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Cascading trade-off studies for robotic deburring systems

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Abstract

Advanced manufacturing technologies play an important role in keeping production in high-cost countries. Due to their flexibility, robot-based solutions have been one of the major enablers in establishing advanced manufacturing capabilities in the traditional high-cost countries. This paper concerns the problem of automated deburring of cast parts. If performed manually, this operation introduces major health, safety, and environmental (HSE) concerns. As such, removal of highly variable casting burrs in the Norwegian context requires a solution based on robots, smart sensors, and advanced algorithms to tackle the problem in a flexible and cost-effective way. Due to the complexity of the task, one is confronted with a breadth of various alternatives to choose from when realizing the desired functionality. These alternatives expand as one considers a pipeline of the subtasks involved in the process. The decisions made in each step cascade throughout the whole pipeline. To tackle the complexity while developing a robotized deburring system, a systemic approach based on cascading trade-off studies is proposed in this paper. This paper is also a contribution to the gap in the literature for cases of trade-off studies in the domain of mechanical engineering. The SPADE (stakeholders, problem formulation, analysis, decision making, and evaluation) methodology has been used as a framework to resolve automation of complex mechanical engineering manufacturing process decisions. The systems engineering (SE) approach proved useful to identify and prioritize the stakeholders and their needs, as well as analyzing the different alternatives in a complex engineering system when dealing with cascading trade studies.

KEYWORDS
cascading, robotic deburring, SPADE, trade-study

1 | INTRODUCTION

There has been a trend over the last three decades that firms in developed countries are outsourcing their production to low-cost countries.[2] Outsourcing of production is one strategy to achieve a competitive advantage by lowering labor costs. Traditionally, many companies have moved their production to China, but as the country's economy is changing, companies in China are also outsourcing to less-developed economies in Asia such as Vietnam.[3] In recent years, a manufacturing reshoring trend has emerged where high-cost countries move their production back home from low-cost countries[4]. Between 2015 and 2018, 85% of 253 reshoring cases were within manufacturing in Europe.[5] The reasons for the strategic decisions regarding reshoring are many and vary across sectors and firms, and they include increasing production costs in emerging economies, growing digitalization in OECD economies, and miscalculation of total costs

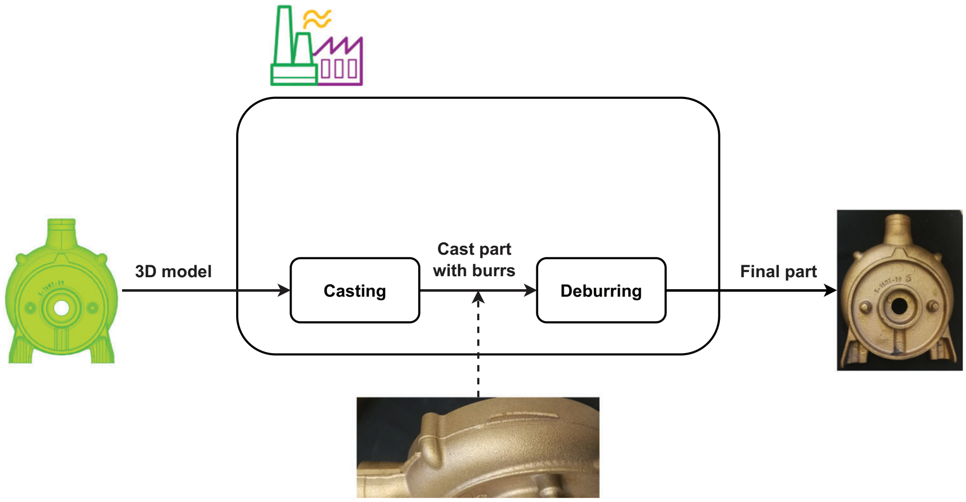

FIGURE 1 Flow in system for producing a cast part

in decisions made prior to offshoring.[4] Lund and Steen[4] observed that advanced manufacturing technologies potentially play an important part in reshoring decisions. Such technologies, often bundled under the term Industry 4.0, can have disruptive effects. The Covid-19 pandemic has also proved to have a disruptive effect. The pandemic has already had, and will continue to have, a substantial impact on national and global economies, as well as on the structure, organization, and management of supply chains in companies.[6] While increasing hazards in global operations have been highlighted in supply chain risk management, the Covid-19 pandemic has demonstrated exactly how disruptive these effects can be. As a result, the call for more self-reliance and reshoring will, and has in some cases already started.

Advanced manufacturing technologies also play an important role in keeping production in Norway. SFI Manufacturing is a multidisciplinary research center for competitive and high value manufacturing in Norway, with an ambition "to show that sustainable and advanced manufacturing is possible in high cost countries, with the right products, technologies, and humans involved." The work presented in this paper is carried out in collaboration with SFI Manufacturing.

Due to their flexibility, robot-based solutions have been one of the major enablers in establishing advanced manufacturing capabilities in the traditional high-cost countries. This paper concerns the problem of automated deburring of cast parts. If performed manually, this operation introduces major health, safety, and environmental (HSE) concerns. As such, removal of highly variable casting burrs in the Norwegian context requires a solution based on robots, smart sensors, and advanced algorithms to tackle the problem in a flexible and cost-effective way. Due to the complexity of the task, one is confronted with a breadth of various alternatives to choose from when realizing the desired functionality. These alternatives expand as one considers a pipeline of the sub-tasks involved in the process. To tackle the complexity while developing a robotized deburring system, a systemic approach based on cascading trade-off studies is proposed in this paper. This paper is a contribution to the gap in the literature for cases of trade-off studies in the domain of mechanical engineering.[1]

This paper continues with some background of the deburring process and pipeline before presenting the SPADE methodology used in this paper. The remaining sections follows the SPADE methodology.[7]

2 | BACKGROUND

One of the industry partners in SFI Manufacturing produces vacuum pumps used in a number of applications. Installation of these pumps sustainably reduces water consumption by up to 90%.[8,9] Some of the parts for the vacuum pump are sand-casted. The process of manufacturing these cast parts consists of several steps, and the process is illustrated in Figure 1. First, a 3D CAD model of the desired part is made. The model is used for making the molds used in the casting process. Output of the casting process is an interim workpiece with burrs. A burr is a raised edge or excess material that remains after a manufacturing process. These burrs must be removed to achieve the desired geometry and functionality for the final part. Burrs are removed in a process called *deburring*. Output from the deburring process is the final part.

