Recommendation Framework for on-Demand Smart Product Customization

Laila Esheiba, Amal Elgammal and Mohamed E. El-Sharkawi
Faculty of Computers and Information, Cairo University, Cairo, Egypt

Keywords: Product-service Systems, PSS Customization, Recommender Systems, Big Data Analytics.

Abstract: Product-service systems (PSSs) are being revolutionized into smart, connected products, which changes the industrial and technological landscape and unlocks unprecedented opportunities. The intelligence that smart, connected products embed paves the way for more sophisticated data gathering and analytics capabilities ushering in tandem a new era of smarter supply and production chains, smarter production processes, and even end-to-end connected manufacturing ecosystems. This vision imposes a new technology stack to support the vision of smart, connected products and services. In a previous work, we have introduced a novel customization PSS lifecycle methodology with underpinning technological solutions that enable collaborative on-demand PSS customization, which supports companies to evolve their product-service offerings by transforming them into smart, connected products. This is enabled by the lifecycle through formalized knowledge-intensive structures and associated IT tools that provide the basis for production actionable "intelligence" and a move toward more fact-based manufacturing decisions. This paper contributes by a recommendation framework that supports the different processes of the PSS lifecycle through analysing and identifying the recommendation capabilities needed to support and accelerate different lifecycle processes, while accommodating with different stakeholders' perspectives. The paper analyses the challenges and opportunities of the identified recommendation capabilities, drawing a road-map for R&D in this direction.

1 INTRODUCTION

Manufacturers today are seeking to fulfill orders on demand by doing their business processes through short-term networks where they negotiate value-adding processes dynamically while taking into consideration customer demands, quality, time, price, viability, sustainability, and other dimensions (Elgammal et al., 2017; Song, 2017; Papazoglou, Elgammal and Krämer, 2018). In order to make themselves unique, manufacturers are not only offering products but they provide products accompanied with services (Product-as-a-Service). Product-as-a-Service starts by sensor-based products that generate data in a continuous manner, these data can be utilized for delivering preventive and proactive maintenance. Product-as-a-Service often called Product/Service Systems (Bustinza et al., 2015).

However, the current state of practice of engineering PSSs still suffer from severe drawbacks (Elgammal et al., 2017; Song, 2017; Papazoglou, Elgammal and Krämer, 2018). The most noticeable drawback is that PSS remains at conceptual level considering a marketing or business perspective and missing solid IT implementation. Furthermore, PSSs do not accommodate growing user preferences or product diversity features to enable effective customization. They are incapable to tackle different stakeholders' views to automatically fit product design to customer's requests in real-time. PSSs are unable to capture a full view of products and services linking product structure with product quality, production processes and services. More importantly, they do not support analysis of product-related data gathered along product lifecycles to improve data-driven decision making.

This demands the use of novel lifecycle, techniques, and technologies to enable manufacturers to connect their data, processes, systems, personnel and equipment to support customers with the aid of product designers and engineers to co-design customized products and services.

In a previous work, we have analysed and conceptually designed and developed a novel PSS customization lifecycle with supporting IT tools and techniques taking a customer-centric approach, which

Esheiba, L., Elgammal, A. and El-Sharkawi, M.
Recommendation Framework for on-Demand Smart Product Customization.
DOI: 10.5220/0007684401770187
In *Proceedings of the 21st International Conference on Enterprise Information Systems (ICEIS 2019)*, pages 177-187
ISBN: 978-989-758-372-8

assures customers' requirements and preferences are taken into consideration and product improvements are attained through the process of PSS customization. The PSS customization lifecycle is established on the basis of the tried and tested knowledge-intensive structures called manufacturing blueprints (blueprints for short), which semantically captures product-service and production-related knowledge (Papazoglou, Van Den Heuvel and Mascolo, 2015; Papazoglou and Elgammal, 2018). Blueprints integrates dispersed manufacturing data from diverse sources and locations, which includes and combines business transactional data and manufacturing operational data to gain full visibility and control, and provides the basis for production actionable "intelligence".

The PSS lifecycle incorporates five core processes (Papazoglou, Elgammal and Krämer, 2018), i.e., *Smart product ideation, PSS Customization, Production Planning, Production Execution and Production Monitoring* (cf. Figure 2). The lifecycle provides a closed monitoring feedback loop that enables continuous product and service improvements. Big data analytics is of utmost value to support the different lifecycle processes from the early stages of smart product ideation and customization all the way to smart product monitoring and improvement (the lifecycle is summarized in Section 6).

Big data analytics are classified into descriptive, predictive and prescriptive techniques (Donovan et al., 2015; Nagorny et al., 2017). Predictive analytics is an advanced branch of analytics that uses data mining, statistics, machine learning and artificial intelligence to make predictions about unknown future events. Predictive maintenance, in which data are gathered from smart, connected machines to predict when and where failures could occur, potentially minimizing unnecessary downtime (Coleman et al., 2018).

