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Towards smart manufacturing process selection in Cyber-Physical Systems

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ABSTRACT

Cyber-Physical Systems (CPS) are becoming increasingly important in manufacturing due to the digitization of the industry driven by advances in technology and connectivity. However, the variation of process selection criteria, both geometric and non-geometric, across the main groups of manufacturing processes, i.e., additive, subtractive, and deformation, makes it difficult to implement smart manufacturing process sequence selection which is an essential step toward achieving an autonomous CPS. This paper presents a conceptual solution to process selection called Constraint Satisfaction Problem for Manufacturing (CSP4M) which leverages current engineering design methods and architectures.

1. Introduction

Digitization has been the primary driving force behind the rise of manufacturing efficiency and quality in recent years. The major catalysts behind this phenomenon are: rise in computational capabilities (power, data, and connectivity); improvements in analytics; improvements in human-machine interaction, and the bridging of the gap between design and finished products brought about by flexible manufacturing processes [1]. Cyber-Physical Systems (CPS), smart interconnected systems with physical and computational capabilities, are the quintessence of this digitization [2]. CPS have state-of-the-art machines and sensors capable of producing huge volumes of data; therefore, data analytics can be used in tandem with the interconnectivity of the machines to create intelligent, autonomous, and robust systems [3–5].

An integral part of CPS for manufacturing will involve the automatic allocation of system resources based on input information. Inputs include part geometry information (geometric features and part dimensions) and constraints (quality, mechanical, and economical). So far, research efforts in defining such an allocator have targeted the primary areas of manufacturing, i.e., subtractive and additive. For subtractive manufacturing, process selection can be done via geometric analysis of features and then matching these features with the appropriate machining processes [6–8]. For additive manufacturing, process selection can be done based on material choice, part size, and build quality [9–12]. This variation in the criteria for process selection across the main groups of manufacturing processes (see Table 1) makes it difficult to create and integrate a generic allocator into a dynamic and autonomous CPS.

The contribution of this work is the description of a conceptual framework for finding the correct manufacturing process sequence based on Constraint Satisfaction Problem (CSP) [13]. Specifically, this work attempts to cast the problem of manufacturing process sequence selection in CPS into a constraint logic problem in which finite domain search can be used to find the sequence of processes that best satisfies the goals prescribed by the constraints. From this perspective, the goal of the search is to find the sequence of processes which manufacture the desired part with constraints on the cost and quality (from the user) and on the capability of the CPS itself. Since there is only a finite number of processes and combination of process in the CPS, constraint logic programming is an ideal tool to perform process sequence selection.

The implementation of a smart process selector must be centered on the interaction between a user and the CPS. To this end, a Constraints Satisfaction Problem for Manufacturing (CSP4M) formulation is proposed. It is used to: transform partial information (geometric input) into a solution space of possible available manufacturing process combinations, apply constraints (user specifications) to reduce the generated solution space via local deductions, and search the reduced solution space for the optimal process sequence(s) using conventional information (Fig. 1). Specifically, Fig. 1 starts with the user providing a CAD geometry along with allowable ranges for the quality, mechanical properties, and cost of the desired manufactured part. Next, this information is passed to the CPS which performs feature recognitions on the geometry and generates a list of candidate manufacturing processes needed to manufacture the part. Finally, expert knowledge from the best practice of the processes and the user defined constraint ranges

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Table 1
Process selection criteria for 3 classes of manufacturing processes.

Class	Criteria	Processes Selection
Traditional Machining	Geometric features and part quality	Milling, Drilling, Turning, etc.
Additive Manufacturing	Material choice, part size, and build quality	Direct Metal Deposition, Powder Bed Fusion, Material Extrusion, etc.
Deformation Manufacturing	Formability and geometric accuracy	Incremental forming, Deep drawing, Bending, forging, etc.

are used to reduce the candidate processes to a final list which meet both the user and CPS requirements.

2. Constraint Satisfaction Problem for Manufacturing (CSP4M)

Constraint Satisfaction Problems rely on logical programming using constraints over a finite domain [14]. In this programming paradigm, an initial problem, consisting of a set of conditions (propagators), and a solution space are first defined. These propagators are then used to sequentially apply constraints to the solution space by making local deductions. Finally, an exhaustive search is done on the reduced solution space to find a case that satisfies the given conditions.

Finite domain search is a plausible solution to process selection in CPS because:

a. All manufacturing processes in the system are known (domain is finite);
b. General information about how classes of manufacturing processes interact is also known, e.g., additive processes are usually followed by subtractive processes, deformation processes can be preceded and/or followed by subtractive processes, etc.;
c. Propagators are well defined, i.e., the part geometry (features and dimensions) and user specification (material, built quality, cost, etc.);
d. Expert knowledge about the system can be added in terms of how each process affects the cost, quality, and mechanical properties of manufactured parts. This includes information like the physical location of machines, size and dimensional limitations of machines, process sequence prediction from big data analytics, costs per machine run, etc.

