Near net shape manufacturing pdf

This article does not provide any sources. Please help improve this article by adding quotes to reliable sources. Non-sources of materials can be challenged and removed. Find sources: Close net form - Newspaper News book scientist JSTOR (December 2009) (Learn how and when to delete this template message) Next to the pure form is an industrial production technique. The name implies that the initial production of the element is very close to the final (clean) form, reducing the need for surface finishing. Reducing traditional finishing work, such as processing or resurfacing, eliminates more than two-thirds of production costs in some industries. Processes Below are the various processes of an almost pure form, classified by materials. Ceramic Gel Casting Ceramic Injection Spray Form Structural Ceramic Production Composites Lanxide Process Plastics Injections Casting Rapid Prototyping Metals Casting Citation necessary Permanent mold casting citation is necessary Powder metallurgy linear friction welding (citation necessary) Friction welding (quote is necessary) Metalworking Expanding it.vte This metalworking article is a stub. You can help Wikipedia by expanding it.vte extracted from the Coming: Machining Up: Representative Systems Previous: Assembling These Processes produce parts in a way that allows you to use the rules to link design attributes to production. Thus, rule-based systems have found great success here. However, the recent trend is to use process physics and modeling knowledge to figure out what is being produced. These processes also have manufacturing defects associated with the process. In many cases, rules link design attributes to the likelihood of different types of defects. The production process is also usually two steps, it is necessary to take into account the production of the toolkit, and the production of the actual part realistically determine the production. Ishii et al. (15,40,41,42) have developed design compatibility analysis tools to help develop products for a variety of lifecycle considerations. Their approach identifies a set of design elements for each lifecycle application. While the designer interactively identifies these elements in the proposed design, she is encouraged to provide information about users and functional requirements. Their system uses a compatibility knowledge base to assess the trade-offs between different design elements and functional requirements. The compatibility knowledge base is a set of domain-dependent rules to calculate the compatibility index. If the design attribute gets bad bad index, the system gives advice, illustrating predetermined cases that lead to good compatibility. Ishii and his colleagues have created a number of project advisory systems using this approach. This task of designing details and identifying interactions between functions can be tedious, and the system can be improved in this regard. In addition, the methodology does not seem to be appropriate in cases where the interaction between functions is very high or the design may have multiple interpretations. Huh and Kim describe a parallel design support system for casting injections. Their interactive expert system encodes the rules for different molding materials and supports the synthesis of additional features that need to be put on the original design. The designer's assistant system when performing tasks such as rib requirements, cross-section ribs, rib frequency and in the design of bosses. Both functions and production opportunities are considered in assisting in these decisions. Interactive feedback is provided to the designer in two forms. First, the likelihood of various forms of manufacturing defects, such as shell marks, deformation, or emission difficulties. The second type of feedback is in the form of a warning message that offers possible problems for the designer to avoid. Feedback is quantitative, in the sense that it gives the probability of common manufacturing defects. However, this information is rigidly encoded in the rules, and the calculated figures can only reflect cases reviewed by the system. Several production systems have been developed to produce clean form (e.g. casting, stamping, casting, sheet metal) Most of these systems use rule-based approaches to study developmental irregularities in gaining strength. For example, Lazaro et al. has developed a system for detecting violations of the rules of the design of sheet metal parts. Rosen et al. 17 developed a system for injection casting and die casting. More work on the overall production of clean form is reported in three parts of Pozny, etc. Their approach is broader and more complete than most others, and takes into account the numerous production processes in the evaluation of components. The evaluation is conducted hierarchically at the configuration and detailed design stages. In addition, they review the functionality of the parts, the information about the tolerance, and provide proposals for redesign. Finally, they also consider assembling components. Their approach brings together many stages of the design and production process. Dissinger et al. developed a three-dimensional simulation system for the design of powder metallurgical components. The design process corresponds to the basic part created by the gunpowder metallurgy: the part is created layer by layer and, with adding each layer or component to the layer, checks are carried out on possible violations of production rules. The system is interactive, alerting the designer about violations of the rules and giving suggestions for changes. Finally, the system only allows you to design production components. Bourne's reports work on an intelligent bending workstation. Developed in the same line as the intelligent processing workstation previously developed, they are introducing an open architectural model for bending the controller to overcome the common difficulties associated with closed controllers in NC machines. This system will be customizable and elongatable for future additions to other modules. Balasubramaniam et al. (Balasubramaniam et al.) proposed a common method of developing production indicators for process-physics, which were dominated by production processes such as extrusion, injectable casting, etc. As an example, they developed metrics for different types of defects in extruded aluminum components for airplanes. They conducted a pilot and statistical review of metrics based on the evidence of the vendors. There are additional works reported by researchers on various types of pure form production, including injectable casting (51,52,53,54,55), casting of death (56), sheet metal work (57.58), casting (59), powder metallurgy (60), extrusion (61) and stamping. Next: Machining Up: Representative Systems Previous: Assembly Generated latex2html-95.1 Fri April 14 13:59:16 EDT 1995 ORIGINAL ARTICLE Open Access Published: 14 December 2019 International Journal of Advanced Technology Production 106, 1967-1987 (2020)Cite this article 1066 Access 2 Citations 1 Altmetric Metrics This article presents a new selection methodology that for the first time supports the identification of near-net form (NNS) processes. The