Descriptive analytics uses data integration and data mining to describe or summarize what happened in the past. For example, reports that provide historical insights regarding the company's production. Prescriptive analytics can be applied to recommend the best course of action for a given situation, such as, the analysis of equipment monitoring data can alert the factory-floor operators of a detected emergent situation that need their attention/action, or may trigger automated corrective action(s) to mitigate the detected disturbances, and prevent any further damage. Prescriptive analytics falls under the bigger class of Recommendation Systems (RSs), which has a potential role throughout the different processes of the smart product lifecycle, which has not been tackled in the literature.

RSs are software tools that are used to make useful suggestions to users taking into consideration their preferences/requirements (Priyanka, 2017). In PSS customization lifecycle, recommendation facilities can be utilized to assist various involved stakeholders in making informed decisions and enable the re-usability of previous successful customization artefacts that are maintained in the blueprints knowledge base. For example, during the early stage of smart product ideation, the customer may be recommended by the top smart product variants (that's previously customized smart product requests/designs). The recommendation in this example is based on the customer's preliminary requirements and the information stored on customers profile such as (business type, business size, location, companies/customers she cooperates with, etc.).

The contributions of this paper is three-fold:

- The analysis and development of a recommendation framework that supports the different processes of the PSS lifecycle introduced in (Papazoglou, Elgammal and Krämer, 2018). The framework is iteratively built on the basis of case study conducts (Hevner et al., 2004) and our intensive involvement with four major industrial partners as part of the H2020 ICP4Life[1] project. The framework identifies the recommendation needs of different stakeholders involved in each lifecycle process, which enables the re-usability of manufacturing knowledge, and assists in informed decision making.
- We have differentiated between the recommendations needs of two distinct business models: Business to Consumer (B2C) and Business to Business (B2B). In the later model (B2B), the customer is actually a business that our findings indicate that her recommendation requirements varies from the former model (B2C). It is worth noting that recommendation approaches proposed in the literature to support B2B is scarce, as opposed to B2C, e.g., (Lu et al., 2015);
- Challenges and opportunities for each identified recommendation feature have been analysed for its realization from both a theoretical and technical perspective, which acts as a roadmap for R&D in this direction.

[1] ICP4Life project: http://www.icp4life.eu/

The rest of this paper is organized as follows: Section 2 presents the background about the different types of recommendation techniques. Related work is analysed in section 3. This is followed by presenting a pilot case in section 4, which will be used as a running example throughout this paper. Manufacturing blueprints are presented in section 5, followed by the proposed recommendation framework for on-demand customization PSS lifecycle in section 6. Finally, the paper is concluded in section 7 by highlighting ongoing and future work directions.

2 BACKGROUND

Recommendation technology is a growing domain of research, and is considered a hot topic in the information technology industry. RSs have been applied in many research areas such as e-commerce, fraud detection, logistics, e-learning, health, transport, etc. RSs are being used to give advice to the user about a decision to make or action to take (Beel et al., 2016). These recommendations are based on the user behavior, preferences, context and/or actions during interaction with a website or an application.

There are several types of recommendation techniques. The most common techniques are:

- Collaborative Filtering (CF) Techniques: these techniques make predictions of what might interest a person based on the taste of many other users. CF techniques are divided into user-based and item-based CF approaches, the former makes suggestions by considering the users having similar interest, while the latter suggests items that are similar to the items that are similar to those items that the people have liked before (Beel et al., 2016);
- Content-Based Techniques: focus on the features of products themselves and the preferences of the user. They recommend items that are similar in features to those items enjoyed by a user in the past. These techniques do not depend on the interaction of other users before recommending a product (Beel et al., 2016);
- Hybrid Techniques: are built based on joining the best features of two or more recommendation techniques into one hybrid technique, to enhance the performance of the traditional recommendation techniques;
- Knowledge-Based Recommender System (KBRS): are presented to tackle the problems of the above techniques. These include: new user problem (cold start), new item problem as well as the grey sheep problem (which occurs when a user can be classified in more than one group of users) (Priyanka, 2017).

In essence, the main components of any KBRS are:

- Knowledge Base: the nature of the KB varies depending on the type of KBRS; that's, it might be a simple database, a set of domain ontologies, or a case base (Bouraga and Jureta, 2016). In this paper the manufacturing blueprints, discussed in section 5 acts as our rich KB;
- User profile: due to the fact that KBRS provides personalized recommendations, a user profile is a major component and must be maintained. A user profile consists of user's preferences, interests, and needs. These pieces of information can be elicited explicitly or implicitly. Explicit elicitation implies for example, using elicitation requirements engineering techniques, such as interviews, while implicit elicitation means an analysis of the user behavior over time to gather information about her preferences.

KBRS distinguishes itself by providing recommendations based on the domain knowledge, it does not take into consideration the behavior of other users. Case-Based Reasoning (CBR) is a common expression of KB recommendation techniques. CBR is the process of solving new problems by reusing the solutions of the most similar past problems based on the assumption that similar problems will have similar solutions. CBR working cycle consists of four sequential steps around the knowledge of CBR system (Aamodt and Plaza, 1994) as follows: (i) *Retrieve*: involves retrieving the most similar case(s) from the case base using a similarity measure; (ii) *Reuse*: reusing the retrieved case(s)to attempt to solve the current problem; (iii) *Revise*: revising the proposed solution -if any- by taking feedback either in the form of a correctness rating of the result or in the form of a manually corrected revised case; (iv) *Retain*: the updated solution is stored in the case base as a part of the new case.

