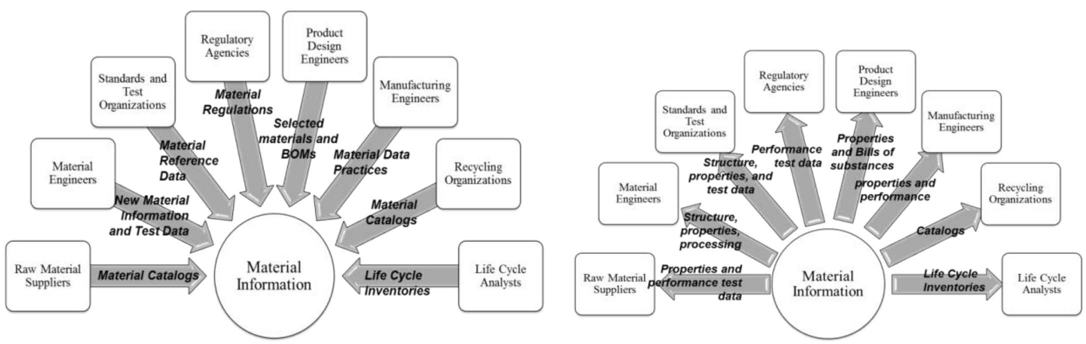

Figure 2.1 Material information and access from various stakeholders

Providing stakeholders access to different factors that are related to each other is key for sustainable decisions during a product's design and manufacture. Explicit metrics (i.e., performance indicators) and decision criteria are necessary to eliminate ambiguities from decision-making. For example, when developing performance metrics it is important to assure that they efficiently and effectively capture useful and relevant information. Resource utilization, quality and productivity are some examples of different decision criteria. Formalized definitions should be able to highlight the purpose of decision metric and the associated level of details required, with respect to time, cost, and data, necessary for any measurements.

When considering modeling needs, the most vital criteria that should be considered in constructing a comprehensive MIMS are gathering related data resources, standardization of the data representation, and managing sustainability assessment across life cycle stages and/or various perspectives. Different data sources represent and store information regarding material in different levels of detail and/or granularity. Information management techniques can provide a means for mapping material properties from and between different data sources and can enable examination of the use of material information based on stakeholder perspective at different levels of granularity.

In addition, MIMS must be able to incorporate a dynamic view of material information, wherein each of these stakeholders will be interested in specific information elements. The information model should be able to access various data types such as testing data, standardized data as well as distributed databases. A MIMS should enable mappings between hierarchical material taxonomies and hierarchical property taxonomies to support different views of material information for multiple stakeholders through mappings into the hierarchies. Table 2.2 categorizes the requirements of a multi-faceted information model to support sustainable thinking. Three stakeholder's objectives (i.e., material selection, information management, and design-time decision-making) are discussed and related them back to stakeholder needs and how meeting such needs facilitates sustainable thinking.

Table 2.2 Sustainable MIM requirements to enable different stakeholders' objectives

Information Model Use Case	**Material Information Model for Sustainability (MIMS) Requirements**
SUPPORT TRANSPARENT INFORMATION FLOW AND TRACEABILITY THROUGH INFORMATION MANAGEMENT	• Support access to material information to engineers from other life cycle stages, such as material sample information and product related aspects (factor in cost associated with the material from other life cycle phases) • Support access to gate-to-gate process information (relative to material and energy efficiency) at design time • Integrate data from different systems, CAD, CAM,CAE, CAPP,MRP,ERP, MES,CRM,SCADA, CAx and provide material information based on specific requirements • Support the mapping and classification of material properties • Support the accurate assessment of supply chain sustainability conformance and status • Support the mapping of production plan constraints regarding material types to product upside supply chain adaptability and flexibility
DEFINE EXPLICIT METRICS AND DECISION CRITERIA THROUGH INFORMATION STRUCTURE	• Express assessment metrics as a function of control variable for representing trade-offs • Ability to represent different form of material properties representations (graph, table, linear and nonlinear formula) • Offering material metrics to processes to predict efficiency of processes
PROVIDE INFORMATION ACCESSIBILITY THROUGH USER INTERFACES	• Enables material selection based on different sustainable metrics (e.g., better recycling/remanufacturing ratio) • Allow material selection based on customer performance requirements/specification/functions of multiple properties associated with products and process properties • Support the sustainability measurement frameworks by aggregation of similar sustainability metrics across the supply chain-from component to assembly to product and enabling comparing performance versus the benchmark • Provide material information based on requirements/ viewpoint of each stakeholder (Language/ Detail/ etc.) • Specifying metrics for performance measurements at different levels of details/granularity. • Account for decisions space to provide alternative sustainable decisions for different stakeholders
ESTABLISH TRANSPARENT DOMAIN INTERACTIONS AND INTEROPERABILITY THROUGH DEFINED RELATIONSHIPS	• Integrating material knowledge regarding people, systems, and technology • Define and support a close linkage of information between engineering material properties and manufacturing processes • Capture interactions between design characteristics and material/ process interaction • Supporting connection/transparent between product and process models • Ability to map materials to product category rule definitions and functional units used therein • Integrate with life cycle analysis tools and data structures • Provide insight into material choice impact on use-stage efficiency when applicable

Transparent information flow and traceability through information management provides a means to ensure that all aspects of a quality management system are satisfied. This means that the provenance of information can be traced, including any established source or uncertainty. To meet this need, and to provide that ability to establish provenance, several conditions a MIMS must satisfy have been identified. Specifically, a MIMS for sustainable manufacturing must be able to provide information support for various stages of the life cycle, it must be able to accommodate information needs of heterogeneous systems, and must provide traceability across the supply chain.

Supporting explicit decision criteria is essential in order to aid decision-makers in their activities. A MIMS must provide deliberately structured information, supporting explicit metrics and decision criteria, to evaluate sustainability criteria related to these activities. A MIMS must be able to accommodate different stakeholder views, meaning the metrics must be presented in a manner that they can be interpreted from multiple perspectives. Material metrics, at the process level, can provide a quantitative mapping of performance and efficiency evaluation. This mapping function can be used to define control space, including firm assets, productivity analysis, and product information.

The current trend of many decision-makers is to leverage technology in such a way that sustainability development is possible. Information accessibility, or ease of access, is vital to decision support, and must be considered in a MIMS development. User interfaces must be accommodated where environmental, economic, and social aspects are provided at each stage in the life cycle of a product. A MIMS seeks to support sustainability measurement frameworks through the aggregation of similar sustainability metrics, associated with inputs and outputs, across systems' activities. For example, in the supply chain domain, from component to assembly to product, material information accessibility enables the comparison of effectiveness and efficiency against a benchmark. Effectiveness of a supply chain will be measured by comparing it with target goals, while efficiency will be measured by linking supply chain performances to resources employed.

Improving manufacturing activities at both the system and process levels (i.e., shop scheduling optimization, process planning, process improvement, optimization) will have a significant impact on manufacturing sustainability. Establishing transparent domain interactions and interoperability requires, for instance, integrating material knowledge regarding people, systems, and technology and supporting connections/transparency between product and process models. MIMS must map manufacturing activities by identifying operational conditions (i.e., input, output, and constraints) and merging different resources, thereby capturing interactions between design characteristics and material/ process interactions.

CHAPTER 3

INTEGRATED SIMULATION AND OPTIMIZATION MODEL FOR SUSTAINABILITY-BASED PROCESS PLANNING

Chapter 2 identified the core requirments that need to be taken into consideration when building a Materials Information Model. This chapter addresses the second problem identified in chapter 1. It presents a systematic methodology for building a multi-criteria optimization model for evaluating alternate process plans that will properly address, describe, analyze, and optimize the performance indicators for these manufacturing activities.

3.1 Background

In this chapter, a model is developed to enable the environmental sustainability and productivity performance assessment for integrated process and operation plans at the machine cell level of manufacturing systems. It aims to determine the best possible process and operation plans out of all possible alternatives that satisfy multiple objectives and constraints. The simulation and optimization model enables "what-if" analysis for candidate scenarios and the selection of the best or preferred alternative from a finite set of alternate process and operation plans. A discrete event simulation (DES) tool is used to model the sustainability metrics (e.g., energy consumption, cost) and productivity metric (e.g., production time) of a shop floor. The methodology provides a systematic procedure to encompass all relevant parameters that have a significant impact on these metrics. Moreover, sensitivity analysis is performed to determine the importance of process parameters on the sustainability and productivity metrics for different process and operation alternatives.[2]

Traditionally, cost and quality are the major factors for considering when selecting manufacturing processes. Today, the increasing awareness of environmental issues is forcing product designers and manufacturers to be more prudent in shop floor decision-making. To assist in planning for the manufacturing processes with consideration of not only productivity, but also sustainability; methods and tools are required for assessing the environment, cost, and productivity impacts in the early stages of the G2G life cycle production and process design [39], [40]. The main focus of process planning is the manufacturing requirements for each job. Operation planning focuses on determining the resources and process settings of each operation of a process plan. The challenge is to assess and optimize the combined impact of the process and operation plans with the consideration of both sustainability and productivity performance. Machining processes consume materials, energy, and cutting tools and also use auxiliary materials such as coolants and lubricants. A process planner can select a process from a set of processes with different parameter settings that typically have different environmental impacts for producing the same product. The combination of both process and process settings affect tools and lubricant usage, energy consumption, emissions, cost, and quality of the product. As noted by [41], in G2G life cycle assessment (LCA), the biggest impact on product sustainability depends on the selected manufacturing

[2] Qais Hatim, Guodong Shao, Sudarsan Rachuri, Christopher Saldana, Deogratias Kibira, and Soundar Kumara . A Simulation-Based Methodology of Assessing Environmental Sustainability and Productivity for Integrated Process and Production Plans. *North American Manufacturing Research Conference (NAMRC43), International Manufacturing Research Conference 2015*-Accepted
Qais Hatim, Guodong Shao, Duck Bong Kim, Sudarsan Rachuri, Christopher Saldana and Soundar Kumara. A Decision Support Methodology for Integrated Machining Process and Operation Plans. Accepted- *International Journal of Advanced Manufacturing and Technology* and approved by NIST peer review process (Editorial Review Board ERB)

methods and sequences. In addition, the machine settings determine the manufacturing time and thereby affect the overall throughput, productivity, and sustainability. If this information is fed back or available to the designer, s/he can specify the product such that it would have the optimal combined impacts on both productivity and sustainability by using analysis techniques.

Modeling and simulation are effective techniques that help reduce manufacturing costs, improve product quality, and shorten time-to-market [42]. A simulation model of a production shop allows users to investigate the combined impacts of process selection and process settings. Simulation of manufacturing operations, in combination with optimization, can be utilized to determine the performance of the shop. The output can be used for actionable recommendations that optimize the process with respect to the key performance indicators (KPIs) such as energy, resources, emissions, and waste. Previous research work has developed heuristics for assessing and optimizing sustainability of a given product, process, or system (e.g., waste minimization, material efficiency, resource efficiency, eco-efficiency) [43]. These studies aimed at guiding decision-making for selecting machines, skills, and stock materials or components and sequencing the processes of cutting, forming, assembly, finishing, and inspection processes [44]. In addition to process selection, machine parameter settings for the process must be determined. For example, higher speeds or depths of cut can be used to produce parts at higher rates [45], [46]. This must be balanced with sustainability concerns.

The major contribution of this chapter is to propose an integrated and systematic methodology that aids for assessing sustainability performance and decision-making for process planning of producing machining parts. Specifically, the detailed contributions within the methodology include (a) the relaxation of the design requirement of the feature sequence selection; (b) application of multiple-criteria decision-making and analytic hierarchy process (AHP) methods [47] when making decisions on KPIs; (c) the generation of generic data structures for integrated process and operation planning.

3.2 Related Work in Process Planning for Manufacturing

3.2.1 Conventional Process Planning Approaches

Process planning deals with the selection of the necessary manufacturing processes and the determination of their operation sequence to convert the designer ideas (i.e. Computer Aided Design (CAD) models) into a physical part. Necessary activities in process planning include process sequence generation that assigns and sequences design features, tooling assignment, set-up generation, machine instruction, and determination of optimal machine settings. In detail, it includes the following activities [48]: interpretation of drawings, evaluation of materials and process selection, selection of machines and appropriate tooling, determination of process settings, identification of set-up devices, selection of quality methods, determination of cost, preparation of routing sheets, and preparation of operations lists. Srinivasan et al. categorized the process planning into two areas: micro-planning [49] and macro-planning [50]. The macro-planning designs an operation sequence to manufacture a part, called 'process plan', while micro-planning determines the resources and process settings of each operation of the process plan, called as 'operation plan.' In general, process planning can contain one predefined operation sequence (linear) or a set of alternative ones (non-linear or undefined) [51].

Two main methods exist for process planning: manual and computer-aided process planning (CAPP). The former method is often time-consuming, sub-optimal and inconsistency exists between different process planners. In order to address these limitations, CAPP approaches have been proposed over the past several decades [52]. Two types of CAPP approaches exist: variant and generative. The variant approach utilizes a computer database and retrieval system. The procedure is as follows: (1) match a new product with a geometrically similar product manufactured in the past and (2) retrieve its process plan for modification as needed. In contrast, the generative approach uses geometric analysis, process knowledge, and logic to semi-automatically develop a process plan. Most of the current research is focusing on the generative process planning, which includes feature-based technologies, artificial neural networks, knowledge-based systems, genetic algorithms, Petri nets, fuzzy logic, fuzzy-set theory, agent-based approaches, and STEP-compliant CAPP. The advantages and disadvantages of each method are discussed in review papers [51], [52]. Although tremendous efforts have been made in developing CAPP systems, the systems have only achieved limited success to provide practical solutions to manufacturing industry in contrast to CAD/CAM systems [53]. It is reported many large companies use a hybrid approach of CAPP and knowledge from experienced process planners, Small and Medium-Sized Enterprises (SMEs) rely more on manual process planning approaches. As the manufacturing industry becomes more globalized and sustainability-aware, process planning should become more integrated, agile, adaptive, and distributed for sustainability and productivity. Therefore, more sophisticated techniques/methods are required to integrate the process planning and sustainability into one unified scheme for better decision-makings.

3.2.2 Process Planning for Sustainable Manufacturing

Integrating sustainability considerations into process planning is a challenge and trade-off between sustainability, asset utilization, and agility exists. Due to the broadness and complexity in process planning, in this subsection, the focus is only on the related work in categories of: environmental-awareness, non-linear process planning, modeling and simulation methods, optimal selection of process settings, multi-criteria and multi-objective decision-making, integrated model for sustainability and productivity, and data structure model. More recently, process-planning researchers have paid attention to environmental awareness. Duflou et al. [54] provided a systematic overview of the state of the art in energy and resource efficiency increasing methods and techniques at multiple manufacturing levels. Le and Pang [55] developed a unified decision support system (DSS) architecture with considerations of energy-efficiency, cost-effectiveness, and reliability by using real-time energy measurements and process operational states. Newman et al. [56] established an energy efficient process planning framework for CNC machining and showed that energy consumption of different machining processes can vary significantly (6% at low loads and 40% at higher loads). Yin et al. [57] proposed a process planning method for carbon emission reduction including four steps: feature identification, generation of alternative operations, selection of operations with lower carbon emissions, and generation of process plan based on a genetic algorithm.

Non-linear process planning (undefined process planning) can provide flexibility when designing and manufacturing a part/product. In contrast, the pre-defined process sequence is difficult to adapt to the unexpected events, which means it is not easy to adjust the process plans in dynamic manufacturing environments. Chung and Suh [58] proposed a new heuristic method for optimizing the non-linear process planning based on ISO 14649 and STEP-NC. Pellegrinelli and Tolio [59] aimed to solve the pallet operation sequencing problem by combining the flexible process planning, network part program logic, and the STEP-NC concept. Zhang et al. [60] proposed a method for process planning optimization with energy efficiency consideration and also used the network part program technique to generate multiple alternative process plans. These approaches will be systematically unified into an integrated methodology in this chapter.

Modeling and simulation has been considered as one of promising solutions for enabling efficient use of resource, resiliency, and agility [61]. In this context, Heilala et al. [62] [63] proposed a simulation-based DSS that can evaluate the capacity of production systems for new orders and unexpected events (e.g., equipment downtime and changes in operations) in those systems. The main idea is to combine the strengths of automatic data analysis, calculations, and simulation with a graphical user interface (GUI). Sproedt et al. [64] developed a simulation-based DSS that combines LCA and discrete-event simulation (DES) for eco-efficiency improvements that incorporated resource accounting, simulation and production control/evaluation. Larek et al. [65] proposed another DES approach to predict workpiece-specific power consumption and energy footprints of a two-axis turning process. Andersson et al. [66] developed a method that performs an economic and environmental impact analysis by combining two methods: activity based costing and DES. Diaz and Dornfeld [67] proposed an optimization methodology for the reduction of cost and energy by utilizing DES. Kohl et al. [68] proposed an efficient DES-based methodology that predicts the energy consumption of each product and the variants without the need for new data model generation. However, these methods are not designed to support the modeling and simulation tasks for process planning that considering both sustainability and productivity.

Optimal process settings with specific objectives can also help achieve sustainability improvements. Rajemi et al. [69] developed a methodology for optimizing energy footprint for a specific part and derived an economic tool-life that satisfies minimum energy footprint. Campatelli et al. [70] proposed a method that determines optimal process settings for minimizing the power consumption in machining by using an experimental approach and response surface method. Kim et al. [71] developed a decision-guidance framework for improving sustainability in manufacturing processes while addressing the deficiencies in existing LCA frameworks and performed a case study of a turning process to find optimal parameter setting. Unfortunately, the above methods only focused on optimal selection of process settings. A holistically integrated method is required in process planning. To this end, multi-criteria and multi-objective decision-making methods have been used in assessment/optimization of manufacturing problems. Vinodh et al. [72] developed a DSS that can assess the sustainability level of a manufacturing organization. Arslan et al. [73] also developed a DSS for machine tool selection by using multi-criteria weighted average with respect to productivity, flexibility, space, adaptability, precision, cost, reliability, safety and environment, and maintenance and service. Zhao et al. [53] proposed an LCA-supported environmentally conscious process planning methodology with a set of ranking/weighting schemes for impact aggregation. It includes (1) an existing process plan, (2) identification of impactful process steps, (3) determination of design features, (4) generation of alternative process plans, and (5) evaluation of the alternative process plans in terms of manufacturing cost and environmental impact to identify the Pareto-optimal process plans. These features will be integrated for the comprehensive methodology in this research.

Recently, integrated models of sustainability and productivity have also been proposed. Singh et al. [74] proposed an integrated method for environmental process planning, which consists of five steps: (1) list all product configurations, (2) utilize the product environmental performance indicators (EPIs) model, (3) select appropriate EPIs, (4) analyze selected EPIs, and (5) evaluate and score product variations. Wang et al. [75] presented an integrated method to simultaneously improve economic benefit and environmental performance and verified the feasibility and validity by applying it to a small machining workshop. Guo et al. [76] proposed a systematic energy-efficient approach that provides optimal results of material stock allowance and process settings considering surface roughness and energy consumption in a machining process. Wang et al. [77] proposed a systematic approach for process planning and scheduling optimization by using multiple objectives (e.g., energy efficiency, productivity) and constraints (e.g., surface quality). In addition, they used an artificial neural network method to establish complex nonlinear relationships between process settings and energy consumption datasets as well as surface quality.

Sustainability-related and productivity-related data are generated via sensing and networking techniques; this information needs to be efficiently managed. To do this, data structure models are built to represent and classify information. STEP-NC standards provide a data model for representing manufacturing information, which enables the representation of product geometry information with the feature catalogue, cutting tools, and technological details. Vichare et al. [78] proposed a unified manufacturing resource model (UMRM) to complement the data models for remaining manufacturing resources in STEP-NC, such as machine tools and auxiliary devices. Dhokia et al. [79] developed a data model for a dematerialized machine tool based on the Unified Modeling Language (UML) models and implemented a relational database and its data schema for life cycle data related to each machine tool using PostgreSQL. However, current data structure models for process planning are neither comprehensive nor generalized for analysis with respect to sustainability and productivity. A generalized data structure model is required to store and represent data to support process planning accurately and efficiently.

Although many research and development efforts focus on each in-depth research area as explained above, most of them are researched, developed, and applied standalone. An integrated and systematic view of process planning for assessing sustainability and productivity performances and its decision-making is necessary. To the best of our knowledge, there is no generalized and integrated methodology that can provide decision-supports for non-linear process planning that considers both productivity and sustainability. To address these issues, an integrated and systematic methodology is proposed in this study. The methodology can provide the optimal operation sequence as well as the optimal process settings by combining the non-linear process planning approach, DES modeling, and MCDM technique. In addition, a generalized data model for the integrated process planning is proposed. The methodology and generic model for the integrated process planning will be explained in the next section.

3.4 Integrated Simulation and Optimization Model Formulation

This section describes a methodology for assessing sustainability and productivity impacts when both process and operation plans are integrated into the G2G life cycle. The steps of the activities in the methodology are shown in Figure 3.1. It includes the following steps: (1) definition of the goal and scope of the model, (2) data structure modeling, (3) generation of the simulation/optimization model, (4) database integration, and (5) result visualization.

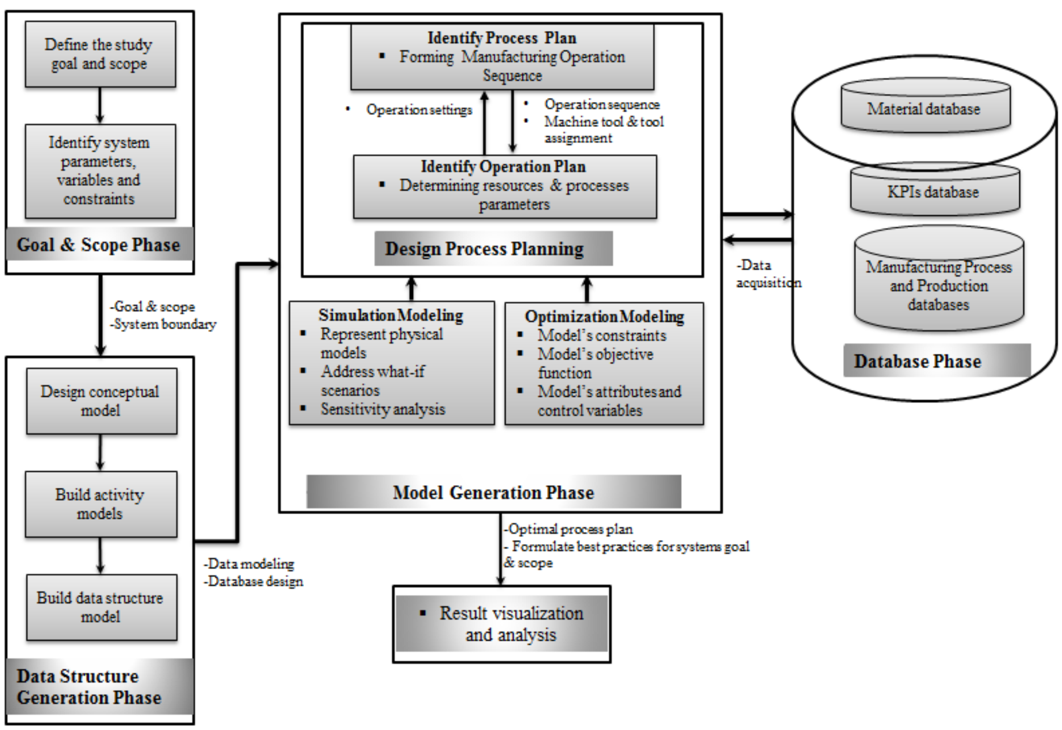

Figure 3.1 Methodology Steps

To use the proposed methodology, users should first define the goals and the scope of the integrated model. For example, the goal may be to assess sustainability performance and selection of an optimal process-operation strategy. The scope of the model can include identification of relevant system applications, parameters, variables, constraints, and stakeholders. Data structure models must be developed to support integration of material information needed for facilitating analytical and numerical unit process models that underlie the integrated simulation and optimization model. The data needed to populate these data structure models is available and can be retrieved from several different archival databases. The mapped local database provides the right data at the right time for decision-making regarding the process and operation plan selection. This requires the understanding of (1) the context in which data is used in a process plan, operation plan, or environmental impact and productivity assessments and (2) how and where the data can be collected. Based on the stated objective, stakeholders have to identify related metrics that can be best used to measure the chosen objectives. Moreover, stakeholders need to interact with the model by inputting user-specified data or forming a query for information located in a specific database. After execution of the simulation/optimization models, a recommended resource and production plan that fits within the context of the identified KPIs' objectives will be provided to the user.

