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Smart Product-Service Systems Solution Design via Hybrid Crowd Sensing Approach

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ABSTRACT The third wave of information technology (IT) competition has enabled one promising value co-creation proposition, Smart PSS (smart product-service systems). Manufacturing companies offer smart, connected products with various e-services as a solution bundle to meet individual customer satisfaction, and in return, collect and analyze usage data for evergreen design purposes in a circular manner. Despite a few works discussing such value co-creation business mechanism, scarcely any has been reported from technical aspect to realizing this data-driven manufacturer/service provider-customer interaction cost-effectively. To fill this gap, a novel hybrid crowd sensing approach is proposed, and adopted in the Smart PSS context. It leverages large-scale mobile devices and their massive user-generated/product-sensed data, and converges with reliable static sensing nodes and other data sources in the smart, connected environment for value generation. Both the proposed hybrid crowd sensing conceptual framework and its systematic information modeling process are introduced. An illustrative example of smart water dispenser maintenance service design is given to validate its feasibility. The result shows that the proposed approach can be a promising manner to enable value co-creation process cost-effectively.

INDEX TERMS Product-service systems, crowd sensing, value co-creation, decision-theoretic rough set, data-driven design, servitization.

I. INTRODUCTION

Nowadays, manufacturing companies are paying ever increasing attention to the sustainability especially environmental impact and economic benefit by providing personalized products with value-added services [1] to meet individual customer demands. Hence, the manufacturing paradigm has progressively shifted from a product-centric manner towards a service-oriented one, and such servitized value proposition is known as product-service system (PSS) [2], [3]. PSS, as a value creation business strategy, underlines delivering the usage and performance of services other than the product itself as a solution bundle [4]. To achieve this, one of the critical issues is to establish a cost-effective mechanism to ensure the success of customized solution (product-service) design. Despite enormous works done in the past on marketing strategies (e.g. crowdsourcing) and systematic design processes (e.g. service blueprint), a typical problem remains not well solved, that is solution design with context-awareness (in-context solution design).

The rapid development of IT has brought various low cost, high performance embedded systems, and hence embraced a promising market of information densely product, viz. smart, connected product (SCP) [5]. Owing to its unique abilities to collect, process, communicate and even "think by itself" with much intelligence [6], it can be utilized as the medium and tool to obtain massive user-generated/product-sensed data in the context-of-usage, and further enables the generation of new services through various analytic tools and business intelligence [7]. Hence, a new paradigm named Smart PSS, was first proposed by Valencia *et al.* [8] as "*the integration of smart products and e-services into single solutions*

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delivered to the market to satisfy the needs of individual consumers''. This IT-driven paradigm can potentially flourish today's manufacturing companies by offering a ''smarter'' way of *servitization* [9], where users and manufacturers are actively interconnected into a value co-creation manner [10], and informatic-based, i.e. data-driven approach serves as the key to identify explicit and latent needs with context-awareness [11]. Nevertheless, except for systematic service design framework [12] and approaches (e.g. lean [13] and service-oriented approach [14]), and an engineering change management approach [15], few works have been reported on a cost-effective approach for Smart PSS solution design.

To address this issue, the state-of-the-art mobile crowd sensing (MCS) concept can be a promising candidate, which leverages large-scale mobile devices and empowers a large number of users to contribute their generated/sensed data for value creation [16]. It extends the scope of participatory sensing by utilizing both participatory sensory data from mobile devices (offline) and user-contributed data from mobile social networking (MSN) services (online). Furthermore, it presents the fusion/collaboration of both human intelligence (i.e. social sensors [17]) and machine intelligence (e.g. pattern recognition, data analytics) in the crowd sensing processes [18].

Inspired by this concept and also to solve the above-mentioned typical problem of in-context solution design, a hybrid crowd sensing approach is proposed by leveraging both the cost-effective MCS with high coverage and static sensing nodes and other data sources with high reliability in a value co-creation manner. Moreover, a novel cost-sensitive machine learning approach, i.e. three-way based decision-theoretic rough set, is adapted to assure the effectiveness of the data collected, and the systematic information modelling process for solution design decision making with wisdoms.