3 RELATED WORK

To keep the discussion focused, this section is mainly focused on surveying prominent related work efforts in (KBRS) in different domains, which represent the basic chosen technique for our recommendation framework presented in Section 6. Recommendations in KBRS depend only on the domain knowledge of the considered problem and do not take into consideration the behavior of similar users. The nature of the knowledge in this direction may take the form of a simple database (Ghani and Fano, 2002), or it may exist in the form of domain ontology (Ajmani et al., 2013) or the knowledge may amount to a case base (Khan and Hoffmann, 2003). Most of the KBRSs apply a case-based recommendation approach, where recommendations are achieved by retrieving the most similar case(s) to the user query by following CBR working cycle as discussed in section 2. Quantitative KB typically applies some sort of a similarity measure (Hsu, Chang and Hwang, 2009) as the recommendation strategy, while qualitative KB follows some sort of a matching technique (Blanco-Fernandez et al., 2008).

Influential related work efforts in case-based recommendations are reported in (Chattopadhyay et al., 2012; Yuan et al., 2013) A case-based reasoning system for medical diagnosis was developed in (Chattopadhyay et al., 2012), where the system focused on a particular medical diagnosis, namely, Premenstrual syndrome. After a number of similar cases are retrieved, human experts verify whether the cases are satisfactory or not. If not, the search process is refined and process continues iteratively until the correct and acceptable diagnosis is reached.

A case-based recommendation system to the real-estate domain was presented in (Yuan et al., 2013), where users are required to input some information, including for example, the desired location, price, and housing unit property. Then the recommendation is carried out based on the similarity between the problem description and the cases on the case base.

Other stream of research work efforts utilizes a conversational case-based approach to perform the recommendations. The purpose of the conversational part is to build users profiles, this conversation is done through a list of questions directed to the user, and then the recommendations are performed based on the Knowledge Base (KB) and the induced user profiles. Work efforts in (Lee, 2004) and (Aktas et al., 2004) follow this direction.

Some authors have adopted a technique similar to the content-based approach (cf. Section 2) (Carrer-Neto et al., 2012), (Kaminskas et al., 2012). Research efforts in this direction typically built a KB and users profiles, and then, a similarity is measured to match items in the KB with a specific user's preferences. In (Carrer-Neto et al., 2012) the authors proposed a social knowledge based recommender system for the movie domain. Elements in users' profiles are categorized according to their preferences. The system gathers information to initiate a movie domain ontology, and then, the recommendation is calculated based on analyzing the user's profile and her links to other users. Analogously, the approach in (Kaminskas et al., 2012) is based on a KB music recommendation system for places of interest. The goal of the system is to generate music corresponding to the place of interest. Similarly, in (Ajmani et al., 2013), a KBRS for personalized fashion recommendation is constructed. The system determines the visual personality of the user, and subsequently, generates recommendation using the ontology for fashion recommendation given the user personality and the occasion.

To the best of our knowledge, no previous work has considered the utilization of recommendation capabilities to assist in the manufacturing domain. In addition, the recommendation approaches in literature to support Business-to- Business (B2B) are scarce, as opposed to Business-to-Consumer (B2C).

4 PILOT STUDY

To improve understanding, we present a comprehensive industrial-strength pilot that was conducted in the context of the EU H2020 ICP4Life project. The pilot was provided by PRIMA Industries (http://www.primaindustries.it/en/) a leading manufacturer of laser and sheet metal machinery. The different requirements of the pilot case are tagged as "*Req#x*", where$x \in \{A, B, \ldots\}$, which will be cited in the framework in Section 6 to exemplify the different components of the recommendation framework.

In this pilot study we assume that a turbine engine manufacturer (customer) is interested in a multi-axis laser processing system and specifies its requirements and preferences, and co-designs the product with the help of stakeholders from an OEM, such as product designers using the novel Product-oriented Configuration Language (PoCL) (Papazoglou and Elgammal, 2018), which is a user-friendly domain-specific language aims at easing the collaborative product design task using the same jargon familiar to customers and other stakeholders, in an abstract and intuitive manner. For example, the customer may specify that the laser processing system features should include a CO2 laser generator, its power is 4000W and its speed is 5 m/min, positioning capability combined with a high-accuracy rotary table motion to enable new manufacturing processes while improving existing ones (*Req#A*). The work area should be X 600 mm – Y 600 mm – Z 600 mm (*Req#B*). The customer wishes to extend the laser welding nozzle of a multi-axis laser processing product with a cross-jet element that provides a high velocity gas barrier to prevent molten metal spatter and weld zone fumes from contaminating the protective lens cover slide (*Req#C*). The aerospace engine manufacturer may also demand to include sensors that meter multiple parameters providing services that measure the actal laser output, motion, temperature, humidity, process gases, and process control in both workstations (*Req#D*). In addition, the customer may enhance the multi-axis laser processing system functionality by specifying safe impact protection services by means of including a capacitive sensor for automatically maintaining the pre-set stand-off from the sheet metal (*Req#E*).