3.4.2 Data Structure Model

Relevant information needs to be managed using well-defined data structures. Data structures to support process planning should include information about part's features and the fabrication process. The main steps in the process of generating a data structure include conceptual data modeling, activity modeling, and formal data structure generation and each are described in the ensuing.

Conceptual Data Modeling: A well-developed conceptual model enables stakeholders to highlight their concerns, provide the appropriate level of abstraction for the problem, identify information exchanged between model's entities, and incorporate objectives and constraints. A schematic representation is necessary to characterize the information flow and resource allocation for a specific goal. In Figure 3.2, eight information layers are designed: design, feature sequence, material, process, machine, tool, process setting, and performance indicator layers. The design layer describes the part's design information, including features' forms, shapes complexities, dimensions, tolerances, and surface conditions. The alternative networks that describe possible feature processing precedence are instantiated at the feature sequence layer. According to the part functionalities and design requirements, preferred material(s) are identified in the material layer. In general, material selection determines a set of processes that can be used in manufacture. Information about material properties and geometrical knowledge are used in mapping suitable processes to manufacture at the process layer. The combinations of machines and tools that can handle the material type and satisfy the design requirements are designated at the machine and tool layers. At the process setting layer, each combination of material, process, machine, and n process setting options are represented. Finally, the performance indicator layer provides information for determining strategies to meet objectives.

Activity Modeling: Activity diagrams illustrate the activities that are performed when assessing system performance, logical processing, and the data flow between activities by incorporating stakeholder inputs. Stakeholder-defined scenarios determine the required information. The data associated with these scenarios are keys for carrying out an effective performance analysis and decision support.

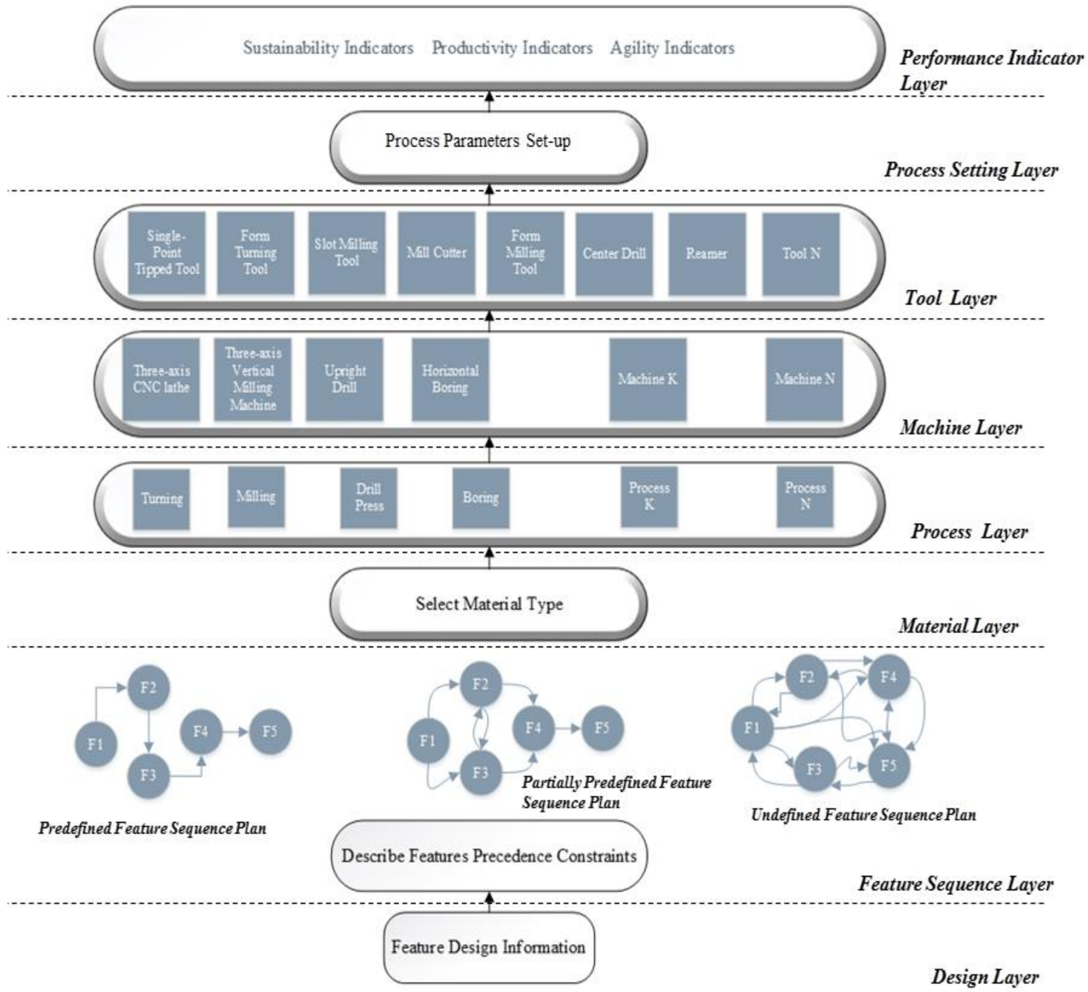

Figure 3.2 Conceptual Data Model

Formal Data Structure Models: The developed conceptual and activity models provide the foundation for building a comprehensive data model of performance analysis. The primary challenge in developing such a model is the ability to capture relevant data to support process planning. Efficiently managing the relevant data based on the activity models and different planning scenarios will effectively reduce modeling and analysis time since 31% of the total project time is used for gathering, extracting, and processing data [80]. Building such a data model requires (1) linking local databases with external databases containing relevant material, design and process information and (2) building information queries to support data exchange across the databases. First, based on the activity model scenarios, different sets of input data must be stored in a local database to support analysis. Building a local database and populating it with data mined from external sources require data categorization. Generally, data is divided into eight distinct groups [41]: abstracting and indexing services, full-text databases, industrial standards and specifications, patents, product information, technical reports, industrial data, and other resources. Data content, units, and formats of these types should also be identified. Different techniques such as hierarchical, network or relational database models could be employed to support design and management of content. Records may store information related to mathematical techniques, statistical methods, and experimental procedures that support the activity entities' requirements. The dispersed data should be integrated to provide required information for designing planning strategies and evaluating their performance. Second, valid queries must be formulated to support data transmission between existing records and management of their contents to support process planning.

3.4.3 Model Generation

Simulation enables setting and modeling production scenarios, identifying the interactions among KPIs and their influence on stakeholder decisions. It provides actionable recommendations on the process plan performance. Simulating the process planning scenarios to determine the impacts on different performance indicators could be time consuming because of extensive comparisons of many alternative planning options.

The solution presented here is to combine simulation with optimization, mathematically formulate process and production planning activities, control variables, data, and constraints for supporting KPI assessments. Mathematical programming models describe optimization of the performance indicator objective function subject to planning constraints. A feasible solution is an instantiation of values of decision variables that satisfy all constraints. The procedure to select the best production and process plans with respect to various KPIs is shown in Figure 3.3 and details are discussed below.

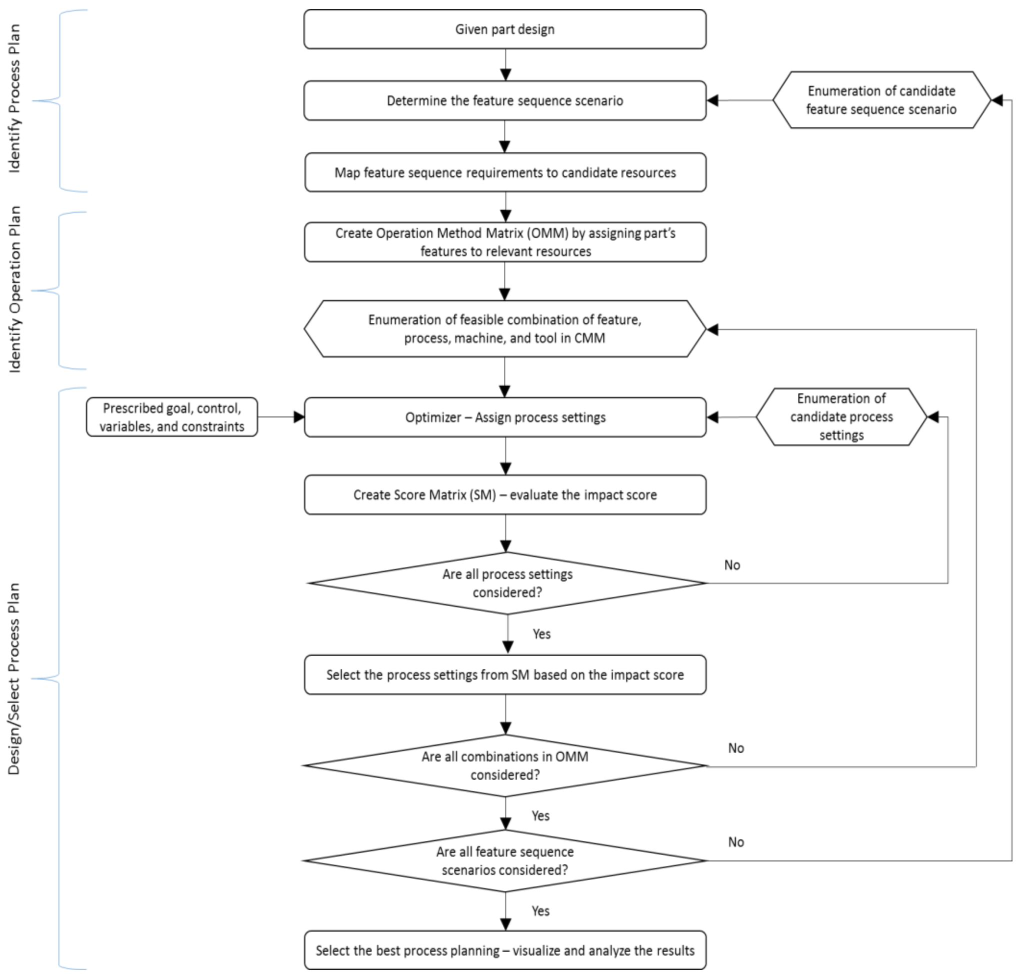

Figure 3.3 Simulation and optimization model generation

1. *Identify Process Plan*: Based on product geometric features and design specifications, different process plans are chosen as candidates to be studied to determine their impacts.

2. *Identify Operation Plan:* A variety of resources may be required to perform a single operation of a given part design. An operation method matrix is constructed by identifying those candidate resources that can be used to fabricate the geometric features. Mapping of processes to resources is also influenced by product design specifications.

3. *Design Process Planning:* Given that alternative resources can generate the same feature on a part, specifying the best set of resources is the main objective of the model. The resources and corresponding processes are specified in the operation method matrix. Before determining the process plan that has the optimal impact on the environmental sustainability and productivity, a range of process plan parameters has to be assigned according to operation method matrix entities. The main steps to employ the process plan evaluation procedure are:

- <u>Assign initial settings</u>: Initial process settings are selected according to the operation method matrix, in which processes, machines, and tools are specified for the part features. Based on the provided information, each performance indicator can be quantified using a known analytical model/expression.
- <u>Perform linear normalization</u>: For each specified process plan, stakeholders must quantify an aggregated environmental and productivity impact using a score matrix. However, aggregating different KPIs is difficult because of the different units used to

describe these quantities. Normalization is required to non-dimensionalize each parameter [81]. Two cases of normalization can be used as follows. If the target value of the performance indicator should be maximized (e.g., quality), then the normalized values for the indicator are evaluated by:

$$N_{ij} = \frac{I_{ij} - \min(I_{ij}, i=1,2,\ldots,M)}{\max(I_{ij}, i=1,2,\ldots,M) - \min(I_{ij}, i=1,2,\ldots,M)}\ , i = 1,2,\ldots,M \ and \ j = 1,2,\ldots,N\ , \quad (1)$$

If the target value of the performance indicator should be minimized (e.g., energy), then the normalized values are evaluated by:

$$N_{ij} = \frac{\max(I_{ij}, i=1,2,\ldots,M) - I_{ij}}{\max(I_{ij}, i=1,2,\ldots,M) - \min(I_{ij}, i=1,2,\ldots,M)}, i = 1,2,\ldots,M \ and \ j = 1,2,\ldots,O, \quad (2)$$

- Perform pairwise comparisons: After normalizing the performance indicators, evaluating the relative importance of each KPI is necessary to prioritize various processes for each feature operation. MCDM methods rank the alternatives from best to the worst based on stakeholder preferences [82], [83]. The analytic hierarchy process (AHP) method, one of the most commonly used ranking methods, uses pairwise comparisons to determine the importance of each indicator. To ensure the preferences provided by the decision-makers at the pairwise comparison matrix are valid and consistent, consistency of the preferences entered by the decision-makers is tested. A stakeholder does not have to decide the exact percentage of the importance (weight) of a specific metric (attribute) and only needs to decide its relative importance. Thus, a square and reciprocal pairwise comparison matrix of order n will be formed based on the relative importance of the performance indicators. AHP utilizes pairwise comparisons to enable the stakeholders to model the importance of each indicator, qualitative or quantitative, relevant to others. A square and reciprocal pairwise comparison matrix $\boldsymbol{A}$ will be formed based on the relative importance of performance indicators. For instance, if n=3, this matrix will be:

$$A = a_{ij} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix},$$

where, a_{ij} is the importance of indicator i relative to another indicator j, $a_{ij} = 1/a_{ji}$ for $i \neq j$ and the diagonal values (a_{ii}) of A matrix all assigned a value of 1. A common scale to assign importance is as follows: 1 indicates 'equal importance' where two indicators contribute equally to the object, 3 indicates 'somewhat more important' where experience and judgment slightly favor one over the other, 5 indicates 'much more important' where experience and judgment strongly favor one over the other, 7 indicates 'very much more important' and 9 indicates 'absolutely more important' where evidence favoring one over the other is of the highest possible validity. Intermediate values of importance are also possible.

To make sure the preferences given by the stakeholders at the A matrix are validated and consistent, the following checks must be performed to verify the importance intensities are consistent if they are transitive, that is $a_{ij} = a_{ik}a_{kj}$ for all i, j, k.

Find both eigenvector (ω) and eigenvalue (λ), where the eigenvector and eigenvalue should hold the following relation:

$$A\omega = \lambda\omega, \tag{3}$$

where for a consistent matrix $\lambda = n$ and the eigenvector is calculated using the geometric mean method:

$$\omega_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij}}}, \tag{4}$$

where $\sum_{i=1}^{n} \omega_i$ must be 1. From this a consistency index is calculated, given by CI:

$$CI = \frac{\lambda_{MAX} - n}{n-1}, \tag{5}$$

where λ_{MAX}= average $(\frac{A\omega}{\omega})$. The consistency ratio CR represents the consistency of the preferences entered by the decision-maker and is computed from CI as follows:

$$CR = \frac{CI}{RI}, \tag{6}$$

where, RI is random consistency attribute entered by the stakeholders. If CR is higher than 10%, the set of judgments given by the stakeholders is inconsistent. This threshold level is a user-specific decision criterion.

- Computation of the Score Matrix: After specifying the weights, the total score for combined environmental and productivity impacts for each process plan can be calculated by applying an additive form of value theory [84]. This theory is selected to rank the plans by obtaining a single aggregate score for each process plan with regard to targeted KPIs. To this end, a score matrix Table 3.1 is constructed based on the normalized data and the subjective weights assigned to the KPIs. A process plan that has the highest score stands for the best choice for fabricating the designed part.

Using the additive form of the value theory, the score S_i is computed as:

$$S_i(x, y, z, r) = \sum_{j=1}^{4} \omega_j n_{ij} \qquad (i = 1,2, \dots, m), \tag{7}$$

where ω_j is the weight of each performance indicator (x, y, z, and r) with $\sum_{j=1}^{4} \omega_j = 1$ and $0 \leq S_i(x, y, z, r) \leq 1$ conditions. Also, each performance metric measured across different operations for each process plan is aggregated into a single score. Equation 2 is to identify the impact of different process plans on that indicator.

$$PM_j = \sum_{k=1}^{z} n_{kj} \tag{8}$$

where, j is a number of performance indicators and k is a resource utilized at operation O_i.

Table 3.1 Score Matrix

Operation	Resource R_i	Sustainability Metrics			Productivity Metric	Score (S_i)
		Power w_1	Water Consumption w_2	CO2 Emission w_3	Production Time w_4	
O_1	R_1	n_{11}	n_{12}	n_{13}	n_{14}	S_1
O_2	R_2	n_{21}	n_{22}	n_{23}	n_{24}	S_2
O_k	R_k	$n_{\mathrm{k}1}$	$n_{\mathrm{k}2}$	$n_{\mathrm{k}3}$	$n_{\mathrm{k}4}$	S_k
O_{k+1}	R_r	$n_{\mathrm{r}1}$	$n_{\mathrm{r}2}$	$n_{\mathrm{r}3}$	$n_{\mathrm{r}4}$	S_{k+1}
O_m	R_z	n_{z1}	n_{z2}	n_{z3}	n_{z4}	S_m
Score (PM_j)		PM_1	PM_2	PM_3	PM_4	

- Validation of the Score Matrix: The knowledge gained by decision-makers is understanding how the change in process settings can affect the outcome for each set of selected processes. The analysts can follow these steps described to obtain the best score value (S_i) and return the associated optimal processes and their settings. Moreover, for the optimal score value (i.e., S_i), an aggregated score (i.e., PM_j) of each performance metric is reported.

3.5 Conclusions and Future Work

The above formulation presents a systematic methodology for enabling the environmental sustainability and productivity performance assessment for integrated process and operation plans at the machine cell level of manufacturing systems. It provides steps to assist decision-making by finding out the best process and operation plan out of all possible alternatives. In addition, it allows the relaxation of the design requirement of the feature sequence selection, the applications of MCDM when deciding KPIs, and the generation of generic data structures for the integrated process and operation planning. The utilization of simulation and optimization techniques enables "what-if" analysis for the candidate scenarios and the selection of the optimal or preferred alternative from a finite set of alternate processes and operation plans. A DES tool is used to model the sustainability and productivity metrics.

Future research includes: (1) applying this methodology to problems at other manufacturing system levels (e.g., enterprise and facility levels) and evaluating production activities' impacts on process and operation planning; (2) modeling and studying different performance indicators for environmental sustainability, productivity, agility, and quality; (3) classifying required information (e.g., potential operation sequences) supports process planning activities in local databases based on both product design specification and implementation as well as goal(s) of a manufacturing system; (4) implementing systems that automate the local database creation; (5) researching and applying non-subjective method such as Knowledge-Based System (KBS) and Artificial Neural Network (ANN) to overcome the subjective disadvantages of the MCDM method when assigning weight for different KPIs; and (6) performing more real world case studies for various manufacturing processes including primary shaping processes, secondary processes, and assembly and test processes to assess their processing and production planning interrelation impacts on selected KPIs.

CHAPTER 4

CASE STUDY: SUSTAINABLE MANUFACTURING OF ACRYLIC GRIDING SHELLS

This chapter demonstrates the applicability of the proposed methodology in chapter 3 through a case study at the G2G life cycle stage. This case study combines multi-criteria optimization model with discrete event simulation in order to integrate process and operation planning activities for evaluating their performances under different realistic scenarios. It pertains to both research problem one and two.

4.1 Background

Among various manufacturing technologies (e.g., primary shaping, secondary, assembly, and test processes), a case study was conducted to study the secondary processes in a small machine shop that produces about 200 parts per day. The processes in the shop are turning, milling, drilling, and boring. A model of this shop is developed to demonstrate the integrated simulation and optimization methodology. A 250 grinding head shell shown in Figure 4.1 is chosen to be a representative part. Based on the given part design, the specific fabricating operations include facing, grooving, threading, spot drilling, and drilling. A DES tool, Arena, is used to model the production/machine cell with a set of KPIs and evaluate the impact of the selected processes and their settings on individual and combined KPIs. OptQuest® is used to optimize the process performance. The objective of the study is to minimize costs and resource usage while maximizing productivity. This chapter will systematically describe and demonstrate the use of the integrated methodology developed in this thesis. The scope of the study is to perform process planning for machining processes in production-to-order domain (i.e., batch manufacturing). The goal is to evaluate the sustainability (i.e., energy consumption and machining cost in this case) and productivity (production time) performance and to assist examination of the effectiveness and reliability of integrated process and operation plans.