methodology, known as Product, Geometry, Production and Materials Compliance (ProGeMa3), consists of four phases that aim to minimize the use of raw materials and processing by adopting the NNS approach. A key component of the methodology is the Process Choice Matrix (ProSMa), which links the shape and volume of component production to its material requirements to reduce the number of NNS candidate processes. The final choice is then made from this shortlist, using fuzzy logic and taking into account other limitations and functional requirements. The ProGeMa3 selection process is illustrated by its application to the industrial component, which has led to changes in the processes used for its commercial production. ProGeMa3 and ProSMa, presented in this paper, strive to be relevant and comprehensive for solid metal produced by casting, forging and additive technology. However, ProSMa is also available as an open source source available for other researchers to expand and adapt. Over the past 30 years, the concept of production has been applied to various processes in many industries. This has led to the emergence of several different Design methodologies for manufacturing, which have a common goal of reducing production costs through the application of general production rules. Almost pure form technologies have expanded these concepts, focusing mainly on the primary process of formation, such as casting or forging. As new methods of production and development of established technologies emerge, the manufacturing engineer must constantly review the processes they use to make sure they are most appropriate. Ideally, the automated system will review component specifications and determine their optimal production process, but in practice the range of shift options and the complex combination of interacting limitations (i.e. quantitative and qualitative) overshadow such automation. Thus, while various methodologies for supporting the selection of production processes have been registered, they have not been widely applied because of the resources and computational tasks required to implement them. In response to these questions, this paper introduces a new process selection methodology, which is designed to analyze the company's portfolio of components and identify opportunities for near-clean formation processes. It is important to note that the approach described quickly focuses the review and the small number of parts and processes of the candidates that appear to be the most economically and technically feasible. This initial filtering reduces the size of the search space to such an extent that computationally intensive methods can be used effectively to determine the best solutions. The Near Pure Form (NNS) concepts are based on the work of 20, 37, 49, 72 and 3, which based their research mainly on metal casting and for foreceing. A close pure form is a relative property, not an absolute one, which determines the combination of product geometry (for production), material and production process (primary formation process) to be minimal in the use of raw materials and finishing processing operations, compared to other possible combinations. However, the selection of the relevant NNS process is often a special procedure focused on the production of new components and based on the personal experience of manufacturing engineers. In contrast, this paper introduces a systematic methodology for selecting the NNS process, corresponding to the existing product. Unlike previously recorded approaches, this selection methodology uses product geometry, production volume and materials to classify NNS candidate processes. To this possible, the scope of the described classification is limited: Metals (material limitations)Solid geometry (bars, tubes and prisms)Casting, forging and supplement supplementation (except for accession and processing processes) Non-variable product requirements Material loss reduction and energy saving are assessed through the NNS approach to production. However, other environmental factors, such as resource savings (energy and water needs), processing (recycling, reuse and repair) and waste management (e.g. hazardous losses) associated with production processes, are not addressed in the process selection methodology developed. These factors can only be quantified after the feasibility study phase using supply chain management and product lifecycle assessment (LCA) tools. The link between the circular economy and the selection of processes in literature has not yet been explored. The quantification of such factors therefore goes beyond the scope of this paper. Similarly, the impact of changing product requirements on process selection was not considered. The following section looks at basic approaches to the selection of production processes based on materials, production volume, component shape and technological and performance, and other requirements comparable to technological attributes. Subsequently, the product, geometry, production and materials methodology (ProGeMa3) is described and then applied to an industrial example. The process and selection of materials in the literatureGeneral process selection procedure usually consists of three stages: screening, ranking and search for supporting information .6, 27. Seven general approaches to choosing the best process for this material, design characteristics and product requirements were identified: 1.Analytical2.Probabilistic (Fuzzy Logic)3.Knowledge Base System4.Manufacturing and Product complexity5. Methodological (quality)6.Optimization algorithms7.Topological (number) Given each of them, in turn, analytical work develops a multi-scale system of equations, quantitatively quantifying the different features of the process and their ability to compare with the requirements of the component. This formulation makes it possible to consider the process with the lowest cost as the best candidate. For example, develop a model based on forecasting production costs. The model provides material (i.e. taking into account only the volume of the product and the cost of the material) and the basic processing costs, depending on the selected processes and cost is calculated through the time of cost and production, using an empirical constant. This cost refers to the production of the ideal component design for the selected process and the ratio (relative cost ratio) adjusts the cost of the process to reflect the geometry for production. The ratio consists of four parameters (defined although empirical graphs) related to shape, reduction/thickness of the section, tolerances and finish of the surface, surface, between current and ideal conditions. Swift and Booker use the 2 formula, presenting a matrix for pre-screen processes. Other authors use cost and cost-assessment functions for pre-screening screening: for example, to measure the compatibility of the casting process for the required production volume, weight input, thick/thin sections, tolerances, and surface finishes. A simple proportion between available capabilities and requirements gives an assessment of compatibility. Each characteristic is weighted, depending on its importance, with a quality system. Thus, casting processes