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Abstract
As additive manufacturing (AM) continues to mature, an efficient and effective method to identify parts which are eligible for AM as well as gaining insight on what values it may add to a product is needed. Prior methods are naturally developed and highly experience-dependent, which falls short for its objectiveness and transferability. In this paper, a decision support system (DSS) framework for automatically determining the candidacy of a part or assembly for AM applications is proposed based on machine learning (ML) and carefully selected candidacy criteria. With the goal of supporting efficient candidate screening in the early conceptual design stage, these criteria are further individually decoded to decisive parameters which can be extracted from digital models or resource planning databases. Over 200 existing industrial examples are manually collected and labelled as training data; meanwhile, multiple regression algorithms are tested against each AM potential to find better predictive performance. The proposed DSS framework is implemented as a web application with integrated cloud-based database and ML service, which allows advantages of easy maintenance, upgrade, and retraining of ML models. Two case studies of a hip implant and a throttle pedal are used as demonstrating examples. This preliminary work provides a promising solution for lowering the requirements of non-AM experts to find suitable AM candidates.

Keywords: additive manufacturing, machine learning, candidate identification, conceptual design

1. Introduction
Additive manufacturing (AM) has the potential to change the way products are designed, produced, and distributed (Thompson et al. 2016). Though many organizations are interested in the idea of incorporating AM into their development process, they are at a natural disadvantage: AM is still in its infancy compared to conventional manufacturing (CM) methods and lacks the centuries of development and knowledge-sharing which leads to an in-depth understanding of how and when it may best be applied. The gap of knowledge vacancy has been identified by the Information and Communications Technology Council of Canada (ICTC) (2017) and other authorities (Wohlers Report 2018). The ICTC also found that only a small amount of companies has used or planned to use AM in the near future. Since AM is not a catch-all solution, educating a workforce on the new technology just to see if it might be of value bears a significant risk. Therefore, as AM continues to push its way into the production manufacturing space, there will inevitably be a lack of talents who are ready and able to deploy it. Those who are in a position to enable this change must first possess the knowledge on how to unlock its unique potentials.

Identifying which parts/assemblies in a repository are suitable for AM is one of such top challenges because there is no clear formula which leads to a successful adoption of the technology. Success varies widely depending on how the needs of the company match up with the unique potentials of AM. Some restrictive rules have been developed which can help guide the decision-making process, such as maximum build volume and batch size (Doubrovski et al. 2011), but the trade-offs between these AM limitations and the geometric, functionality, economic, and societal benefits are less often discussed. To solve the problem of identifying part candidacy, a few methods including heuristic ones (Klahn et al. 2014; Booth et al. 2017; Reiher et al. 2017) and computational ones (Yang et al. 2018; Yang et al. 2019c; Yao et al. 2017) have been reported. These approaches are either highly expertise-dependent or only focused on specific AM potentials (e.g. part consolidation or lightweight). Moreover, as the scale of targeted part repositories (e.g. a complex system with thousands of parts or even more) increases, efficiency and computational cost is of significant concerns. Therefore, an automated method which can quickly identify potential candidates for AM applications and present insights on what values AM may add to a product is needed. Such an approach can serve as a first-level filter for novice AM users (e.g. product managers) to narrow down the scope of potential part candidates, and then AM expertise is sought for further examination.

To achieve the above objectives, comprehensive literatures are first reviewed on the beneficial aspects of AM as well as the existing approaches of part candidacy identification (Section 2). Then a methodological framework to support the automation of identifying part candidacy is presented (Section 3). Implementation of the proposed framework and its validation are illustrated in Sections 4 and 5 respectively. This paper ends up with discussions and future work.

2. Literature review

This section mainly reviews work on: 1) AM potential analysis, and 2) existing part candidacy identification methods. The first part will provide a comprehensive insight of potential advantages of adopting AM in product development, which helps to yield a set of decision criteria to justify the conditions of "AM suitability". The second part summarizes the ongoing efforts of AM part candidate detection and comparison of its transferability.

2.1 Dimensions of AM potentials and its breakdown

AM potentials refer to the opportunistic aspects that encourage the adoptability of AM processes compared to conventional fabrication methods. Although the restrictive aspects of AM, such as material availability, overhang issues, and dimensional accuracy as reviewed in literatures (Laverne et al. 2015; Thompson et al. 2016), are also critical for the decision making of justifying AM's suitability, this paper only focuses on the potential perspective that motivates the consideration of AM. This strategy can help to improve screening efficiency and avoid neglecting parts that fail manufacturing rules but may have big gains if redesigned for AM. Moreover, given the diversity of AM processes and machines, the applicability of AM feasibility investigation at the early design stage is tedious and the feasibility changes from one process to another. Various efforts have been reported to classify the AM potentials. In general, the potentials cover three main perspectives: design + geometric complexity, economic advantages, and social and environmental benefits. The overall AM potential mind map is depicted in Figure 1. Design and geometric complexity mainly focus on functionality and performance improvement as well as expanded manufacturing capability due to AM adoption. The aspect of cost and time savings are distributed in categories of intertwined production and supply chain. Potential influences on organizational management and ecology are also discussed. The breakdown of each AM-potential dimension is represented by the branches connected to the bold box respectively.

Design + geometric complexity

Design, here, refers to the potential to improve in terms of functionality and performance via AM, while geometric complexity refers to the potential to fabricate as is without altering the design. Conner et al. (2014) constructed a three-dimensional space with part complexity, level of customization and production volume being the axes and eight production scenarios were discussed. Numerical metrics were derived for each dimension of a part, and then parts are assessed and assigned to one of the production scenarios, which further indicates the selection of AM or CM. Klahn et al. (2014) identified four design potentials of AM as *integrated design*, *individualization*, *lightweight design*, and *efficient design*. A more expanded classification of design potentials was released by the ISO/ASTM 52910 standards (2015) outlining six items: customization, lightweight, internal channel/structures, function integration, surface structures, and material options (e.g. hybrid materials). These works help to educate engineers the potential enhancement in terms of product functionality and performance to be gained when changing from CM to AM.