2.1 | Deburring applications

Deburring can be time-consuming, expensive, and is considered a non-value-added process.[10] The cost of deburring can range from being a very small percentage of the part cost to being the single largest contributor to the total part cost, and if an inappropriate method is used, it can eliminate the economic justification for the product.[11] Manufacturers in a country with very low labor cost can produce fine hand-finished products at a cost that is difficult to match by a machine in industrialized countries. Manual deburring is the most widely used deburring method as it requires minimal floor space and capital investment.[11] Other arguments for employing a manual process is that it is very flexible which is convenient if there are small production volumes, and the burr size and location varies. During

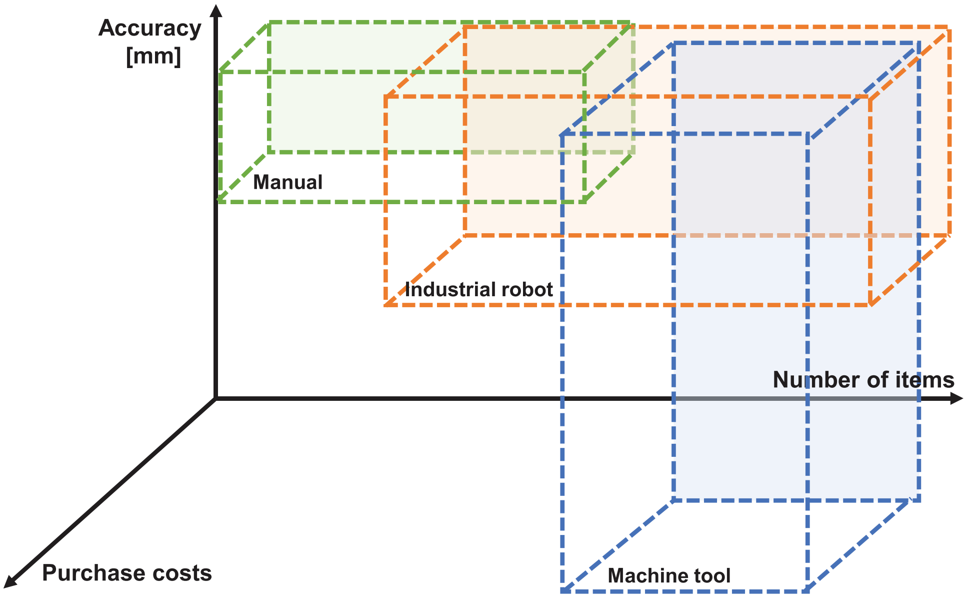

FIGURE 2 Comparison between working accuracy, number of items in the batch, and purchase costs for the different deburring technologies[29]

manual deburring, workers are exposed to high noise and vibration levels, which contribute to poor HSE working conditions. The process is also a very repetitive task, such that it is increasingly difficult to find workers willing and able to do the work.[12]

Deburring of cast parts can be very challenging and large burrs on large casting most often are removed manually. An alternative to manual deburring is using special purpose computer numerical control (CNC) machines. These machines are able to deburr small-to-medium-size parts, but they also have a very high investment cost. An alternative to both manual deburring and CNC machines are industrial robots. Industrial robot solutions are very flexible and the cost of an industrial robot solution for machining compared to a CNC machine is typically 1/5-1/3.[13] Despite the lower cost, only approximately 3% of industrial robots in industry are used for machining. A robot machining systems have two main limitations that can explain the low number. The first limitation is the limited rigidity of the robot that impacts the machining accuracy. The second limitation is the long programming/setup time.[14] As a result, robotic cleaning of castings is currently limited to large production series.

The appropriate deburring method depends on several criterion. Three of them are required accuracy, production volume, and investment cost. An illustration of the different methods evaluated based on these criterion is shown in Figure 2. If the production volume is relatively low, and the required accuracy is not that strict; manual deburring can be applied. If, on the other hand, the production volume is high, there are strict requirements of the accuracy of the product, and the firm has money to invest; CNC machines should be applied. Today, robotic applications are placed in between the two other methods. If the two mentioned limitations of a robotic systems are improved, that is, limited rigidity and setup time, a robot application could replace a larger portion of both manual and CNC applications.

2.2 | The deburring pipeline

The robotic deburring pipeline commonly consists of two main steps; planning and motion execution. The most important part of the planning step is the planning of the robot path. Other aspects such as tool-path correction and machining parameter estimation can also be a part of the planning process. The motion execution step is the step where the physical deburring process occurs. Within this step, mechanical deburring is the main component. Real-time feedback control can be added to improve the process, often using force measurements. The different steps and component of the deburring pipeline are illustrated in Figure 3.

For a robot manipulator to perform a deburring process, a tool path is necessary. Within robotic deburring, there are three main approaches for generating a path. These are (1) teaching through human demonstration, (2) selecting the path based on the CAD model using CAD/CAM software, or (3) by automatically generating the path based on sensor input.

2.2.1 | Human demonstration

The most common approach to programming a robot is human demonstration.[15] This can be achieved by indirect demonstration, which is guiding the robot manually using a teach pendant or a similar device. Sensors, such as force sensing, can be used to improve the interaction between the user and the environment.[12] It is also possible to move the manipulator manually and record the joint positions. This is called direct demonstration.

If the deburring path is curved, the path needs to be approximated by many straight line segments, meaning that lots of points have to be

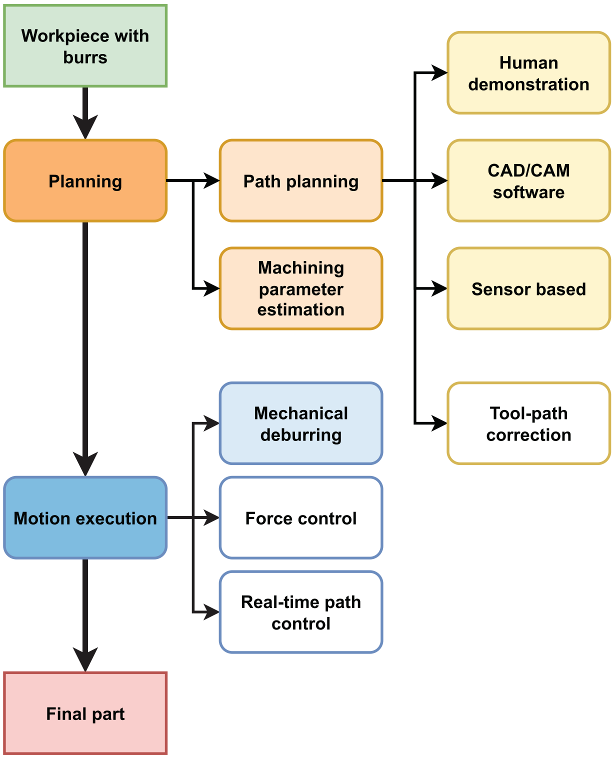

FIGURE 3 Flowchart of the deburring pipeline[29]