are ranked according to their compatibility values. Rao and Padmanabhan use graph theory and a matrix approach to screen additive-layer production processes. The combination of these two methods can provide a multi-criterion solution that determines the interaction between the attributes of choice. Process attributes can be both qualitative and quantitative, and their reactions to product requirements, as well as their relationships, are summarized in a single index. To rank casting processes, use the cost function with compatibility ranges to determine possible processes and rank them. This first step is the best process, and the next step is to complete the process (tolerances, working sizes, surface roughness) and economic opportunities, giving a complete overview of the possibilities of the production process of the desired product. The work is based on a previous study, comparing the target design and product requirements (material, size, product shape, mechanical accuracy and cost) with those that are within the capabilities of a large number of processes, looking for a subset that is capable of making a component. Then the subset is ranked by economic criteria. The probabilistic approach aims to develop a statistical correlation between process capabilities and product requirements. In particular, several authors used fuzzy logic (artificial intelligence technology in control systems and image recognition). It is based on the observation that people make decisions based on inaccurate and numerical information. Fuzzy models, or sets, are a mathematical means of presenting vagueness and inaccurate information, hence the term fuzzy. Unlike the traditional probability, fuzzy sets are able to represent, use and manipulate data that have a range of values because of their uncertainty. Therefore, in fuzzy logic, the distinction between full compatibility (one) and incompatibility (zero) is gradual between the extreme ranges of a fuzzy set. Figure 1 illustrates a fuzzy logical approach. Several authors have applied slightly different versions of the fuzzy approach to process selection and decision-making in [19, 30, 54, 60, 73]. Where L (min and abs) is an absolute minimum value, Lmi n is the minimum typical, Lmax is a typical maximum value, and L (max and abs) is the absolute maximum function of the process under study. Lreq is the requested cost of a product function (e.g., the required roughness of the surface). Compatibility assessment can be done by comparing from a qualitative description (low, low and medium, medium, medium and high) to numerical values. Figure 1Fuzzy process feature (adapted from 59)Giachetti (30), Ravi (59) and Daws et al. (19) determine compatibility by the required value and four values that define a fuzzy set. If the requested value is outside the set (4), compatibility is invalid. If it is in the normal range, the request is fully compatible (1). If the value falls between normal and extreme ranges, the intermediate value is between 0 and 1, determined by linear behavior (2, 3). $$ (начало)array (rcl@) P_ L_ «req» 1, <> <L_{max} \end{array}= $$$$= \begin{array}{@{}rcl@{}}= p_{l_{req}}&=&\frac{L_{req}-- l_{min-abs}}{l_{min}--= l_{min-abs}},if=></L_{max}> <> <L_{min} \\= \end{array}= $$$$= \begin{array}{@{}rcl@{}}= p_{l_{req}}&=&\frac{L_{max-abs}--L_{req}}{L_{ax-abs}m-L_{max}},if></L_{min}> <> <L_{max-abs} \\= \end{array}= $$$$= \begin{array}{@{}rcl@{}}= p_{l_{req}}&=& 0,if=></L_{max-abs}> <L_{min-abs},or l_{req}=>если теория возможностей L_ «мин» L_ «max-abs» (конец) $Using «22» определяет два различных случая, которые происходят при оценке совместимости: определены возможность и необходимость. Opportunity assesses the extent to which the function satisfies the request (optimistic selection strategy); on the other hand, the need expresses the extent to which the function certainly satisfies the request. The latter adapts the pessimistic selection strategy by measuring the impossibility of the opposite event, determined by the additional probability of the event itself. Figure 2 illustrates the process of doing calculations using equalizers. 1 to 4 to determine the value of the opportunity and the need for a linear query. A unique number of compatibility is required to assess the values of opportunity and necessity, a factor called β is used, which is a level of optimism or pessimism acceptable to decision-makers. Factor β 1 for the decision-makers and 0 for the negative (so there is always a value in the β ∈ interval (0.1)). The weighted average is calculated for each requirement between opportunity and necessity, mediated by β (opportunity) and 1 β (necessity). Using methodology, a compatibility measure was appointed with each process/product selection function. The geometrically weighted average is used to aggregate all n th (5) compatibility values. Weight (w) is assigned to each function using linguistic values. Each of the L_ of the L_ is calculated as in Eq. 6. $$ ПЯ L_ (req_{1}),L_ (req_{2} limits_),,,L_ eq_ L_ (req_)) $$\$r'frac 'w_'i'sum'i'i'1'n' w_ 'i'i's $$Giachetti .30) применяет эту теорию к первым этапам проектирования продукта и выбора процесса, включая широкий спектр процессов и материалов в качестве возможных кандидатов. Perzyk and Meftah use fuzzy logic to design for the production of a single component. Functional requirements, production rules and material processes are assessed by one component using the process index, taking into account the estimate of production volume, appearance, surface properties, measurement tolerances and material structure. The index is a fuzzy triple number that is combined with the ideal process (depending on product requirements). Daws et al. limit the search to casting processes, including investments, mold (permanent, ceramic and full), shell, sand, dies and compresses casting. Similarly, when applying a fuzzy logical approach to the selection of the cutting process takes into account the attitude to the thickness of the material, the speed of cutting, the complexity of the figure and the possibility of tolerance to the process. Fig. 2Shematic capabilities (left) and the need (right) for linear requirement calculations (30) Knowledge-based systems use empirical data (usually collected in databases) to support the selection process. Knowledge-based systems tend to be flexible and leave the decision-making process to the user, providing all the information they need to work with. The innovative system, based on knowledge in this field, was created to help designers choose the best alloy and casting process for a certain set of specifications. The database displays both numerical and linguistic descriptions of processes that are appropriate for a particular material. The database includes a list of available materials, choosing before the production process (i.e. the first list of processes are material compatible). The designer qualitatively chooses the best processes from his description, excluding inappropriate (i.e. related to the specifications of the material and product). Yu et al. develops a computer routine that combines geometric factors, material and production factors to determine the most appropriate process (i.e. a choice of casting