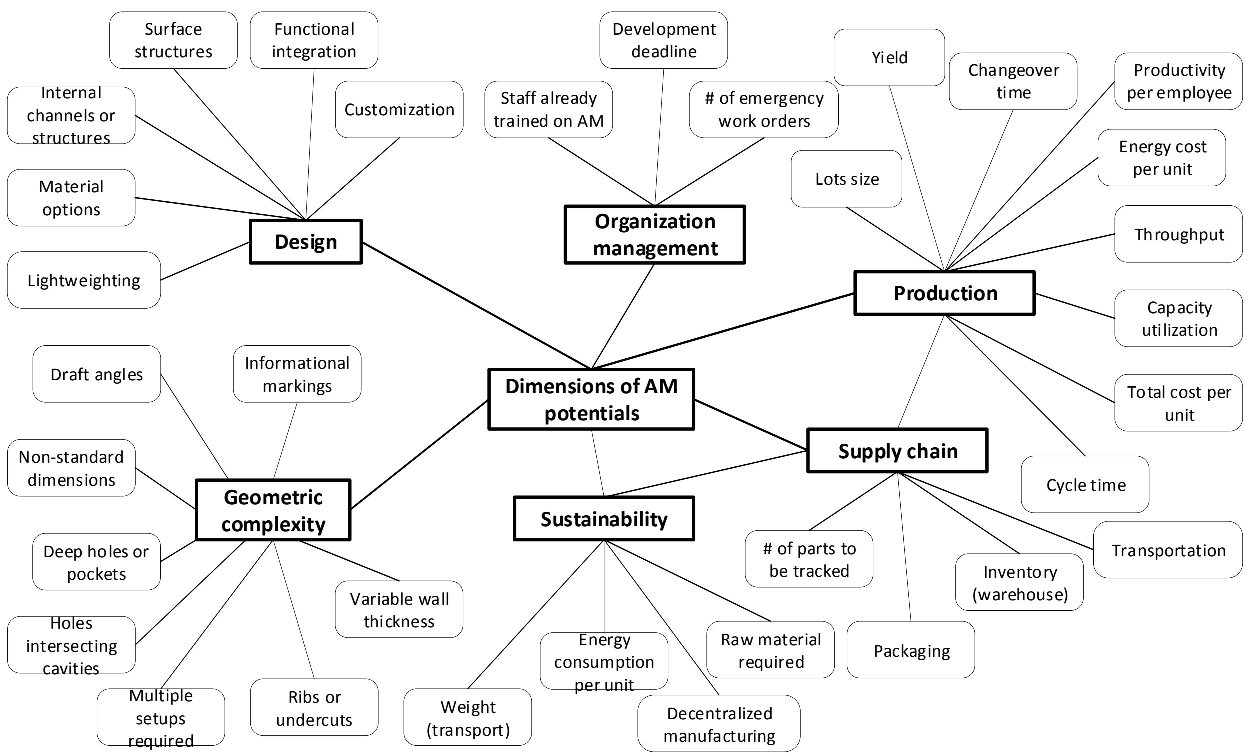


Figure 1 the mind map of dimensions of AM potentials.

There is a significant difference between how CM and AM respond to geometric complexity. This disparity makes the complexity of a part a good indicator of which manufacturing method should be used (i.e. CM or AM). In CM context, geometric complexity normally is measured by difficulty-to-manufacture features. Investigation of part features that are designed for CM boosts the appreciation of much expanded manufacturing capabilities of AM. As shown in Figure 1, such features of CM include but not limit to deep holes, large draft angle, cavities and undercuts. A geometric complexity factor was particularly developed for evaluating the shape complexity of castings (Joshi and Ravi 2010). The factor was based on geometric parameters such as the number of cored features, volume and surface area of part, core volume, section thickness and draw distance. In contrast, with the help of AM, metrics of geometric complexity should no longer be bounded by these features. Parts with more organic shapes and hierarchical structures created by techniques such as topology optimization (Rozvany 2009) and cellular structures (Tang et al. 2015) require more effective metrics for AM applications. Based on the previous work (Joshi and Ravi 2010), Conner et al. (2014) proposed a weighted complexity factor with aggregation of part volume ratio, surface area ratio, and number of holes or slots. Other computational approaches also used the number of triangles in the STL file (Valentan et al. 2008) and convexity ratio (Fera et al. 2018) as a measure of geometric complexity.

Economic considerations

The potential reduction of production cost and development time is one of major benefits of AM. Economic analysis of whether AM can compete with CM not only needs to consider direct production cost but also the associated cost in the alternation of supply chain(Deppe et al. 2015). A set of metrics for evaluating productivity of conventional manufacturing system was established in (Huang et al. 2002) as shown in Figure 1. It covers a wide range of parameters including yield, throughput, lot size, etc. In AM field, Deppe et al. (2015) developed a specific cost evaluation model for aerospace components in the sector of Maintenance, Repair, and Overhaul. The established model fully investigated the influencing factors such as machine, material, part, and general costs of labor, maintenance, capacity, and depreciation. Compared to conventional production system, AM depicts small lot-size advantages. The absence of tooling, individual set-up procedures, and equipment changeover makes AM more favorable, and the lot size of 1 becomes economic (Tuck et al. 2008). The small lot size advantage further enables rapid iteration of new product development and enhances the communication efficiency within the development team. Combined with the design potentials of customization and improved functionality, economic lot size, incremental product launch, reduced production tools, rapid prototyping, and process concentration are concluded as value clusters to support AM decision making (Fontana et al. 2019).

Another big change of the production philosophy brought by AM is the shortened supply chain. The possibility of consolidating assemblies into a single part as well as the inventory level significantly reshape the spare parts management and distribution strategy (Huang et al. 2013). The consequential effects include reduction in the need for warehousing, transportation, and packaging. For spare parts supply chain, the key performance indicators are the response time for an unpredictable demand, and the total costs for production, storage, and logistics of a spare part. Several researchers have investigated the use of AM in spare parts management (Hasan and Rennie 2008; Holmström et al. 2010; Thomas 2016; Knofius et al. 2019; Knofius et al. 2016). The advantages of increased responsiveness and robustness in a discontinuous supply chain by AM has been outlined by these authors. Repair and remanufacturing can also be highly advantageous from a cost and lead time perspective, as little backup inventory is required and replacement parts can be built at any time (Zhang et al. 2018)

Social and environmental benefits

Sustainability advantages of AM can be concluded as less manufacturing waste, higher material efficiency, reduced energy consumption, and subsequent reduction in the transportation and inventory waste. On the social sustainability aspect, the social issues concerning AM are the work condition and worker's health (Huang et al. 2013). Potential health benefits may be gained by avoiding long-term exposure to harsh and hazardous work environment. Another social benefit comes from the change of consumption patterns. In contrast with the passive customer behavior, the easy access of CAD software and 3D printers enables a new concept of "prosumer" who consumes and produces a product. Matos et al. (2019) further explored the AM social impacts of intellectual properties, work, and education and skills. Particularly, the social impacts on skills and education requirements are discussed because the immaturity and knowledge gaps of this new technology makes AM not well integrated with the education and engineering training. With special interests of analyzing the impacts of advanced manufacturing technology on organizational structure, Ghani and his colleagues (2002) enumerated the characteristics of a typical organization and concluded the need for proactive planning to facilitate changes to maximize productivity to take advantages of new technology. On the environmental potency of AM processes and materials, various aspects have been discussed including lightweight benefits (Huang et al. 2015; Tang et al. 2016a), part consolidation (Tang et al. 2016b; Yang et al. 2019a), energy efficiency (Baumers et al. 2017; Watson and Taminger 2015), raw material (Kellens et al. 2017), decentralization (Bogers et al. 2016), hybrid manufacturing (Caligiana et al. 2017), and process selection (Watson and Taminger 2015; Paris et al. 2016; Priarone and Ingarao 2017).