5 MANUFACTURING BLUEPRINT ENVIRONMENT

Manufacturing data and knowledge come from a wide range of sources such as: shop-floor equipment, control systems, quality tracking systems, PLM systems, monitoring systems, CAD/CAM systems and maintenance systems. These data and knowledge are not completely captured nor gathered in a digital, searchable form. These massive amounts of knowledge and data will be useless unless they are transformed into actionable insights. To overcome this problem, manufacturing data must be captured, stored, structured and inter-related through a formal knowledge model. To achieve this objective, in a previous work (Papazoglou, Van Den Heuvel and Mascolo, 2015; Papazoglou and Elgammal, 2018) we have developed a knowledge-driven manufacturing framework.

This framework depends on the novel concept of Manufacturing Blueprints. Manufacturing blueprints rely on model-based design techniques to manage and inter-link product data and information (both its content and context), product portfolios and product families, manufacturing assets (personnel, plant machinery and facilities, production line equipment), and in general, help meet the requirements (functional, performance, quality, cost, time, etc.) of an entire manufacturing network. This information can be collated and put within a broader operational context, providing the basis for manufacturing actionable "intelligence" and a move toward more fact-based decisions.

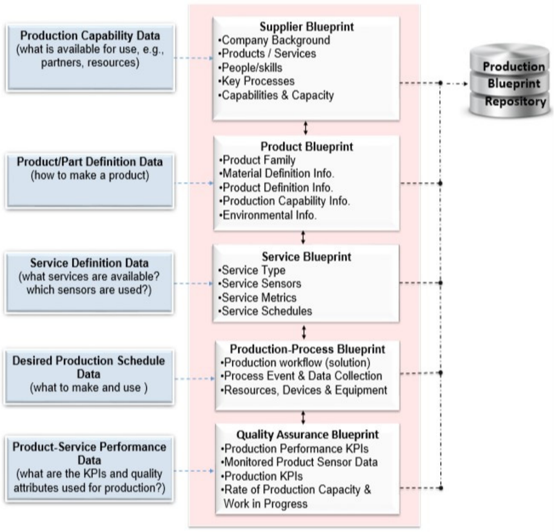

Figure 1: Manufacturing blueprint models.

As shown in Figure 1, the suppliers, product and production knowledge are encapsulated in the five interconnected extendable abstract knowledge as described below, which called blueprint images:

- Supplier Blueprint: describes business and technical details of a partner firm such as production capabilities, production capacity and stakeholder roles.
- Product Blueprint: defines the details of base or configured product, product parts, and materials. Such information is coupled with other relevant data such as machine parameters, personal skills, machine and tool data and all entities that is necessary to represent a full product. It also includes definitions of product families and connects them to products, product parts and materials.
- Production Process Blueprint: this blueprint captures the standard assembly and production solutions in addition to suitable production execution plan, embedding end-to-end processes into workflows and linking the events of discrete activities associated with all aspects of actual production on the factory-floor.
- Quality Assurance: Blueprint: it defines process performance and product quality metrics (KPIs) to monitor production operations and solve operation problems across supply production-chains. The objective of this blueprint is to increase process efficiency and asset utilization, equipment health and consumption levels.

- Service Blueprint: according to PSS, smart connected products require a number of services across the full lifecycle of the product. These services range from how the product is operated, maintained and upgraded. Instances of this blue print define the characteristics of all services that are coupled with the physical product. These include services types, sensors, service metrics, scope of plans, service schedules, and work orders created from service plans, compliance standards, service history and cost estimates.

6 THE RECOMMENDATION FRAMEWORK

This section presents the recommendation framework that supports the novel smart product PSS lifecycle we introduced in (Papazoglou, Elgammal and Krämer, 2018) (cf. Figure 2). The results presented in this Section have been iteratively identified, refined and validated by ICP4Life Industrial partners, which ascertains the applicability, efficacy and utility of the work presented in this article (Hevner et al., 2004).

Based on the findings of the literature review presented in Section 3, we have selected the KBR technique as the main technique supporting the proposed recommendation framework, due to the advantages cited in Section 2. The next subsections discuss the recommendation capabilities at each PSS lifecycle process by accommodating with relevant stakeholders' views/requirements involved in each process.

6.1 User Engagement and Smart Product Ideation

The lifecycle starts by the Smart Product ideation process (the left hand-side of Figure 2) such that a customer wishing to configure and customize a base product or a previously customized PSS variant that s/he can retrieve from the PSS library to meet her unique requirements (step-1 in Figure 2).

During this phase, the customer collaboratively with the designer/engineer elicit and validate requirements of extending base products with pluggable parts and services, quality attributes, etc., to enable product-service differentiation. During the user engagement process, customers may specify product requirements, parts and preferences and co-design the digital product with the help of OEM product engineers using the novel PoCL.

As shown in Figure 2 the main identified and validated recommendation capability for this process concerns itself with "*Recommending previously customized product variants or base products*". This acts as a starting point of the customization process, and enables the re-usability of product and service knowledge, maintained in the blueprints knowledge rep. (cf. Figure 1). For example, reverting back to the pilot case in section 4, *Req#A* describes the main requirements of the customer, which we regarded by the KBR technique as a new case. In addition to these requirements, the information stored in the user profile such as (business type, business size, location, with whom he co-operates (companies or customers), etc.) may be taken into consideration for doing suggestions/recommendations. Assume that there are three previously customized product variants V_1, V_2, V_3, the content of these variants is represented in terms of their parts' attributes and their associated values as shown in Table 1.