processes, hot and cold forging). The algorithm uses a design compatibility approach that quantifies the compatibility of each analyzed category of parameters (Fig. 3) by comparing the required values with the datasets for each process reviewed. Darwish and El-Tamimi offer a knowledge-based casting process selection algorithm, basing their decision-making criteria on the attributes of design, production and production. The author compares the attributes of the production process quantitatively (minimum thickness, surface roughness, size of economic lot), qualitative (porosity, accuracy of measurements, mechanical properties), as well as cost (tooling, labor, finishing and scrap cost). The available range of materials is used as a criterion for selection of processes. Similarly, a casting selection system is being developed, including a comparative cost routine (Figure 3). According to previous works, the authors check processes at different levels (alloy casting, geometric complexity, casting accuracy, production quantity and comparative costs). Unlike other researchers, geometric complexity has been quantified through issues relating to the product (e.g. undercuts or internal presence holes). The selected material was used as a screening factor, taking into account the received and necessary mechanical properties. Xu et al. develops a knowledge-based system for the production of additives, including the cost of the process as a decision criterion. Figure 3Casting Process of Selecting Parameters and Their Interaction 25 Complexity Measurement is another tool adopted by the researcher to quantify and rank the production process in order to select the most appropriate one. The logic of the complexity approach defines the lowest complexity of the process chain (including process and product design) as the easiest component to produce. The complexity of the product directly affects the complexity of production, so an effective understanding of the nature of complexity and its relative measure can directly connect them. The complexity of the product increases with the number and variety of functions that must be manufactured, as well as the nature and complexity of the tasks required to create functions. Cooper et al. (16) measured the complexity of the product as a weighted average; meanwhile, entropy is used to estimate the information number. ElMaraghy and Urbanic have developed a complete formula for assessing the complexity of a product by measuring its entropy (given the information number and uniqueness of o features) and the complexity of each of its features. Characteristics and specifications are defined and evaluated for each characteristic, assigning them a coefficient (0 low effort, 0.5 average effort, 1 high effort). All factors are included in the function complexity factor and are weighed by the percentage of presence in the component. A matrix methodology is used to determine the relative complexity factor. The Complexity Matrix describes all the characteristics and specifications of the product. The coefficient indicates relative efforts to produce them or to perform a related task. Characteristics and specifications are defined and evaluated for each characteristic, assigning them a coefficient (0 low effort, 0.5 average effort, 1 high effort). All factors are included in the complexity of functions and are weighted by percentage in the component. The complexity index (derived from the correspondent matrix) is the complexity of the component's production. The number of complexity indexes alone does not matter. Comparison of complex process indices determines the closest to the final form, in terms of less necessary production efforts. Wiendahl and Scholtissek (75) are extending the concept of complexity to the entire manufacturing process, including product design, operation (process equipment, tools and manpower) and structure. Like previous authors, the amount of complexity produced using an entropical approach. Their model evaluates both the different types of components and the technologies used in the production system by the structural complexity of the system. The authors use their model, choosing the lowest complex configuration of the engine cylinder head production system. Kerbrat et al. use the complexity of production to assess how to combine the subtraction process and additive layer to produce mold. A modular CAD tool has been developed to compare each shape, which is less difficult to produce. Guenov defines two measurement systems for high-level decision-makers. The goal is to compare alternatives during pre-competitive research or in the process of architectural design of composite systems. Similarly, previous authors, the first measure is the difficulty of assessing Boltzmann's entropy, while the second measure is designed to assess the costs and benefits associated with the performance of the system. Methodological studies use a qualitative approach to determine the best choice of process. The outputs of these works are usually within or flowcharts. For example, develop a complex framework for the selection of materials and processes, taking into account the entire life cycle of the product. The framework analyzes the product's lifecycle, immersing it in three main stages: production, maintenance and design/development. The dedicated part of the framework tries to rationalize the activity of the definition of requirements (design) and satisfaction (process). Xu et al. (77) is developing a system to assess the impact of various applications of rapid prototyping processes. Using product requirements and process cost, the methodology can quantify the characteristics of the process and compare different processes. Shercliffe and Lovatt define the interaction between the process, the material, and the design of each process category (e.g., the differences between molding and welding an aluminum alloy). For authors, product requirements must meet the attributes of the process one by one: these requirements may be related to design (e.g. mechanical properties or dimensions) associated with production (e.g. production volume and speed or related to processing. Processing. attributes can be related to process, material, or design. Pair comparisons are evaluated by technical feasibility, avoiding defects in the process, product performance (i.e. end product characteristics) and economic fundamentals. Unlike all other authors, they try to develop a link between process modeling and process choice. They define cost models and technical models, mostly used in the selection process, to test the process candidate. Chakraborty and Day use a quality feature development chart, commonly called a quality home, to meet technical and design requirements, and to connect them to customer requirements. The authors developed a total score from this well-known quality improvement tool using the score matrix. Some authors were able to incorporate process selection into optimization algorithms by developing complex models to assess the applicability of the process. Working on reconfigurable production systems, we use genetic algorithms and modeling optimization to plan processes for one type of product, taking into account fluctuations