2.2 Part candidacy identification methods

Identification of suitable parts and applications for AM is one of the challenges for its wider adoption in industry. Some early efforts tried to provide guidence of selecting the pilot study projects and help the practitioners to gain valuable experience. Among which, one research stream follows the path of manfuacturability evaluation. These research works emphasized on using process constraints, such as material availablility, volume size, tolerencing, and geometric complexity, as the filtering criteria of AM eligibility based on the current design. Representative literature includes manufacturing process selection (Lovatt and Shercliff 1998), geometry-based manfucturability evaluation (Tedia and Williams 2016), and DfAM worksheet (Booth et al. 2017). However, these filtering criteria are overly rigid and eliminate the opportunities for AM redesign and added value. For instance, AM-enabled new design may drastically differ from the current design; therefore, the constraints of volume limitation become less important.

To encourage more active learning and application of AM, this paper focus mostly on the opportunistic aspects so that potential candidates will not be missed in the first round of screening in the part repository while improving the screening efficiency. Related work in this stream is compared against the rules of candidacy criteria, comprehensiveness (i.e. single potential V.S. multiple potentials), AM expertise requirements, and implementation method as summarized in Table 1. Overall, none of these research has provided an automatic solution for novice AM users in exploring multiple AM potentials. Prior studies with higher AM comprehensivenss generally required good knowledge of AM to interpret the heuristic questions. More detailed discussions follow after the table.

Table 1 summary of part candidacy identification methods

	Candidacy Criteria		**Comprehensiveness**		**AM expertise**		**Implementation**	
	Constraint	Potential	Single	Multiple	Novice	Skilled	Heuristic	Computation
Merkt et al. (2012)	✓	✓		✓		✓	✓	
Klahn et al. (2014)		✓		✓		✓	✓	
Materialise (2014)	✓	✓		✓	✓			✓
Lindemann et al. (2015)	✓	✓		✓	✓	✓*	✓	

Leutenecker-Twelsiek et al. (2017)		✓		✓		✓	✓	
Reiher et al. (2017)	✓	✓		✓	✓	✓	✓	
Senvol LLC (2017)		✓	✓		✓		✓	
Yao et al. (2017)		✓	✓		✓			✓
Yang et al. (2018)		✓	✓		✓		✓	
Yang et al. (2019c; 2018)		✓	✓		✓			✓

* The first stage requires AM neutral knowledge, while the second stage needs AM experts to evaluate the response.

Merkt and his colleagues (2012) are amongst the first ones to draw attention to the problem of part candidacy identification. They proposed an Integrated Technology Evaluation Model (ITEM) in which the part candidacy via Selective Laser Melting (SLM) is established through a four-stage evaluation. It covers product process analysis, economic analysis, economic potential analysis, and technology potential analysis. However, detailed metrics for AM potentials were not discussed except geometric complexity. Lindemann et al. (2015) and Reiher et al. (2017) created a Trade-off Methodology (TOM) matrix to compile a shortlist of potential candidates through two stages. The TOM is filled out first by a company employee and then by an AM expert to evaluate the employee's responses and apply weightings to each criterion that covers domain-specific interests (e.g. buy-to-fly ratio). As pointed out by their recent work (Kruse et al. 2017), a significant amount subjectivity may occur by the types of questions and weighting scheme of Likert scale. Leutenecker-Twelsiek et al. (2017) etablished an Experience Transfer Model (ETM) to transfer AM experience relating to part candidate identification and design through steps of theoretical education, implementation, and reflection. AM eligibility was assessed based on their previous work (Klahn et al. 2014) which needed inputs of part information and expected AM design benefits. The latter requires pre-acquired AM knowledge through educational workshops, and the heuristic nature introduces bias and uncertainty.

Different from the heuristic methods, some researchers sought for computational ways to identify part candidates concerning reduction of AM expertise requirement and more importantly, efficiency improvement. The first tool was developed by Materialise (i.e. one of the main OEMs in AM field) named as *3D Print Barometer* (Materialise 2014). As shown in Figure 2, it takes minimum part information such as size, geometric features, project budget, volume size, and purpose. Then, an analytic score of AM necessity is produced. The limited functions fail to provide what AM potential a part prosseses and the predicted result requires AM expertise for further analysis. A more recent and comprehensive work was reported by Yao et al. (2017). In their work, a non-exclusive list of AM design feature (e.g. honeycomb structure and integrated rotational joint) and a triplet descriptor $(loadings, objectives, properties)$ of each AM design feature were established and numerically coded. Upon which, existing industrial examples were analyzed in terms of its implemented AM design features, and they were used for training. The triplet descriptor was applied for the targeted application, and then a hybrid machine learning algorithm combining classification and clustering was proposed for recommending possible AM design features in a specific part design. This design requirements-rooted approach shows promise in identifying applicable AM-specific design features (e.g. lattice) but lacks considerations of other AM potentials. Moreover, intensive user inputs limit its flexibility in highly complex systems.

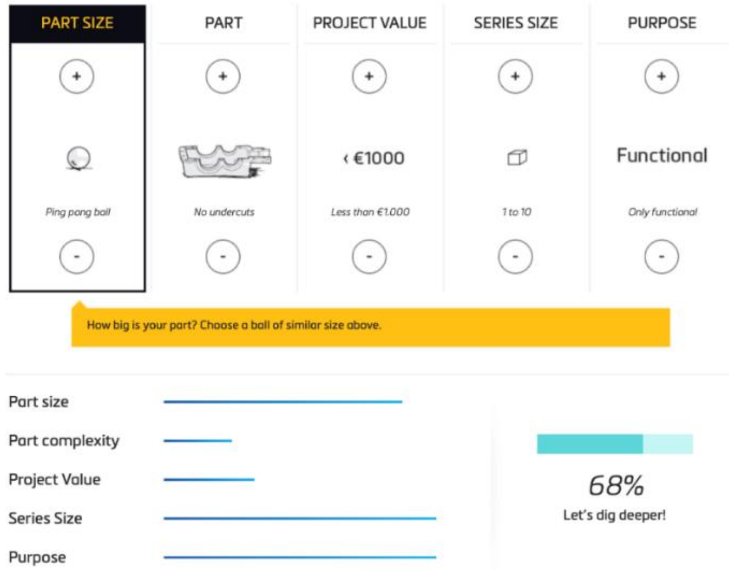


Figure 2 3D printing Barometer (Materialise 2014).

Beyond the work on miscellaneous AM potentials, some progress on identification of single potential is also reported. Such work is focused on supply chain benefits (Senvol 2017) and part consolidation (Yang et al. 2019c; Yang and Zhao 2018; Yang et al. 2018). Particularly, the literature (Yang et al. 2019c) incorporated the consideration of modularization in finding part consolidation candidates with reasonable computational cost, which made it deployable at the system level rather than simple assemblies.

Overall, prior methods on part candidacy identification may differ in strategies, but mostly show deficiency in comprehensiveness, efficiency, and objectiveness. Therefore, a fast decision support system that requires the least user inputs and minimum AM expertise but computationally produces reliable recommendation of AM eligibility, is demanding in the task planning and conceptual stage of product redesign.