Table 1: Examples of previously customized products.

Variants	Attributes			
	Laser generator	Laser power	Laser speed	Workpiece
V_1	Co_2 laser	3000w	5 m/min	Rotary table
V_2	YAG laser	4000w	7 m/min	Rotary table
V_3	YAG laser	3000w	5 m/min	X-Y table

Given the initial requirements of the customer described in the pilot case as Req#A, this recommendation capability may find the most similar case(s) (product variant(s)) from the variants stated before (cf. Table 1), by using a possible similarity measure such the Nearest-Neighbor function in (1), that computes the similarity between the stored cases (previously customized products) and the new input case (Customer requirement) based on weighted features.

$$\text{similarity (CaseI, Case R)} = \frac{\sum_{i=1}^{n} Wi \times sim(f_i^I, f_i^R)}{\sum_{i=1}^{n} Wi} \quad (1)$$

Where Wi is the importance weight of a feature, sim is the similarity function and f_i^I and f_i^R are the values for feature i in the input case and the retrieved cases respectively.

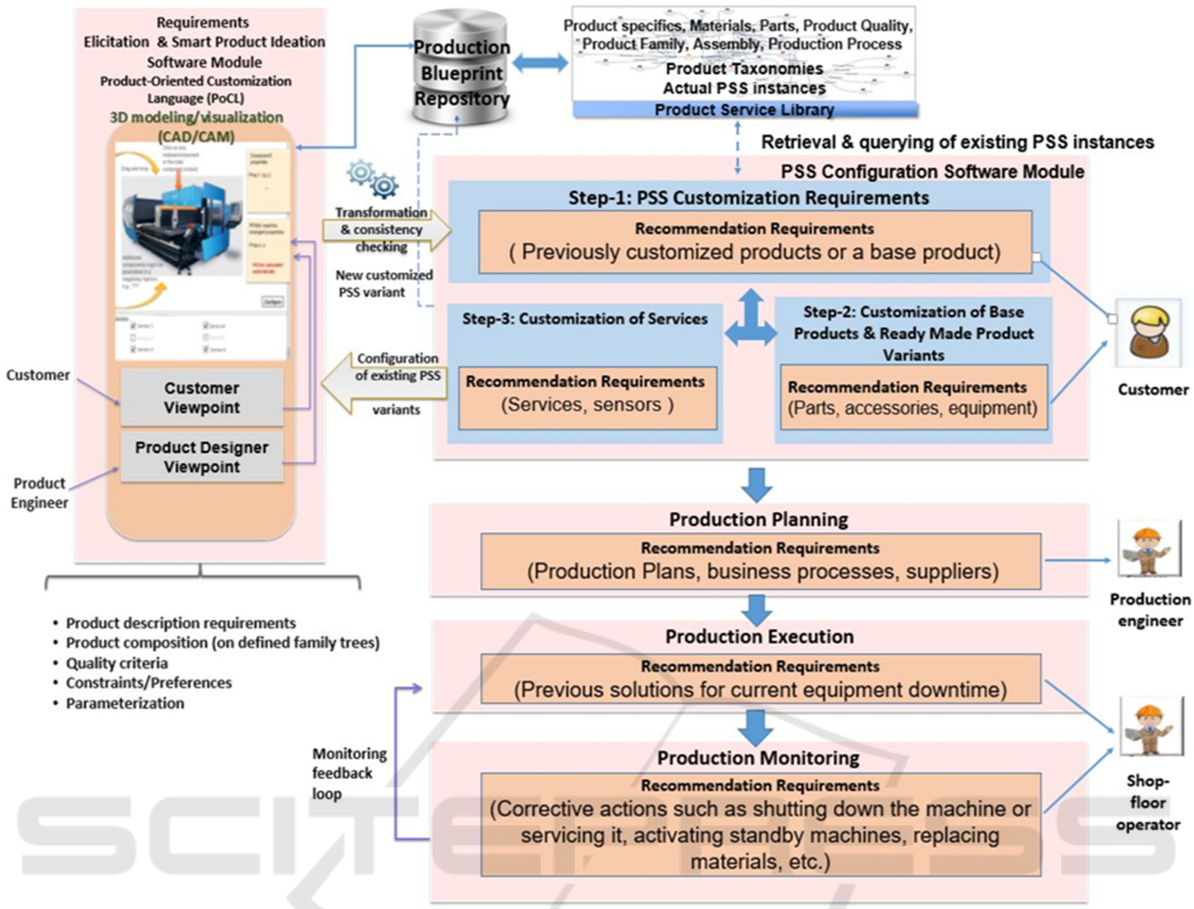

Figure 2: Recommendation framework for PSS customization.