The implementation of manufacturing process selection in CPS as a CSP4M is shown in Fig. 1. First, partial information in the form of a solution space over the possible sequences of process classes can be generated using the input geometry information. Then, this solution space, which contains all the permutations for available process sequences, can be constrained using the user specifications (material, built quality, cost, volume, etc.), and finally a search can be done using expert knowledge about the system capabilities to produce a list of candidate process sequences for the user.

2.1. Partial information

Before constraint satisfaction can be performed, an initial problem and search space have to be defined. The initial problem is defined by user specified geometric information, in the form of CAD, and a complete list of all the manufacturing processes available in the CPS grouped by hierarchies (additive, subtractive, deformation, etc.). Very sophisticated geometry analysis methods

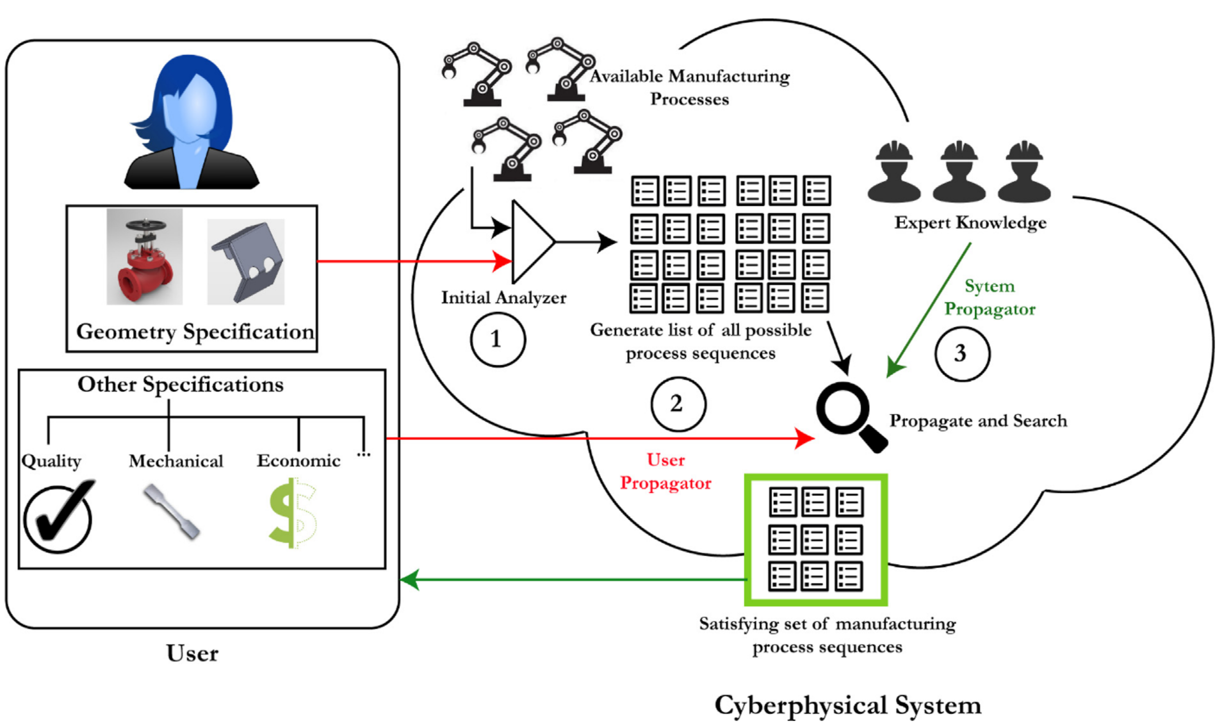

Fig. 1. Constraint Satisfaction Problem for Manufacturing (CSP4M).