3. The methodological framework of the proposed DSS

The proposed methodological framework is intended to develop a fast decision support system (DSS) to fill the gap of automated identification of AM part candidacy. The proposed DSS framework is shown in Figure 3. Overall, it is comprised of three main sections - candidacy criteria, data acquisition, and decision model, as marked in sequence. The candidacy criteria are to establish a set of conditions based on which AM eligibility can be justified. As reviewed in Section 2.1, AM potentials cover such a wide range from economic analysis to design potentials that having all criteria to be analyzed in the same time is not cost-efficient. As such, two “filtering principles” are set to down sampling the candidacy criteria.

- **Principle of efficiency**: how can the data that is used for justifying the AM candidacy be easily accessible?
- **Principle of objectiveness**: can the candidacy criterion be objectively measured with minimum biased information?

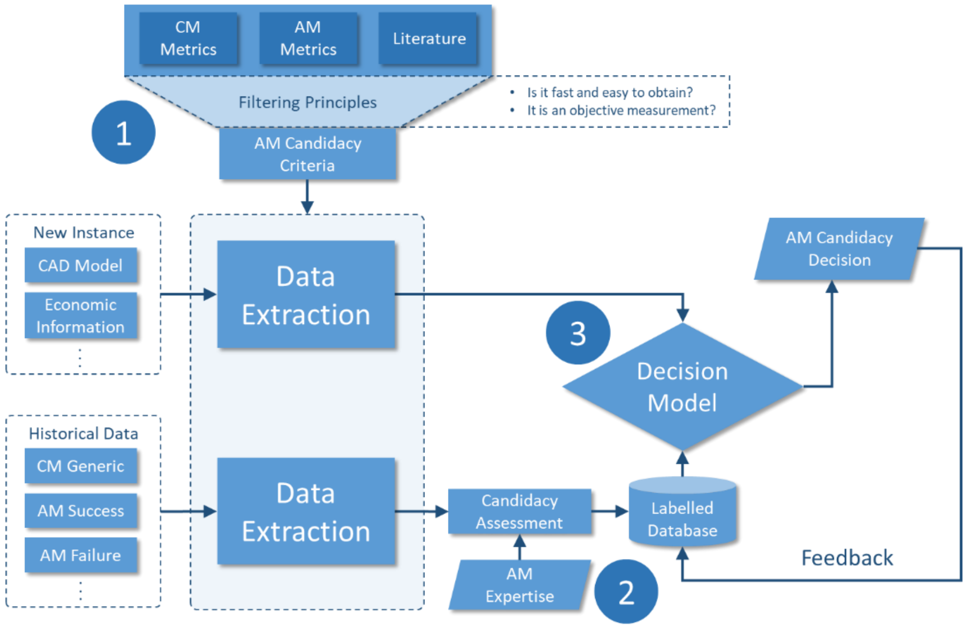


Figure 3 The proposed framework of the decision support system for AM part candidacy identification.

With these two principles being the guideline, AM candidacy criteria obtained from CM metrics, AM metrics and publications are down-sampled and parametrized in Section 3.1. The second branch of the DSS framework is to extract useful information (i.e. parameters) from diversified historical data including non-AM applications (e.g. for CNC milling), successful AM applications and failed AM instances. Each instance is evaluated against the candidacy criteria by AM experts and labelled with which AM potentials possess. As the number of labelled instances increases, the database can provide more concrete support for decision models in the next step. Details can be found at Section 3.2. The last part is how to construct decision models referring to existing instances and predict the AM candidacy of a targeted application. In this paper, machine learning algorithms are utilized because it is a promising solution to the problem of subjectivity in part selection, as it can eliminate the need of experts on individual basis and accelerate the decision process in case of massive information intake (see Section 3.3). The output of the DSS will return a list of potentials at a percentage scale. In the end, the targeted instance is fed into the labelled database to further improve the prediction accuracy.

3.1 The parameterized candidacy criteria

Comprehensive AM candidacy evaluation of a part requires assessment of both potential design improvement and process limitations. However, this paper mainly aims at establishing a fast-screening tool to narrow down the candidate pool; therefore, only criteria that meet the principles of efficiency and objectiveness are reserved. As such, manufacturability examination of a part is excluded at this early shortlisting stage. These criteria are categorized as geometric analysis, model analysis, economic analysis, and design potential analysis as shown in Table 2. Detailed discussions were reported in our previous work (Page et al. 2019). It should be noted that this criteria list is nonexclusive, and other criteria satisfying these two principles can be appended in future work. Further, these criteria are parametrized to determine the decisive factors of "being potential". Taking geometric analysis for example, traditional feature-based complexity metrics either require massive human interpretation or become problematic in case of compound features (Babic et al. 2008). Feature-less computational complexity assessment based on ratios of volume/surface, surface/bounding box (BB) volume, and volume/BB volume is highly favored (Valentan et al. 2008). Model analysis is particularly applied for part consolidation potentials by taking the information of the number of components, fasteners, and assembly interfaces. This information reflects the complexity of assembly, and the higher complexity indicates more needs of part consolidation. The sources of the parameters are identified as user, computer-aided design (CAD) model, and Enterprise Resource Planning (ERP) systems from which decisive information can be automatically extracted.

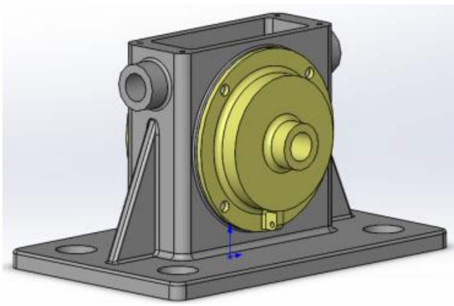
Table 2 Selected candidacy criteria and its key parameters.

Candidacy criteria	**Decisive parameters**	**#**	**Units**	**Source**
Geometric analysis	Ratio of part volume to part surface area	DP1		CAD
	Ratio of part surface area to bounding box volume	DP2		CAD
	Ratio of part volume to bounding box volume	DP3		CAD
Model analysis	Number of components	DP4		CAD
	Number of fasteners	DP5		User
	Number of assembly interfaces	DP6		User
Economic analysis	Manufacturing cost	DP7	$/part	ERP
	Batch size	DP8	# of parts	ERP
	Lead time	DP9	days	ERP
	Inventory costs	DP10	$	ERP
	Imports/exports cost	DP11	$	ERP
Design potential analysis	Does the part contain internal channels/structures?	DP12	Y/N	User
	Does the part have any surface markings?	DP13	Y/N	User
	Are there similar parts with similar modifications?	DP14	Y/N	User
	Does the part require human body compliance?	DP15	Y/N	User

3.2 Data acquisition and coding mechanism

Existing applications of both AM parts and CM parts are sought to increase data diversity. A greater variety of instances with differing manufacturing processes, sizes, shapes, complexities, etc., will lead to more success in analyzing future parts. These data are primarily extracted from reported literature and open-source repositories such as GrabCAD. Although data mining methods may be applied to augment the database and accelerate the data acquisition process, some preliminary test showed that publicly accessible data differ in a wide range and lead to poor quality. The extracted poor-quality data led to meaningless results. As such, the exemplified database is manually constructed to validate the proposed DSS framework. The database currently holds approximately 200 instances. Amongst all the decisive parameters, economic analysis is replaced by using an instant quoting plugin – Xometry (2017), offered by an online manufacturing service provider whose business covers manufacturing processes from 3D printing to CNC machining. The plugin is used for estimating lead time and costs with a 5% margin. If the costing tools led to very different estimations, that instance was scrapped.