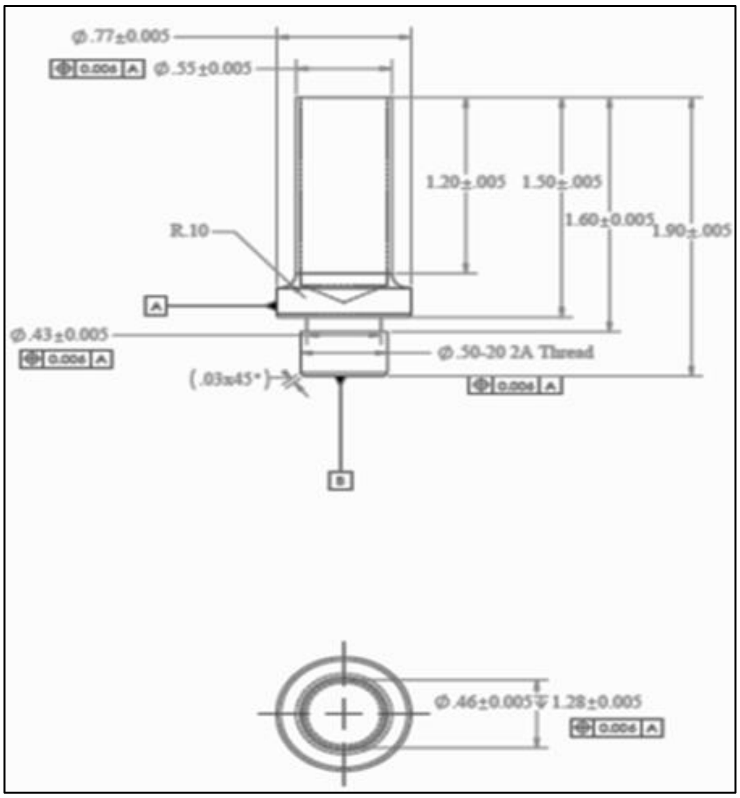

Figure 4.1 Custom-made 250 grinding head

4.2 Data Structure Model

Design Conceptual Model: The eight layers that were shown in Figure 3.2 describe the necessary information flow required to assess the environmental sustainability and productivity for a selected process plan. Important decisions are made at each level regarding suitable manufacturing processes and methods, clamping strategy, machining strategies, cutting tools, and cutting data. In this case study, three feature sequence plans (i.e., predefined, partially defined, and undefined sequences) are discussed. In the predefined plan, a strict machining flow is defined. A partially defined plan relaxes some of these constraints on machining flow while the undefined plan does not specify any priority for features precedence during machining. Despite the fact that Clear Acrylic has been chosen in this case study, other materials could be also allocated at this layer and the same analysis procedure could be performed. The process layer provides alternative processes such as turning, milling, drilling and boring. The planning also involves specifying machine types for each process selected. Three-axis CNC lathe, three-axis vertical milling, drill press-upright drill, and boring mills-horizontal boring are machines selected, respectively. For each operation, one or more tools can be chosen to meet required specification. Cutting tools for turning (single-point tipped tool, form turning, drill), milling (slot milling, mill cutter, form milling), drilling (center drill, reamer), and boring (boring tool) are specified at the tool layer. At the process setting layer, priority is given to establishment of feasible ranges of three cutting parameters (i.e., cutting speed, feed rate, and depth of cut). Data regarding feasible process settings are mapped from published data to the process setting layer. Finally, energy consumption, time, and cost are performance indicators that will verify optimal selection out of different alternatives on previous layers.

Build Activity Models: Activity models illustrate the requirements for supporting the high-level activities performed at each layer described in the conceptual model. For illustration, at the process layer, among many stakeholders' scenarios, the main manufacturing engineering scenario is: *for a given material type and product design, select process from a set of processes that has optimum impact on environmental* *sustainability*. The activity model will be built for evaluating process selection impact on energy consumption. The highest level of abstraction for the activity model is shown in Figure 4.2. The following requirements are identified: (1) part nominal geometry constraints, (2) part dimensioning and tolerance specifications, (3) material type properties and processability, (4) surface and subsurface specification, and (5) process type constraints. At the second tier, the machinability of a material dominates the quality of surface finish and integrity, tool life, and force and power requirements. Therefore, stakeholders should consider the machinability of a material in process selection activities. In this scenario, processes that consume less energy will be assigned to produce the features. Thus, at the sustainability tier, information from previous tiers that contribute to energy evaluation will be aggregated. A data model is necessary to facilitate this type of information mapping.

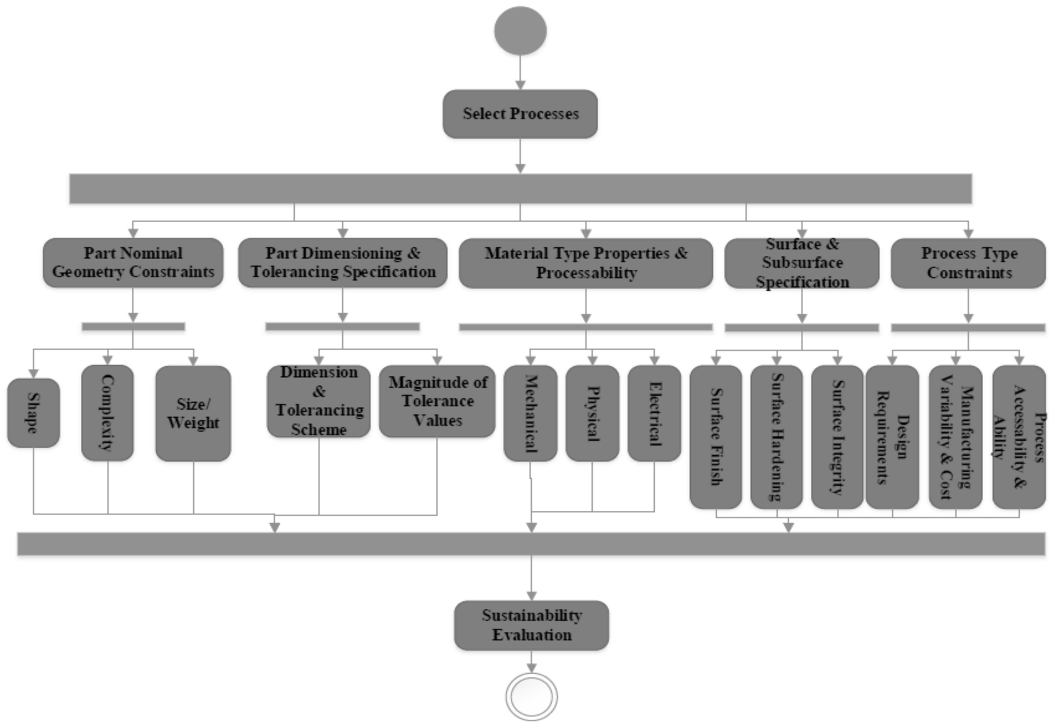

Figure 4.2 Activity diagram for sustainability evaluation of process selection

Build Data Structure Models: A relational database is designed for functional assessments regarding different performance indicators. A database management system, MySQL, is used to build various local databases to store data extracted from sourcing databases. This data model is developed to classify activity model information in an efficient way so that it enables the easy accessing of appropriate KPI information required to assess the performance. Moreover, the data model also fulfills various stakeholders' query requirements. The data model is represented using the entity-relationship (ER) diagram as shown in Figure 4.3, where the development of the entities and their relationships is based on activities listed in the activity model. In the ER diagram, the "material" table represents material, while material categories are stored in the “mat_cat” table. For processes and process category, the information is stored in the “mfg_process” table and the “process_cat” table, respectively. Machine information is stored in the “machine” table. The selection of manufacturing processes and machines is limited by what material is considered so that the “material”, “mfg_process”, and “machine” tables are correlated by the “material_process_machine” table. Given the combination of material, process, and machine, recommended values of process setting are stored in the “process_setting_value” table. Information about tool, cutting fluid, and fixture are stored in the “tool”, “cutting_fluid”, and “fixture” tables, respectively. Even though in the “user-defined_setting” table, part nominal geometries of hole initial and final diameters are tabulated and provide a model for the purpose of demonstration, part shape complexities, tolerance, and surface specification are out of the scope of this work. Different mathematical models are adopted to evaluate indicators and the “calculation_result” stores the result for the selected performance indicator.

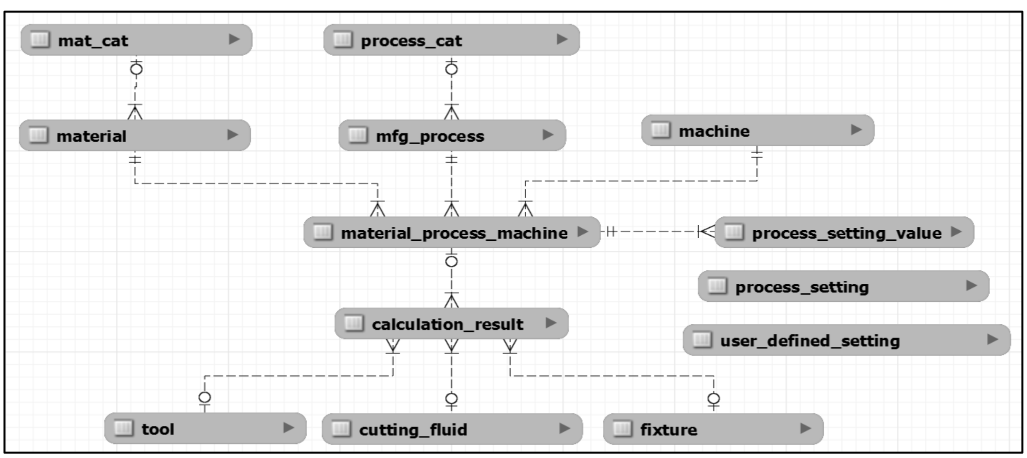

Figure 4.3 Entity relationship diagram

4.3 Simulation and Optimization Model Generation

4.3.1 Model Framework

Identify Process Plan: In this case study, three alternative networks for feature processing precedence (i.e., operations sequence), called process plan scenarios, are chosen to assess the plans impacts. First, the parts were run according to a *predefined process plan* where constraints on feature sequencing are predetermined. Next, some restrictions are relaxed on the operational order of some parts features in a *partially defined process plan*. Finally, the *undefined process plan* is tested such that there are no restrictions on feature precedence. For each of these three types, different operation plans are tested and for each combination (process plan, operation plan), impacts on the KPIs are evaluated.

Identify Operation Plan: The activity model for process selection provides the knowledge for assigning processes for each feature. Processes that can fabricate a part according to the blueprint specification are listed as potential process for that specific feature. Resources compatible to fabricate a 250 Grinding Head Shell part of Clear Acrylic material are listed in Table 4.1. Based on the associated activity model, each part feature (i.e., cylindrical shape, groove, external thread, spotting a hole, through hole) is assigned to relevant resources (i.e., process, machine, tool) based on Table 4.1 and this information is utilized to form an operation method selection matrix.

Table 4.1 Resources information for the 250 grinding head shell part

Process		Machine		Tool	
No.	**Type**	**No.**	**Type**	**No.**	**Type**
P1	Turning	M1	Three-axis CNC lathe	T1 T2 T3	Single-point tipped tool Form turning Drill
P2	Milling	M2	Three-axis vertical milling machine	T4 T5 T6	Slot milling Mill cutter Form milling
P3	Drilling	M3	Drill press-upright drill	T7 T8	Center Drill Reamer
P4	Boring	M4	Boring mills-horizontal boring	T9	Boring tool

Design Process Planning: To explicitly identify the unique resources for each part's feature, an integrated simulation and optimization model is generated to investigate the sustainability and productivity impacts for all the alternatives when several processes and operation plans scenarios are employed. Before building simulation and optimization models, key operation parameters (i.e., process settings, tool wear, tool angle, cutting fluid types, material specifications, temperature rise) are categorized as dependent or independent variables. Process settings are considered as the control variables in optimizing process plan while the other parameters are system attributes (i.e., constants). For example, regarding the resources in the operation method selection matrix, the optimal process settings may be the ones that enable the minimization of energy consumption, production time, and operation cost. Relevant machining constraints need to be considered when optimizing these objectives. Since this case study is focusing on rough machining, several constraints such as tool life, surface roughness, tolerance, and operation are adopted and modeled for feasible solutions. The model inputs include everything that enters or is consumed by the manufacturing process such as intermediate products, work-in-progress, raw materials, lubrication, energy, and disturbance factors that occur during production. The required manufacturing process operations for the part design are facing, grooving, threading, spot drilling, and drilling. Arena™ is used to model the machine shop with a set of KPIs and OptQuest® for Arena™ is used to optimize these KPIs. The simulation model of the shop is used to evaluate the impact of selected plans and processes, machine parameter settings on individual and/or combined KPIs. Within Arena™, the main simulation modules are part arrival, data requirements for the part and process, the part routing to various machines, part exit, and statistics generation. This research defines manufacturing processes as events, parts as entities, buffers as queues, parts and processes specification data as attributes, and KPIs parameters as variables. Mathematical expressions are used for evaluating the productivity and sustainability metrics, and parameters are defined as variables. Depending on process plan type, a sequence is used to define feature precedence constraints. Constant distribution with a mean of 120 is defined as the inter-arrival time between successive batch arrivals; each batch includes 15 identical parts.

The *first section* of the model deals with parts arrival and data assigning. A part is assigned its property information such as feature dimensions, operation list, and the operation orders. The part is then sent to the *second section* of the model where operations are chosen. From the operation method selection matrix, numerous permutations of feature-process-machine-tool assignments can be implemented in the model. Visual Basic® is used to simplify the model logic and determine what feature is performed next and which operation will be used. This is done by considering all the resources that a part could use and using a specified performance indicator to decide the best possible combination. Moreover, queuing times and machining time are modeled. Once an operation is completed, the routing of the part will be decided according to the information assigned earlier.

Once the part arrives at a particular machine for specific operations, various possibilities for process settings can be assigned. To specify exactly what decision to make at the process level, performance indicators are assessed for an optimal impact based on stakeholder preference. Thus, an optimization model is constructed using OptQuest® and integrated with the simulation model to reduce the search space of each performance indicator for optimal process settings. In OptQuest®, system constraints on all resources, such as machine, material; control variables, attributes; constraints and objective function are established. Integration of the simulation and optimization models allows what-if analysis and optimal process planning.

4.3.2 Mathematical Models for Process Planning

The accuracy of the simulation and optimization results is highly related on the availability and quality of data within these models as well as the expressions to calculate tool life and cost during turning. In this case study, two main methods are identified for populating data for these models. Published data in previous studies and mathematical models are used in these models. Mathematical expressions and published data for estimating the energy consumption, production time, and cost are listed in Table 4.2.

Table 4.2 Mathematical expression use

Indicator	Turning process	Milling process	Drilling process
Machining Cost [85], [86], [87]	$C_{ij} = C_L T_{m_{ij}} + C_{TC_{ij}} \frac{T_{m_{ij}}}{T_{TL_{ij}}}, T_{TL_{ij}} = \frac{C\, T_{TL_{ijf}}{}^{N} f_{ijf}{}^{0.6} d_{ijf}{}^{0.15}}{v_{ij} f_{ij}{}^{0.6} d_{ij}{}^{0.15}}$		
	$T_{m_{ij}} = \frac{\pi D_i L_i}{v_{ij} f_{ij}}$,	$T_{m_{ij}} = \pi D_c (\frac{(L_i + \sqrt{d_{ij}(Dc - d_{ij})})}{v_{ij} z f_{ij}})$ *Peripheral milling (Plain milling),* $T_{m_{ij}} = \pi D_c (\frac{L_i + 0.5[Dc - \sqrt{(Dc^2 - w_i{}^2)}]}{v_{ij} z f_{ij}})$ *face milling* $D_c > w_i$ *and cutter is centered over the workpiece,* $T_{m_{ij}} = \pi D_c (\frac{L_i + \sqrt{w_i(Dc - w_i)}}{v_{ij} z f_{ij}})$ *face milling* $D_c > w_i$ *and cutter is offset to one side over the workpiece,* $T_{m_{ij}} = \pi D_c (\frac{L_i + 0.5 D_c}{v_{ij} z f_{ij}})$ *face milling* $D_c < w_i$ *or* $D_c = w_i$	$T_{m_{ij}} = \frac{\pi D_c (d_i + 0.5\, D_c \tan(90 - \frac{\theta}{2}))}{v_{ij} f_{ij}}$
Energy Consumption & Carbon Emission [88], [89], [90], [91], [92], [93]	$E_{ij} = \frac{844\, f_{ij}{}^{0.725} v_{ij}{}^{0.8987}\, d_{ij}{}^{0.75}}{6120}$	$E_{ij} = \frac{68.2\, a_{ij}\, z\, D_c{}^{-0.86} f_{ij}{}^{0.72}}{6120}$	$E_{ij} = \frac{133.6\, f_{ij}{}^{0.6561} v_{ij}}{6120} T_{m_{ij}}$
	$carbon\ emission = \delta\, E_{ij}$ $\delta = \frac{1}{1000.\eta} * [112 * \text{coal(C)} + 49 * \text{Natural Gas(G)} + 66 * \text{Petroleum(O)}]$		
Production Time [94]	$T_{P_{ij}} = V_{ij} \frac{\left[1 + \frac{T_{C_{ij}}}{T_{TL_{ij}}}\right]}{[v_{ij} f_{ij} d_{ij}]}$	$T_{P_{ij}} = V_{ij} \frac{\left[1 + \frac{T_{C_{ij}}}{T_{TL_{ij}}}\right]}{\left[\frac{w_i d_{ij} v_{ij} z f_{ij}}{\pi D_c}\right]}$	$T_{P_{ij}} = V_{ij} \frac{\left[1 + \frac{T_{C_{ij}}}{T_{TL_{ij}}}\right]}{\left[\frac{D_c v_{ij} f_{ij}}{4}\right]}$

In general, machine tool energy consumption contains both a constant energy consumption, which includes the startup operations (e.g., servos, spindle key, and coolant pump) and certain runtime operations (e.g., tool changes), and variable energy consumption that fluctuates with different machine loads. Energy is consumed at any machine tool regardless whether they are idle or cut a workpiece. In this case study, standby and additional load loss power is ignored, so the energy consumed during processing is the only energy considered. Since main power source is electricity; therefore, carbon emission generated by the electricity consumption is also evaluated. Operation time required to fabricate part features is a function of material removal rate, cutting tool life, set-up time per feature, machining time per feature, and tool change time. For machining cost, cost is given by the sum of the cost for machining a part and associated tooling cost.

Manufacturing organizations must continuously strive for higher levels of production rate where the resource usage, such as materials, machines, energy, labor, capital, and technology, are optimized [95]. For optimizing these objectives (i.e., cost, energy consumption, carbon emission, time), constraints need to be identified to define the feasible search space. Equations (1) to (9) are the constraint expressions. Power should not be higher than the operational power transmitted to cutting point by the machine tool:

$$\boldsymbol{P_m} \geq \frac{\boldsymbol{P_c}}{\boldsymbol{\eta}} \quad . \tag{1}$$

For the permissible quality *tolerance*, both the *surface roughness* and *radial deflection* of the workpiece are considered. Machine tool, operation type, cutting tool geometry, and process settings are the main parameters that affect surface roughness [96]. In this case study, the geometric factors is considered as they result in ideal or theoretical surface roughness in the absence of the other factors. The surface roughness of *turning*, *boring*, and *drilling* is given by [97] [98] and should not exceed the design permitted value.

$$\boldsymbol{R_{a_{ij}} = B_r NR^{\varepsilon R} BHN^{\theta R} v_{ij}{}^{\alpha R} f_{ij}{}^{BR} \leq R_{a_{ijmax}}}, \tag{2}$$

While the ideal surface roughness in milling can be evaluated using equation (3) [99]:

$$\boldsymbol{R_{a_{ij}} = z\,(\frac{f_{ij}{}^{2}}{32\,NR}) \leq R_{a_{ijmax}}} \tag{3}$$

Since the clamping conditions affect directly the radial deflection of the workpieces, the permissible radial deflection on turning, milling, and drilling processes are given below (expressions (4), (5), and (6) respectively) [100], [101]:

$$\boldsymbol{2\,K_b \frac{844\, f_{ij}{}^{0.725} v_{ij}{}^{-0.1013}\, d_{ij}{}^{0.75} L_{ij}^{3}}{ED_i^4} \leq \delta_{d_{ij}}} \tag{4}$$

$$2\,K_b \frac{68.2\, a_{ij}\, z\, D_c{}^{-0.86} f_{ij}{}^{0.72}\, d_{ij}{}^{0.86} L_{ij}^{3}}{ED_i^4} \leq \delta_{d_{ij}} \tag{5}$$

$$2\,K_b \frac{133.6\, f_{ij}{}^{0.6561} L_{ij}^{3}}{ED_i^4} \leq \delta_{d_{ij}} \tag{6}$$

Tool-chip interface temperature is estimated to predict the effect of process settings (i.e., cutting speed, depth of cut, feed rate) on cutting temperature [102]. High temperatures have main effects on tool life (i.e., shortening tool life), product quality (i.e., uncontrollable thermal expansion), and dangerous work conditions (i.e., worker subjects to hot chips). The temperature during machining can be calculated using expression (7):

$$\Delta \boldsymbol{T} = \frac{\mathbf{0.4}\, \boldsymbol{U}}{\boldsymbol{\rho}\, \boldsymbol{C_p}} \left(\frac{\boldsymbol{v_{ij} f_{ij}}}{\boldsymbol{\alpha_w}} \right)^{\mathbf{1/3}} \leq \boldsymbol{T_{max}} \tag{7}$$

Machines specification is the source for retrieving specific machine data (e.g., permissible maximum power) [103]. For the *tool life*, there is an acceptable range where the tool replacement time can be achieved by using equation (8) [104][105]:

$$\boldsymbol{t_r} = \boldsymbol{t_e}\, \frac{\boldsymbol{T_{m_{ij}}}}{\boldsymbol{T_{TL_{ij}}}}\ ; \boldsymbol{t_{rmin}} \leq \boldsymbol{t_r} \leq \boldsymbol{t_{rmax}}\ . \tag{8}$$

Finally, the maximum and minimum process settings values must be in the range determined by the selected process specifications.

$$\begin{aligned} &\boldsymbol{v_{ijmin}} \leq \boldsymbol{v_{ij}} \leq \boldsymbol{v_{ijmax}} \\ &\boldsymbol{f_{ij_{min}}} \leq \boldsymbol{f_{ij}} \leq \boldsymbol{f_{ij_{max}}} \\ &\boldsymbol{d_{ij_{min}}} \leq \boldsymbol{d_{ij}} \leq \boldsymbol{d_{ij_{max}}} \end{aligned} \tag{9}$$

4.4 Database Integration and Visualization

Tables in Appendix A.1 represent several of the databases that provide most of the data used in this research. However, to use the databases, the designers must provide part information, such as material type and geometric specification/description. Blueprint information is intended to act as a guide in selecting processes, machines, process settings, cutting tools, fixtures, and cutting fluids for the manufacturability. Finally, manufacturing engineers and production planners utilize these data to design process and operation planning. A GUI has been developed to provide a user-friendly interface. Once a query is created, the GUI extracts the required inputs to run both simulation and optimization models to produce the corresponding outputs. The GUI is built using HTML, Java Script, and PHP. The PHP, MySQL, and Apache server are employed together to realize the development of the web application. PHP is used to perform the following tasks: connect to the database in MySQL, write SQL queries and retrieve the query results, and write HTML codes. A visualization of this GUI is provided in Figure 4.4. All information regarding the process and production plans will be stored in the MySQL database once the “Submit” button is clicked.