in market demand and minimum production (i.e. for production to be feasible). Optimization features are defined as machine costs and changes, cost of configuration change, tool usage, and change costs. The genetic algorithm (i.e. optimization of product and machine data) and demand modeling software (i.e. provision) provide the most economical chain configuration. Vinodh et al. use a fuzzy analytical network, using different criteria to evaluate the best process and the best provider to choose from. The qualification points were assigned to different process/supplier evaluation criteria. The matrix assigns value to the process for each criterion, and the algorithm ranks different possible combinations. The criteria chosen are coefficients that relate to business improvement, product quality, supplier service, and risks. Topological models describe how elements (Finite Element Analysis) are limited and connected. These numerical analyses are used to numerically describe product features (for example, using proximity rules, FEM elements identify the undermining). Thus, the algorithm can evaluate all the features of the component and evaluate the best process of their implementation. Holland et al. will develop an algorithm based on CAD, which can determine cost-effective options for metal processing. The comparison is based on the forms and functions of the database. Optimal and economic processes associated with each function are also stored in the database. The orientation of the function is determined by the algorithm. This determines the most appropriate process that determines the direction of formation and Features. A similar approach was used in 43 to develop a process-oriented in cold extrusion to develop the Process Choice Module (CAPP). The module is able to detect the shape of the object, the main sizes and volumes, connecting them with the most appropriate version of the cold extrusion process (i.e. also specifying the number of steps). Materials selection studies can be taxonomed using the same process selection categories. As for the choice of process, most of the author uses working material as a screening for available processes. However, some authors include the choice of material in their method of selection of processes: 1 includes the choice of material in its methodological approach. Giachetti also uses fuzzy logic to select material, using a variable query to predict different end properties. This allows the author to expand his probabilistic approach to material selection. Brechet et al. 11 revises the methodology for selecting materials, pointing to the effectiveness of selecting multi-purpose criteria. Ashby is a pioneer of this field with several works (some of which extends to material selection). Ashby determines, first, some material performance index. The author develops tools for the selection of material, mapping the young module on the density of various materials and linear expansion of thermal conductivity. Display depends on the final requirements for the product (heat distortion): special procedures need to be developed to measure the material attributes for a particular product design. Ashby applies optimization of one and several criteria to the choice of material. The authors receive from objective function some differential equations, using as restrictions several input variables and boundary conditions. When selecting multiple criteria, solving equations is a compromise of Pareto's surfaces. The author uses the mass minimization of the component as one goal. In his applications, the author uses multi-criteria to minimize mass and cost (defining Pareto's compromise solution) or using combination parameters to minimize (depending on component requirements and functionality). For example, the author uses a product of cost and density on an elastic limit (i.e. a square root) and density on an elastic limit (i.e. a square root), forming another compromise choice of Pareto. Kutz considers some quantitative methods of selection of materials, pointing to the fundamental role of expert systems and numerical assistance (databases and the choice of knowledge base). Recently, the use of stochastic and gevrist algorithms for the selection of materials is growing rapidly. For example, apply the Analytical Network Process (ANP) to the selection of multi-criteria: material characteristics taken into account are density, thermal attributes (operating temperature, conductivity), properties, fatigue and and Feature. The network is able to set a rating of different materials for uniform product requirements. A review of synthesisIn conclusion, fuzzy logic is able to rank a candidate's processes in the order of compatibility of their functions with requested. Typically, these features include technological and other quantifiable requirements (e.g. tolerances, superficial rough edges), although they can be easily extended to all necessary functions (e.g. materials, labor costs). Compatibility values can rank processes and materials for these requirements. Fuzzy logic is also able to quantify the compatibility of quality compatibility functions and cope with uncertainty.Complexity approaches have similar potential, although their application seems to be focused on product redesign and supply chain simplification. Similarly, topological optimization combines CAD and feature identification, which is currently used in many software packages. However, it does not address complex issues with uncertainties. Analytical models are less subjective and have achieved the highest accuracy in quantifying compatible process/material, especially when only a few features are considered. However, they are limited in dealing with uncertainty and complex links between options. In addition, analytical documents are limited to considering several selection criteria in their selections. Optimization tools overcome this problem by relying on probabilistic and analytical models, combining them with numerical capabilities and iteration. High-quality, methodological and knowledge-based approaches are the most flexible and can handle the complex interactions between material, design and production process. However, the inability to quantify function compatibility and generally low level of subjectivity limit them to choosing relatively limited categories of processes and materials. The authors propose an NNS selection methodology that expands the capabilities of registered systems (known as product, geometry, production and matching materials (ProGeMa3).) The methodology is schematically illustrated in the pic. The purpose of the methodology is to combine the existing product design with a combination of material and process in order to identify the most appropriate NNS production operations. Fig. 4Production Geometry, Production and Materials Compliance (ProGeMa3) Methodology Schematization Methodology consists of four main stages: 1.Economic Screening Capabilities: Determines Opportunities for NNS2 Applications. Material selection: Chooses the material according to its functional requirements3. Process Screening Matrix (ProSMa): filter, establishes viable processes for a combination of form, material and production volume.4.Assessment of