Expert input regarding the AM potential assessment for each instance is required. To secure data integrity, two AM experts who have more than 3-year experience of product design and AM-related industrial projects work together, and a consensus must be reached with regard to each type of AM potentials. Figure 4 presents a labelled instance with input parameters and identified AM potentials. Each potential is graded by a binary system. It should be admitted that individual bias still exists at its current status; however, real industrial data acquired from its own ERP system should compensate its reliability and form robust decisions.



(a) Gearbox assembly

COLUMN_NAME	IS_NULLABLE	DATA_TYPE	Example Assembly Values
id	NO	varchar	ee51hdb-183bjda-ffahs2
volume	YES	float	614489.2
surface_area	YES	float	154840.06
bounding_box_x	YES	float	203.2
bounding_box_y	YES	float	127
bounding_box_z	YES	float	120.65
components	YES	int	3
fasteners	YES	int	8
assembly_interfaces	YES	int	2
cost	YES	float	183.68
batch_size	YES	float	30
lead_time	YES	float	15
inventory_cost	YES	float	0
import_export_cost	YES	float	0
surface_markings	YES	bool	FALSE
internal_channels	YES	bool	FALSE
similar_parts	YES	bool	FALSE
size_variation	YES	bool	FALSE
human_body	YES	bool	FALSE
result_eco_feas	YES	float	1.0
result_lightweight	YES	float	1.0
result_pc	YES	float	1.0
result_custom	YES	float	0.0
result_internal	YES	float	0.0

(b) Decisive parameters and identified potentials

Figure 4 an example of labeled instance with input parameters and identified AM potentials.

3.3 Decision model

The decision model aims at predicting AM potentials with machine learning (ML) assistance to improve subjectivity as well as efficiency. Different from the traditional way of examining a part whether it meets a special threshold (e.g. lot size of 1000 parts) of an explicit criterion, machine learning helps to identify hidden patterns and produce a probability estimation for further reference. Machine learning, as a promising tool, has been successfully applied in traditional manufacturing processes such as production planning (Rodríguez et al. 2019), flexible manufacturing system control (Chaturved et al. 1992) and monitoring (Yang 2016), cutting parameters prediction (Jurkovic et al. 2018), and material identification (Penumuru et al. 2019) and various AM-related fields, such as manufacturability prediction (Lu 2016), process optimization (Aoyagi et al. 2019), material property estimation (Hamel et al. 2019), dimensional accuracy analysis (Francis and Bian 2019). However, the combination of machine learning with AM candidacy prediction is rarely investigated. In this section, three main research questions are discussed: 1) small sample problem, 2) selection of suitable ML algorithms, and 3) how the ML model is trained.

3.3.1 Small dataset problem

The difficulty of obtaining numerous training samples is often the case in design fields. This situation is because knowledge as an intangible asset is hard to extract and quantify. The most valuable knowledge is often not easy to identify or share as it is stored within the minds of experts through years of experience (Dalkir 2013). This form of knowledge is also referred as tacit knowledge in contrast with explicit knowledge. The other facet of the small sample size comes from the limited understanding of AM and the need of intellectual property protection. As such, feature selection (Raudys and Jain 1991) and domain knowledge (Hartmann et al. 2017) have been identified as the most critical points in preparing data for machine learning especially for small sample sizes. The process of applying domain knowledge allows for a deeper understanding of what facets of the input data led to the output decision, and information-rich features will lead to a more successful model as there will be less noise from unnecessary features which causes errors. Corresponding to the AM candidacy identification problem, the domain knowledge and features are equivalent to the candidacy criteria and decisive parameters in this application.

3.3.2 ML model comparison and analysis

Determining the right algorithm is of great importance when applying machine learning, especially in small-sample learning where the computational requirements are typically less demanding. Regression and classification are the main techniques in a supervised learning model. Regression denotes that the output of the model will be continuous values such as print time or component cost, and it has been applied to a broad range of AM process optimization problems like bin packing, nesting, and scheduling (Dvorak et al. 2018). Choosing regression over classification allows the user to see the potential on a percentage scale rather than just receiving a boolean decision. Since machine learning algorithms are not one-for-all solution when it comes to different data and performance is highly dependent on the unique algorithm/dataset combination (Hastie et al. 2005), it is necessary to determine the best ML algorithm for each application. Popular ML libraries such as *Scikit learn* (Pedregosa et al. 2011) and *Tensorflow (2020)* provide good platforms for preliminary suitability test. In this application, *Scikit learn* is chosen over *Tensorflow* because the former provides easy ways to build standard ML models while the latter is widely used for deep learning applications with large amount of labeled data such as sound, images, and text (Géron 2019; Patel 2015).

The initial test of ML algorithms was performed using Python and *scikit learn* (Pedregosa et al. 2011). Five common regression algorithms are preliminarily tested for each AM potential including linear regression, bayesian linear regression, neural network regression, boosted decision tree regression, and decision forest regression. The root-mean-square error (RMSE) is used as the error evaluation metric for the tested ML algorithms because it represents the average distance from the regression line to each individual training instance. Given the training set of 200, 10% of the samples were set aside for cross validation. The comparison result is summarized in Table 3. From the RMSE of each ML model trained for each AM potential, the Boosted Decision Tree Regression (BDTR) algorithm outperforms all the others for the given training samples. This is because BDTR shows strength to extract complex relationships and operates well on small-sample datasets (Roe et al. 2005; Coadou 2013; Xia et al. 2017). Therefore, BDTR is selected as the principle ML algorithm for predicting the AM candidacy. Meanwhile, it is found the RMSEs of other regression algorithms are higher than expected due to the coding mechanism of the labelled data. Current labeling scheme only asks for yes/no with regard to AM potentials to reduce manual inputs and confusion. Therefore, AM potential of each instance will only be put 0 or 1, which makes the model more likely to produce rounded scores instead of the accurate scale. This leads to a higher RMSE when training the models because instances that have a true score of say a 0.67 were labelled as a 1.0; thus, if the training model scored a 0.7, it would have an error of 0.3 as opposed to 0.03. This problem will decrease as the training set is populated with more instances labelled on a percentage scale.

Table 3 Error comparison of ML models.

	Root Mean Square Error of Machine Learning Algorithms				
	Economic	**Lightweight**	**Part consolidation**	**Internal structures**	**Customization**
Boosted Decision Tree Regression	0.259907	0.115436	0.140231	0.159223	0.099288
Neural Network Regression	0.568563	0.483725	0.256403	0.470125	0.201107
Linear Regression	0.361987	0.407623	0.163127	0.342522	0.139623

Decision Forest Regression	0.367457	0.20334	0.142428	0.241523	0.147326
Bayesian Linear Regression	0.452348	0.501598	0.160878	0.295722	0.107149

3.3.3 Training the models and prediction

Training of the BDTR model is as follows. First of all, BDTR works in a fashion to create ensemble of regression trees using boosting which means that each tree is dependent on prior trees. The algorithm learns by fitting the residual of the trees that preceded it. Thus, boosting in a decision tree ensemble tends to improve accuracy with small risk of less coverage. BDTR has the advantages of handling different types of predictor variables and accommodating missing data; thus, there is no need for prior data transformation or elimination of outliers. It can also fit complex nonlinear relationships, and automatically handle interaction effects between predictors (Elith et al. 2008). The training and prediction experiment of BDTR model is conducted by using Microsoft Azure studio (2014b), which offers a well-established visual drag-and-drop graphic interface to build and deploy predictive analytic solutions.