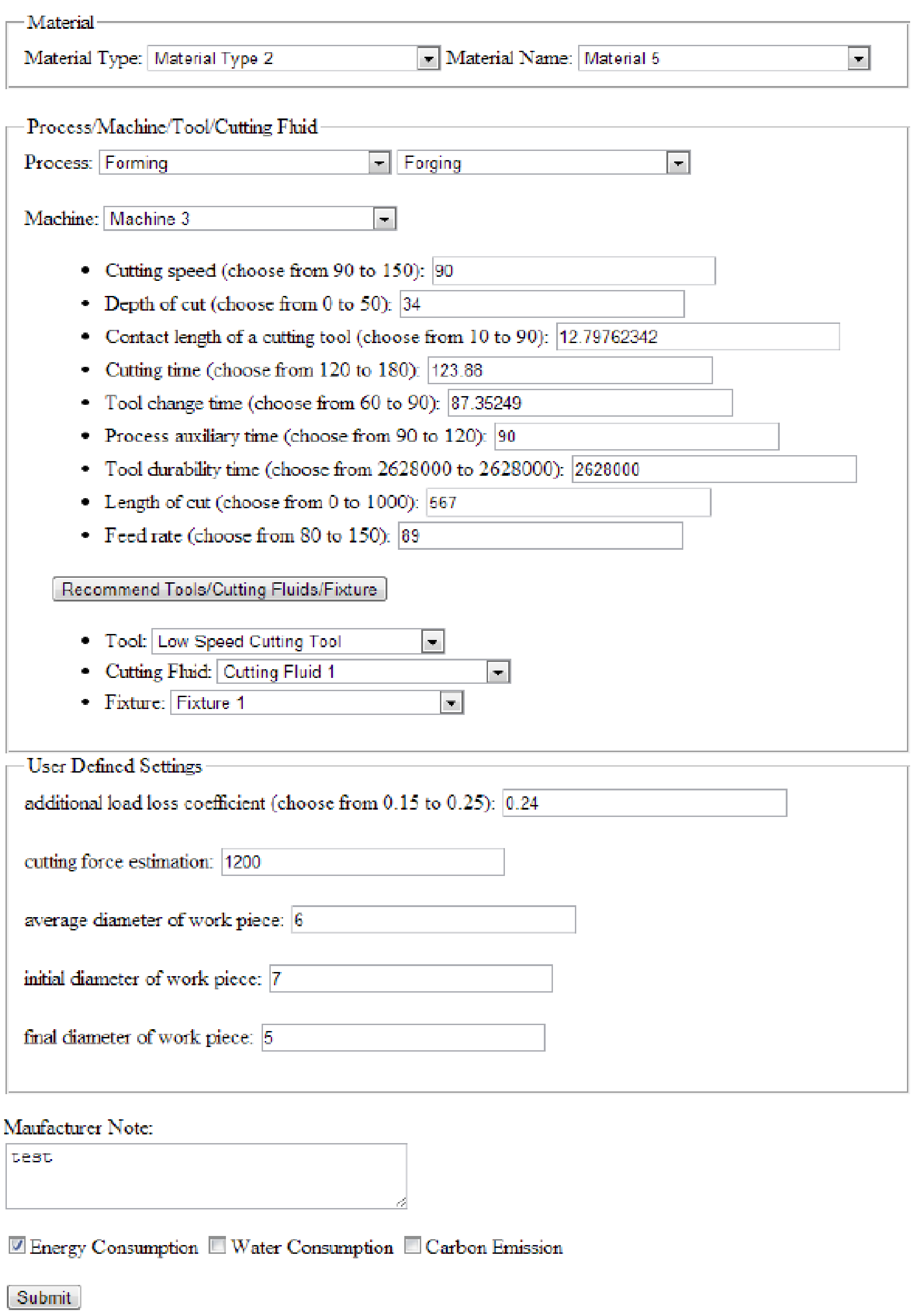

Figure 4.4 The graphical user interface

4.5 Simulation and Optimization Model Results

4.5.1 Single-Objective (SO) Decision Making Scenarios

The results ar discussed in this section. For each operation's resource(s) with the three feature precedence scenarios (feature sequence plans), the sustainability indicators (cutting power consumption, CO_2 emission, production cost) and the productivity indicator (machining time) are given. Table 4.3 shows that one or more resources could be allocated for each operation based on the capability of these resources and the stakeholders' objective function (e.g., minimizing production time). Various process plans are considered in fabricating the given part according to its design as shown in Table 4.4. The stakeholders could recognize the best process plan(s) that minimizes production time at each feature sequence plan, its energy consumption (e.g., cutting power required for machining), and the production cost as shown in Figure 4.5. The process plans PP_5, PP_1, and PP_4 are the ones that fabricate the given part design with minimum production times at the predefined, partially defined, and undefined feature sequence plans, respectively. However, stakeholders will probably select the predefined plan since the process plan PP_5 has the minimum production time among the others ($i.e., PP_1$ and PP_4).

Table 4.3 Resources' performance indicators impacts for minimizing production time

Feature Sequence Plan	Operation	Resource R_i	Sustainability Indicators			Productivity Indicator
			Cutting Power (KWh)	CO_2 Emission (Kg)	Cost(US $)	Time (hr.)
Predefined Feature Sequence Plan	Facing	R_1=P1-M1-T1	25.977	5.01367E-08	2.4279132	0.1987088
		R_2=P2-M2-T5	16.204	3.12754E-08	0.1704893	0.014185
	Grooving	R_3=P2-M2-T4	16.204	3.12754E-08	0.1704893	0.014185
	Threading	R_4=P1-M1-T2	7.793	1.5041E-08	0.7164750	0.0596126
	Spot Drill	R_6=P1-M1-T3	6.927	1.33698E-08	0.6368667	0.0529890
		R_7=P3-M3-T7	5.9150	1.1416E-08	2.6577420	0.2213626
	Drill	R_6=P1-M1-T3	17.318	3.34245E-08	1.5921667	0.1324725
		R_9=P4-M4-T9	8.4769	1.63604E-08	1.6971622	0.1413561
Partially Defined Feature Sequence Plan	Facing	R_2=P2-M2-T5	16.204	3.12754E-08	0.1704047	0.014185
	Grooving	R_3=P2-M2-T4	16.207	3.12754E-08	0.1704047	0.014185
	Threading	R_4=P1-M1-T2	9.1331	1.76269E-08	1.3507773	0.1124441
	Spot Drill	R_6=P1-M1-T3	8.1183	1.56684E-08	1.2006909	0.0999503
		R_7=P3-M3-T7	5.9150	1.1416E-08	2.9166734	0.2429692
	Drill	R_9=P4-M4-T9	8.47690	1.63604E-08	1.6968811	0.1413561
Undefined Feature Sequence Plan	Facing	R_2=P2-M2-T5	16.3139	3.14858E-08	0.1746218	0.0145290
	Grooving	R_1=P1-M1-T1	5.19551	1.00273E-08	0.4776500	0.0397417
		R_3=P2-M2-T4	16.3139	3.14858E-08	0.1746218	0.0145290
	Threading	R_4=P1-M1-T2	7.79327	1.5041E-08	0.7164750	0.0596126
	Spot Drill	R_7=P3-M3-T7	6.16903	1.19062E-08	3.1445062	0.261905
	Drill	R_6=P1-M1-T3	17.31838	3.34245E-08	1.5921667	0.1324725
		R_8=P3-M3-T8	15.75751	3.0412E-08	8.033609	4.7172487
		R_9=P4-M4-T9	16.039056	3.04858E-08	16.971622	1.4135619

Table 4.4. Types of process plans for different feature sequence when minimizing the production time

Feature Sequence Plan	Process Plan PP_j	Facing	Grooving	Threading	Spot Drill	Drill
Predefined Feature Sequence Plan	PP_1	R_1	R_3	R_4	R_6	R_6
	PP_2	R_1	R_3	R_4	R_6	R_9
	PP_3	R_1	R_3	R_4	R_7	R_6
	PP_4	R_1	R_3	R_4	R_7	R_9
	PP_5	R_2	R_3	R_4	R_6	R_6
	PP_6	R_2	R_3	R_4	R_6	R_9
	PP_7	R_2	R_3	R_4	R_7	R_6
	PP_8	R_2	R_3	R_4	R_7	R_9
Partially Defined Feature Sequence Plan	PP_1	R_2	R_3	R_4	R_6	R_9
	PP_2	R_2	R_3	R_4	R_7	R_9
Undefined Feature Sequence Plan	PP_1	R_2	R_1	R_4	R_7	R_6
	PP_2	R_2	R_1	R_4	R_7	R_8
	PP_3	R_2	R_1	R_4	R_7	R_9
	PP_4	R_2	R_3	R_4	R_7	R_6
	PP_5	R_2	R_3	R_4	R_7	R_8
	PP_6	R_2	R_3	R_4	R_7	R_9

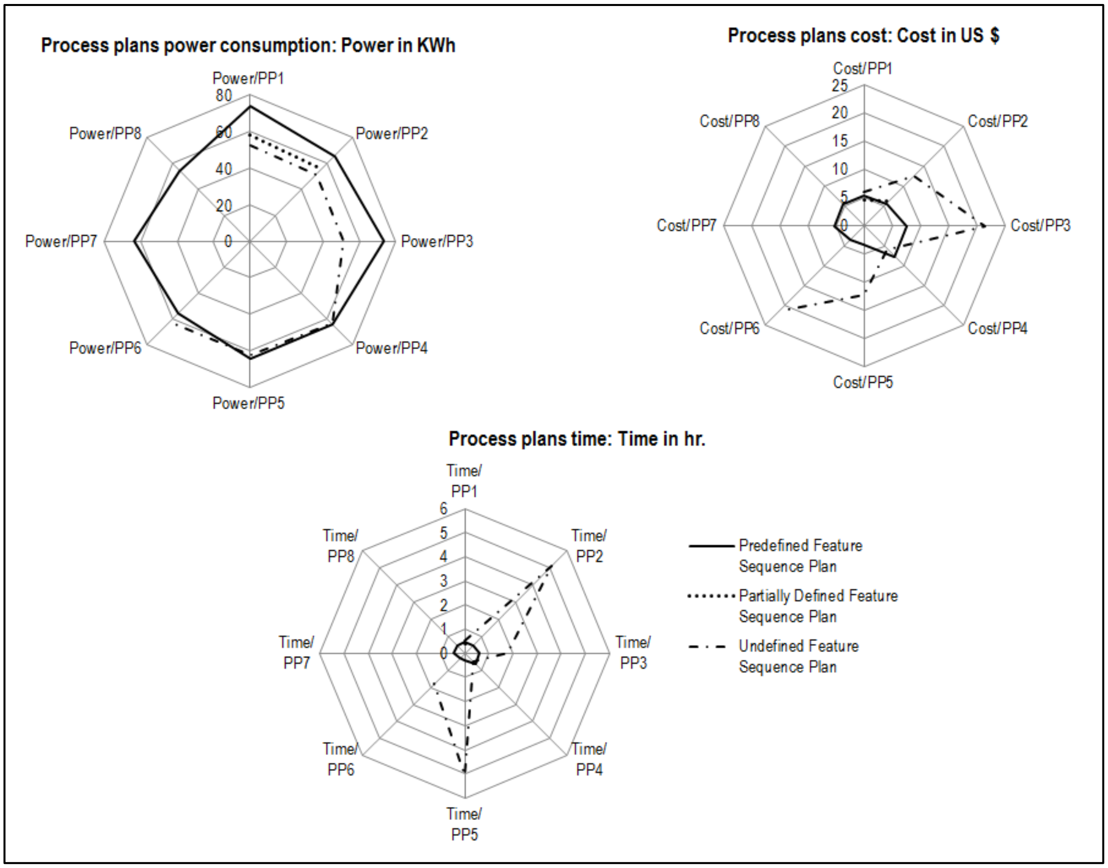

Figure 4.5 KPIs' values for minimizing process plan time

The impact of minimizing production power on selecting process planning is listed in Table 4.5.

Table4.5 Resources' performance indicators impacts when minimizing production power

Feature Sequence Plan	Operation	Resource R_i	Sustainability Indicators			Productivity Indicator
			Cutting Power (KWh)	CO2 Emission (Kg)	Cost(US $)	Time (hr.)
Predefined Feature Sequence Plan	Facing	R_1=P1-M1-T1	9.67646	1.86756E-08	3.44506	0.28681
		R_2=P2-M2-T5	16.96128	3.27353E-08	0.29000	0.02414
	Grooving	R_3=P2-M2-T4	16.96128	3.27353E-08	0.29000	0.02414
	Threading	R_4=P1-M1-T2	2.90293	5.60267E-09	1.03352	0.08604
	Spot Drill	R_6=P1-M1-T3	2.58039	4.98015E-09	0.91868	0.07648
		R_7=P3-M3-T7	6.48424	1.25146E-08	5.64257	0.47006
	Drill	R_6=P1-M1-T3	6.45097	1.24504E-08	2.29671	0.19120
		R_8=P3-M3-T8	16.56261	3.19659E-08	14.41447	1.20068
Partially Defined Feature Sequence Plan	Facing	R_1=P1-M1-T1	8.79037	1.69654E-08	2.66796	0.22207
	Grooving	R_1=P1-M1-T1	1.75807	3.39309E-09	0.53359	0.04441
	Threading	R_4=P1-M1-T2	2.63711	5.08963E-09	0.80031	0.06662
	Spot Drill	R_6=P1-M1-T3	2.34410	4.52411E-09	0.71145	0.05921
	Drill	R_6=P1-M1-T3	5.86025	1.13103E-08	1.77864	0.14804
Undefined Feature Sequence Plan	Facing	R_1=P1-M1-T1	8.79031	1.69654E-08	2.66796	0.22207
	Grooving	R_1=P1-M1-T1	1.75807	3.39309E-09	0.53359	0.04441
	Threading	R_4=P1-M1-T2	2.63711	5.08963E-09	0.80039	0.06662
	Spot Drill	R_6=P1-M1-T3	2.34410	4.52411E-09	0.71145	0.05921
	Drill	R_6=P1-M1-T3	5.86025	1.13103E-08	1.77864	0.148047

As indicated in the table above, one or more resources could be allocated for each operation based on the capability of these resources to address the stakeholders' objective function (minimizing production power). Therefore, various process plans are considered in fabricating the given part design Table 4.6.

Table 4.6 Types of process plans at different feature sequence when minimizing production power

Feature Sequence Plan	Process Plan PP_j	Facing	Grooving	Threading	Spot Drill	Drill
Predefined Feature Sequence Plan	PP_1	R_1	R_3	R_4	R_6	R_6
	PP_2	R_1	R_3	R_4	R_7	R_6
	PP_3	R_1	R_3	R_4	R_6	R_8
	PP_4	R_1	R_3	R_4	R_7	R_8
	PP_5	R_2	R_3	R_4	R_6	R_6
	PP_6	R_2	R_3	R_4	R_7	R_6
	PP_7	R_2	R_3	R_4	R_6	R_8
	PP_8	R_2	R_3	R_4	R_7	R_8
Partially Defined Feature Sequence Plan	PP_1	R_1	R_1	R_4	R_6	R_6
Undefined Feature Sequence Plan	PP_1	R_1	R_1	R_4	R_6	R_6

The stakeholders could recognize the best process plan(s) that minimizes production power at each feature sequence plan, its production time, and production cost is shown in Figure 4.6.

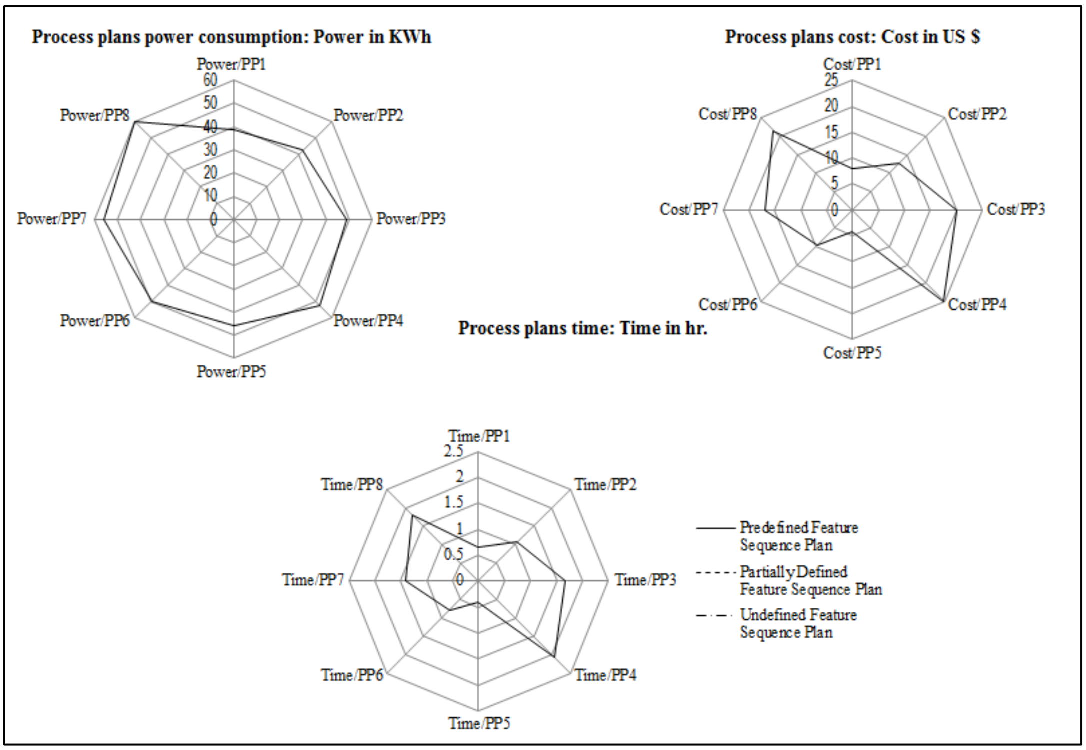

Figure 4.6 KPI's values for minimizing process plan power

The process plan, $PP_{1,}$ fabricates the given part design with minimum production power at the predefined, partially defined, and undefined feature sequence plans. However, at the partially defined and undefined scenarios the resources for grooving vary as compared to the fully defined scenario, which is indicated in Table 4.6. The stakeholders will select the partially and undefined plans since their best process plans have the minimum production power than the best predefined plan. The impact of minimizing production cost on selecting process planning will be discussed. Table 4.7 listed the sustainability and productivity indicators values for each operation's resource (s) at the three feature precedence scenarios.

Table4.7 Resources' performances indicators impacts when minimizing production cost

Feature Sequence Plan	Operation	Resource R_i	Sustainability Indicators			Productivity Indicator
			Cutting Power (KWh)	CO2 Emission (Kg)	Cost(US $)	Time (hr.)
Predefined Feature Sequence Plan	Facing	R_1=P1-M1-T1	19.90097	3.840E-08	2.58309	0.21495
		R_2=P2-M2-T5	16.20486	3.127E-08	0.17046	0.01418
	Grooving	R_3=P2-M2-T4	16.20481	3.127E-08	0.17046	0.01418
	Threading	R_4=P1-M1-T2	5.97029	1.152E-08	0.77492	0.06448
	Spot Drill	R_6=P1-M1-T3	5.30692	1.024E-08	0.68882	0.05732
		R_7=P3-M3-T7	6.33649	1.224E-08	3.49993	0.29152
	Drill	R_6=P1-M1-T3	13.26731	2.569E-08	1.722067	0.14330
		R_9=P4-M4-T9	8.81718	1.701E-08	2.19107	0.18251
Partially Defined Feature Sequence Plan	Facing	R_2=P2-M2-T5	16.20487	3.127E-08	0.170481	0.01419
	Grooving	R_3=P2-M2-T4	16.20487	3.125E-08	0.17048	0.01419
	Threading	R_4=P1-M1-T2	7.79326	1.501E-08	0.71647	0.05963
	Spot Drill	R_6=P1-M1-T3	6.92735	1.338E-08	0.63686	0.05299
	Drill	R_6=P1-M1-T3	17.31838	3.342E-08	1.59216	0.13247
Undefined Feature Sequence Plan	Facing	R_2=P2-M2-T5	16.20487	3.127E-08	0.17048	0.01419
	Grooving	R_3=P2-M2-T4	16.20487	3.127E-08	0.17048	0.01419
	Threading	R_4=P1-M1-T2	7.79326	1.504E-08	0.71647	0.05963
	Spot Drill	R_6=P1-M1-T3	6.92735	1.336E-08	0.63686	0.05299
	Drill	R_6=P1-M1-T3	17.31838	3.342E-08	1.59216	0.13247

The best process plan(s) among various process plans listed in Table 4.8 can be recognized based on the minimal production cost as illustrated in Figure 4.7.

Table 4.8 Types of process plans at different feature sequence when minimizing production cost

Feature Sequence Plan	Process Plan PP_j	Facing	Grooving	Threading	Spot Drill	Drill
Predefined Feature Sequence Plan	PP_1	R_1	R_3	R_4	R_6	R_6
	PP_2	R_1	R_3	R_4	R_7	R_6
	PP_3	R_1	R_3	R_4	R_6	R_9
	PP_4	R_1	R_3	R_4	R_7	R_9
	PP_5	R_2	R_3	R_4	R_6	R_6
	PP_6	R_2	R_3	R_4	R_7	R_6
	PP_7	R_2	R_3	R_4	R_6	R_9
	PP_8	R_2	R_3	R_4	R_7	R_9
Partially Defined Feature Sequence Plan	PP_1	R_2	R_3	R_4	R_6	R_6
Undefined Feature Sequence Plan	PP_1	R_2	R_3	R_4	R_6	R_6

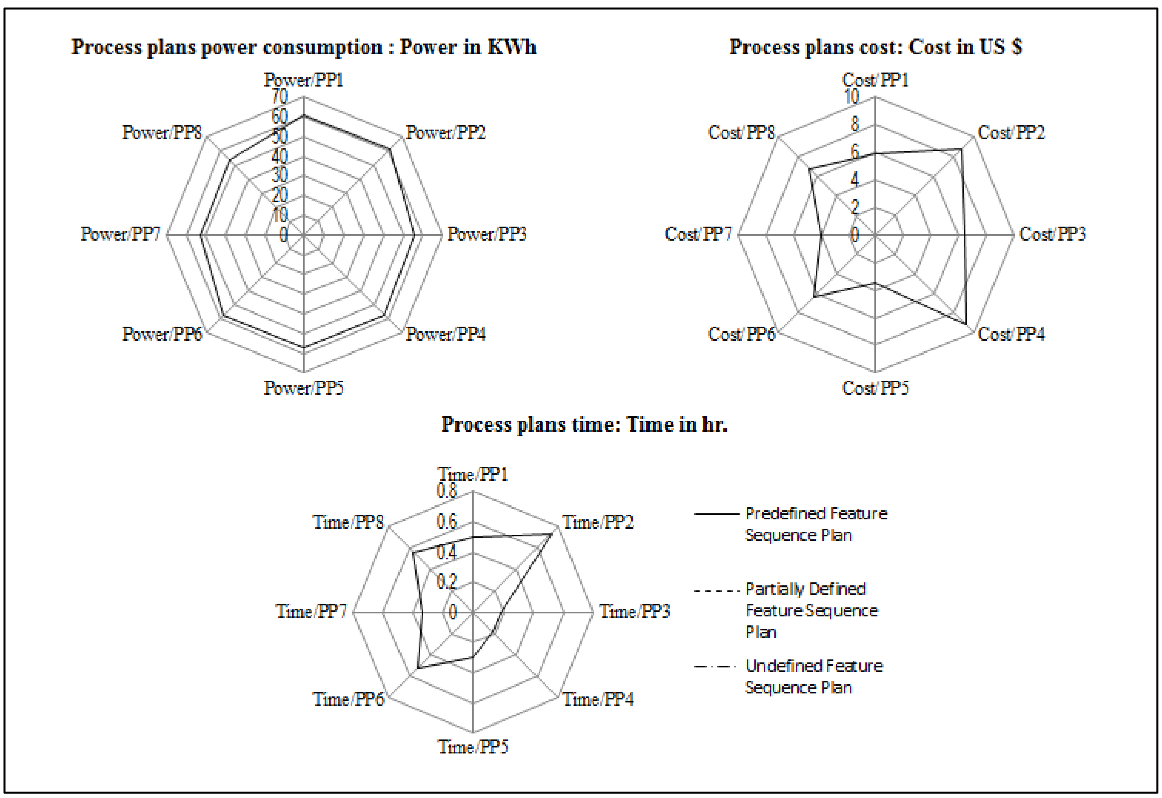

Figure 4.7 KPIs' values for minimizing process plan cost

Moreover, production time and power for all process plans including the optimal one are shown in this figure. The process plans PP_5, PP_1, and PP_1 are the ones that fabricate the given part design with minimum production cost at the predefined, partially defined, and undefined feature sequence plans, respectively. However, stakeholders will select the partially and undefined plans since their best process plans (i.e. PP_1) have the minimum production cost than the best predefined plan (i.e. PP_5).