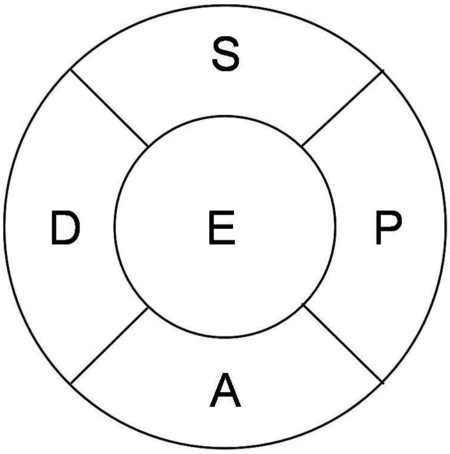

FIGURE 4 SPADE methodology/framework graphical representation[7]

programmed.[16] The programming can be very time-consuming and the operator must be experienced to determine the necessary density of the points along the path.

2.2.2 | CAD/CAM software

Computer-aided design (CAD) software is commonly used for designing the part to be manufactured while computer-aided manufacturing (CAM) software is used for planning the machining process, especially the tool path. There exists a vast selection of CAM software such as Solidworks CAM and NX CAM. The tool path can be planned, generated, and simulated in the CAM software. Output of the system is commonly a type of numerical control (NC)-code, for example G-code, but robot-specific language is also possible. If the output is robot-specific language, the CAM software has to compile the program into robot language.[14] The quality of the robot program then strongly depends on the quality of the post-processor implemented in the CAM software.

2.2.3 | Sensor-based path generation

The vision-based approach is the least common compared to the two aforementioned methods. A vision system is used to recognize the edges of the workpiece. As with the CAD/CAM method, the outline formed by the edges of the workpiece become the deburring path.[17,18]

2.2.4 | Tool path correction

A workpiece can have deformations due to the casting process or caused by clamping and gravity forces. The generated path then needs to be corrected based on these geometric variations and becomes a part of the planning process. First, a path is generated using one of the mentioned path planning methods. Then, the part is scanned using a 3D vision system. The generated point cloud is then registered to find the transformation between the reference tool path and the actual workpiece. The transformation is then applied to the reference tool path to adapt it to the workpiece.[19–21]

2.2.5 | Machining parameter estimation

The last component of the planning step is the machining parameter estimation. Burrs vary in size, especially burrs on cast parts. To improve the machining process, research has been done on optimizing machining parameters such as feed rate based on burr size.[22,23]

3 | RESEARCH METHOD

Systems engineering (SE) was used to get a better understanding of the project and system as a whole. The SPADE methodology was first introduced by Haskins[7] and is graphically represented in Figure 4. SPADE is an acronym constructed from the words **S**takeholders, **P**roblem formulation, **A**nalysis, **D**ecision-making and **E**valuation. The methodology/framework is a nonlinear representation that can be entered at any point and traversed left or right. Evaluation is in the middle of the figure because this activity touches all other activities and because it

TABLE 1 Stakeholder overview

Stakeholder	Influence	Importance	Needs
SFI Manufacturing	High	Medium	To develop industrial-oriented research on the cutting edge of international research.
Industry partners	High	High	To improve their competitiveness through faster and better production, and to improve the HSE conditions
Academia	Medium	Medium	To gain knowledge through the research, and to improve collaboration with other institutions. The university is also motivated by publications that can lead to recognition and more financing.
Other companies	Low	Low	Take advantage of the new knowledge.
Producers	Low	Low	Potentially expanded market for their products.
The development team	High	Medium	To develop a system that satisfies the needs and requirements set by the other stakeholders.

is a continuous process. The following sections will elaborate on each of these activities. In addition, trade-off studies were used to inform the important decisions. Trade-off studies are a staple of the systems engineer's toolkit,[24] and an integral part of the evaluation conducted through the project. The process of making balanced decisions when there are multiple stakeholders with competing objectives is commonly referred to as a trade-off study. Trade-off studies are needed to support sound project management and systems design decisions.[1] A trade-off study begins by determining the objective of the study, that is, what is the choice that must be made and what are the alternative options for achieving the objective. Then the criteria and their priorities are explicitly listed and formulated at the start to avoid introducing selection bias near the end of the process. There are a number of methods appropriate to evaluate the relative strengths and weaknesses of the options, and the analytical hierarchy process is chosen for this study because of its relative ease of use.[25] The sections that follow describe the application of SPADE to choose the trade-off study parameters for evaluation.

4 | STAKEHOLDERS

A stakeholder can, according to the oft-quoted Freeman,[26] be described as follows:

> *A stakeholder in an organization is (by definition) any group or individual who can affect or is affected by the achievement of the organization's objectives.*

For a project to be successful, it is crucial to identify its stakeholders and their needs. They have requirements, expectations and can set limitations on the project. They can also set success criterion's and measure success. For the project to be successful, it is also important to map potential conflicting interests from the stakeholders as soon as possible.

The identified stakeholders for this research are listed below. An estimate of the stakeholders influence and importance, as well as their needs is given in Table 1.

1. **SFI Manufacturing** is a cross-disciplinary center for research-based innovation for competitive high-value manufacturing in Norway.[27] Their vision is to show that sustainable and advanced manufacturing is possible in high cost countries, with the right products, technologies, and humans involved. SFI Manufacturing is funded by the Research Council of Norway and industry partners, and works as a bridge between academia and industry.
2. **Industry partners** contribute financially to SFI Manufacturing and suggest relevant research challenges from their own production which can become research problems in the SFI.
3. **Academia** is involved through the researchers.
4. **Other companies** can benefit from new solutions and knowledge. A solution for more flexible and automated methods for deburring is likely relevant for other companies outside SFI Manufacturing.
5. **The producers of sensors and robots**. In the research, various sensors will be used to make the robotic system smarter. This can enable new robotic applications to expand the applications for both sensors and robots.
6. **The development team** are the ones developing the system. Their knowledge is both an enabler and a limitation.