If the value of feature i belongs to numerical class then the similarity function will be defined as the absolute difference between f_i^I and f_i^R as in (2)

$$sim\ (f_i^I, f_i^R) = 1 - \frac{|\, f_i^I - f_i^R \,|}{feature\ value\ range} \tag{2}$$

If the value of the feature i belongs to categorical class, then the similarity function will be defined as in (3)

$$sim(f_i^I, f_i^R) = 1(f_i^I = f_i^R) \tag{3}$$

Implying that the features having the same value get a similarity score of 1 and 0 otherwise. Now assume that the weights of the features as follows: laser generator (0.5), laser power (0.1), laser speed (0.1) and workpiece (0.3).

By using the above function, the similarity values between the customer requirements (input case) and the stored cases (variants) will be as follows:

Similarity (case I, V_1*)* =0.97, *Similarity (Case I,* V_2*)* = 0.47 and *Similarity (case I,* V_3*)* = 0.175.This recommendation facility will rank the stored previously customized variants and will display in a user-friendly and intuitive manner the ranked recommendations that the customer can scrutinize.

Assume that customer chooses to base her new smart product customization effort on recommended V_1. The customer can then tweak the new customized product in many aspects.

If there are no previous cases that match the customer's requirements, we identify two scenarios:

- Scenario 1: the customer may need to update her requirements and the recommendation process described above restarts. This process repeats iteratively until a recommended smart product variant is satisfactory enough to the customer to start with.
- Scenario 2: the system will recommend a base product (base laser machine) where the

customer starts customization efforts from scratch.

Any of these three identified scenarios will eventually result in a new smart product variant that is also stored in the blueprints KB for further reusability.

This recommendation facility opens these opportunities such as: (i) Offering varying levels of product differentiation to accommodate with diverse customers' requirements which will increase the customer retention and satisfaction, (ii) Reducing the time and the cost of doing customization from scratch.

We envision the R&D challenges to support this recommendation facility as follow: (i) Visualizing /presenting recommendations in a user friendly manner, which may be incorporated by utilizing domain-specific languages, 3D visualization, and Augmented and Virtual Reality (White et al., 2016); (ii) Explaining why each of the recommended artefacts are recommended, which would assist the customer to make a more informed decision. This belongs to the stream of descriptive analytics described in section 1. Prominent visualization techniques in this area are tables, text- highlighting, images, diagrams, rating and animation (Richthammer, Sänger and Pernul, 2017). These may be combined with advanced visualization capabilities described above.

The output of this process is a set of validated and well-documented requirements that act as inputs to the next process: "PSS Configuration and Customization".

6.2 PSS Configuration & Customization

Once the user input from Step-1 is validated, the PSS customization process begins. Here, products and services are customized according to the user requirements. At this stage the flow moves to the "PSS Configuration" process (Step-2 in Figure 2) where a customized product is created. This process is interleaved with service customization (Step-3 in Figure 2) where services for the customized products are created in a manner that enables a seamless product and service integration. It is worth noting that PSS customization varies according to the business model, whether it is a B2B or a B2C. In the B2B model, the customer is an advanced customer who can adaptively customize the PSS by adding/removing/replacing components and parts. However, in a B2C model, Customers are typically novice, so, more guide and control should be provided during customization.

Step-2 and Step-3 in Figure 2 are described as follows:

6.2.1 Customization of Base Products & PSS Variants

The customization of base products or PSS variants can be done through two customization scenarios:

- Parameterized Product Customization: the customer with the help of product designer/engineer, performs parameterized customization by adjusting the feature values of the newly customizer PSS. This is done by adjusting desirable values for parameters defined in the respective blueprints models e.g., material types, product dimensions, etc. This results in a new product configuration or variant.
- Adaptive Customization: a more advanced customization can be created by extending a base product with additional pluggable parts, or by replacing existing parts of a base product with new pluggable parts that achieve better functionality while preserving operational consistency.

As shown in Figure 2 the main identified and validated recommendation capabilities for this customization activity are:

- Recommending top N parts, that meets customer requirements;
- Recommending parts that are frequently ordered in line with certain product's part;
- Recommending accessories (e.g., laser glasses, safety curtains, ESD protection).

These recommendation capabilities are provided based on both the customer requirements and the information stored in her profile.

For example, according to the customer requirements described in the pilot case section 4, Req#C, we could recommend the top N cross jet elements to the customer. We may recommend other parts or elements that are frequently ordered when requesting this cross-jet element. In addition, accessories (e.g., welding glasses or safety curtains) are recommended to the customer.

6.2.2 Customization of Services

It involves expansion of existing products by adding smart sensors or Internet of Things communication devices to improve product usage. As shown in Figure 2, the recommendation capabilities identified for this customization activity are:

- Recommending services;
- Recommending sensors.

For example, according to the customer requirements identified in Req#D and Req#E in the pilot case, the recommendation facility will recommend another services that are always accompanied with the requested service such as services to measure humidity or process gases. In addition, sensors and IOT devices that are used to realize the requested service(s) are recommended.

The same challenges and opportunities for the recommendation capabilities identified in the user engagement and smart product ideation process apply here.

6.3 Production Planning

The main aim of this process is to interconnect every step of the production process by transferring individual product specifications into plans, working instructions, and machine configurations, which are to be dispersed to the respective facilities on the shop-floor. As shown in Figure 2 the main identified and validated recommendation capabilities for this process targeting the production engineer are:

- Recommending suppliers: which may provide the production engineer with the best supplier for supplying a certain product's part (e.g., Angle- torch). The recommendation strategy maybe based on machine learning approaches, i.e., Ranking Neural Network (RankNet) (Zhang et al., 2016);
- Recommending previous production plans and business processes: by re-using the production plans and production business processes of previously customized products that are most similar to realize the new customized PSS request.