The flows of training are depicted in Figures 5. The training flow starts with importing training data from an SQL database as described in Section 3.2. Next, missing data is cleaned using probabilistic primary component analysis, which '*replaces the missing values by using a linear model that analyzes the correlations between the columns and estimates a low-dimensional approximation of the data, from which the full data is reconstructed* ' (Azure 2014a). Applying SQL transformation is to single out the decisive parameters by column for its corresponding candidacy criterion to avoid overwhelming the learning model with unnecessary information (e.g. cost for lightweight potential) and improve result accuracy. Each sub-dataset by column is further split into training and validation sets. Then, these datasets are fed into the hyper-parameter tuning module which trains the model from the training set, then tests it on the validation set by calling the BDTR algorithm as shown in Figure 5. Finally, once each model has been optimized, it can be saved and exported as a trained model and be used in the prediction analysis. In Microsoft Azure studio, the new input data is edited to be a format compatible with the type of trained models, and the predicted result will be presented in a numeric form.

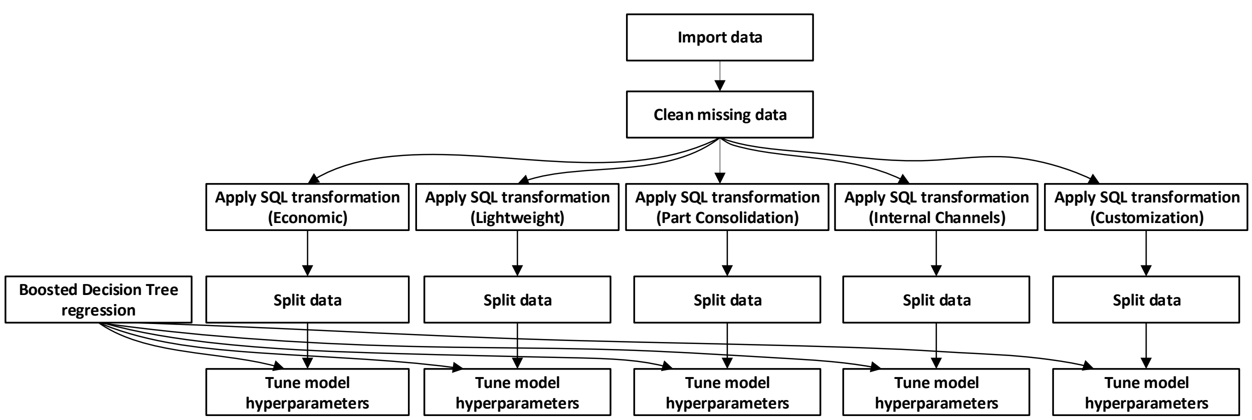


Figure 5 the graphic view of training procedure of Boosted Decision Tree regression in Microsoft Azure studio.

4. Cloud-based tool implementation

The proposed DSS framework is implemented as a cloud-based tool so that it can be easily accessed and allow for instant update regarding training samples and trained models. The developed tool is available at the website ((ADML) 2019b), and the open-source code is also available at GitHub ((ADML) 2019a). The architecture and user interface of the tool are introduced in the following sections.

4.1 Architecture

The tool is designed to be compatible across platforms to facilitate easy access and encourage wider applications. A variety of state-of-the-art technologies were used to support the functionalities as well as easy maintenance. The communication between these technologies are presented in Figure 6, which contributes to the main architecture of the tool. Since multiple third-party services are utilized in the development of this application, PHP (Hypertext Preprocessor) is used as the liaison for communication between these APIs (Application Programming Interface) as it allows API keys to remain hidden and avoid the same access restrictions as HTTP (HyperText Transfer Protocol). In this tool, three main services are called: Autodesk Forge, Microsoft Azure and AJAX (Asynchronous JavaScript And XML) request. Autodesk Forge is mainly used for CAD format conversion (e.g. SolidWorks file to STL), metadata extraction by using Model Derivative API, and remote storage of CAD models. Microsoft Azure services including training database management and machine learning, are integrated via APIs. Lastly, user interfaces of the web application are developed by using the React JavaScript library (Facebook OpenSouce 2019) to create a multi-state application on a single web page. AJAX calls enable client-server communication without the need of refreshing the webpage.