compatibility (fuzzy logic): after the static selection tool (ProSMa), (ProSMa), Logic acts with a dynamic selection of viable processes selected in the previous StepEach of these steps are being detailed: Economic screening capabilities (step 1) are mainly devoted to screening and identifying components whose production costs could potentially be improved by the application of alternative NNS processes. Each stage of the production chain of the component needs to be studied in order to identify production processes with the following features: High processing speed High level of raw material costs affects The high volume of productionResoce the time of the highest complexity of product design and production chain may be other factors in identifying the capabilities of the NNS. However, quantifying the complexity of the process chain is difficult, and it is therefore necessary to sell rough estimates in order to identify possible existing products for the target assessment. After this phase, you need to get the information you need to produce the components. The material selection (step 2) was made after the components selected in step 1 using the 6 method. Using fuzzy logic, you can choose the best material based on component requirements and terms of use. When choosing this order of operations (i.e. material before the process is selected), ProGeMa3, similar to 17, 25, 70, effectively limits the number of combinations and interactions received. The Process Screening Matrix (ProSMA) (step 3) considers the technical feasibility of candidate processes to reduce the number of possible production processes for research. Central to this stage is the Choice Matrix (ProSMa), whose lines and columns are input-related are component geometry and production volume selected in step 1, and the material selected in step 2 (or, as an alternative, the material currently used), provides a set (array) of viable processes (which could include processes used in the original component production). Production, material and form are classified into the following categories: Material: irons, steel (carbon); Steel (alloy, tool); Stainless steel; Copper and alloys; Aluminium and alloys; magnesium and alloys; zinc and alloys; tin and alloys; lead and alloys; Nickel and alloys; titanium and alloys. Production: very low (from 1 to 100); Low (100 to 1000); Low to medium (1,000 to 10,000); Medium to high (from 10,000 to 100,000); High (100,000 euros); Component form: 12 different component shapes can be selected as a cross in Table 1. The categories include three common geometric shapes (i.e. round, bar, tube) and five possible forms derived from them (i.e. even section, change at the end, change in the center, transverse element and irregular). Material categories production volumes are adapted from 39, 61 and 70. Determining the shape from Table 1 is quality quality non-existent form compared to general cases. Table 1 Component Form of Selected Combinations and Items, adapted from 61ProSMa, is presented in tables 2, 3, 4 and 5. The matrix is an extension of the work, although their PRIMA matrix uses only production volume and material as input. The number of casting and formation processes defined in the matrix does not take into account innovative technologies, while ProSMa includes processes such as semi-solid metal casting processes. In addition, ProSMA, additive layer manufacturing processes have been added. ProSMa's design is based on a review of the process from No.7, 8, 10, 18, 21, 23, 28, 29, 31, 33,34,35, 38, 51,52,53, 55, 56, 61,62,63, 66, 69, 70, 76, 80. Manufacturing processes were indexed and divided into three macro categories as follows: Casting: Sand Casting (C.1); Shell sculpting (C.2); plaster stucco (C.3); Lost foam casting (C.4); Investment Casting (C.5); Ceramic mold casting (C.6); Gravitational-Die Casting (C.7); Gravitational-Die Casting (C.8); Vacuum death casting (C.9); pressure to die casting (C.10); true-centrifugal casting (C.11); semi centrifugal casting (C.12); centrifuges (C.13); Compression casting (C.14); thixocasting, reocasting (C.15); thixoforming (C.16). Formation: forging open death (F.1); Closed forging (F.2); Isothermal forging (F.3); Accuracy of forging (F.4); Cold Education (F.5); Injecting forging (F.6); rotary forging (F.7); Haircut formation (F.8); Flow formation (F.9); Hydroforming (F.10); Powder forging (F.11); F.12; injectable metal moulding (F.13). Additive layer production: selective laser caking (SLS) (AM.1); Selective Laser Melting (SLM) (AM.2); Direct Metal Laser Caking (DMLS) (AM.3); E-ray melting (EBM) (AM.4); Laser Metal Deposition (LBDM) (AM.5); Electronic beam-based metal deposition (EBMD) (AM.6); plasma deposition (PDM) (AM.7). ProSMa is designed to be used for existing products that are designed as a single component part. Referring to Table 1, for all round (R), Barr (B) and Tubular (T) basic geometry, irregular (complex) forms (classified as 4) is designed to absorb all cases that are not included in other categories (uniform section, change at the end, change in the center, cross-section). If the form cannot be identified by spatial complexity (not related to any of the form 0-4 categories), the entire process for the identified underlying geometry (Round, Barr or Tube) (all from 0 to 4) should be considered for the volume of material and production considered. ProSMa can be used as a guide to mapping the production effects of design changes (transition from category to another). Although ProSMa is not designed to create new product designs (given the difficulty of representing all functional functions) and similarly cannot be used to attach components or assembly processes. However, it can provide guidance for the production of combined geometries (for example, the transition from two different simple components to one). Process compatibility assessment (phase 4) uses fuzzy logic that identifies the most appropriate production processes from viable processes selected in Phase 3. This stage has a dual function: Final screening: the processes that form the features of the components are excluded at this stage (e.g. thickness section). Process Rating: All viable processes are ranked in the order of their compatibility (between product requirements and process capabilities). A fuzzy logical approach allows you to achieve these two goals by linking the query with a four-tier fuzzy description of the process's capabilities. The possibilities of the process are described by four levels and trapezoidal probabilistic probabilistic behavior: the average levels (2 and 3) are associated with normal process capabilities, so the assigned probability of achievement is 1. Extreme ranges (i.e. 1 and 4) are the maximum and minimum opportunities achieved by the process. Between these values and normal operating ranges (i.e. between 1 and 2 and between 3 and 4) you need to consider a fuzzy probability, suggesting linear behavior between the two points. Using equi. 1, 2, 3, 4, 5 and 6, you can determine process compatibility by assessing the required levels by by a number of product attributes, and comparing them with four levels of capability (fuzzy trapezoidal form) processes. The following four characteristics are taken into account: technological attributes (tolerances and roughness of the surface)Properties of feasibility (minimum section and weight)As a result of mechanical propertiesProcess costs (tool, equipment and labor) The first two categories are numerical, while the last two are usually evaluated on a qualitative scale. The linguistic score scale is shown in Table 6: this way you can translate a qualitative score into numerical and use the result to calculate probability. Calculated compatibility for each characteristic is combined with a single compatibility value with the use of equalizers. 