The same approach used in the user engagement and product ideation process will be used to find the most similar previously customized product then, its associated production plan and production business process in the Blueprints KB are recommended to the production engineer to reuse. In the example explained in Section 6.1, V_1 is the most similar product to the customer requirements, its associated production plan will be recommended to the production engineer as a consequence.

The presence of these recommendation capabilities will open these opportunities: (i) Reducing the time and cost of constructing production plans and processes from scratch; (ii) Avoiding mistakes by adapting the previous successful plans/business processes; (iii) Automatic selection of the best suppliers may reduce the time of locating a supplier manually by the production engineer.

Nevertheless, the existence of opportunities does not mean the absence of obstacles and challenges: (i) Adoption/adaptation of effective and efficient adaptation techniques that will be used to make updates on the recommended solution (e.g., Production plans); (ii) Visualizing/presenting these recommendations in a user friendly manner.

6.4 Production Execution

The purpose of this process is to execute production processes and manage order execution, equipment downtime, assets and manufacturing operation execution. During this process, some machines may be broken down. As shown in Figure 2 the main identified recommendation capability for this process concerns itself by *"recommending previous solutions for current equipment downtime*" that will assist the shop-floor operator.

The recommendation technique may be based on the CBR approach. The knowledge base amounts to a case base, the case represents a diagnostic situation and contains description of the symptoms, the failure and the cause, and description of a repair strategy. By using the Nearest-Neighbor function in (1) the most similar case will be retrieved, reused, refined and stored as a new solution for the current machine problem.

Obviously, the existence of this recommendation capability will open new horizon of opportunities including: (i) Reducing the time and cost for doing maintenance/repair by adopting previous successful solutions; (ii) Increasing customer's trust and retention by promptly and effectively reacting to shop-floor disturbances.

These recommendation facilities face the same challenges of the recommendation capabilities identified in the production planning process.

6.5 Production Monitoring

The aim of this process is to continuously monitor Key Performance Indicators (KPIs) and quality attributes, to ensure quality manufacturing by identifying early signs of problems. In order to assist the factory-floor operator, the main identified recommendation capability for this process is "*recommending a set of corrective actions*" based on the nature of the predicted error, such as shutting down the machine or having it serviced, activating standby machines, etc.

The recommendation strategy to realize this facility may be based on the analysis of machine sensor data, operational data, and process data by applying predictive analytics techniques such as machine learning, data mining and deep learning. Comparing the results of this analysis to historical data stored in quality assurance blueprint, problems are predicted and as a consequence a set of corrective actions are recommended using prescriptive techniques.

The opportunities identified for this recommendation capability are: (i) Increasing machine life time; (ii) Reducing maintenance cost; (iii) Increasing customer trust by committing to delivery time; (iv) Faster detection and correction of problems.

The realization of these recommendations will face some challenges such as: (i) Adoption/adaptation of effective and efficient techniques for collecting vast real-time data and integrating it with historical data are required; (ii) Pre-processing and processing of this large volume of data requires powerful processing tools and techniques; (iii) The availability of condition monitoring tools and sensors is very costly.

7 CONCLUSIONS AND FUTURE WORK

Big data analytics help organizations exploit their data and use it to identify new opportunities. This leads in turn to smarter business moves, more profits and satisfied customers, and more efficient operations. Prescriptive analytics falls under the bigger class of Recommendation Systems (RSs), which has a potential role in assisting involved stakeholders throughout the different processes of the PSS lifecycle for informed decision making.

In this paper we have analyzed and identified a novel recommendation framework that supports all processes of the PSS customization lifecycle introduced in (Papazoglou, Elgammal and Krämer, 2018). In this framework a set of recommendation capabilities are identified for each process. For each recommendation capability, we have identified the challenges and opportunities for its realization. The framework is iteratively built on the basis of case study conducts and the intensive involvement of four major industrial partners as part of the H2020 ICP4Life project.

Future work efforts are ongoing into a number of parallel and complementary directions. This includes extending the blueprints models to meet the realization of the identified recommendation capabilities; in addition, tackling the challenges identified for each recommendation facility and building efficient and effective/theoretical conceptual solutions by utilizing the recent advances in ICT, and developing an integrated manufacturing recommendation tool-suite.

REFERENCES

Aamodt, A. and Plaza, E. (1994) 'CBR: foundational issues, methodological variations and system approaches', *AI Communications*, 7, pp. 39–59.

Ajmani, S. et al. (2013) 'An ontology based personalized garment recommendation system.', in *Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2013 IEEE/WIC/ACM International Joint Conferences on*, pp. 17–20.

Aktas, M. S. et al. (2004) 'A web based conversational casebased recommender system for ontology aided metadata discovery', in *Proceedings of the 5th IEEE/ACM international workshop on grid computing, IEEE Computer Society*, pp. 69–75.