5 | PROBLEM FORMULATION

Formulating the problem is the activity of understanding the needs of the stakeholders and address conflicting needs, analyzing the current situation, and hypothesizing about alternative futures, and establishing measures of effectiveness (MoE).[7] It can be tempting to decide on a problem formulation too soon and to apply a quick fix. Problem formulation is a never-ending activity that should be reiterated throughout the project to ensure that the best possible solution emerges from the efforts.

5.1 | What is the problem?

When asking what the problem is, you will most likely get a different answer from the various stakeholders. To address this, we will look at the problem from the aspect of the most important and influencing stakeholders.

5.1.1 | SFI manufacturing and academia

As stated in Table 1, the need of SFI Manufacturing is to support industrial oriented research on the cutting edge of international state-of-the-art. For academia, the main objective is to generate new knowledge through research that will lead to recognition and publications. The challenge for the SFI and academia is to take the problem given by the industry partner and transfer that into a research-relevant topic of international interest.

A common conflicting interest between industry and academia that is very relevant for this project is the level of research. The industry wants a solution to their problem that works. Academia needs research that is publishable and that might not always correspond to the problems or challenges of industry.

5.1.2 | Industry partners

SFI Manufacturing has several industry partners and one of them has provided the research problem context. This is to produce cast parts for pumps. One of their parts, and the relevant process, is shown in Figure 1. Today, they rely on manual deburring in their production. Manual deburring is a hazardous and repetitive task, and the company wants to improve the HSE conditions by automating the deburring process. The production is high-mix low-volume and the required accuracy is not very tight. Given the process, a flexible deburring solution using robot manipulators will be the most appropriate choice. The problem is that the cast parts have large burrs and that the workpieces vary in geometry due to the solidifying in the casting process. This means that a predetermined tool path does not work. The path needs to be adapted according to the geometric variations and burrs. The problem can be understood better by studying the context diagram given in Figure 5.

The main input to the system is the output of the casting process, namely, a cast part with burrs. Geometric information of the workpiece is also an input. There are strict tolerances to follow manufacturing parts as well as HSE guidelines, and both if these impose limitations on the eventual solution. Mechanisms for the system are development and the available facilities. There are three main activities in the system; deburring planning, robotized deburring, and process monitoring. Deburring planning includes all processes and subsystems necessary prior to the mechanical robotic deburring as described in Section 2.2. This includes a system for deburring strategy, path planning, and machining parameter optimization. The system of systems is presented in Figure 6. The second activity, robotized deburring (deburring in Figure 6), is where the mechanical deburring occurs. To monitor and optimize the system, the activity process monitoring was added. The output from the activities is the final cast part without burrs.

It has been stated that a tool path needs to be adapted according to the geometric variations and burrs. To adapt the tool path, a type of measuring system is necessary to capture the relevant geometries. Then a system for analyzing the result is necessary. This is represented in Figure 6 by the measuring system and the burr detection system, respectively.

The feedback from the process monitoring box in the deburring system to the planning represents data collected from sensors that are used to monitor the deburring process and then made available to improve the planning process using machine learning.

5.2 | Measures of effectiveness (MOE)

To evaluate and validate a system, some measure of success and/or effectiveness has to be determined. MOE represent the view of the stakeholders and are meant to help in the validation process.[28] The three first MOE are given by the industry partner and the last one from SFI Manufacturing and Academia. The MOE for this project are:

1. The need for manual deburring is reduced by 80%.
2. The final part is visually appealing and has no sharp edges.
3. Accuracy of the deburred parts is within the given tolerances, typically ±0.5–1.0 mm.
4. The research produces useful industry benefits and publications.

Generation of MOE support clear communication about the problem under investigation without any prejudice toward the final solution. MOE also gave the industry stakeholder an opportunity to express their priority, which is expressed in MOE 2.

6 | ANALYSIS: CASCADING TRADE STUDIES

In a complex engineering system like the robotic deburring system, there are many alternative methods and solutions that need to be evaluated. The decision made in one step of the system will affect the next step, but also limits the choices in the previous step. The result is cascading trade-offs. To look closer into the cascading trade-offs, we will focus a on smaller part of the system.

Robotic deburring begins with a workpiece with burrs, planning the process for removing the burrs, and motion execution where the machining takes place. Output is a workpiece with the burrs removed. This pipeline (Figure 3) and state-of-the-art is described in Onstein et al.[29] The presented pipeline is a general one that goes from a workpiece with burrs all the way to a workpiece without burrs. There are many steps and processes in this pipeline and it is, therefore, necessary to split the deburring system into subsystems. The focus in this work will be on the planning step, more specifically on generating a tool path for removing the burrs from the workpiece. A suggested pipeline for tool path generation using 3D sensors is shown in Figure 7. Input to the system is the physical workpiece with burrs and a CAD model of the reference workpiece. To capture the geometric variations of the part, the workpiece is scanned using a 3D scanner, for example, a laser or a structured light sensor. The output of the 3D scanning

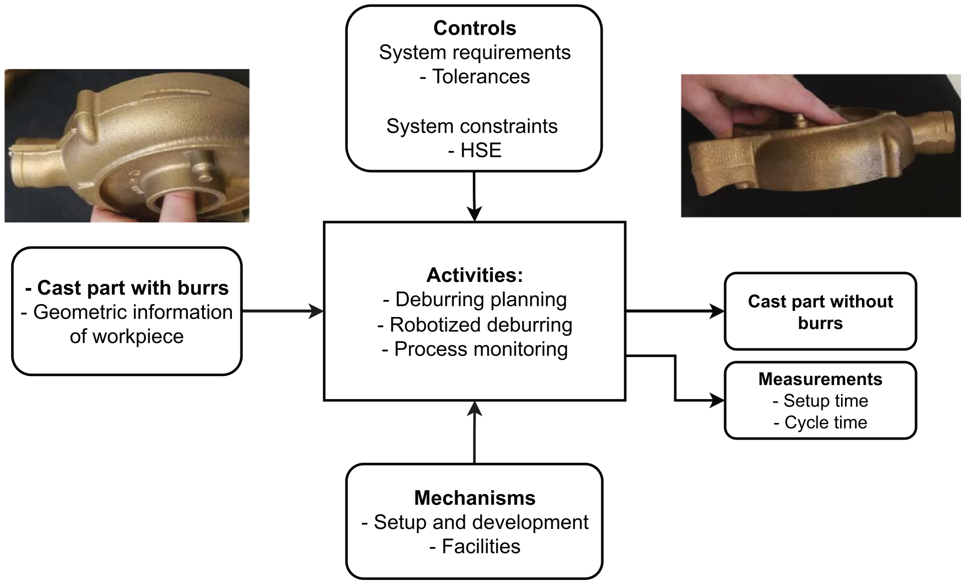

FIGURE 5 Context diagram of a robotic deburring system, with part with rough edges as input and clean part as output