5 and 6. Compatibility values are ranked on the weigh-in scale shown in Table 7. As mentioned earlier, 30 introduced a method of combining opportunities and necessity measures, presented here as Eq. 7. $$C_ iP_'i (beta) N_ i (1-beta) $$For each of the i th: Ci attribute is compatibility for one attribute; Pi is able to probabilisticly evaluate a request; Ni is a need for a probabilistic assessment; β level of optimism. Table 6 Linguistic Score Scale used in fuzzy logicBlably 7 Weight scale in fuzzy logic. 1, 2, 3 and 4, which calculate the probability of a single function, should be changed depending on the form of the request. If the query is a single value (Req), the value of opportunity and necessity is calculated in tables 8 and 9 using four levels of capability (Lev1,Lev2,Lev3,Lev4). Similarly, if the query is less or more than certain values, the formulas of opportunity and necessity must be changed accordingly, as shown in tables 10, 11, 12 and 13, respectively. Table 8 Probability Probability Probability For Request - Probability Calculation ValueTable 9 Need for a Request - Probability Calculation ValueTable 10 For a request for a zlt; ValueTable 11 Probability calculation for a request for a zlt; ValueTable 12 Probability Probability Calculation for the Request by the Company's ValueTable 13 Probability Calculation of necessity for the request of the valueThe ProGeMa3 methodology was applied to the production of the control valve (Figure 5) Commercial privacy prevents some parts of components and the purpose of their production, as reported here. Fig. 5Control (case study): Build and component items The following paragraphs describe the application of each step of the ProGeMa3 method. Step 1: Component screening - Examination of current production parameters (general details, data, table 14), resulting in the valve cell (Figure 6) being recognized as the highest processing rate and raw material cost ratio among control valve components (Figure 5) production. Fig. 6Component selection for the NNS (Cage) control valve cell has a large number of options in size (50 to 600 mm) and material (various stainless steel), so the most frequently produced sizes and combination of material were selected (300 mm and 420 stainless steel) for the study. Production is less than 100 units per year. Extensive processing and very high material cost (i.e. stainless steel) are the main reasons for choosing this component. Currently the component is forged as a solid empty and process (turn and drill) to the final shape. Step 2: Material selection - In the valve cell case, the choice of material was limited to three factors: the material is selected for the necessary erosion/corrosive resistance, especially for fracking pumps, centrifugal and vertical pumps. Changing the material requires careful testing. Production options: All components already include different material variants selected at the customer's specific needs. Industrial sector: the choice of materials is dictated by the customer's request to pumps/vale (i.e. the oil and gas sector) and the standards of products for valves (i.e. the nuclear sector). The customer is unwilling to accept any new materials for these components, without Check. Thus, the choice of material remains unchanged (i.e. stainless steel). Step 3: Process Choice Matrix Application - As appears in Table 14, the selected component can be categorized using Table 1, as well as certain material categories and production volume ranges. The valve cell can be classified as: Geometry: T1. Tube with one section change at the end (Table 1)Material: stainless steel production: low (lt; 100 units per year). Using these inputs, ProSMa (tables 2 and 3), identify the cell that contains the following potential NNS process: Sand castingLost foam castingInvestment castingCeramic castingFlow formingTable 14 also shows the application of ProSMa to other assembly components. Table 14 ProSMa application for valve control manufacturingStep 4: Process compatibility assessment - To apply fuzzy logical screening and ranking of these candidates, the following characteristics were selected (both for component and processes). Radial (or planner) tolerance (±mm) (number score). Axyan (or vertical) tolerance (±mm) (number score). Surface roughness (Ra) (number score). The thickness of the section (mm) (number score). Weight (kg) (number score). The result is mechanical decency (linguistic evaluation). The cost of the tool (linguistic assessment). Equipment cost (linguistic assessment). Labor costs (linguistic assessment). These characteristics will be evaluated by the requested characteristics (product and goals) and the working ranges of processes (fuzzy sets) and compared between them. Four levels were taken from the literature to determine the fuzzy sets of centrifugal casting. In particular, fuzzy ranges were obtained from No.12, 18, 39, 61, 62, 70, 71; at the same time, the work weights and thickness ranges of the sections are defined for the processes under study, as in No4, 12, 14, 39, 61, 62, 67, 68, 70. The resulting mechanical properties No.2, 4, 39, 57, 61, 76, as well as the cost of equipment, equipment and manpower No.4, 15, 39, 61, 70 were evaluated to determine quality levels (i.e. low, moderate and low, moderate, moderate and high, high). The requested levels of the features reviewed are shown in Table 15. Component requirements are determined by industrial data (tolerances, rough edges, size and weight), quality targets (mechanical properties) and production (costs). The required tolerances, roughness of the surface, working thickness and working weight levels were taken from the current properties of the components for the chosen size (300 mm in diameter). As a result, mechanical decency was set to be more than an assessment of current and necessary mechanical decency. Similarly, the required costs are set at the level current production costs. Table 15 15 Levels for a process-compatible assessment using fuzzy Table 15 logic also display weight ratios for the features reviewed. The highest weight (value no. 5) was given to the working mass and thickness of the section, as these properties determine the viability of components made with this process. Surface tolerances and roughness have been assigned with high relevance (value No. 4) because the NNS approach should aim to reach properties as close as possible to the query specification. The average (value no. 3) was given mechanical properties, due to the low resistance required by the component. The weight of compatibility for labor costs, equipment and tools was set at medium (value No. 