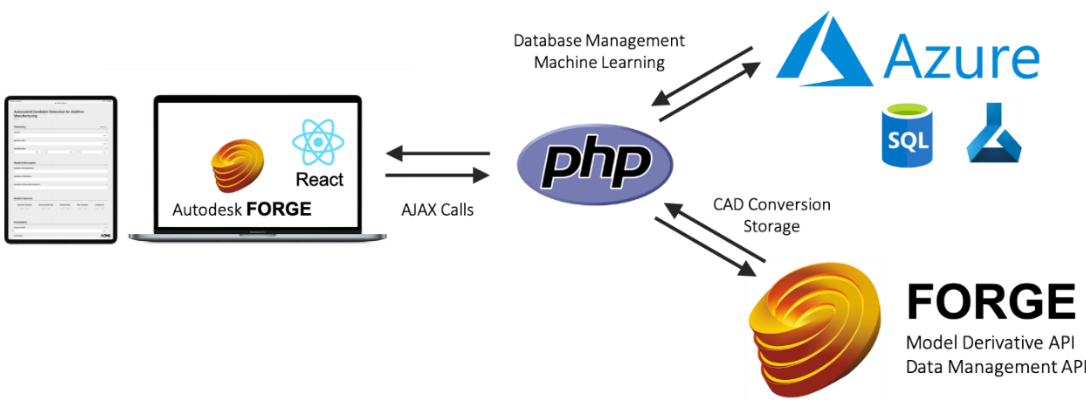
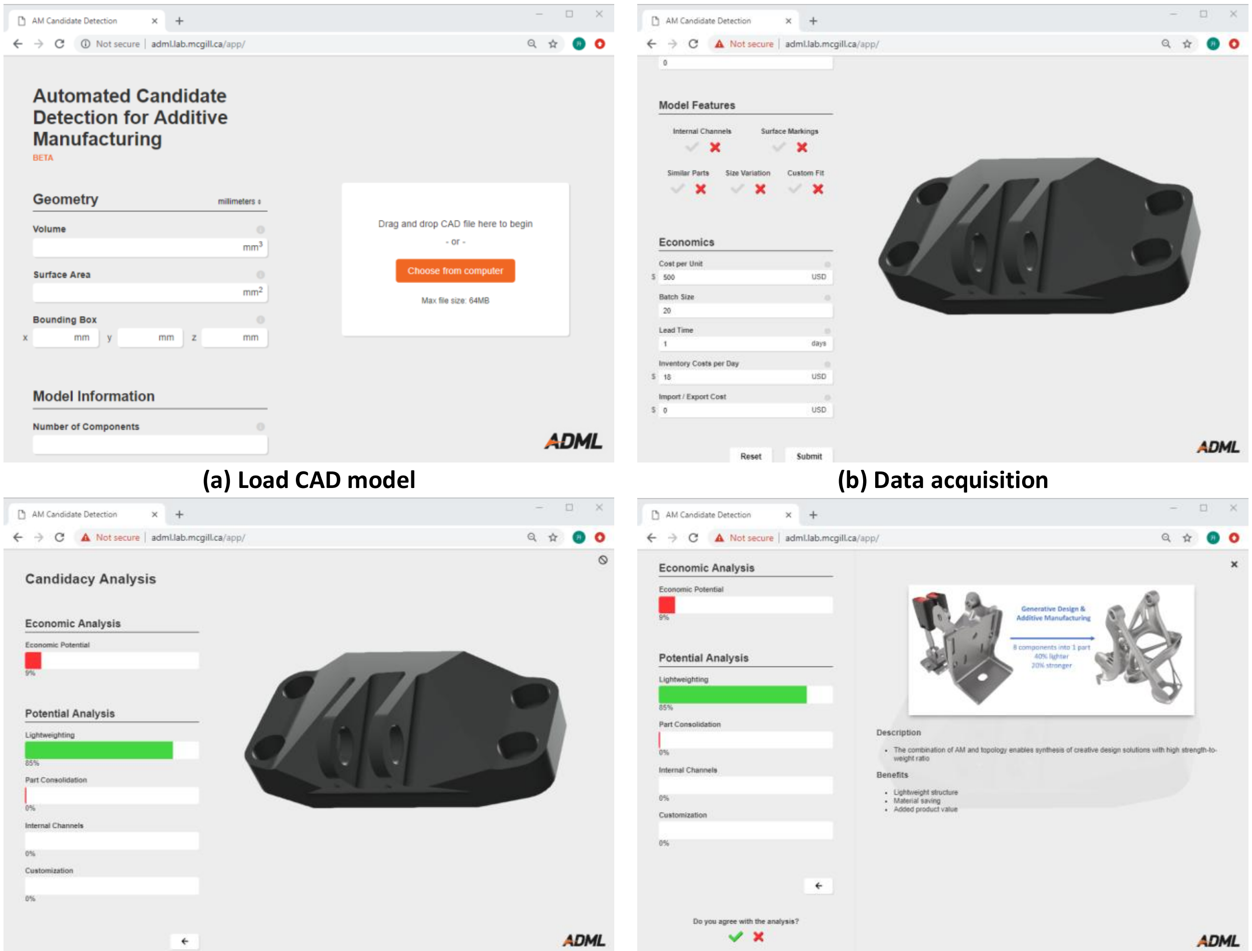


Figure 6 The architecture of implementation of the DSS framework.

4.2 User interfaces

Following the workflow of 1) load CAD model, 2) new data acquisition, and 3) candidacy prediction, the main user interfaces are presented in Figure 7. The developed web application is able to load common CAD files and automatically extract geometric information of volume, surface area, and number of components. Then, users are requested to fill missing data of model information (e.g. number of interfaces), model features (e.g. whether exist internal channels), and economic considerations (e.g. lead time). It should be advised that some of these manual inputs can be replaced by connecting to an ERP system in future iterations. With these inputs, the tool produces candidacy scores for each potential (See Figure 7 c). To learn about the specific AM potential, tutorials can be accessed by hovering above the item (e.g. *lightweight* bar in Figure 7d). These tutorials will help the novice AM users to develop a better understanding of the potential gains by using AM, as echoed by prior research (Yang et al. 2019b). With a further goal of improving the accuracy of the tool, it provides a feedback loop for the user to decide whether the new instance is valuable for expanding the training dataset; otherwise, the item will be discarded.



(a) Load CAD model

(b) Data acquisition

(c) Candidacy prediction

(d) Lightweighting potential tutorials

Figure 7 A collection of snapshots of the developed tool.

5. Case study

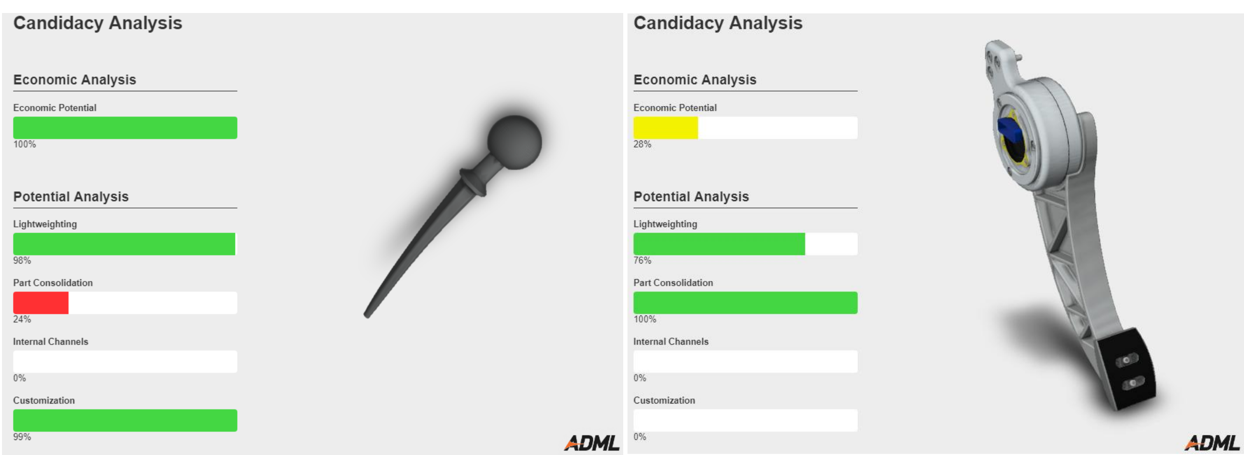
Two examples of a hip implant (Ryan et al. 2006) and a throttle pedal (Yang et al. 2019c) are presented to demonstrate the effectiveness and usefulness of the proposed DSS framework and the developed cloud-based tool. These case studies were chosen because their AM potentials have been already studied in literatures, which cross validates the predicted results of the tool. The details of the examples are summarized in Table 4. The hip implant model is downloaded from GrabCAD (Fuentes 2012) and cost-related data is estimated from publicly available data on the internet. The predicted potentials of the hip implant are shown in Figure 8a. From the result, it is expected to have high potentials of economics (100%), customization (99%) and light-weighting (98%) and low potentials of part consolidation (24%) and having internal channels (0%). The predicted trends of each potential generally agreed with the work reported by Fraunhofer IWU (Schnabel et al. 2017) where *MUGETO* implant used lattice structures to reduce weight. The economic benefits mainly derived from the advantages of low lots size, while one-of-its-kind characteristic and anatomy compliance highlight the customization potential. As for part consolidation potential, the number of parts and interfaces is not sufficient; therefore, consolidation verification will need further examination by using a specialized tool as developed by Yang et al. (2018).