4.5.2 Multi-Criteria Decision Making (MCDM) Scenarios

The MCDM technique was used to identify the best process plan when relative importance weights are assigned to the targeted indicators. Weights are allocated to the indicators using the specified technique discussed in the methodology section. Sensitivity analysis is performed to determine the impacts on the outcomes by varying the KPIs weights. In this study, the combined model that aggregate time, energy, carbon emission, and cost uses two different settings for the weight values of [0.35, 0.4, 0, 0.25] and [0.2, 0.2, 0, 0.6], respectively. To avoid duplicating the influence of energy and carbon emission on the aggregated objective function, zero weight is assigning to the carbon emission indicator since both carbon emission and energy consumption are dependent on each other. Selecting the best compromise process plan at each feature sequence plan is based on users' preferences since the notion of optimal alternatives does not exist in MCDM. Consequently, the MCDM method is to rank the alternatives from the best to the worst, based on the stakeholder's preferences. A combined model 0.35/0.4/0/0.25 is built that aggregate time, energy, carbon emission, and cost in one model when 0.35, 0.4, 0, and 0.25 weights are assigned to these KPIs, respectively. Process plans for different sequence plan, including the best ones, are listed in Table 4.9 and their KPIs' values are shown in Figure 4.8.

Table 4.9 Process plans at different sequence plans when minimizing combined 0.35/0.4/0/0.25 objective function

Feature Sequence Plan	Process Plan PP_j	Facing	Grooving	Threading	Spot Drill	Drill
Predefined Plan	PP_1	R_1	R_3	R_4	R_6	R_6
	PP_2	R_1	R_3	R_4	R_7	R_6
	PP_3	R_1	R_3	R_4	R_6	R_8
	PP_4	R_1	R_3	R_4	R_7	R_8
	PP_5	R_2	R_3	R_4	R_6	R_6
	PP_6	R_2	R_3	R_4	R_7	R_6
	PP_7	R_2	R_3	R_4	R_6	R_8
	PP_8	R_2	R_3	R_4	R_7	R_8
Partially Defined Plan	PP_1	R_1	R_1	R_4	R_7	R_6
	PP_2	R_2	R_1	R_4	R_7	R_6
Undefined Plan	PP_1	R_2	R_1	R_4	R_7	R_9

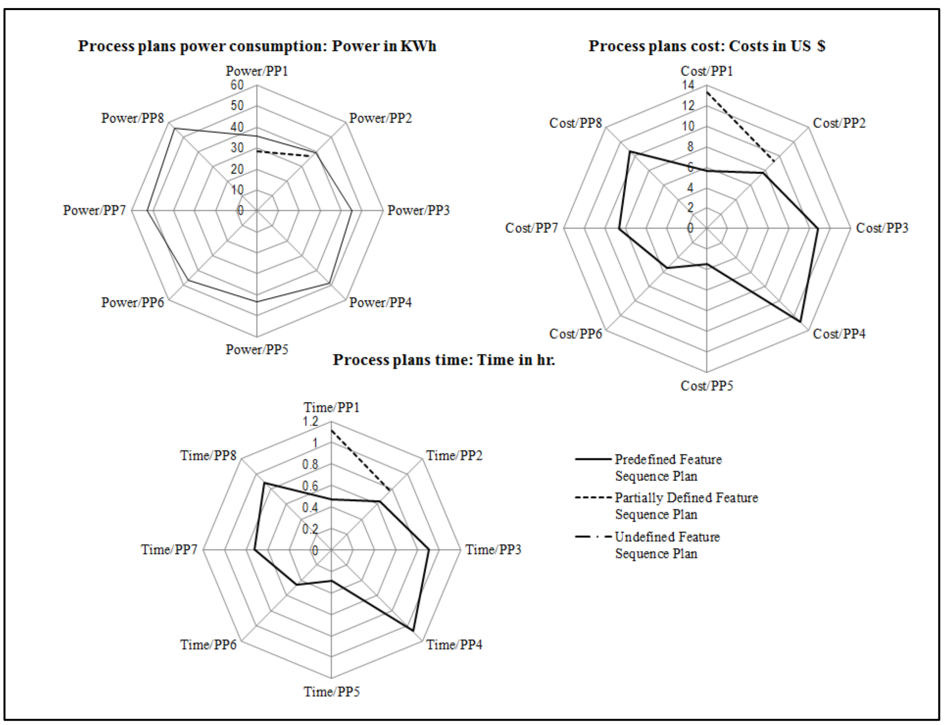

Figure 4.8 KPIs' values for the 0.35/0.4/0/0.25 objective function model

For instance, process plan PP_1 as the predefined plan shows the minimum power consumption among other process plans using the predefined sequence while PP_1 is not optimal with regard to production cost and time. However, PP_1 is selected as the best process plan as it is the optimal plan that minimizes the combined objective function for the predefined sequence with specific weights assigned for the three individual objectives (i.e., power, cost, and time).

A combined model 0.2/0.2/0/0.6 is built that aggregate time, energy, carbon emission, and cost in one model when 0.2, 0.2, 0, and 0.6 weights are assigned to these KPIs, respectively. Score matrix Table 4.10 is formulated based on the normalized KPIs.

Table 4.10 Score matrix for combined 0.2/0.2/0/0.6 model

Feature Sequence Plan	Operation	Resource R_i	Sustainability Metrics			Productivity Metric	Score (S_i)	Rank
			Cutting Power (0.2)	CO2 Emission (0)	Cost (0.6)	Time (0.2)		
Predefined Plan	Facing	R_1=P1-M1-T1	0.53493	0.53495	0.65696	0.65709	0.63256	2
		R_2=P2-M2-T5	0	0	1	1	0.8	1
	Grooving	R_3=P2-M2-T4	0	0	1	1	0.8	1
	Threading	R_4=P1-M1-T2	0.97889	0.97887	0.92284	0.92288	0.93406	1
	Spot Drill	R_6=P1-M1-T3	1	1	0.93551	0.93551	0.94841	1
		R_7=P3-M3-T7	0.74232	0.74237	0.63105	0.63089	0.65329	2
	Drill	R_6=P1-M1-T3	0.74635	0.74636	0.78356	0.78366	0.77613	1
		R_8=P3-M3-T8	0.07927	0.07908	0	0	0.01582	2
Partially Defined Plan	Facing	R_1=P1-M1-T1	0	0	0	0.11222	0.02244	2
		R_2=P2-M2-T5	0.33189	0.38481	0.37064	1	0.48865	1
	Grooving	R_1=P1-M1-T1	0.86192	1	0.88952	0.90192	0.88632	1
		R_3=P2-M2-T4	0.33189	0.38481	1	1	0.86627	2
	Threading	R_4=P1-M1-T2	0.75343	0.87521	0.77834	0.80321	0.77833	1
	Spot Drill	R_7=P3-M3-T7	0.82909	0.96278	1	0	0.76581	1
	Drill	R_6=P1-M1-T3	1	0.41667	0.37064	0.44126	0.51063	1
Undefined Plan	Facing	R_2=P2-M2-T5	0	0	1	1	0.8	1
	Grooving	R_1=P1-M1-T1	0.74629	0.74628	0.87557	0.87571	0.84974	1
	Threading	R_4=P1-M1-T2	0.57517	0.57511	0.77886	0.77912	0.73816	1
	Spot Drill	R_7=P3-M3-T7	0.69129	0.69124	0	0	0.13825	1
	Drill	R_9=P4-M4-T9	1	1	0.38637	0.38639	0.50909	1

At each sequence plan, the resource that has the highest score is selected as the best choice for fabricating that operation. Process plans at different sequence plans, including the best ones, are listed in Table 4.11 and their KPIs' values are shown in Figure 4.9.

Table 4.11 Process plans at different sequence plans when minimizing combined 0.2/0.2/0/0.6 objective function

Feature Sequence Plan	Process Plan PP_j	Facing	Grooving	Threading	Spot Drill	Drill
Predefined Plan	PP_1	R_1	R_3	R_4	R_6	R_6
	PP_2	R_1	R_3	R_4	R_6	R_8
	PP_3	R_1	R_3	R_4	R_7	R_6
	PP_4	R_1	R_3	R_4	R_7	R_8
	PP_5	R_2	R_3	R_4	R_6	R_6
	PP_6	R_2	R_3	R_4	R_6	R_8
	PP_7	R_2	R_3	R_4	R_7	R_6
	PP_8	R_2	R_3	R_4	R_7	R_8
Partially Defined Plan	PP_1	R_1	R_1	R_4	R_7	R_6
	PP_2	R_1	R_3	R_4	R_7	R_6
	PP_3	R_2	R_1	R_4	R_7	R_6
	PP_4	R_2	R_3	R_4	R_7	R_6
Undefined Plan	PP_1	R_2	R_1	R_4	R_7	R_9

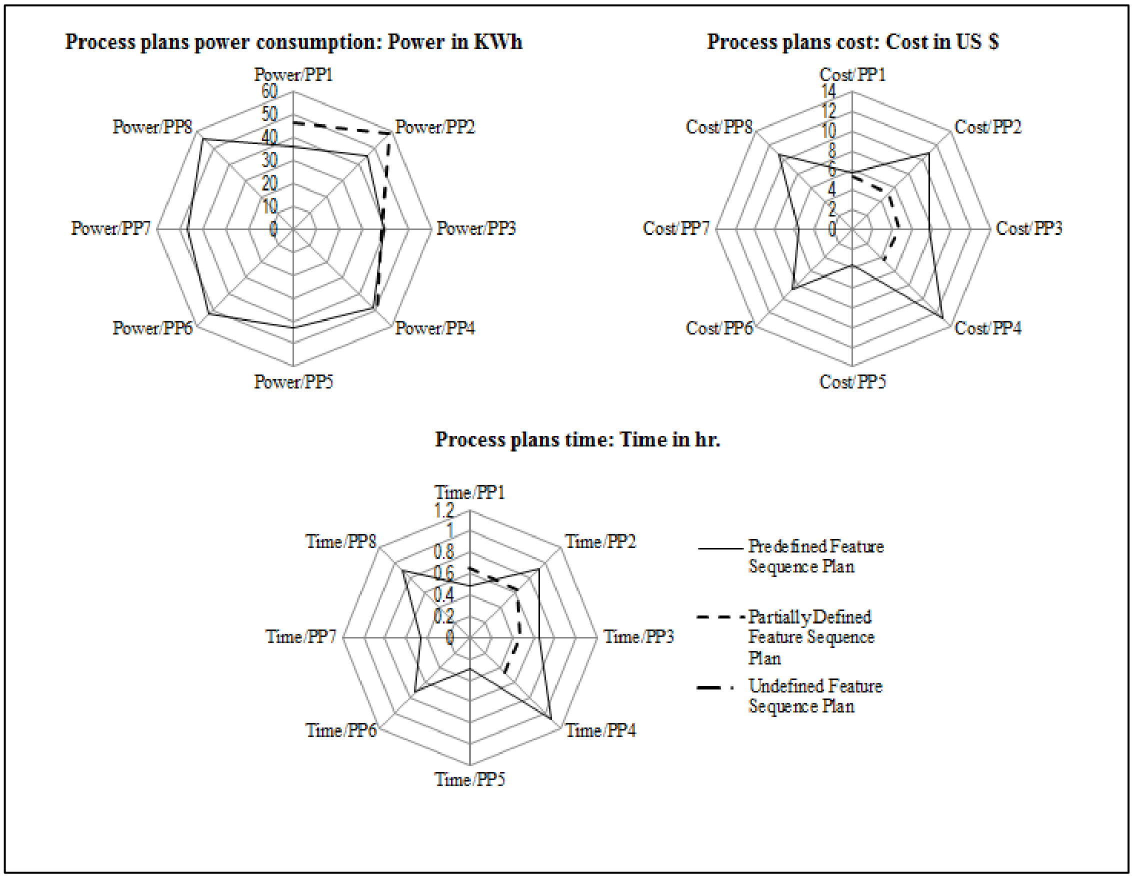

Figure 4.9 KPIs' values when minimizing a combined 0.2/0.2/0/0.6 objective function

As illustrated in Figure 4.9 that process plan PP_5, for example, at the predefined plan displays the minimum production cost and time among other process plans at the predefined sequence while PP_5 is not optimal regarding power consumption compared to other plans with the same sequence. PP_5 is selected as the best process plan as it is the optimal plan that minimizes the combined objective function for the predefined sequence with specific weights assigned for the three individual objectives (i.e., power, cost, and time).

4.5.3 Comparisons between MCDM and SO Decision Scenarios

Time versus MCDM (0.35/0.4/0/0.25) Scenarios

The best process plans operation time, power, and cost for both models for the three plans sequences are shown in Figure 4.10.

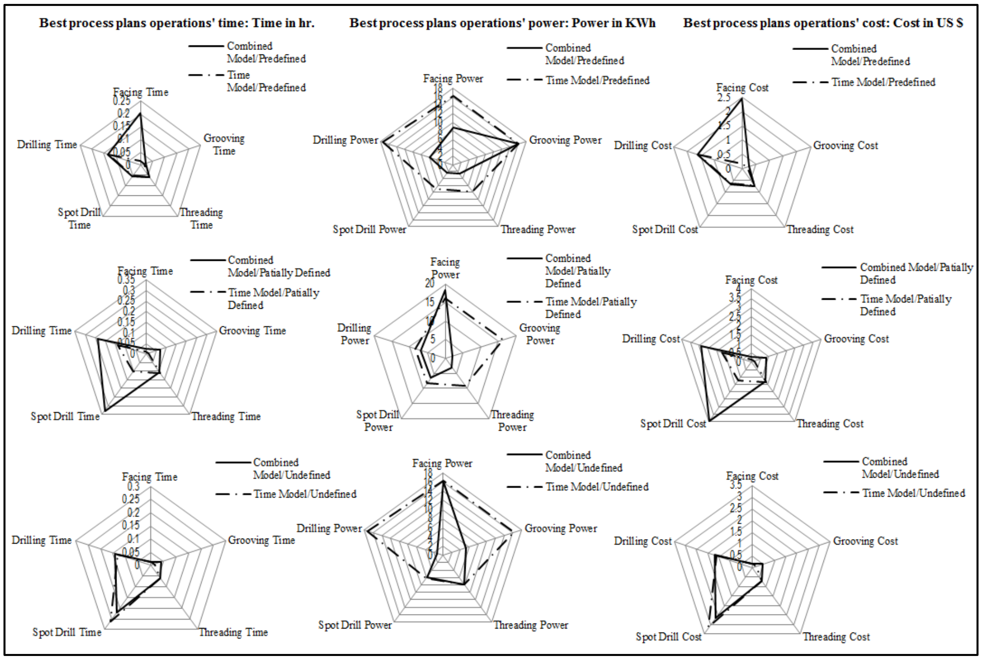

Figure 4.10 Time, power and cost values for the best plan process in 'time only' and the 'combined with weight values of 0.35/0.4/0/0.25' models

For instance, the impacts of the best process plan regarding facing, grooving, threading, spot drill, and drilling times at each sequence plan can be recognized when comparing the two models as shown in the left section in Figure 4.10 under the "Best process plans operations' time: Time in hr." Stakeholders can then identify the operation(s) that have a significant impact on each indicator modeled for additional examination. Furthermore, regarding all process plans, including the best ones in Table 4.4 and Table 4.9, the impacts for each operation are mainly dependent on the optimal process settings of cutting speed, feed rate, depth of cut, the queue capacity at each operation, tool change time, and part transport time from one operation to another. The depths of cut are assumed as constants and their values are adopted from different published data. Cutting speed and feed rate for each process (turning, milling, press drill, and boring) and each machining operation (facing, grooving, threading, spot drill, and drill) for the best process plan in the “time only” model and the “combined with weight values of 0.35/0.4/0/0.25” model are shown clearly in Figure 4.11.

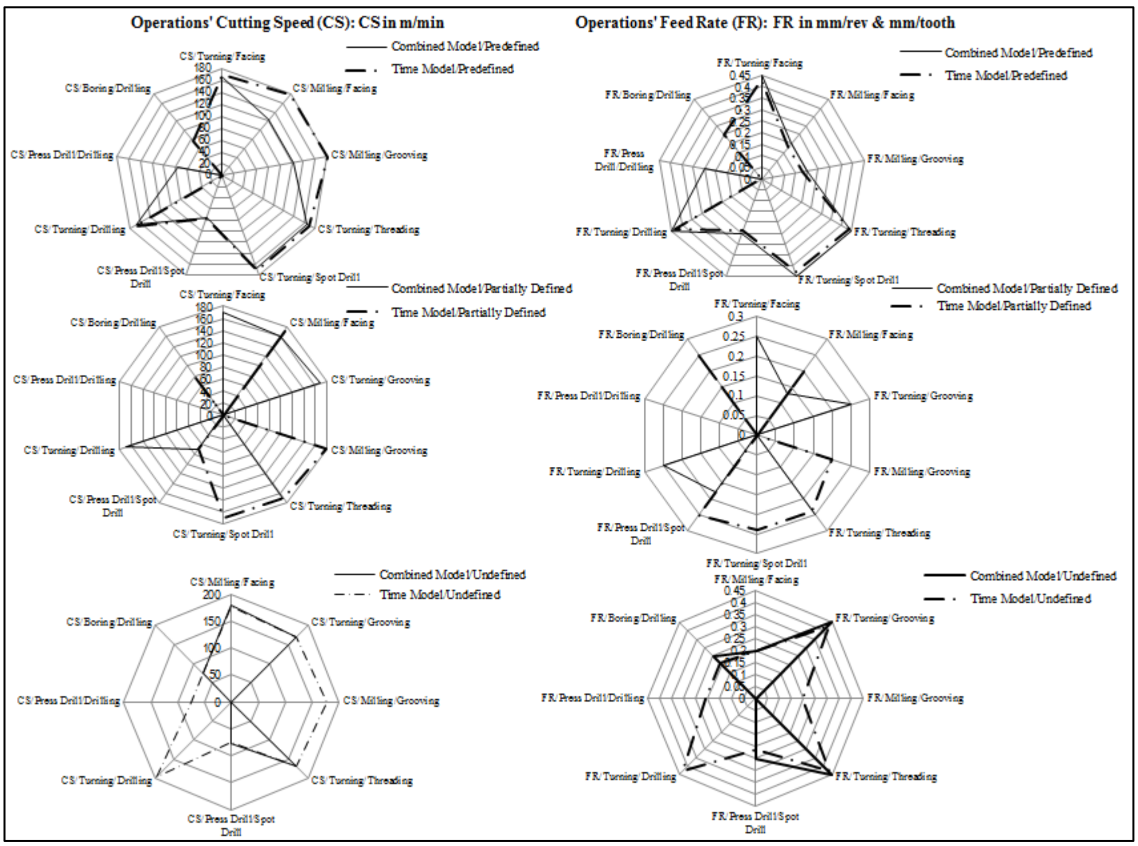

Figure 4.11 Cutting speed and feed rate values for the 'time only' and the 'combined with weight values of 0.35/0.4/0/0.25' models

Table 4.12 lists the impacts of the optimal process plans on KPIs for the two models. Adopting a predefined process plan for these two models decreases average processing time for a given part design about 49.83% and 22.23% compared to the other two scenarios (i.e., partially defined, undefined plan), respectively. Moreover, utilizing the predefined plan also lowers the cost on average about 50% and 22.3% as well. However, the partially defined plan lowers the power consumption on average 13.63% and 13.67% than the predefined and undefined plans, respectively. In summary, the predefined plan provides significant time and cost reductions while the partially defined plan results in the decrease of energy consumption.

Table 4.12 Optimal process plans KPIs' impacts at different feature sequence plans

KPI	Feature Sequence Plan	Model	
		Time	Combined 0.35/0.4/0/0.25
Time (hr.)	Predefined	0.27345	0.47259
	Partially Defined	0.38212	1.10492
	Undefined	0.48305	0.47626
Power (KWh)	Predefined	64.4487	35.83671
	Partially Defined	58.13809	28.48321
	Undefined	63.90848	36.42758
Cost (US $)	Predefined	3.28649	5.67103
	Partially Defined	4.58916	13.26881
	Undefined	5.80241	5.71952

Time versus MCDM (0.2/0.2/0/0.6) Scenarios

Figure 4.12 compares the best process plan for the two models and impacts on facing, grooving, threading, spot drill, and drilling time, power, and cost.

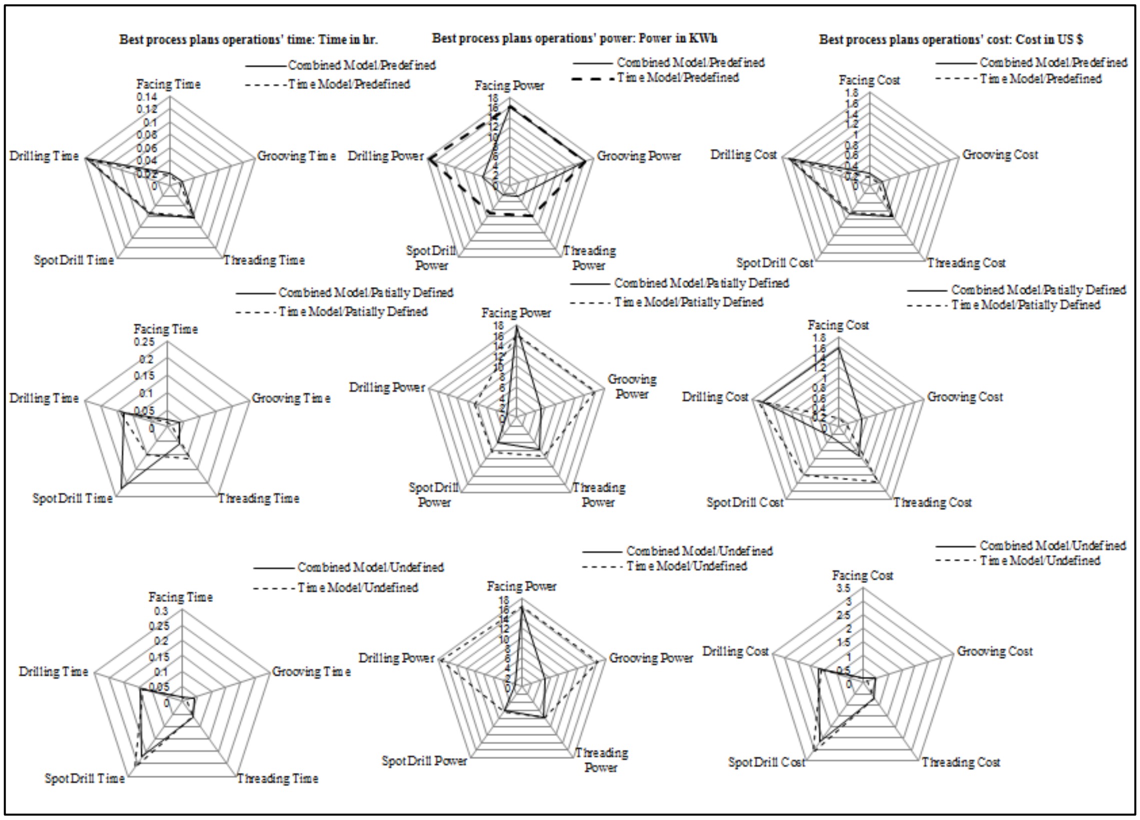

Figure 4.12 Time, power and cost values at the best process plans in Time and Combined 0.2/0.2/0/0.6 models

Regarding all the process plans, including the optimal plans of Table 4.4 and Table 4.11, the impact of each operation mainly depends on the optimal process settings of cutting speed, feed rate, depth of cut, queue capacity at each operation, tool change time, and part transport time from one operation to another. While depth of cut is assumed as constant, optimal settings for both cutting speed and feed rate for each process (turning, milling, press drill, and boring) and each machining operation (facing, grooving, threading, spot drill, and drill) are shown clearly in Figure 4.13.