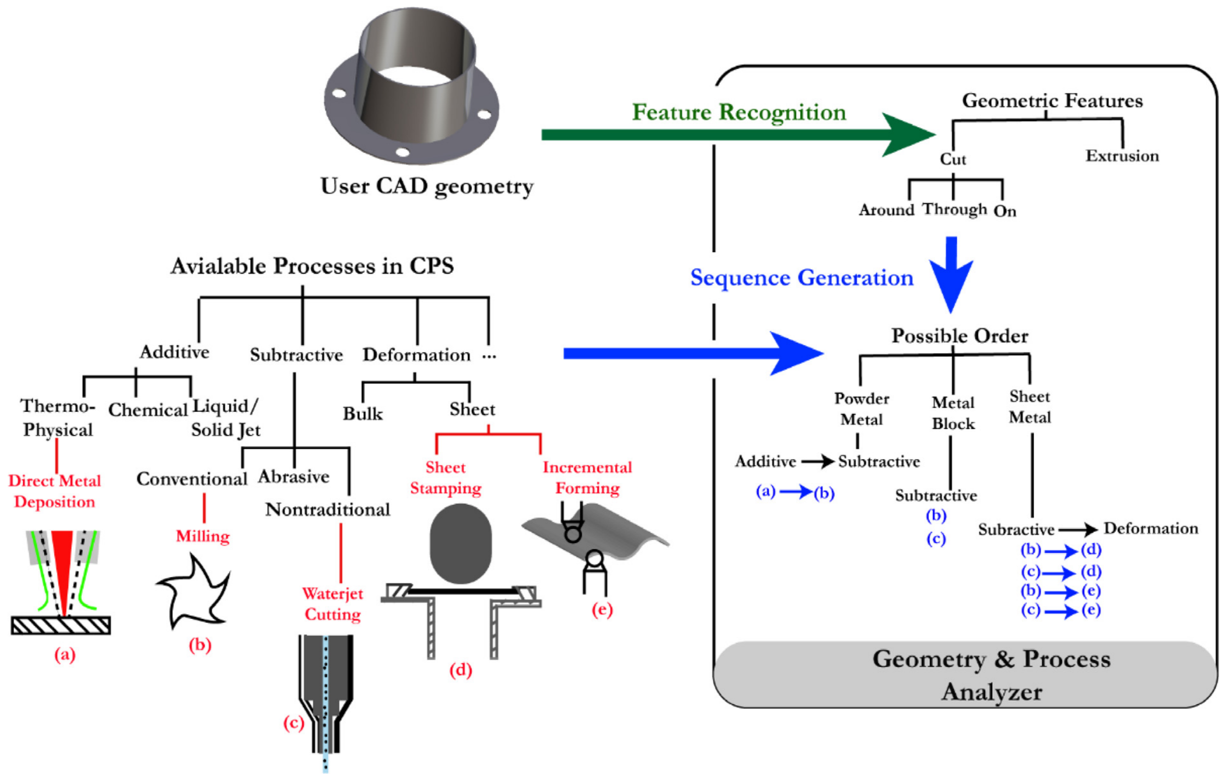

Fig. 2. Process sequence search space generation in CSP4M.

already exist for selecting subtractive manufacturing processes, and these methods are capable of performing feature recognition [6–8], toolpath generation based on the recognized features [15,16], dimensional analysis, tolerance analysis [17], etc. Similar analysis methods also exist for selecting additive [9–12] and deformation processes [18,19]. The list of possible sequences of manufacturing process classes can be generated based on the available process in the CPS as shown in Fig. 2 for a stainless steel flange.

In the example shown in Fig. 2, the initial geometry analysis reveals the presence of a combination of extrusion and cut features. The process sequence search space is then generated by choosing a raw material (powder, block, or sheet for steel), and then identifying the physical processes needed to manufacture the geometry using the chosen raw material. After this high level process sequence has been identified, processes under the identified categories are selected from those available in the CPS. Specific manufacturing procedures can then be generated using conventional methods.

2.2. Constraint propagation

Given the search space of all the individual process sequences that fall into each of the aforementioned process groups, the user specifications (quality, mechanical, or economic) can then be used as propagators to constrain the search space by making local deductions. For this to be achievable, the effects of each processes has to be quantified relative to all the other processes in the CPS using process selection metrics [20] like the ones shown in Table 2.

After the performance of all of the processes have been quantified on a relative scale for all the measurable metrics, the user can then specify a range with the ideal performance for their application (max) and the lowest acceptable performance (min) for each one of the metrics. Using the user-specified metrics, the search space of possible process sequences can then be reduced by removing process sequences that result in performance outside the user-specified range. In this sense, the user specifications serve as propagators which constrain a range in the solution space by making local deductions which is a classical constraint logic programming problem [13].

Table 2
Performance metrics for manufacturing processes.

Class	Performance Metrics
Quality	Surface roughness, dimension tolerance, surface finish roughness, etc.
Mechanical	Material strength, porosity defects and voids residual stresses, etc.
Economic	Production rate, lead times, material utilization percentage, tooling cost, etc.

Such a constraint propagation system can be implemented for manufacturing processes by leveraging similar artificial intelligence inspired methods that already exist for parametric and knowledge-based frameworks in engineering design. These include architectures for formulating geometric and topological design [21] and knowledge based engineering systems with declarative style programming languages [22].