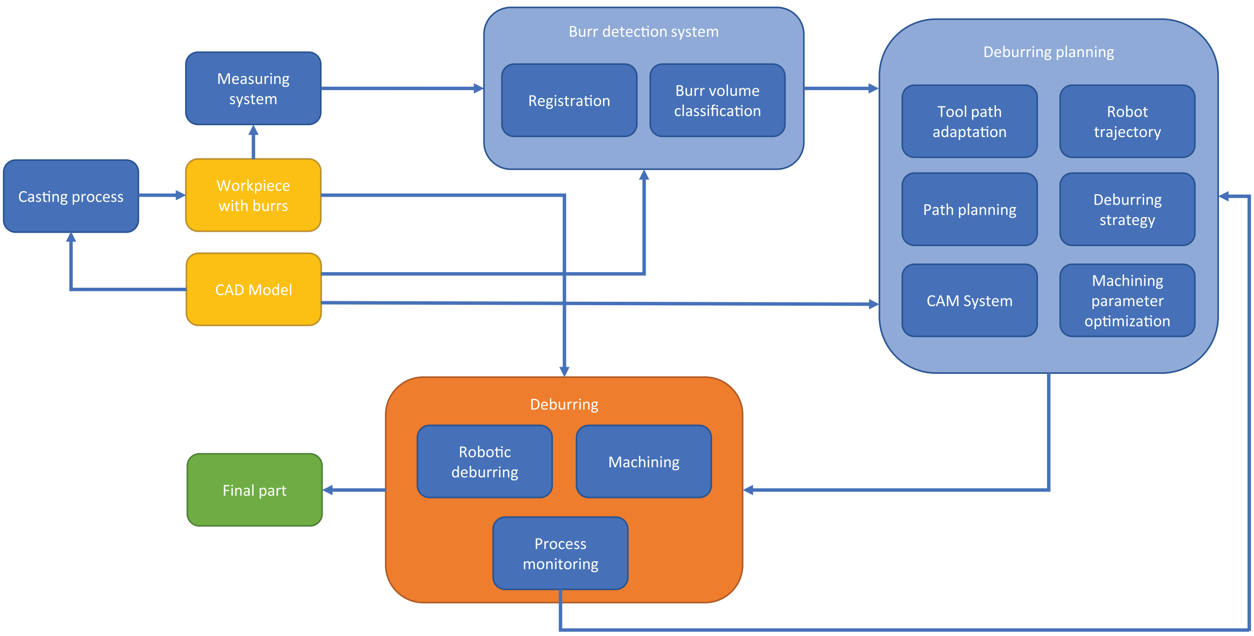

FIGURE 6 Systems of systems for flexible and automated robotic deburring

are several point clouds from various angles of the workpiece. These scans have to be combined into one joint point cloud. This is achieved through registration. The CAD model can also be used for reference in the registration process. Output of the registration process are all the scans in the same reference frame. These scans can then be combined into one joint point cloud. This joint point cloud is then fed into a tool path planning algorithm that uses the sensor data, and CAD model, to generate a tool path to remove the burrs. The following sections will go into more detail on each process of the tool path planning pipeline.

6.1 | Geometric representations

While images have a dominant representation as 2D pixel arrays, raw data from 3D sensors can have a number of forms such as point cloud, depth map, and polygons. The raw data often requires further processing before further analysis. A point cloud is represented as a set of 3D points where each point is a vector of its (x, y, z) coordinate plus extra feature channel such as color and normal.[30]

There is a wide range of systems for representing geometric 3D data. 3D data representations serve as an intermediary between data