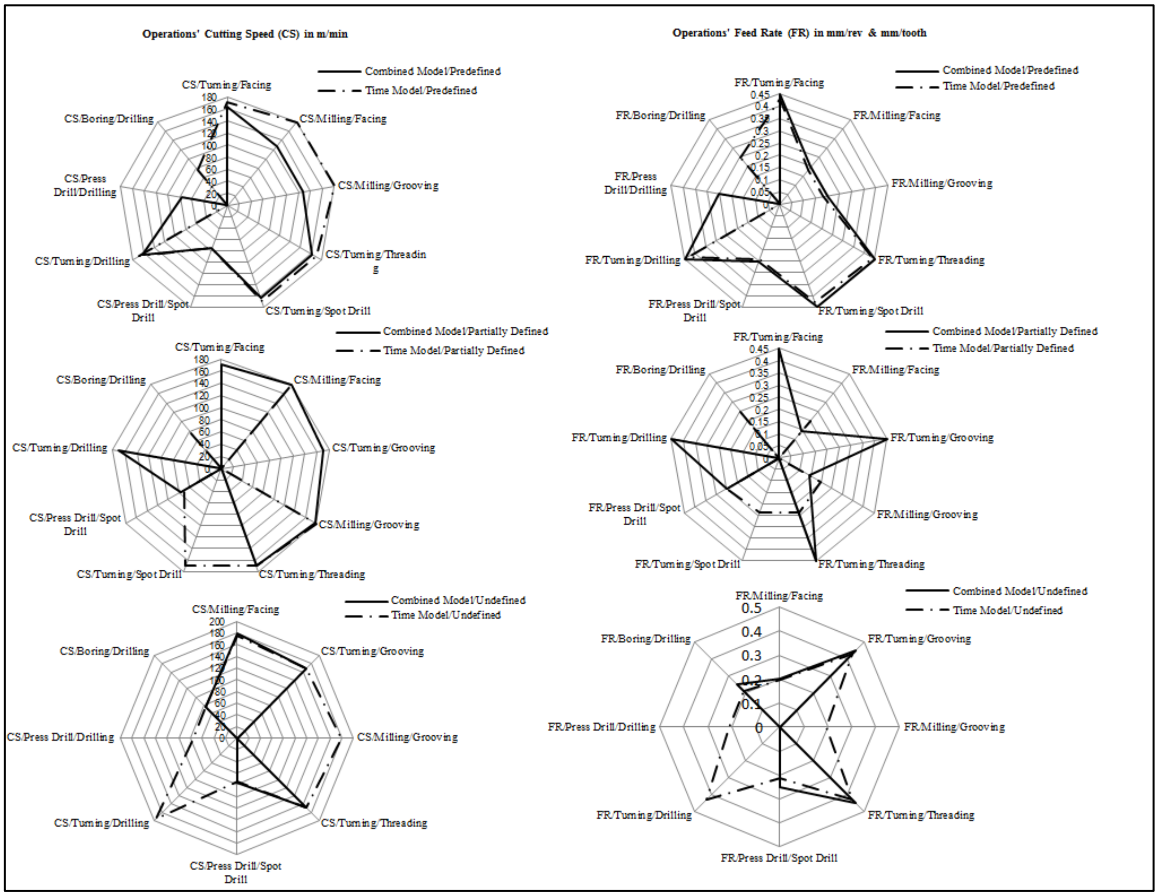

Figure 4.13 Cutting speed and feed rate values at the Time and Combined 0.2/0.2/0/0.6 models

Therefore, adopting a predefined sequence plan, production time and cost decreases on average about 35.916% and 34.2% compared to the other two scenarios (i.e., partially defined and undefined plan), respectively. However, adopting partially defined plan lowered power on average by 1% and 11.1%, respectively, compared to the other plans.

Power versus MCDM (0.2/0.2/0/0.6) and MCDM (0.35/0.4/0/0.25) Scenarios

Comparisons between Power scenario and the MCDM scenarios listed above are illustrated in Figure 4.14 and Figure 4.15.

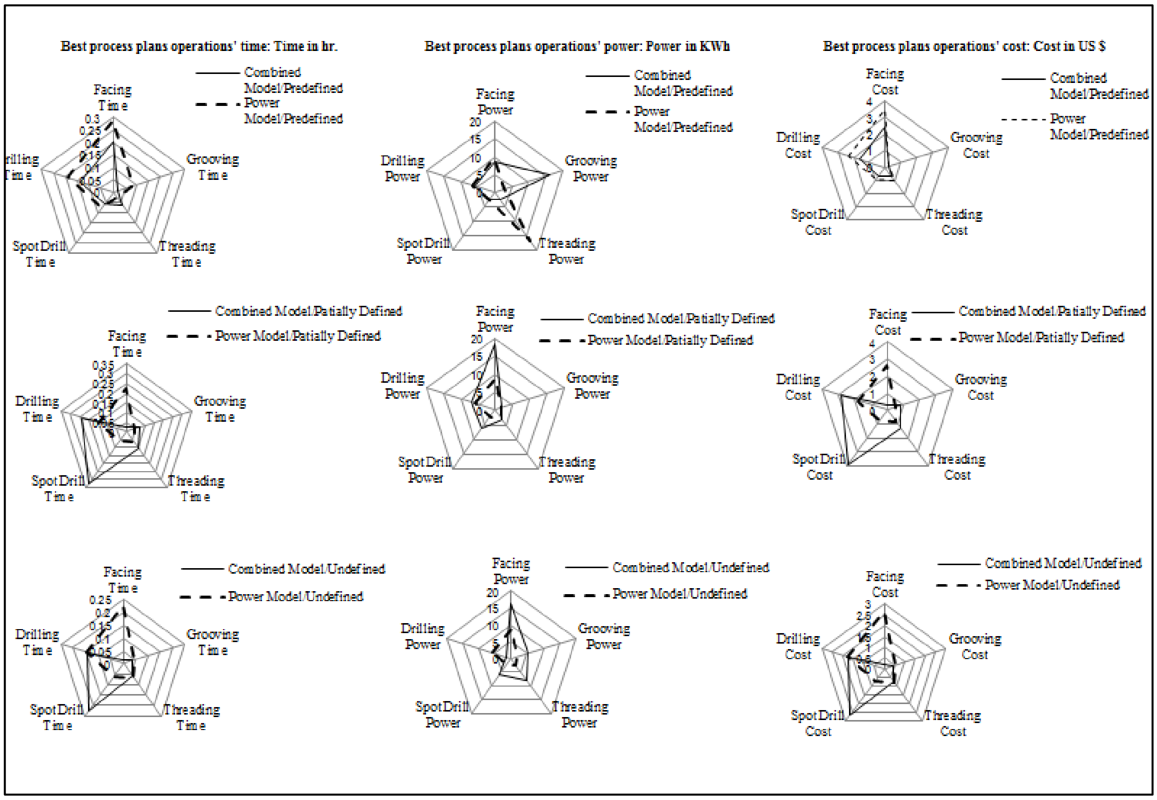

Figure 4.14 Time, power and cost values at the best process plans in Power and Combined 0.35/0.4/0/0.25

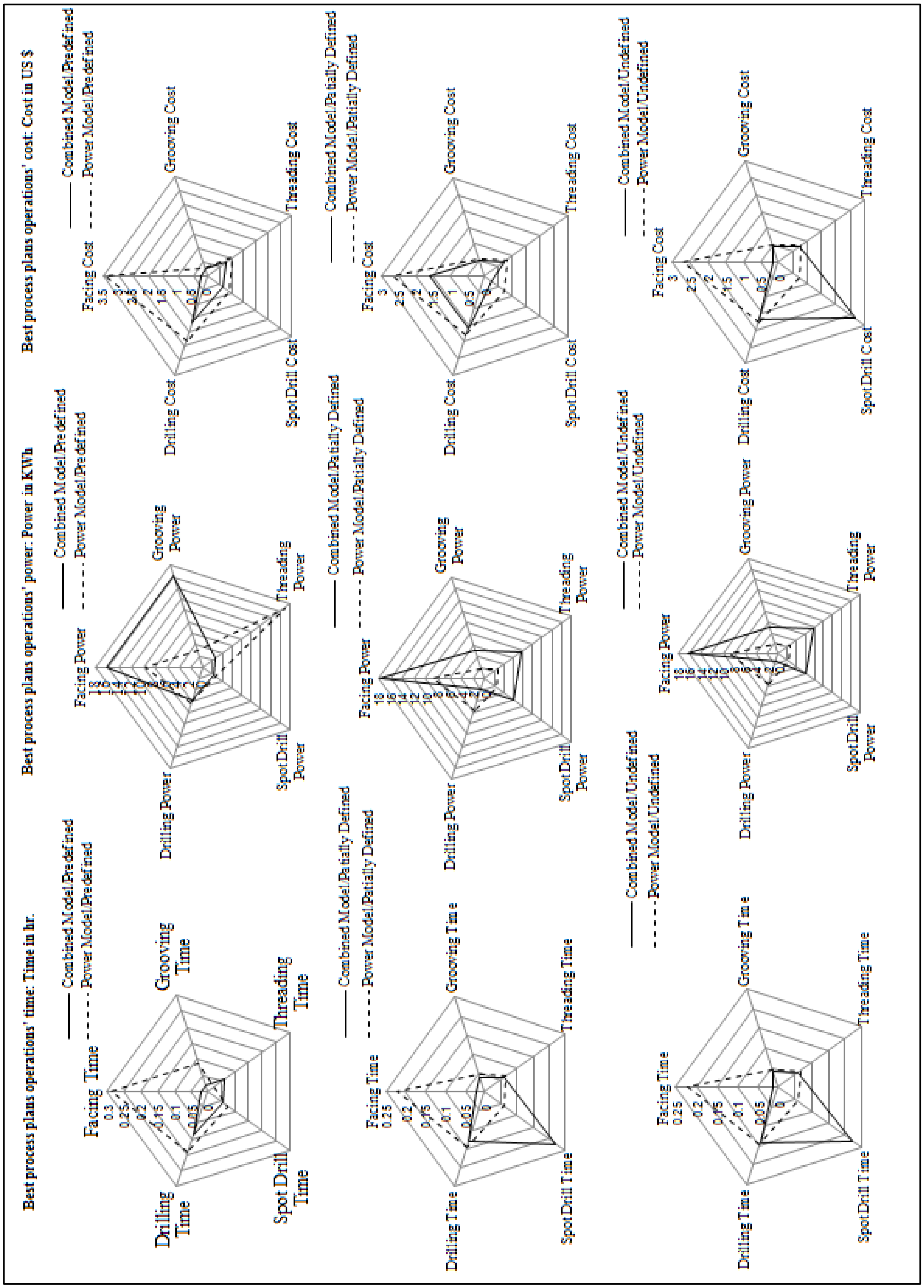

Figure 4.15 Time, power and cost values at the best process plans in Power and Combined 0.2/0.2/0/0.6 models

The optimal process settings for the best process plans for the power model of Table 4.6 in comparison to both combined 0.35/0.4/0/0.25 model of Table 4.9, and combined 0.2/0.2/0/0.6 model of Table 4.11, are shown in Figure 4.16 and Figure 4.17, respectively.

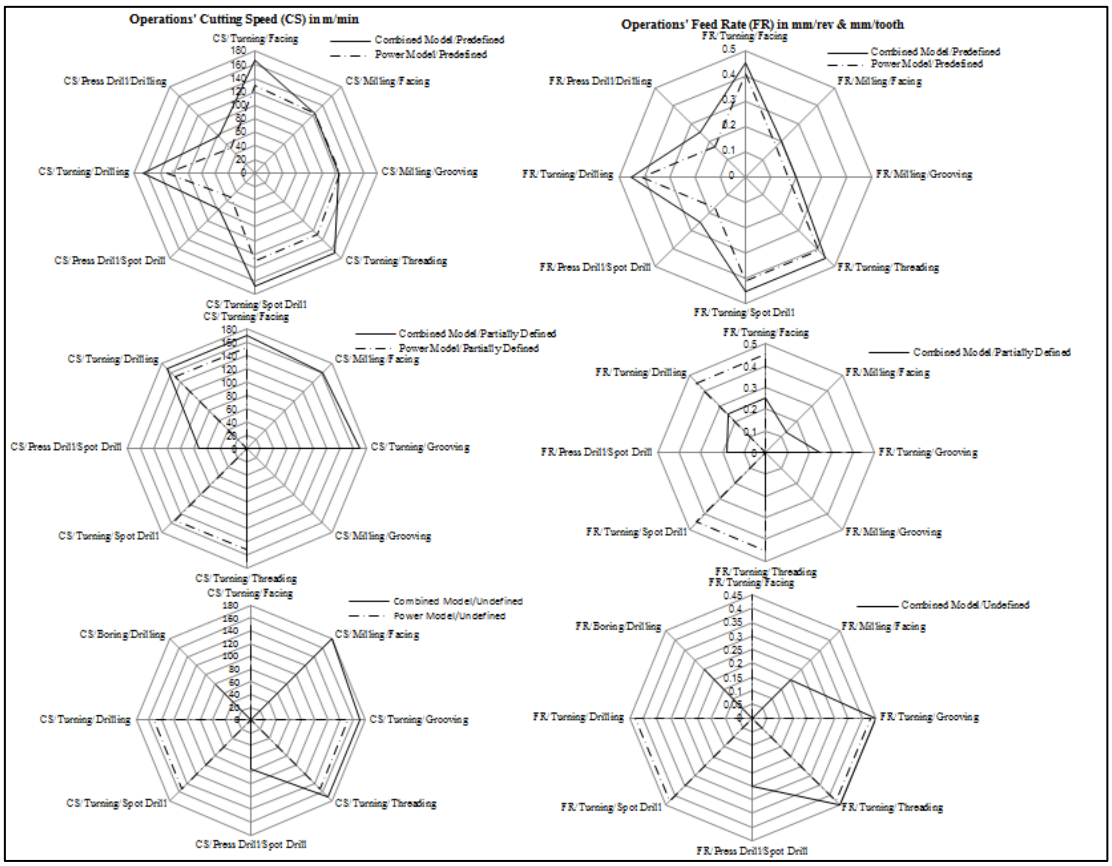

Figure 4.16 Cutting speed and feed rate values at the Power and Combined 0.35/0.4/0/0.25 models

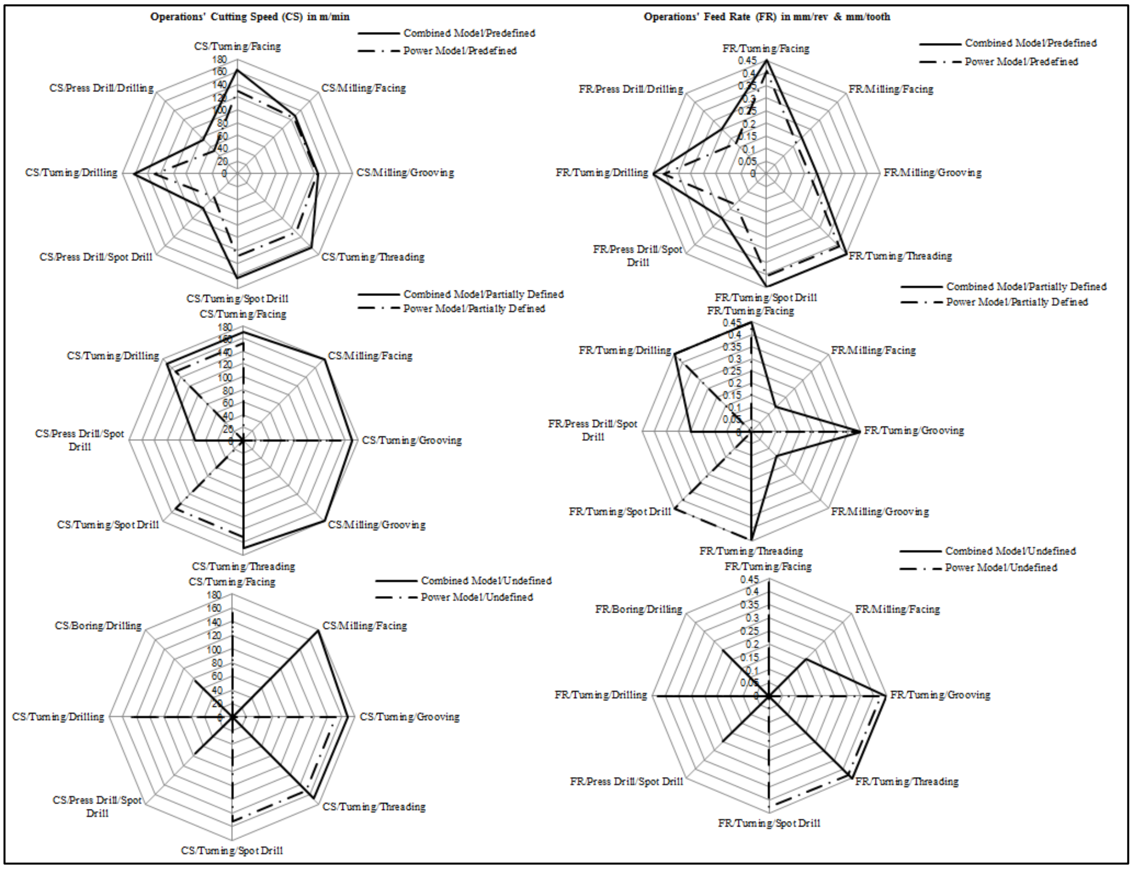

Figure 4.17 Cutting speed and feed rate values at the Power and Combined 0.2/0.2/0/0.6 models

From the figures, adopting partially defined and undefined plans with the Power model decreases on average processing time, power and cost by about 18.7%, 44.5% and 18.68% than the predefined process sequence, respectively. However, adopting a partially defined sequence plan for the combined 0.35/0.4/0/0.25 reduced power on average by 15.668% compared to the predefined and undefined plans, and reduced time and cost on average by 22.233% compared to the partially defined and undefined sequence plans. A predefined plan for the Combined 0.2/0.2/0/0.6 scenario decreases average processing time and cost for a given part design by about 34.2% compared to the other two scenarios. Further, adopting a partially defined plan for the Combined 0.2/0.2/0/0.6 scenario reduced power on average by 11.1% compared to other plans.

Cost versus MCDM (0.2/0.2/0/0.6) and MCDM (0.35/0.4/0/0.25) Scenarios

Figures 4.18 and 4.19 compare the impacts on sustainability and productivity indicators for the Combined 0.35/0.4/0/0.25 and Combined 0.2/0.2/0/0.6 scenarios, respectively.

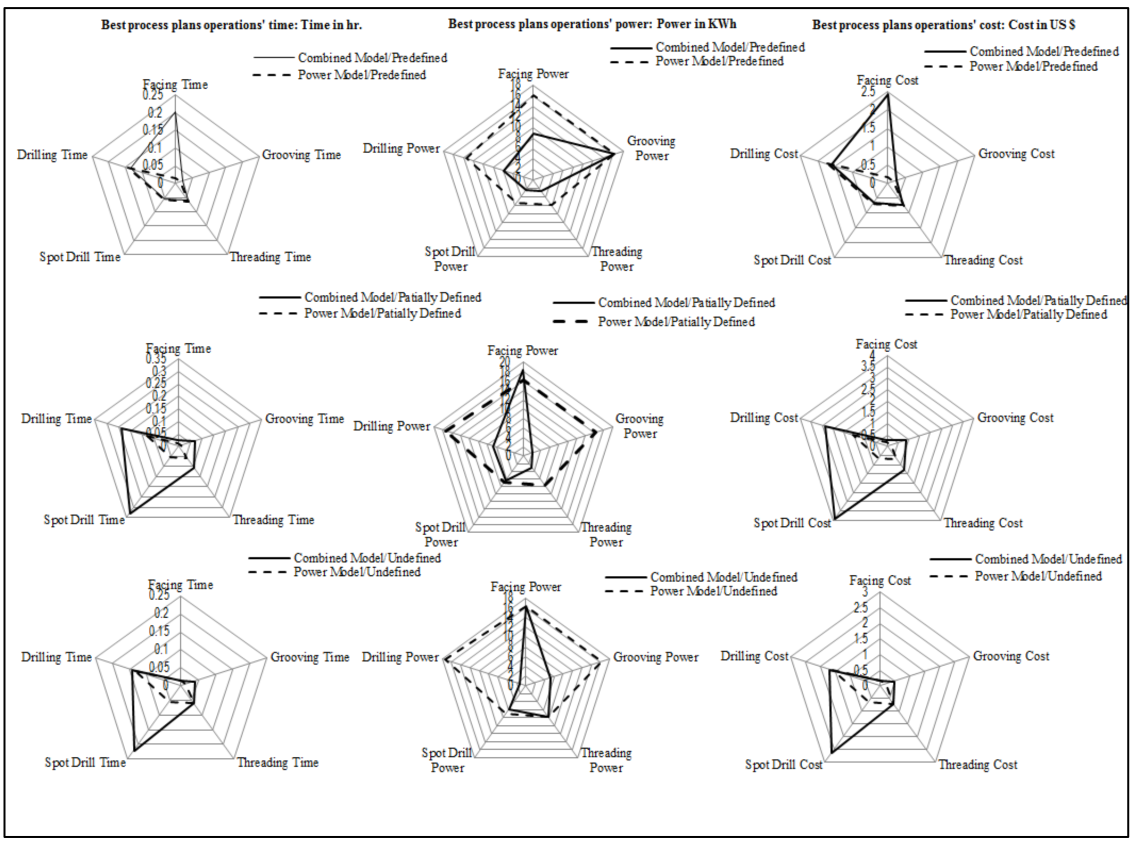

Figure 4.18 Time, power and cost values at the best process plans in Cost and Combined 0.35/0.4/0/0.25 models

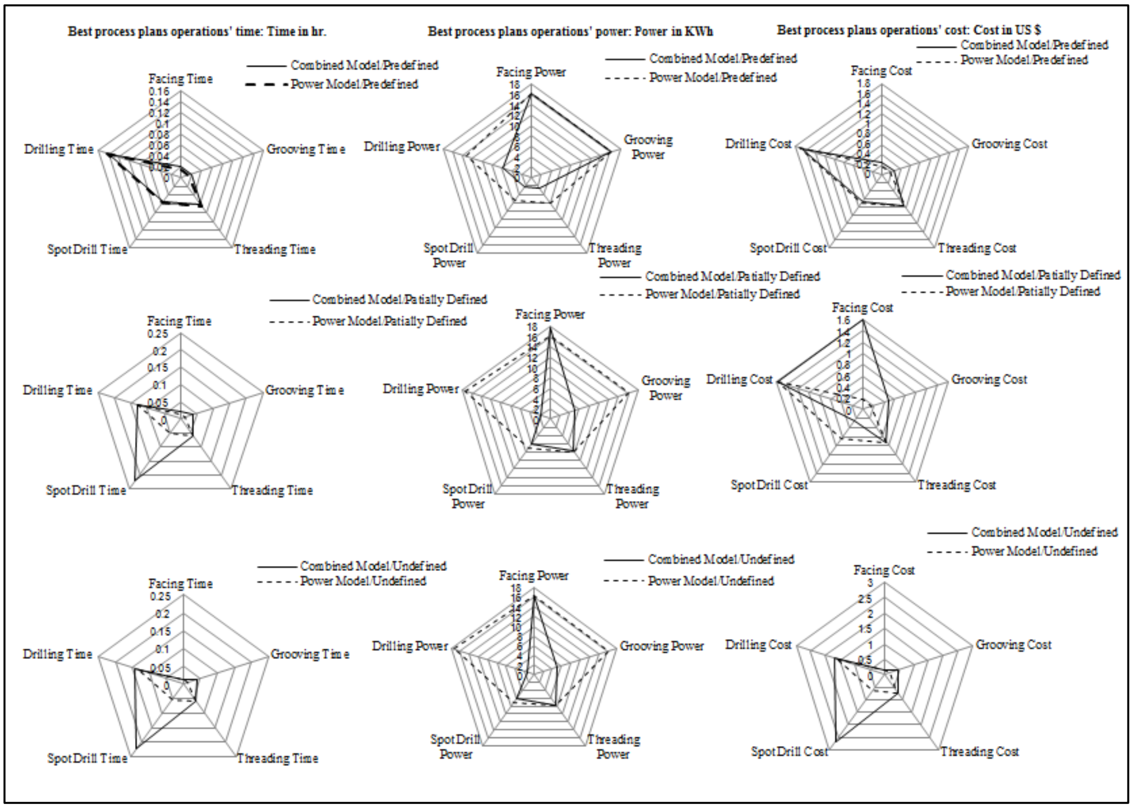

Figure 4.19 Time, power and cost values at the best process plans in Cost and Combined 0.2/0.2/0/0.6 models

The optimal process settings for all operations and the optimal process plans for the cost model in comparison to both combined 0.35/0.4/0/0.25 and combined 0.2/0.2/0/0.6 models are also illustrated in Figures 4.20 and 4.21, correspondingly.