2.3. Search using expert knowledge

The final stage of process selection is to search the space of all the process sequences that fall within the ranges of the user-specified performance metrics for the optimal solution for the CPS (Fig. 3).

At this stage, expert knowledge about the CPS, i.e., system specific information obtained from big data analytics, cost analysis, and system constraints which reside in the cloud [23], can be used to make the final shortlist of candidate process sequences. In a CPS, data for analytics can be obtained by using data acquisition tools in

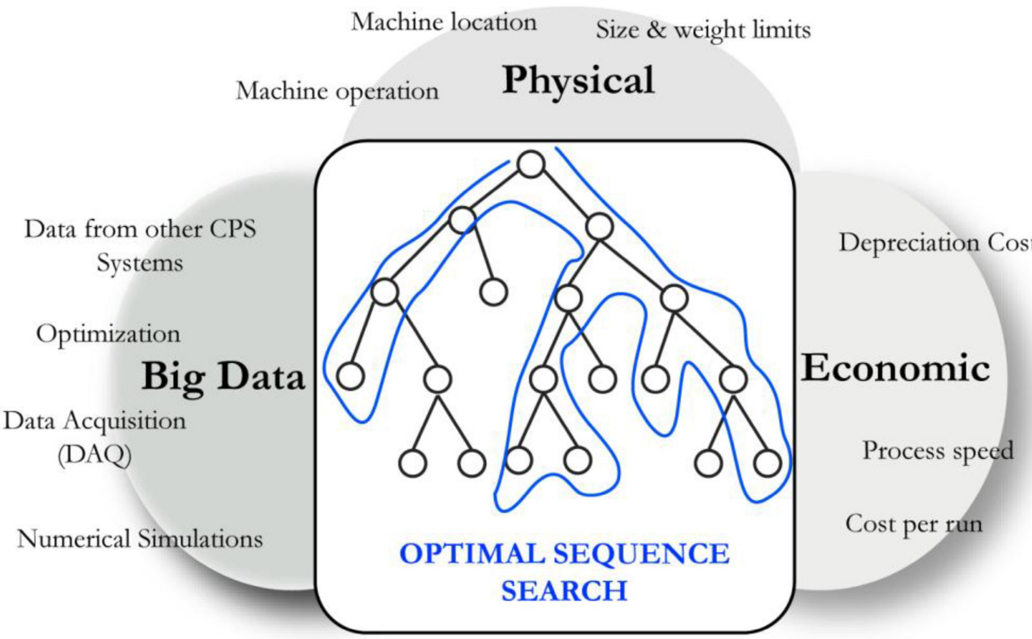

Fig. 3. Optimal Process sequence search using CPS specific knowledge.

the manufacturing processes or directly from other CPS systems [3]. Data about material properties like porosity, cooling rate, residual stress, etc. which are very difficult to measure directly can be obtained using numerical simulation techniques [10]. Models capable of detecting patterns in process selection for similar geometries, which are essential for the final search for the optimal process sequence, can be defined using this data [24]. Economic information about the CPS, i.e., the cost per machine run (including depreciation) and the speed of the process sequence, can also be used to pick the optimal process sequence. A detailed study on doubling the manufacturing speed for a group of additive, subtractive, and deformation processes revealed that constraints like machine stiffness, actuator acceleration, heat transfer, and delivery of fluids need to be considered [25]. Lastly, constraints on the CPS itself like the physical location of the machines, weight and size limitation for each manufacturing process, machine capability, etc., have to also be used to search for the optimal process order. As shown in Fig. 3, this expert search [26–28] can be used to obtain a list of candidate process sequences that best satisfy the user specifications and also meet the physical and economic requirements of the CPS.

2.4. Implementation

The CSP4M can be implemented on the cloud or the CPS-side, and an interface can be provided for clients to input CAD models and other constraints to kick-start the process selection process. The logic programming in the CSP4M can be implemented using the *core.logic* library of the Clojure programming language [29]. In addition to supporting logic programming, Clojure's core.logic also supports the implementation of constraints on finite domains of numbers which makes it a good candidate for this implementation.

3. Conclusion

With trends in CPS like Industry 4.0, there has been an increasing need to define a methodology for smart manufacturing process selection for manufacturing systems. This paper presents a very practical concept for performing this task based on constraint satisfaction at the user level and the knowledge about the system itself. By addressing this monumental problem, it provides a guideline for the implementers in the manufacturing industry to follow in the quest to build smart, autonomous, ubiquitous, and cloud-based systems for value-added manufacturing.

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