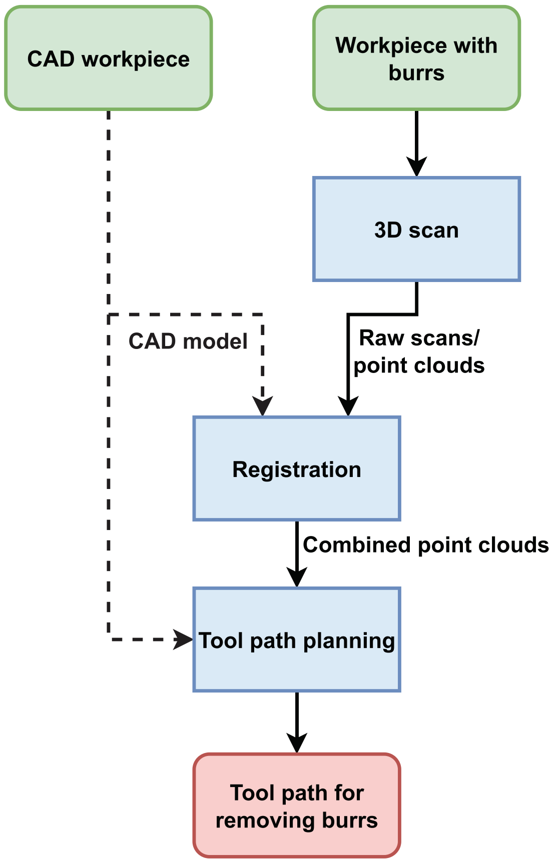

FIGURE 7 Workpiece to tool path pipeline

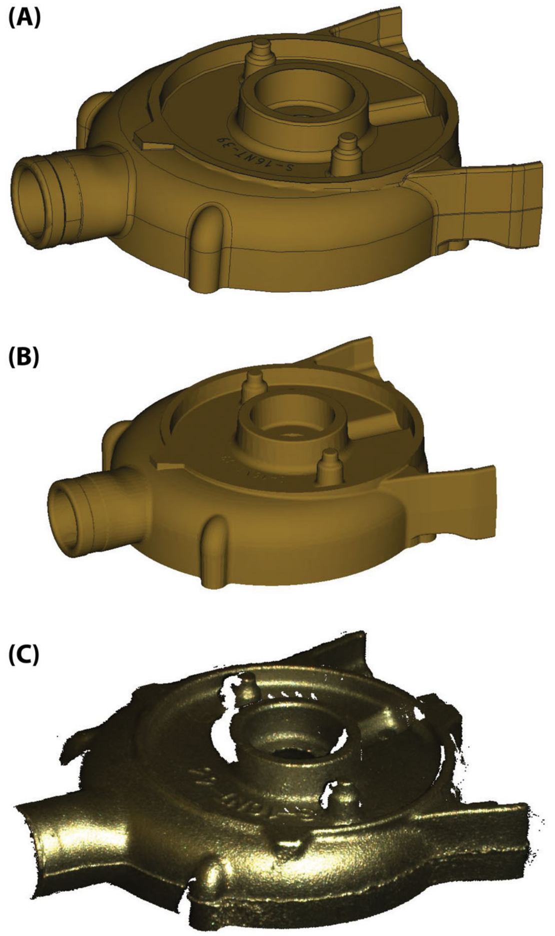

FIGURE 8 (A) Solid—boundary representation. (B) Surface—triangular mesh. (C) Raw data—point cloud

acquisition and application, with constraints imposed from both.[31] The various representations can be distinguished based on what is being represented, the amount of information available without derivation, and what information that can and cannot be derived. In many cases, the data acquisition method determines the native geometric representation. For example, output of a structured light sensor can be represented as a point cloud with color and normals. In other cases, it is the target application that imposes constraints on the geometric representation. For example, certain algorithms are more efficient on a specific representation. Since both the data acquisition method and the application impose constraints on the geometric representation, it might not be enough with one representation throughout the system. It can be necessary to convert between representations with some level of approximation.[31]

3D representation can be categorized as raw data, surfaces, and solids.[31] Raw data are data that are delivered by a 3D sensor. Examples of these different representations can be seen in Figure 8. Solid modeling contains, explicitly or implicitly, information about the closure and connectivity of the volumes of the solid shapes. It also guarantees closed and bounded objects. A form of solid modeling is boundary models that represent the solids in terms of their bounding faces, which are bounded by edges and the edges by vertices. A type of boundary model is NURBS, which stands for Non Uniform Rational B-splines.[32] NURBS are the most generally used representation due to its flexibility, and it is heavily utilized in CAD/CAM software. The main drawback of B-splines is the fact that continuity across surface patches is hard to maintain. STEP is a widely used data exchange format that can be used to represent CAD models by boundary representation. STEP stands for "Standard for the Exchange of Product model data" and is the informal name of the ISO10303 standard.[33] ISO 10303 is an International Standard for computer-interpretable representation of product information and for the exchange of product data.

Most geometric algorithms in computer vision and graphics operate on representations of 3D data based on surfaces.[31] Polygonal mesh, and more specifically triangular mesh, is by far the most common surface representation. It is a collection of vertices, edges, and faces that defines the shape of the object. The faces are usually triangles. The motivation for using polygonal mesh is the ability render objects in real time, that the mesh can be acquired from sensors, and that there are many algorithms for manipulation of triangle meshes.[32] Polygonal mesh is the most widely used representation in geometry processing, and other representations are often converted to polygons before rendering. Polygon mesh does, however, have some important issues that are worth-mentioning. Over- and undersampling are an issue when it is hard to distinguish between region of high or low degree of geometric detail. Topological issues are also important.

6.2 | 3D scan

Recent years have been characterized by an increased availability of sensing solutions for optical 3D shape imaging. These technologies are aimed at noncontact sensing of the surrounding environment and reconstruction of the scene in three-dimensional form, commonly as a point cloud. One distinguishes between passive and active 3D data acquisition devices. The former reconstruct three-dimensional scene from two-dimensional images, using multi-view stereo, shape from X, and model-based approaches for known shapes. To tackle the inherent difficulties with utilizing images, active acquisition systems are applied. Their principle is based on projecting different forms of illumination on the scene, and measuring the resulting responses. Technologies falling into this category include time of flight (measuring phase difference between the projected and the reflected laser pulse), interferometry (analyzing interference fringes of the projected striped light patterns), and structured light (measuring deformation of the projected light pattern).[34]

Structured light solutions have gained an increased interest lately, mainly due to commercialization advances allowing for more low cost and high accuracy 3D sensors, most notable Kinect, Structure Sensor, and Intel RealSense™.[35,36] These sensors have become particularly useful in robotics research due to their compact footprint and being a relatively cheap source of 3D information. Zivid, a 3D sensor recently developed in Norway, provides an increased acquisition and reconstruction accuracy achieved by the application of time-coded structured light and a series of changing patterns aimed at avoiding unwanted artifacts due to reflection and shiny surfaces.[37]

Three-dimensional point cloud is the typical raw output from 3D sensors. The point cloud may contain only the points' coordinates, or be augmented with colors and normal vectors. Alternatively, the RGBD representation may be acquired, constituting an RGB image with additional depth channel. Using further computational steps, point clouds can be triangulated into mesh models, which can later be joined with mesh models as imaged from other perspectives to form a more complete tessellated surface. This approach is widely used in handheld laser scanners workflows, where a human operator applies the sensors and the associated software to iteratively recreate a scanned model of an object of interest.[32]

6.3 | Registration

Many geometric 3D models of real objects originate from a 3D scanning process. These scans are usually only partial scans of the object in question. To get a complete 3D model of the object, it is necessary to combine scans from different angles into one model. This task is called model reconstruction.[38] The major challenge with this is to get the partial scans into a common reference frame or coordinate system. It is rarely known with sufficient accuracy how the object moved relative to the scanner between scans.[32] To get the partial scans into the same reference frame, is it necessary to register them to each other where corresponding points are identified. Output is a transformation that minimizes the distance between the scans. A popular approach to solve the registration problem is the iterative closest point (ICP) method.

ICP is used to match two surfaces and determines corresponding points as the closest one between the two surfaces.[32] Then, the two surfaces are aligned to minimize the distance between the corresponding points. The process is repeated until convergence. Convergence can be when the closest point correspondences does not change. The algorithm uses a greedy optimization strategy. This means that it will not always converge to a global optimum. Adequate initialization is important for a good result. Several random initializations can also be attempted.