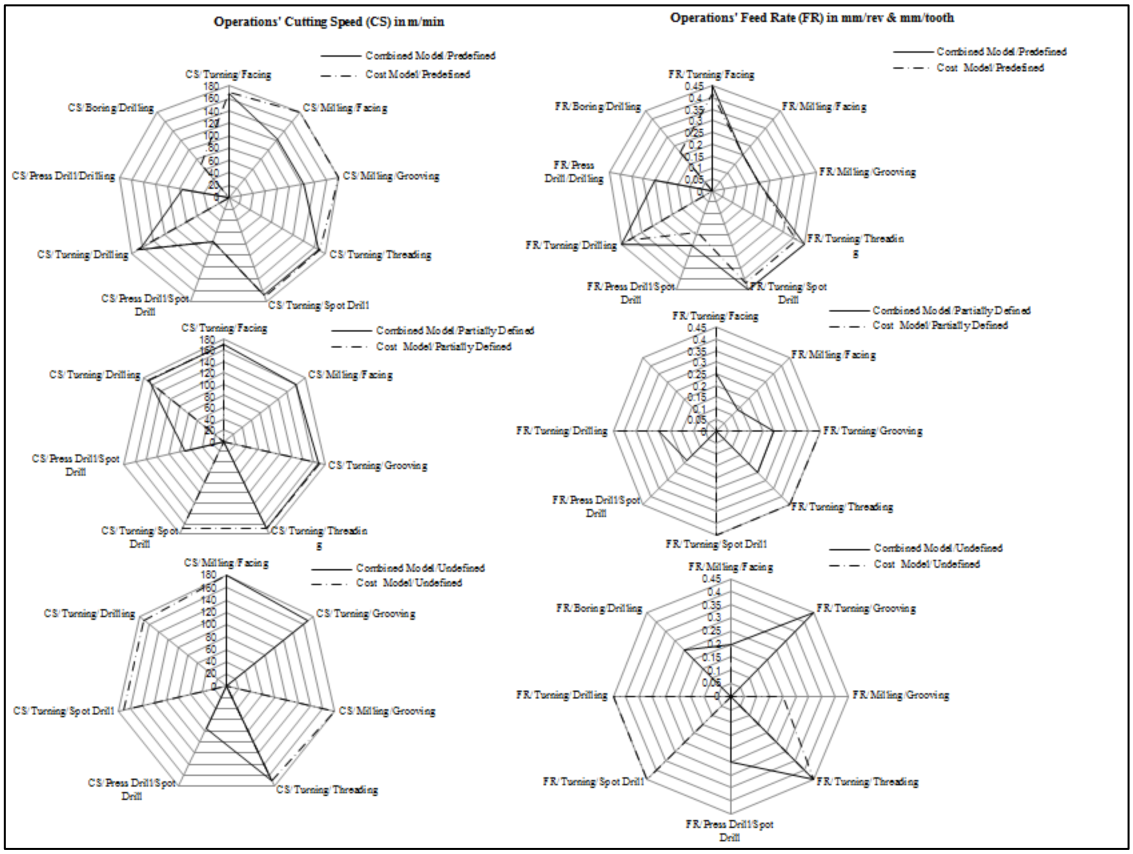

Figure 4.20 Cutting speed and feed rate values at the Cost and Combined 0.35/0.4/0/0.25 models

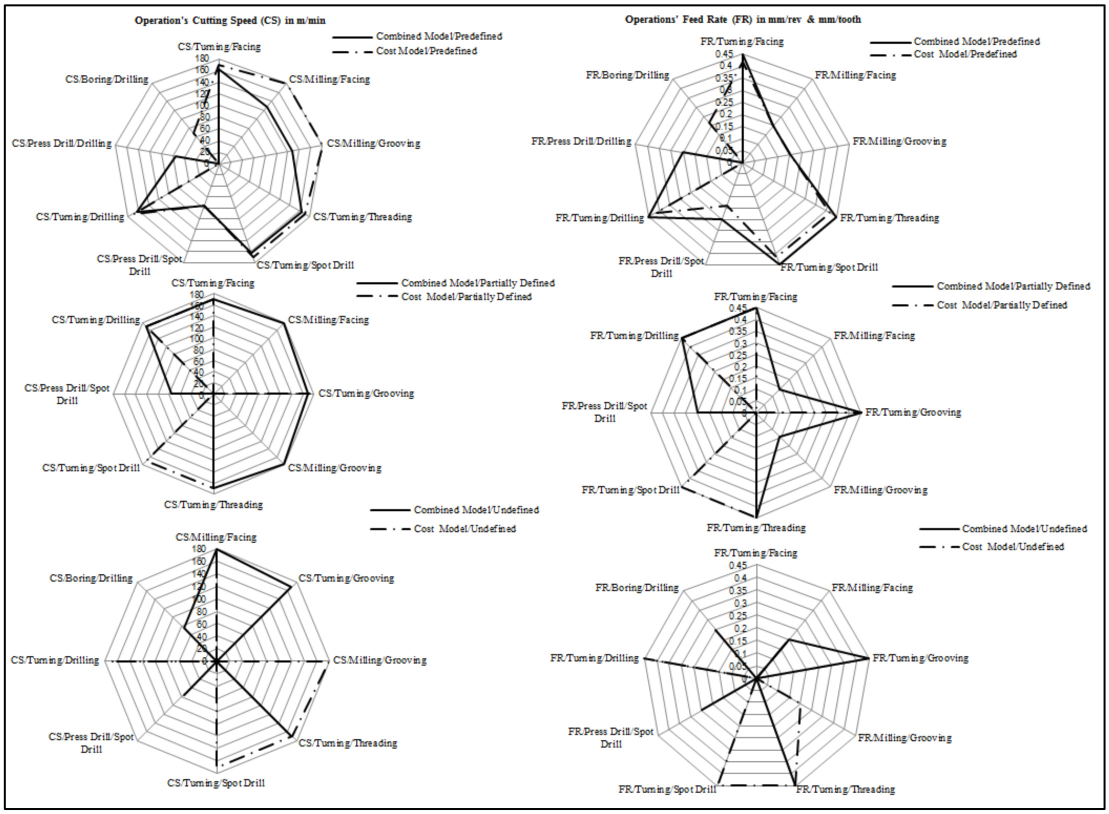

Figure 4.21 Cutting speed and feed rates values at the Cost and Combined 0.2/0.2/0/0.6 models

From these figures, adopting partially defined and undefined plans with the Cost model decreases average processing time and cost for a given part design by about 6.825% and 7% compared to the predefined sequence, respectively. A predefined sequence plan using the Cost model decreases average processing power by 11.63% compared to the partial and undefined plans. Adopting a partially defined sequence plan for the combined 0.35/0.4/0/0.25 scenario reduces power on average by 15.668% compared to the predefined and undefined plans, respectively. Further, a predefined sequence plan for the combined 0.35/0.4/0/0.25 scenario minimizes time and cost on average by 22.233% compared to the other two scenarios. A predefined plan for the combined 0.2/0.2/0/0.6 scenario decreases average processing time and cost for a given part design by about 34.2% compared to the other two. Finally, adopting partially defined plan for the Combined 0.2/0.2/0/0.6 scenario lowers power on average by 11.1% compared to other plans.

4.6 Conclusions and Future Work

A machining case study of a machine shop that produces grinding head shells has been performed to demonstrate the methodology. Different scenarios of sequencing the processes and machine settings are analyzed to determine one with optimal performance for the selected KPIs. Sensitivity analysis is performed to determine the importance of the parameters on these metrics for different process and production alternatives. The simulation results indicate that using this methodology is more effective in encompassing all relevant parameters that have a significant impact on these performance metrics. This provides the basis for future work in more complex part manufacturing sequences that encompass a greater range of product manufacturing activities.

4.7 Nomenclature

$i \ and \ j$= workpiece i processed by process j,

C_{ij}= production cost,

C_L= cost per unit time of the labor and machine tool,

$T_{m_{ij}}$= machining time,

$T_{TL_{ij}}$= tool life,

$C_{TC_{ij}}$= tool cost,

D_i, L_i= workpiece diameter and length,

v_{ij}, f_{ij}, d_{ij}= cutting speed, feed rate, and depth of cut,

D_c= diameter of the milling cutter or the drill diameter,

z= No. of teeth in milling cutter or No. of flutes in a tap,

θ= drill point angle,

V_{ij}=volume of the removed material,

MRR_{ij}= material removal rate,

t_e= time required to exchange a tool,

t_r= tool replacement time,

BHN= workpiece hardness (Brinell hardness number),

E= young's modulus of elasticity,

NR= nose radius on the tool point,

$r_{e_{ij}}$= tool radius nose

ΔT= mean temperature rise at tool-chip interface

ρ = density of workpiece material

C_p= specific heat capacity of workpiece material

α_w= thermal diffusivity of the workpiece material

CHAPTER 5

SUMMARY AND CONCLUSIONS

This thesis, first, is an attempt to understand the complexity of material information models, the requirements for defining a high level material information model and to explore the possibility of formalizing material information model for sustainability MIMS that can capture this information across different stakeholders and life cycle stages. Therefore, this thesis addresses these requirements. In the first stage the different ways in which materials and material information influence the decision-making process were analyzed. The proposed methodology offers insights into material choices that offer sustainable solutions. For this purpose information modeling techniques were employed to generate manufacturing scenarios. The analysis helped in identifying locations where materials factor into the decision-making process, the key information requirements that help build a material information model for sustainability. This is highly relevant to the increased emphasis on sustainable solutions in the global industry, particularly as the ability to assess the manufacturing life cycle sustainability at the design stage enables better utilization of resources that optimize and maintain system desired performance(s). Assessing environmental sustainability impacts regarding material/process selection for fabricating a given design is a complex issue that requires detailed understanding of the necessary information with respect to this selection over the entirety of product life cycle. A comprehensive Material Information Model (MIM) is central to evaluating the impact of material properties on sustainability in the product life cycle. It is almost imperative that standardized distributed material information models be developed to address the needs from both different perspectives in the product life cycle (manufacturing, quality and testing perspectives etc.) and different types of life cycles (i.e. cradle-to-gate, gate-to-gate, and cradle-to-grave). In the second stage of this research, a systematic methodology was developed for enabling the sustainability and productivity performance assessment for integrated process and operation plans at the machine cell level of manufacturing systems. This methodology is aimed to help find out the best plan(s) out of all possible alternatives.

5.1 Summary

This research addressed a number of important objectives. First, activity models were used as a means of analyzing manufacturing life cycle scenarios to collect and categorize key concepts towards building a material information model for sustainability (MIMS). Second, a methodology was proposed to incorporate relevant information in the manufacturing life cycle, which particularly has a significant impact on sustainability and productivity performances. Third, techniques were developed to calculate different sustainability and productivity metrics. Fourth, sources of data needed for sustainability and productivity assessments were mapped. Lastly, a data model was constructed that captures the parameters needed for determining these metrics.

Both Unified Modeling Language (UML) and local MySQL database were used to support the data structure generation. MySQL stored activity diagrams data in tables and facilitated these data flow by creating relationships among tables. Arena simulation and OptQuest optimization technique and Visual Basic were used in the model generation phase. The information in mapped databases was retrieved by writing SQL queries to relate these data and retrieve precise information for performing sustainability and productivity analysis. For the purpose of result visualization and analysis, a graphical user interface (GUI) was built to compile information and results for different stakeholders. The GUI maintained a connection with the MySQL database so that the stakeholders can directly deal with the user interface without knowledge of SQL queries to the database. PHP and Apache server were utilized to develop a user interface and provide a good data visualization. Finally, to identify the techniques to calculate different sustainability and productivity metrics, DES was combined with OptQuest optimization to search for optimal solutions for process and operation planning.

5.3 Conclusions

This research helped accomplish a requirement analysis for building MIMS. It also led to the conceptualization and implementation of a decision support methodology for integrating machining process and operation planning. The results establish the feasibility of applying performance analysis at different manufacturing levels in the manufacturing enterprise and supply chain.

In the course of this research the following specific features have been observed:

- Activity models provide a means to analyze manufacturing life cycle scenarios to collect and categorize key concepts towards building a Materials Information Model for Sustainability.
- Without integrating the process and operation plan only local assessments could be reached. In this research process and operation plans are integrated through a

systematic gate-to-gate life cycle methodology for a globalized assessment of sustainability and productivity.

- Multi-Criteria-Decision-Making framework using AHP are developed to optimize process planning activities based on the impact of conflicting sustainability (energy, carbon dioxide and cost) and productivity (time) metrics.
- Discrete event simulation is utilized to enable 'what if' analysis for the candidate process and operation plan scenarios (i.e. feature sequencing).
- Sensitivity analysis is performed to determine the significant parameters of the simulated models on the sustainability and productivity metrics for the modeled process planning scenarios.
- The synthesis of optimization and simulation assisted in capturing the complexities and dynamics of process planning activities.
- This approach brings an additional viewpoint to discrete event manufacturing simulation analysis by optimizing simulation models to find optimal configurations or operating policies for the G2G life cycle process and operation plans.
- Local database and graphical user interface are built to complile information and results for different stakeholders' usage in process planning. Systematizing how information regarding the G2G life cycle activities related to the sustainability and productivity implications can help not only the design of new products but also the improvement of manufacturing from a sustainability and productivity point of view.

CHAPTER 6

FUTURE WORK

6.1 Future research

Several techniques exist for assessing the sustainability of a given product, process, or service designs. Waste minimization, material efficiency, resource efficiency, and eco-efficiency are some sustainability strategies that stakeholders could utilize. Even though these techniques tackle economic, environmental, and social domains regarding the sustainability analysis, almost all these techniques are limited in their scope. They do not declare the systematic way to understand the relationship between the stakeholders' functionalities and various assessment principles, strategies, actions, and tools related to the three sustainability pillars, economy, society, and environment. With future research in this area, the material information model can thus be extended to provide the right combinations of information to each stakeholder at other life cycle domains i.e. cradle-to-gate, gate-to-gate, and cradle-to-grave. This will reduce product and process life cycle time for other domains as it shares inputs with other systems (e.g workforce welfare as a social impact), and produces outputs for other systems (e.g. enterprise).

With a careful analysis of the feasible activities during the entire life cycle of product and process, the obstacles in integrating materials' information from various life cycle stages beyond the G2G life cycle can be addressed. By examining, quantifying, interpreting, and comparing activities within different domains, the requirement anaylsis could be extended to other life cycles within a unified material information model.

Moreover, the most vital criteria that should be considered in constructing such a material information model are effective gathering of data resources, standardizing material data model and demonstration. To ease the stakeholders' navigation and support queries, future research should aim to meet necessities such as completeness, generality, extensibility, flexibility, ease of understanding, reusability, and must consist of a minimum number of necessary concepts. These necessities can be achieved by utilizing standards in manufacturing systems.

Research could also guide how to establish metrics selection in the conceptual foundation of MIMS for sustainable decision-making in product design and manufacturing stages. A successful MIMS will support classification and multiple representations of a single metric within these stages. As different stakeholders may refer to the same material property in different ways, this could be expanded to support multiple representations of a single material property. For example, one stakeholder may represent a varying material property as an equation, while another stakeholder may represent the same property as a table. In this research, to select a set of model specifications (input parameters and assumptions) a wide range of parameters are possible as inputs for the scenarios discussed in previous chapters. Models are, therefore, required for selecting the best parameters and their combinations capable to capture the complexities and dynamics of the system. Applying data analytics (data mining methods) for the existing manufacturing data will enable researchers to discover relevant variables, attributes and rules that dynamically change with real world scenarios and those that are significantly relevant to the scope of the model.

APPENDICES

A.1: Data Used in Populating the Local MySQL Database

Table A.1 A list of the most involved databases in this research

Database	Publisher	Coverage	Reference	Type
MatWeb Material Property Data	MatWeb	Data sheets for over 64,000 metals, plastics, ceramics, and composites. Free registration	www.matweb.com/	Open Access, documents are free
CISTI	National Research Council, Canada	All fields of engineering, technology and sciences	http://cisti-icist.nrc-nrc.gc.ca/main_e.html	Free searching, documents may be purchased
Compendex	Elsevier Engineering Information, Inc.	One of the most comprehensive interdisciplinary databases for engineering	www.ei.org/databases/compendex.html	Subscription based product
CSA Materials Research Database with Metadex	CSA / ProQuest	Composites industry, engineered materials, and Metadex.	www.csa.com/factsheets/engineering-set-c.php	Subscription based product
INSPEC	The Institution of Engineering and Technology	Information technology, manufacturing, mechanical engineering, physics, electrical and electronic engineering.	www.iee.org/publish/inspec/	Subscription based product
Recent Advances in Manufacturing – RAM	TechXtra, Heriot Watt University	It covers all aspects of manufacturing engineering, management, and technology	www.techxtra.ac.uk/ram/index.php	Free searching, documents may be purchased
IHS Global Engineering Documents	USA	With over 800,000 it is one of the major worldwide distributors for industrial standards, specifications and codes	http://global.ihs.com/	Free searching, documents may be purchased.
Machinery guide of UK manufacturing and engineering data.	Findlay Publications Ltd	It covers 39,000 suppliers for production engineering equipment, supplies or services	www.machinery.co.uk/Buyers-uide/index.aspx	Free searching, documents may be purchased.
Energyfiles	US Department of Energy –OSTI	This portal provides access to over 500 databases and web sites.	www.osti.gov/energyfiles/	Free searching and Open Access.

Table A.2 Constant parameters' values in Taylor's tool life formula (*C*)

		"*C*"			
		Non-steel cutting		Steel cutting	
Tool Material	***N***	m/min	ft/min	m/min	ft/min
Plain carbon tool steel	0.1	70	200	20	60
High-speed steel	0.125	120	350	70	200
Cemented carbide	0.25	900	2700	500	1500
Cermet	0.25			600	2000
Coated carbide	0.25			700	2200
Ceramic	0.6			3000	10000

Table A.3 Allowable cutting speed for some cutting tool material type

	Allowable Cutting Speed			
	Non-steel cutting		Steel cutting	
Tool Material	m/min	ft/min	m/min	ft/min
Plain carbon tool steel	Below 10	Below 30	Below 5	Below 15
High-speed steel	25-65	75-200	17-33	50-100
Cemented carbide	330-650	1000-2000	100-300	300-900
Cermet			165-400	500-1200
Coated carbide			165-400	500-1200
Ceramic			330-650	1000-2000

Table A.4 Carbon emission signature values

Countries	Total Energy [TWH/year][a]	C%	G%	O%	δ [g O2/kJ]	EIE[kg CO2/kWh]
G8 Countries						
France	575	5%	4%	1%	0.023	0.083
Germany	637	46%	14%	1%	0.173	0.622
Italy	319	15%	54%	10%	0.147	0.530
Japan	1082	27%	26%	13%	0.150	0.541
United Kingdom (UK)	389	33%	45%	2%	0.176	0.632
United States (USA)	4369	49%	21%	1%	0.193	0.696
Canada	651	17%	6%	2%	0.069	0.247
Canada (Ontario)[b]	100	8%	14%	0%	0.047	0.169
Russia	1040	19%	48%	2%	0.134	0.481
Emerging Countries						
Brazil	463	3%	6%	4%	0.025	0.091
China	3457	79%	1%	1%	0.263	0.946
India	830	69%	10%	4%	0.248	0.893
Mexico	259	8%	51%	19%	0.137	0.493
Other						
Australia	257	77%	15%	1%	0.277	0.995

Notes:
a Data acquired for 2008 from IEA Statistics -Electricity/Heat (by Country)
b Data for 2010 from IESO

Table A.5 General surface roughness related to some machining operations

	Tolerance Capability		Surface Roughness	
Machining Operation	**mm**	**in**	**μm**	**μ-in**
Turning, Boring			6.3<R_a<0.4	250<R_a<16
D < 25 mm	± 0.025	± 0.001		
25 mm < D < 50 mm	± 0.05	± 0.002		
D > 50 mm	± 0.075	± 0.003		
Drilling			6.3<R_a<1.6	250<R_a<63
D < 2.5 mm	± 0.05	± 0.002		
2.5 mm <D < 6 mm	± 0.075	± 0.003		
6 mm <D < 12 mm	± 0.10	± 0.004		
12 mm <D < 25 mm	± 0.125	± 0.005		
D > 25 mm	± 0.20	± 0.008		
Milling			6.3<R_a<0.8	250<R_a<32
Peripheral	± 0.025	± 0.001		
Face	± 0.025	± 0.001		
End	± 0.05	± 0.002		

Table A.6 K_b at different clamping conditions

Type of clamping condition	**K_b**
Workpiece held between chuck and tailstock	0.6
Workpiece held between centers	1.4
Workpiece held in chuck	22.4

Table A.7 Power requirement in milling process

Type of Milling cut	Cutter Diameter (in.)	MRR Maximum $(\frac{in.^3}{min.})$	Power Maximum (kW)
Rough	3/4	80	20.142
	1	100	25.364
	1.5	150	37.3
	2	200	49.236
Semi-rough	3/4	80	20.142
	1	100	25.364
	1.5	150	37.3
	2	200	49.236
Semi-finish	3/4	50	12.682
	1	60	14.92
	1.5	100	25.364
	2	120	29.84
Finish	3/4	36	8.952
	1	50	12.682
	1.5	60	14.92
	2	75	18.65

Table A.8 General recommendations for turning operations (Kennametal, Inc.)