The throttle pedal model is also available at GrabCAD (Miessner 2015) and the cost-related data is estimated from publicly available data. The predicted potentials are depicted in Figure 8b. The throttle pedal is claimed to have high potentials of part consolidation (100%) and light weight (76%), and it scores low in terms of economics (28%), customization (0%), and internal channels (0%). The result generally agreed with the work of Yang et al. (2018).

In conclusion, it is interesting to observe how the developed DSS tool helps to predict the AM candidacy potential without AM expertise inputs. The tested examples proved that the tool would be a promising solution to lower the requirements of AM knowledge for finding suitable candidates at early design stage in industrial applications. It should be advised that the predicted scores only indicate the possibility of having a specific potential rather than a definite answer because manufacturing constraints need to be considered in the next step.

Table 4 Details of the tested examples.

Name	**Figures**	**Volume (mm^3)** **Area (mm^2)** **BD box (mm^3)**	**# Components** **# Fasteners** **# Interfaces**	**Cost** **Quantity** **Lead time** **Inventory** **Import/export**	**Markings** **Channels** **Similar parts** **Size variance** **Human custom fit**
Hip implant		55910.32 12367.67 166.38*106.46*39.97	2 0 1	2000 1 1 0 0	0 0 0 0 1
Throttle pedal		210367.17 112685.27 156.22*218.77*56.48	41 17 15	350 10000 1 2 0	0 0 0 0 0



(a) Potential prediction of hip implant **(b) Potential prediction of throttle pedal**

Figure 8 AM candidacy prediction of the hip implant and the throttle pedal.

6. Conclusions

Identification of part candidates for AM applications is one of the challenges for its wider industrial deployment. Existing methods are not suitable as they are either too complex and rely too heavily on the user who already has expertise in AM, or they are too simple to provide the user with any real insight. This paper is specially focused on providing an efficient and automated solution for screening of parts for AM potentials at early design stage. A decision support system framework is proposed with carefully selected candidacy criteria and machine learning-assisted workflow which helps to predict AM candidacy of parts. The presented framework is implemented as a cloud-based tool to serve as an accessible platform of training database management, machine learning service, and AM knowledge dissemination. The open architecture makes the maintenance, upgrade, and retraining machine learning models easy to manage. Two case studies of a hip implant and a throttle pedal are presented to demonstrate the workflow and effectiveness of identifying various AM potentials. This preliminary work has proven the potential of employing machine learning methods to identify part candidates for AM applications in the early conceptual re-design stage.

7. Limitations and future work

It should be acknowledged that current prototype is in its infancy state and helps to establish the pipelines for a ML-assisted decision tool for AM candidacy detection. There are several directions should be further explored before being deployable in industry.

First of all, the number of instances and the diversity of AM/CM parts are still low, but the cost of data acquisition is relatively high. Other factors such as intellectual protection and data security further increase the difficulties. A commonly established data-sharing framework is highly recommended across different industries and labs to enrich data diversity, which in turn could increase the prediction accuracy of trained model. Taking the trained model of “lightweight” as an example, dataset size effect was investigated at the scale of 50%, 60%, 70%, 80%, and 90% of overall raw data (i.e. 200 instances), the Rooted Mean Square Error of each dataset was 0.352, 0.289, 0.253, 0.155, and 0.115 respectively. Similar approach of examining dataset size effect was adopted in the literature (Li et al. 2019). Therefore, the authors hold strong belief that the predictive performance of the trained model will improve as more data feed in. In this experiment, an interesting finding was also observed that the developed tool failed to identify the internal channel potential for the hip implant as the MUGETO implant design (Schnabel et al. 2017) demonstrated. In their project, internal channels were added to the new hip implant for medicine deposition. This deficiency of the current tool highlights the necessity of expanding the diversity of instances and potentially including functions of labelled data as one learning feature as well so that certain new functions can be integrated to the new design. In addition, current data was retrieved from various industries ranging from aerospace, sports, automobile, and medicine. However, the economics model is highly sensitive to the specific field. As such, a more accurate ML model should be customized by taking data from the collaborative company’s ERP system in the future.

Second, the AM potential of material options was originally included in the training model. However, preliminary tests with various machine learning algorithms found that this potential could not be accurately determined based on current built-in training samples. These samples did not contain enough information regarding the material properties. To prevent the complication of the criteria through adding material-specific questions which led to little improvement in the results due to the insufficient data, the specific material options potential was removed. It is possible that in the future more complete data will be available and another iteration of the DSS will be able to support material options for AM.

Third, the decisive parameters of part consolidation potential in this paper include the number of components, interfaces, and fasteners. Although it is able to find a chunk of components, it is difficult to more precisely locate the parts to be consolidated. A promising solution is to trace the product hierarchy. As shown in Figure 9, if the first level of an assembly (e.g. an engine) is found to have minimum part consolidation potential, the searching process continues to the next level. Candidacy evaluation repeats until the nearest child demonstrates part consolidation potential. Repeat the same procedure for other branches until all branches are exhausted. However, tracing of product hierarchy requires access to the ERP system of the company. The accessibility of other data such as lead time and cost also requires permission of the ERP system.

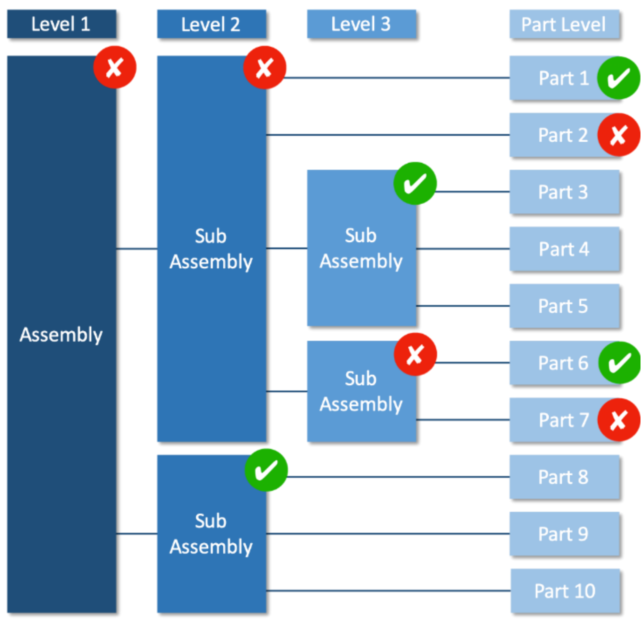


Figure 9 The screening strategy of identification of subassemblies for part consolidation potential.

Fourth, current candidacy criteria are determined to fulfill the principles of efficiency and objectiveness, and they concentrate on the opportunistic aspects of employing AM technology. Although the need of simultaneous consideration of restrictive rules is not encouraged at the very first round of screening, certain manufacturing constraints can be integrated directly thereafter to further gauge the AM candidacy. Other future work may also include changing the labeling system from 0/1 to Likert scales to show more insights of each potential by a percentage scale. Lastly, Although Boosted Decision Tree algorithm works well for current scales of training samples, as more data kicks in, further optimization of machine learning algorithms will be demanded.

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