3) due to the low approximation level. The β ratio (7) was set at 0.5 on the basis of the 30 recommendation. The specific requirements and relative weight ratios have been determined in collaboration with the research company. For each process, overall compatibility (7) is calculated using selected weights (table 15) and weight rank calculation (6). Table 16 shows the overall compatibility of the sample component with each NNS candidate process identified and ranked by ProGeMa3. Table 16 Ranking Compatibility Processes by Fuzzy LogicNoal Results for Sand Casting, Investment Casting and Lost Foam Casting suggest that they are not suitable for the production of NNS valve cells. This is because tolerances, rough edges, and mechanical properties that are compatible with values make this casting process less appropriate for this application. For sand casting and lost foam casting, tolerances, roughness and mechanical properties, the possibilities are not enough to allow the process to produce the requested characteristics. Investment casting is also not suitable because of its high costs. However, three processes (centrifugal casting, ceramic molding and flow formation) are considered compatible with the requirements of the valve cell production. The most appropriate process is centrifugal casting (0.92), followed by flow formation (0.77) and ceramic molding (0.68) (Figure 7). Fig. 7 Process compatibility rating for the production of the NNS component for casefigure 8 research shows the compatibility of single functions for all review processes. Centrifugal casting satisfies almost all requested levels. The flow formation exceeds the capacity of centrifugal casting in some functions. However, like ceramic stucco, different ranges of working thickness and weight reduce their overall compatibility (taking into account the weights applied to the coefficients). results in the highest compatibility of centrifugal casting compared to ceramic molding or flow formation. Fig. 8 Process of compatibility breakdown for the production of NNS in the case of component study As a direct result of this analysis, centrifugal casting was adopted to produce valve cell generation 26.5%, saving 490 machine hours and 18.9 tons of raw materials. Information on the feasibility study and details of the NNS process can be found in .46. Compared to literature, ProGeMa3 only studies metals (similar to 25 and 12), although both are limited in casting processes. Swift and Booker explore metals, composites and plastic, but the approach is limited to traditional manufacturing processes. The 1, 30 and 5 methodologies can be applied to all material and targeted processes. General methodologies (No1, 30) and 5) are also the most adaptable, and casting approaches are the least flexible. Jacetti uses a fuzzy logical approach to process selection, ranking the feasibility study of the candidate process for targeted production, while using a combination of the selection matrix (used as a filter) and cost analysis (use the final decision-making criteria). In contrast, ProGeMa3 combines its key functions using a combination of process selection matrix and fuzzy logic to rank process candidates using NNS criteria. The effect of product accuracy on process selection is lower on less quantitative (based on archival data) or qualitative methodology. Meanwhile it heavily affects the quantitative ones, for example in 5 by selecting the criteria and purposes of value functions. Procedures based on fuzzy logic depend to a large extent on the accuracy of the measurements required by product requirements and therefore have a significant impact on the ranking process. Unlike 12, 70 and 1, ProGeMa3 doesn't rely only on static archival data that's less appropriate for identifying new and emerging processes. Fuzzy (such as ProGeMa3 approaches) and ProGeMa3 can adapt to experimental data and be updated flexibly. ProGeMa3 selects material before selecting the process (e.g. 12, 70 and 25), while the 30 and 5 approaches have an interactive process and a selection of materials. Albinyana and K. Vila, as well as Ayr and Diaz, use both qualitative methods, the first of which uses a choice of frameworks based on knowledge, and the second - a choice based on rules. Different methodologies consider different attributes for the selection process. ProGeMa3 cost of use, product geometry, mechanical properties, production volume and materials (used in the matrix phase of choice. Giachetti takes into account more variables, material, product geometry, process features, mechanical properties, Manufacturing cost in his fuzzy logic model. In a different way from 30 and 5, ProGeMa3 is unable to assess the optimal choice, as it limits its work field through ProSMa.The ProGeMa3 methodology has been successfully applied to industrial research. The assumption that the material is consistent with the selection process is viable in the application of examples and is consistent with previously reported approaches in the literature. The methodology could potentially be expanded to include ceramic and plastic materials, including their specialized processes. Similarly, sheet production and continuous processes could be added to the process selection matrix. The methodology can be automated as an online service with a graphical user interface to facilitate its use by non-expert users. Customer needs and market influences are difficult to quantify, although they have a big impact on the definition of requirements and the stability of the supply chain. The difficulty of quantifying this type of information makes it difficult to incorporate these characteristics into the quantitative methodology. Potential quality improvement (associated with different processes) is difficult to quantify at the selection stage. Similarly, the variability of output and changes in relation to any other changes. Similarly, the impact on the environment and energy is difficult to quantify during the selection phase, although they have a significant impact on the sustainability of the supply chain. In this sense, ProGeMa3 can be linked to other quantitative methodologies, such as life cycle assessment (LCA), to quantify the impact of process selection on environmental impact. However, the dependence of supply chain management and product lifecycles on product requirements, suppliers and external factors (such as government policy and market rules) makes these factors highly event-dependent and difficult to classify. The combination of a selection matrix and fuzzy logic provides a very effective mechanism for quickly focusing the selection process on a small number of potential candidates. Once process databases are created, the ProGeMa3 methodology reduces the subjectivity of the process and therefore supports non-user experts. Determining requirements is crucial because they can lead to different outcomes when selecting a process. In this sense, the availability of information is crucial for the application of section methodologies. The ProSMa matrix is available for download with the original files so that other studies can expand and update the methodology (available electronically at 45).

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