Workpiece material	Cutting tool	Depth of cut		Feed rate		Cutting speed	
		mm	in.	mm/rev	in./rev	m/min	ft/min
Low- C and free machining steel	Uncoated carbide	1.5-6.3	0.06-0.25	0.35	0.014	90	300
	Ceramic coated carbide	1.5-6.3	0.06-0.25	0.35	0.014	245-275	800-900
	Triple coated carbide	1.5-6.3	0.06-0.25	0.35	0.014	185-200	600-650
	TiN coated carbide	1.5-6.3	0.06-0.25	0.35	0.014	105-150	350-500
	Al_2O_3 ceramic	1.5-6.3	0.06-0.25	0.25	0.010	395-440	1300-1450
	Cermet	1.5-6.3	0.06-0.25	0.30	0.012	215-290	700-950
Medium and high-C steels	Uncoated carbide	1.2-4.0	0.05-0.20	0.30	0.012	75	250
	Ceramic coated carbide	1.2-4.0	0.05-0.20	0.30	0.012	185-230	600-750
	Triple coated carbide	1.2-4.0	0.05-0.20	0.30	0.012	120-150	400-500
	TiN coated carbide	1.2-4.0	0.05-0.20	0.30	0.012	90-200	300-650
	Al_2O_3 ceramic	1.2-4.0	0.05-0.20	0.25	0.010	335	1100
	Cermet	1.2-4.0	0.05-0.20	0.25	0.010	170-245	550-800
Cast iron, gray	Uncoated carbide	1.25-6.3	0.05-0.25	0.32	0.013	90	300
	Ceramic coated carbide	1.25-6.3	0.05-0.25	0.32	0.013	200	650
	TiN coated carbide	1.25-6.3	0.05-0.25	0.32	0.013	90-135	300-450
	Al_2O_3 ceramic	1.25-6.3	0.05-0.25	0.25	0.010	455-490	1500-1600
	SiN ceramic	1.25-6.3	0.05-0.25	0.32	0.013	730	2400
Stainless steel, austenitic	Triple coated carbide	1.5-4.4	0.06-0.175	0.35	0.014	150	500
	TiN coated carbide	1.5-4.4	0.06-0.175	0.35	0.014	85-160	275-525
	Cermet	1.5-4.4	0.06-0.175	0.30	0.012	185-215	600-700
High-temperature alloys, nickel based	Uncoated carbide	2.5	0.1	0.15	0.006	25-45	75-150
	Ceramic coated carbide	2.5	0.1	0.15	0.006	45	150
	TiN coated carbide	2.5	0.1	0.15	0.006	30-55	95-175
	Al_2O_3 ceramic	2.5	0.1	0.15	0.006	260	850
	SiN ceramic	2.5	0.1	0.15	0.006	215	700
	Polycrystalline cBN	2.5	0.1	0.15	0.006	150	500
Titanium alloys	Uncoated carbide	1.0-3.8	0.04-0.15	0.15	0.006	35-60	120-200
	TiN coated carbide	1.0-3.8	0.04-0.15	0.15	0.006	30-60	100-200
Aluminum alloys Free machining	Uncoated carbide	1.5-5.0	0.06-0.20	0.45	0.018	90	300
	TiN coated carbide	1.5-5.0	0.06-0.20	0.45	0.018	105-150	350-500
	Cermet	1.5-5.0	0.06-0.20	0.45	0.018	395-440	1300-1450
	Polycrystalline diamond	1.5-5.0	0.06-0.20	0.45	0.018	215-290	700-950
Copper alloys	Uncoated carbide	1.5-5.0	0.06-0.20	0.25	0.010	260	850
	Ceramic coated carbide	1.5-5.0	0.06-0.20	0.25	0.010	365	1200
	Triple coated carbide	1.5-5.0	0.06-0.20	0.25	0.010	215	700
	TiN coated carbide	1.5-5.0	0.06-0.20	0.25	0.010	90-275	300-900
	Cermet	1.5-5.0	0.06-0.20	0.25	0.010	245-425	800-1400

	Polycrysalline	1.5-5.00	0.06-0.20	0.25	0.010	520	1700
Tungsten alloys	Uncoated carbide	2.5	0.10	0.2	0.008	75	250
	TiN coated carbide Cermet	2.5	0.10	0.2	0.008	85	275
Thermoplastics and thermosets	TiN coated carbide	1.2	0.05	0.12	0.005	170	550
	Polycrystalline diamond	1.2	0.05	0.12	0.005	395	1300
Composite, graphite reinforced	TiN coated carbide Polycrystalline diamond	1.9 1.9	0.075 0.075	0.2 0.2	0.008 0.008	200 760	650 2500

Table A.9 General recommendations for milling operations (Kennametal, Inc.)

Workpiece material	Cutting tool	Feed mm/tooth	in./tooth	Speed m/min	ft/min
Low-carbon and free machining steels	Uncoated carbide, coated carbide, cermets	0.13-0.20	0.005-0.008	120-180	400-600
Alloy steels, Soft **Alloy steels, Hard**	Uncoated, coated, cermets Cermets, PcBN	0.10-0.18 0.10-0.15	0.004-0.007 0.004-0.006	90-170 180-210	300-550 600-700
Cast iron, gray, Soft **Cast iron, gray, Hard**	Uncoated, coated, cermets, SiN Cermets, PcBN, SiN	0.10-0.20 0.10-0.20	0.004-0.008 0.004-0.008	0.08-0.38 120-210	90-1370 400-700
Stainless steel, Austenitic	Uncoated, coated, cermets	0.13-0.18	0.005-0.007	120-370	400-1200
High-temperature alloys, Nickel based	Uncoated, coated, cermets, SiN, PcBN	0.10- 0.18	0.004-0.007	30-370	100-1200
Aluminum alloys, Free machining **Aluminum alloys, High silicon**	Uncoated, coated, PCD PCD	0.13-0.23 0.13	0.005-0.009 0.005	610-900 610	2000-3000 2000
Copper alloys	Uncoated, coated, PCD	0.13-0.23	0.005-0.009	300-760	1000-2500
Plastics	Uncoated, coated, PCD	0.13-0.23	0.005-0.009	270-460	900-1500

Table A.10 General recommendations for drilling operations (Kennametal, Inc.)

Workpiece material	**Surface speed**		**Feed, mm/rev (in./rev) Drill diameter**		**rpm Drill diameter**	
	m/min	**ft/min**	**1.5 mm (0.060 in.)**	**12.5 mm (0.5 in.)**	**1.5 mm**	**12.5 mm**
Aluminum alloy	30-120	100-400	0.025 (0.001)	0.30 (0.012)	6400-25000	800-3000
Magnesium alloys	45-120	150-400	0.025 (0.001)	0.30 (0.012)	9600-25000	1100-3000
Copper alloys	15-60	50-200	0.025 (0.001)	0.25(0.010)	3200-12000	400-1500
Steel	20-30	60-100	0.025 (0.001)	0.30 (0.012)	4300-6400	500-800
Stainless steels	10-20	40-60	0.025 (0.001)	0.18 (0.007)	2100-4300	250-500
Titanium alloys	6-20	20-60	0.010 (0.0004)	0.15 (0.006)	1300-4300	150-500
Cast irons	20-60	60-200	0.025 (0.001)	0.30 (0.012)	4300-12000	500-1500
Thermoplastics	30-60	100-200	0.025 (0.001)	0.13(0.005)	6400-12000	800-1500
Thermosets	20-60	60-200	0.025 (0.001)	0.10(0.004)	4300-12000	500-1500

Table A. 11 Power factor values for different material types

Material	**Hardness Bhn**	***P* factor**
Plain carbon & alloy steels	90-200	0.75
	200-275	0.92
	300-375	1.02
	375-450	1.18
	45-52 R_c	1.45
Gray cast iron	300	0.25
Alloy cast irons & ductile irons	300	0.50
Stainless steel (austenitic)	300	0.96
Stainless steel (martensitic)	300	0.81
Titanium alloys	300	0.87
Aluminum alloys	300	0.20
Magnesium alloys	300	0.15
Copper alloys	Soft - R_B 20-80	
	Hard - R_B 80-100	
Tool steels	300	1.10
Cobalt based alloys	300	1.25
High-temperature alloys	300	1.45
Non-ferrous free-machining alloys	300	0.45

A.2 Arena^{TM}Models

Sample of Arena^{TM} models that run in this work are represented through Figures A.1 to A.3.

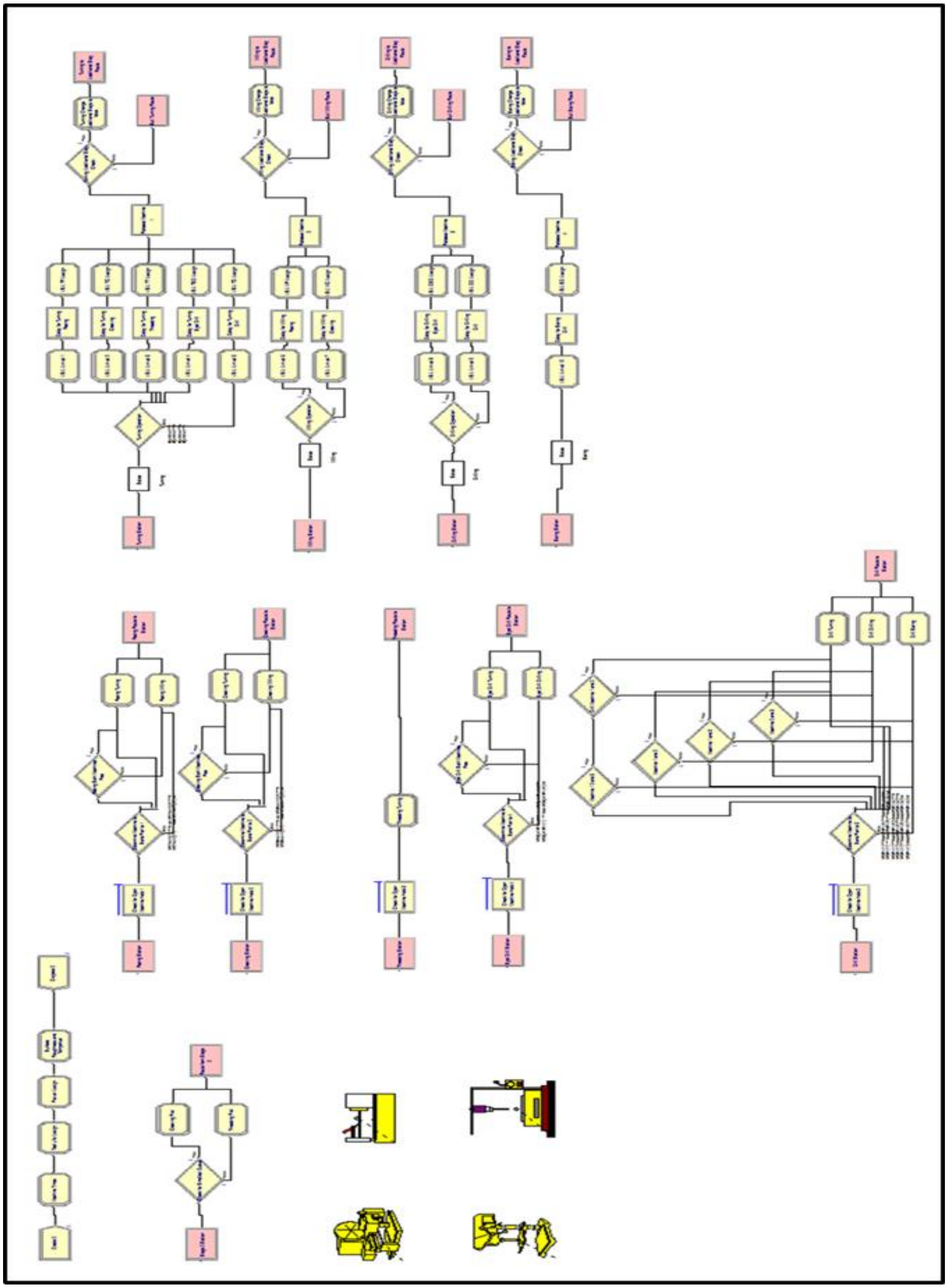

Figure A.1 An ArenaTM sample model for the production time at the predefined scenario

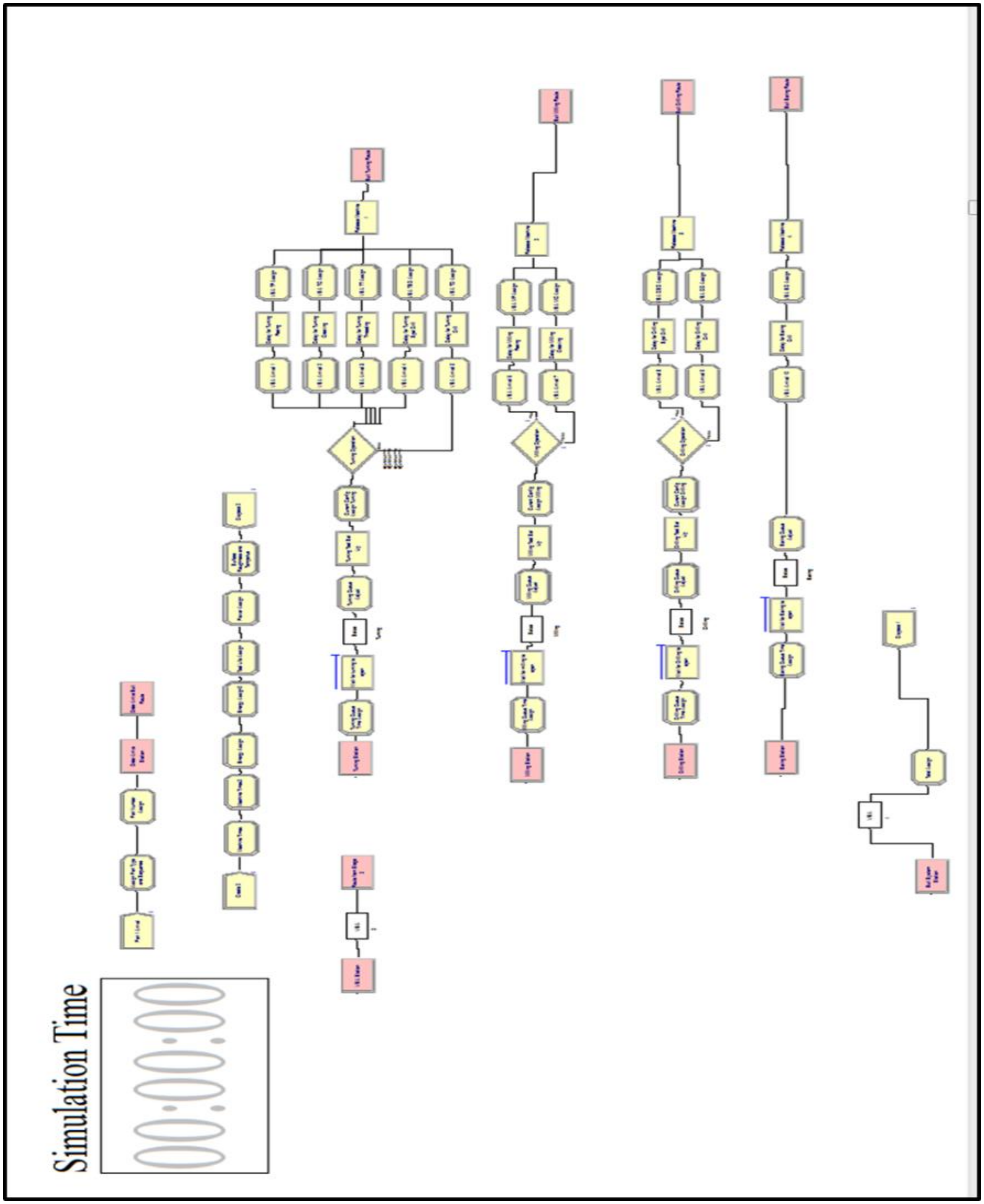

Figure A.2 An ArenaTM sample model for the production cost at the partially defined scenario

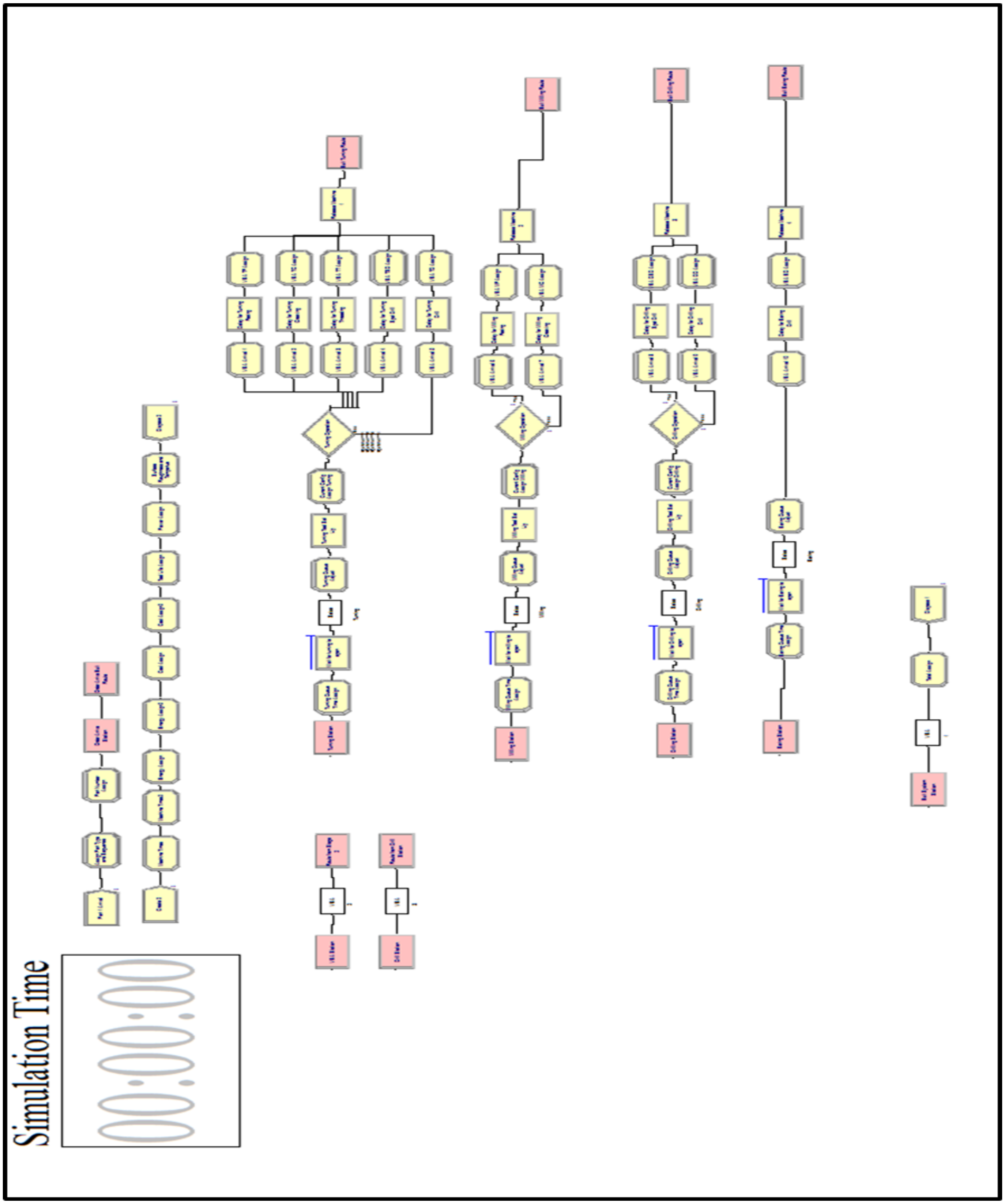

Figure A.3 An ArenaTM sample model for the energy consumption at the undefined scenario

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List of Publications

1. **Qais Hatim**, Guodong Shao, Sudarsan Rachuri, Christopher Saldana, Deogratias Kibira, and Soundar Kumara . A Simulation-Based Methodology of Assessing Environmental Sustainability and Productivity for Integrated Process and Production Plans. North American Manufacturing Research Conference (NAMRC43), International Manufacturing Research Conference 2015-Accepted
2. **Qais Hatim**, Paul Witherell, KC Morris, Sudarsan Rachuri, Christopher Saldana, and Soundar Kumara Requirement Analysis for a Material Information Model to Enable Sustainability Assessment – submitted to Information Systems Frontiers and in NIST peer review process (Editorial Review Board ERB)
3. **Al-Khazraji, Qais.Y.**, Saldana, C., Sudarsan, R., Kumara, S. (2013). Material Information Model across Product Life Cycle for Sustainability Assessment. Appeared in 20th CIRP Conference on Life Cycle Engineering LCE 2013
4. **Al-Khazraji, Qais.Y.**, Saldana, C., Donghuan, T., and Kumara, S. (2013). Information Modeling to Incorporate Sustainability into Production Plans. Appeared in 9th 2013 IEEE International Conference on Automation Science and Engineering (CASE 2013)
5. **Qais Hatim**, Deogratia Kibira, Guodong Shao, and Soundar Kumara. Integrating data analytics with simulation methods to support manufacturing decision-making- WinterSim Conference 2015-Accepted
6. **Qais Hatim**, Guodong Shao, Duck Bong Kim ,Sudarsan Rachuri, Christopher Saldana and Soundar Kumara. A Decision Support Methodology for Integrated Machining Process and Operation Plans. Submitted to International Journal of Advanced Manufacturing and Technology-Accepted
7. David Dornfeld, **Qais Y. Hatim**, Moneer Helu, Sanjay Jain, Soundar Kumara, Senthilkumaran Kumaraguru, Yung-Tsun Tina Lee , Stefanie Robinson, Christopher J. Saldana, Sudarsan Rachuri. Classification Framework and Conceptual Models for Smart Manufacturing Systems Performance Metrics- Submitted to International Journal of Production Research.