In recent years, deep learning has been exploited to improve registration algorithms.[38] Emerging 3D related applications like autonomous driving and augmented reality have increased the demand for more robust and powerful 3D analyzing algorithms.[30] Deep learning has great success in processing data such as images, videos, audio, and text. It is only recently that researchers started exploring learning on 3D data such as meshes and point clouds, partially because of the increase in its availability. This field is named 3D deep learning. The growth of 3D data is due to two main forces.[30] The first is progress in 3D sensing technology. Access to depth cameras, such as Kinect and StructureSensor, has increased as the cost of sensors has decreased. More accurate 3D sensors are also available such as LiDARs and ZiVID. The second force is the availability and popularity of free 3D modeling tools. Deep learning methods for registration are based on the general idea of using data-driven approaches that learn the relevant registration criteria from the data. To ensure a robust solution that is not overfitted on a small dataset, it is necessary with large datasets.

6.4 | Tool path planning

Most burrs of cast parts are removed manually today. The industry wants to automate this process using robots. To remove the burrs, the robot needs a tool path to follow. The two most common approaches for generating the tool path today are human demonstration and using CAD/CAM software. In both cases, the tool path is generated based on a reference and not on the specific workpiece. The challenge is that both the workpiece geometry and the burrs vary in shape, size, and location as a result of the casting process. It is, therefore, not possible to use a predetermined reference tool path to remove the burrs. This means it is necessary to use some form of sensor input to compensate for the geometric variations. There are several sensors that potentially can be used to address the geometric variations such as force control, probing, and 3D sensors.

7 | DECISION-MAKING

Having addressed the nature of the trade-off studies, the next SPADE activity is to select a way forward.

7.1 | System boundaries

One of the system stakeholders presented in Section 4 is the development team. In this project, there are two different research groups working together; one is specialized on smart sensor systems and the other on robotic systems. There are two groups working together because the system is complex and requires different expertise. The smart sensor systems group is responsible for developing the 3D scan system as well as the registration system, and selecting the corresponding geometric representations. This is represented as the burr detection system in Figure 6 and as 3D scan and registration in Figure 7. The robotics group is responsible for developing the tool path planning system. Tool path planning is the last process in the planning pipeline, which means that the robotics group has to use the output from the smart sensor system group. The tool path planning step is represented as the deburring planning system in Figure 6 and as the tool path planning in Figure 7. The choices the smart sensor system group has made are listed below.

1. **3D sensor**: Zivid
2. **Registration**: Deep learning
3. **Geometric representation registration**: Point cloud

7.2 | Design requirements

To evaluate the different alternative solutions in the pipeline (Figure 7), it is necessary to establish a set of design requirements. The overall system for moving from a CAD model and workpiece to a tool path has one set of requirements. Each step in the pipeline also has its own set of requirements. The focus of this trade study will be on the overall system design requirements and the design requirements for the tool path planning system. Each requirement begins, "The system shall ..."

7.2.1 | Overall system: CAD and workpiece to tool path

The design requirements for moving from CAD and workpiece to tool path describes the functionality of the system. The functional design requirements for the system are listed below.

1. Generate a tool path to remove the burrs based on CAD and 3D-scan.
2. Generate a tool path that satisfies the given tolerances for the part.
3. Have a setup time for a new part that is less than one working day.
4. Generate a path without interaction from the human operator.
5. Support integration in production facility.
6. Provide guidance for a human operator.

7.2.2 | Tool path planning

The design requirements for the tool path planning system are listed below. These are more technical than the ones describing the overall system.

1. Calculate a path that is able to handle the geometric variations induced by the casting process.
2. Generate a tool path that is feasible for use by an industrial manipulator.
3. Operate with a computational speed that does not increase the cycle time of the current deburring process.
4. Accept input data from multiple sources; that is,, CAD model and registration data.
5. Be maintainable for a human operator.

Identifying the design requirements and focusing on keeping them nonsolution-specific helped to focus on the problem and open up the number of alternative solutions considered by reducing researcher design bias.

7.3 | Industry aspects

Some of the design requirements suggest that computational and setup times should be as short as possible. For the industry partner, the overall goal with automating the deburring process is to reduce the need for manual deburring, as stated in MOE 2, to improve the HSE conditions. They have stated that it does not matter if the cycle time increases slightly as long as the process is automated. This means that the system must be efficient, but the main focus is not to make is as fast as possible.

One design requirement is about maintainability. This includes how easy it is to make adjustments to the system and to potentially add new parts. Ideally, the system should be maintainable for a human operator. In that way, the operator can make changes to the system quickly to optimize the process. The challenge is that in a complex system such as the tool path planning system, maintaining the systems requires a high proficiency in robotics engineering. This is likely to be outside the skill set of a human operator. It is, therefore, essential to find the balance between what the operator can and should maintain and what a skilled professional need to maintain.

8 | EVALUATION

The computational paths for robotic deburring along its pipeline is very complex. There are many aspects to take into consideration in every

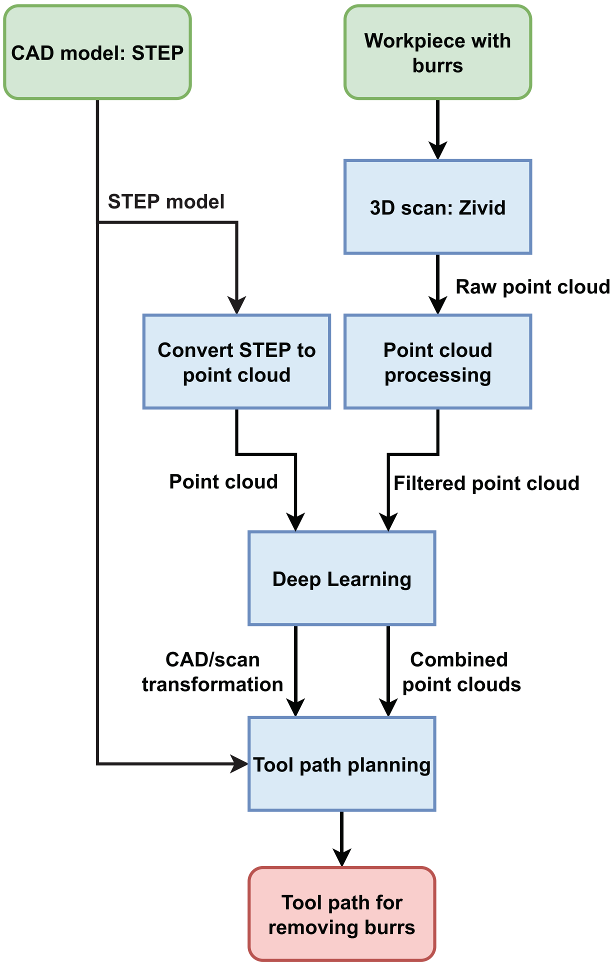

FIGURE 9 Updated pipeline of workpiece to tool path based on the choices made

step of the pipeline. Every decision made cascades throughout the rest of the pipeline. A methodology from SE was used to get a better understanding of the project and system as a whole. Fotland et al.[39] applied the same methodology to a trade study on cranes for offshore vessels. The focus in this work is on generating a tool path for removing the burrs from a workpiece.