Beel, J. et al. (2016) 'Research-paper recommender systems : a literature survey', *International Journal on Digital Libraries*. Springer Berlin Heidelberg, 17(4), pp. 305–338. doi: 10.1007/s00799-015-0156-0.

Blanco-Fernandez, Y. et al. (2008) 'A flexible semantic inference methodology to reason about user preferences in knowledge-based recommender systems', *Knowledge-Based Systems*, 21(4), pp. 305–320.

Bouraga, S. and Jureta, I. (2016) 'Knowledge-based recommendation systems : A survey Knowledge-Based Recommendation Systems : A Survey', (January). doi: 10.4018/ijiit.2014040101.

Bustinza, O. F. et al. (2015) 'Servitization and Competitive Advantage: The Importance of Organizational Structure and Value Chain Position', *Research-Technology Management*, 58, pp. 53–60.

Carrer-Neto, W. et al. (2012) 'Social knowledge-based recommender system. application to the movies domain.', *Epert Systems with Applications*, 39(12), pp. 10990–11000.

Chattopadhyay, S. et al. (2012) 'A case-based reasoning system for complex medical diagnosis', *Expert Systems*.

Coleman, C. et al. (2018) 'Making Maintenance Smarter: Predictive Maintenace and the digital Supply Network', *Deloitte*.

Donovan, P. O. et al. (2015) 'Big data in manufacturing : a systematic mapping study', *Journal of Big Data*. Journal of Big Data. doi: 10.1186/s40537-015-0028-x.

Elgammal, A. et al. (2017) 'Design for Customization: A New Paradigm for Product-Service System Development', *Procedia CIRP*, 64(December), pp. 345–350. doi: 10.1016/j.procir.2017.03.132.

Ghani, R. and Fano, A. (2002) 'Building recommender systems using a knowledge base of product semantics.', in *Proceedings of the Workshop on Recommendation and Personalization in ECommerce at the 2nd International Conference on Adaptive Hypermedia and Adaptive Web based Systems.*, pp. 27–29.

Hevner, A. et al. (2004) 'Design Science in Information Systems Research', *MIS Quarterly*, 28, pp. 75–105.

Hsu, C. K., Chang, C. K. and Hwang, G. J. (2009) 'Development of a reading material recommendation system based on a multi-expert knowledge acquisition approach.', in *Advanced Learning Technologies. ICALT.*, pp. 273–277.

Kaminskas, M. et al. (2012) 'Knowledge-based music retrieval for places of interest.', in *Proceedings of the second international ACM workshop on Music information retrieval with user-centered and multimodal strategies, ACM*, pp. 19–24.

Khan, A. S. and Hoffmann, A. (2003) 'Building a case-based diet recommendation system without a knowledge engineer', 27, pp. 155–179.

Lee, W. P. (2004) 'Applying domain knowledge and social information to product analysis and recommendations: An agent-based decision support system.', *Expert Systems*, 21(3), pp. 138–148.

Lu, J. et al. (2015) 'Recommender System Application Developments: A survey', *Decision Support Systems*, pp. 1–38.

Nagorny, K. et al. (2017) 'Big Data Analysis in Smart Manufacturing : A Review', pp. 31–58. doi: 10.4236/ijcns.2017.103003.

Papazoglou, M. and Elgammal, A. (2018) 'The manufacturing blueprint environment: Bringing intelligence into manufacturing', *2017 International Conference on Engineering, Technology and Innovation: Engineering, Technology and Innovation Management Beyond 2020: New Challenges, New Approaches, ICE/ITMC 2017 - Proceedings*, 2018 (August), pp. 750–759. doi: 10.1109/ICE.2017.8279960.

Papazoglou, M., Elgammal, A. and Krämer, B. (2018) 'Collaborative on-demand Product-Service Systems Customization lifecycle', *CIRP Journal of Manufacturing Science and Technology*.

Papazoglou, M. P., Van Den Heuvel, W. J. and Mascolo, J. E. (2015) 'A reference architecture and knowledge-based structures for smart manufacturing networks', *IEEE Software*, 32(3), pp. 61–69. doi: 10.1109/MS.2015.57.

Priyanka, P. (2017) 'A Survey Paper on Various Algorithm's based Recommender System', *IOSR Journal of Computer Engineering*, 19(3), pp. 27–32. doi: 10.9790/0661-1903042732.

Richthammer, C., Sänger, J. and Pernul, G. (2017) 'Interactive Visualization of Recommender Systems Data', *Proceedings of the 4th Workshop on Security in Highly Connected IT Systems - SHCIS '17*, (September), pp. 19–24. doi: 10.1145/3099012.3099014.

Song, W. (2017) 'Requirement management for product-service systems: Status review and future trends', *Computers in Industry*, 85, pp. 11–22.

White, M. et al. (2016) 'Tech Trends 2016', *Deloitte University Press*, p. 19. Available at: http://www2.deloitte.com/global/en/pages/technology/articles/tech-trends.html.

Yuan, X. et al. (2013) 'Toward a user-oriented recommendation system for real estate websites', *Information Systems*, 38(2), pp. 231–243.

Zhang, R. et al. (2016) 'Learning to Select Supplier Portfolios for Service Supply Chain', pp. 1–19. doi: 10.1371/journal.pone.0155672.