8.1 | Cascading (in)accuracy

Figure 9 is an update of Figure 7 including the choices made by the smart sensor system group. This section will present the consequences on downstream processing in the pipeline and itemize the options. The options with the corresponding input, output, method, and considerations are also summarized in Table 2.

As Figure 9 shows, the output of a 3D scan using Zivid is a point cloud. This raw point cloud must then be processed to remove noise and to crop out the background. The CAD model is provided by the industry partner in the STEP format. The deep learning registration system requires that both inputs have the same geometric representation. This means that the CAD model has to be converted to a point cloud. A STEP model is defined as a solid while a point cloud is defined as raw data. To convert the STEP model into a point cloud it usually has to be converted to a surface model first, such as a tessellated model. The tessellated model can then be converted into a point cloud. Both the conversion from solid to surface and from surface to point cloud is an approximation of the input object. How accurate the approximation depends on the number of triangles in the tessellated model, and the number of points in the point cloud. A higher point density in the point cloud usually means a higher accuracy. Another aspect of a more dense and accurate point cloud is the computational time. It requires more computational time to generate a high density point cloud than one with a lower density. It also requires more computational time to do calculations on a more dense point cloud. This affects the registration and tool path planning further along the pipeline.

One of the design requirements for the tool path planning system is that it has to accept the input data. Based on the given choices, this means point cloud from the registration system. The CAD model, on the other hand, is not determined. It is possible to use the STEP format provided by the industry directly. This, however, means that either the CAD model or the registration information, or both, will have to undergo a conversion between geometric representations. An alternative to using the STEP model is to use the already converted CAD model represented in the point cloud format.

The tool path planning system has to be compatible with the input data. It also has to cope with the quality of the input data. This includes the quality of the 3D scan and the accuracy of the registration. The quality of the input data directly affect the tool path planning design requirements such as generating a tool path that is able to handle the geometric variations. If the accuracy of the input is poor, it is challenging to calculate an accurate tool path and it can be challenging or impossible to handle the wide range of geometric variations from the casting process. The same argumentation goes for one of the overall functional requirements, that the generated tool path satisfies the given tolerances for the part.

8.2 | Conflicting interests for stakeholders

It was mentioned in Section 5.1 that one common conflicting interest between academia and industry is the level of research. This could potentially effect some of the design requirements. Maintainability was already mentioned in the previous section. The more advanced the solution is, the harder it can be to maintain. One example is the deep learning network for registration. This is a method that is very research-oriented and highly publishable for academia. A deep learning network can be hard to maintain, even for experienced developers.

Support of integration in production facility is another design requirement that potentially can have conflicting interest. The safest way to ensure easy integration is to use the systems already present at the production facility. These systems may not, however, enable a research oriented solution.

Advanced manufacturing technologies play an important role in both reshoring decisions and keeping production in Norway, as stated

TABLE 2 Considerations in cascading trade studies

Subsystem	Input	Output	Method	Considerations
3D scan	Workpiece	Raw point cloud	Zivid	– Accurate mounting of workpiece – 3D scan of metal part
Raw point cloud processing	Raw point cloud	Filtered point cloud	Point cloud filtering – Removing noise – Crop out background	– Threshold for noise removal – Defining background for removal
CAD model conversion	STEP model	1) STL model 2) Point cloud	CAD model conversion	– CAD model approximation – Most appropriate representation
Registration	1) Filtered point cloud 2) CAD model as point cloud	1) Registered point cloud 2) Transformation matrix	Deep Learning	– Accuracy of 3D scan – CAD model representation – Accuracy of algorithm – Computational speed
Tool path planning	1) Registered point cloud 2) Transformation matrix 3) CAD model	Tool path for robot manipulator	TBD	– CAD model representation – Feasibility – Accuracy – Maintainability – Setup time – Computational speed

in the introductory section. Many of these technologies, like deep learning, have to be further researched and verified in industrial applications to be accepted by the industry. It is therefore important to find the right way of doing this validation with both stakeholders in mind.

9 | CONCLUSION

A SE approach was proposed to tackle the complexity with developing a robotized deburring system. The approach has proven proven useful to identify and prioritize the stakeholders and their needs, as well as analyzing the different alternatives in a complex engineering system when dealing with cascading trade studies. Furthermore, the SPADE methodology provides a simple set of iterating activities to support robust SE research. The paper has provided the contribution of the phrase “cascading trade studies” to describe the interdependency of trade-off studies for complex systems.

9.1 | Advantages of applying SE approach

SE as a set of systemic and systematic practices has assisted this research in the following ways:

1. Creating the context diagram in Figure 1 and then the expanded view in Figure 5, and the eventual recognition of the whole process as a system of systems, Figure 6, provided valuable artifacts to establish a shared vision among the project stakeholders.
2. Explicit identification of stakeholders supported earlier recognition of the duality involved in the process process and the allocation of different priorities within the research group.
3. Explicit requirements formulation and creation of MOE helped to focus on the problem definition by removing biases introduced by preconceptions of the solution.
4. Identifying the potential for cascading inaccuracies.
5. Making the criteria for decision making more transparent and shareable within the research team and with industry partners.

Framing the problem using SE disciplined processes has created a clearer path for the researcher, and use of the artifacts produced for this paper has helped in communication with academic supervisors and industry partners.

9.2 | Future work

Applying a SE approach to resolve automation of complex mechanical engineering manufacturing process decisions has proven valuable to create a shared understanding for the stakeholder of the problem domain using MOE and design requirements. Future work consists of development of a technical solution as well as experiments in collaboration with both research groups. This requires close coordination between the research groups that is made easier through the shared understanding.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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