The rest of this paper is organized as follows: Section II reviews related works. Based on that, Section III proposes a conceptual framework to support industrial Smart PSS solution design innovation via hybrid crowd sensing. Section IV further depicts the systematic information modelling process, based on the proposed cost-sensitive machine learning approach. To validate the feasibility and effectiveness of the proposed hybrid crowd sensing approach, an illustrative example of smart water dispenser maintenance service innovation is given in Section V. Finally, the main contributions and future works are concluded in Section VI.

II. RELATED WORKS

To better understand Smart PSS, a review of related works in industrial PSS design with smartness, and MCS with its incentive mechanisms is given below.

A. INDUSTRIAL PSS SDESIGN WITH SMARTNESS

Smart industrial PSS solution design (both engineering and service design) is an emerging topic with the development of IoT, cyber-physical system (CPS) and Big Data [19]. This informatics-based design process emphasizes ''creating valuable information'' [11] and is enabled by massive user feedback and devices equipped with sensing, identification, processing, communication, and networking capabilities [20]. Opresnik and Taisch [21] concluded that it is a data-intensive process, and effective approaches should be adopted to exploit data for new revenues in manufacturing companies. Based on the data source, it can be further classified into two categories, i.e. *user-generated design* and *product-sensed design*.

User-generated design stands for the ones triggered by massive user-generated data acquired from online reviews/comments, audio or video-based text, etc. For instances, Tanev *et al.* [22] examined the value of product-enabled services by utilizing web search tools and online data from end-users. Takenaka *et al.* [23] conducted an analytical study including 600 users' smart appliance logs and their response of the survey on their lifestyles to identify their daily behaviors for new designs. Zheng *et al.* [24] utilizes users' product configuration data and online feedback for customized respiratory mask design and mobile APP services.

Product-sensed design stands for the ones stimulated by the large amount of sensing data generated from SCPs (e.g. machines, wearables). For instances, Ding *et al.* [25] proposed a real-time big data gathering algorithm based on an indoor wireless sensor network for the risk analysis service of industrial operations. Wan *et al.* [26] offered a manufacturing big data solution for active preventive maintenance in a cloud-based manufacturing environment. Tao *et al.* [27] considered the digitalization service innovation, and introduced digital-twin enabled manufacturing services, such as real-time monitoring, fault prediction, energy consumption, etc.

Nevertheless, relying solely on the user-generated data or sensing data is not reliable enough for accurate decision making. Other types of data originated from service reports, maintenance records, can also be utilized as a hybrid way to achieve better wisdom [15]. Moreover, the existing methods to acquire reliable data sources, especially user-generated data are quite costly and time-consuming.

B. MOBILE CROWD SENSING AND ITS INCENTIVE MECHANISM

Smart mobile devices (e.g. smartphones and wearables) own ever-increasing computation and communication capabilities and are equipped with various built-in sensors that allow them to generate data and communicate to the Internet [28]. Meanwhile, such ubiquitous computing is moving from individual sensing to social and urban sensing [16]. Hence, an emerging concept named MCS was first coined by Ganti *et al.* [29] referring to a broad span of community sensing paradigms, with participatory sensing and opportunistic sensing at the two ends considering the level of user involvement. By leveraging large-scale mobile devices and empowering massive users to share surrounding information or accomplish specific sensing tasks, MCS has the advantages of high mobility, scalability and cost effectiveness, which is superior to the static sensing infrastructures and can often replace them [30]. Owing to its great advantages, MCS has been widely adopted in many areas, such as traffic planning [31], unmanned vehicle control [32], landmark measurement [33], to name a few. Guo *et al.* [18] further introduced a concept named mobile crowd sensing and computing (MCSC) by taking both machine (e.g. sensing data) and human intelligence (e.g. crowdsourcing) in the MCS into an overall consideration. It extends the scope by leveraging both participatory sensory data from mobile devices (offline) and user-contributed data from MSN services (online). Hence, other than only collecting data from physical sensors, the MCS participants, acting as the ''social sensors'', have the ability to analyse data and transform into valuable knowledge with context-awareness [17].

Meanwhile, the success of MCS highly depends on the quantity of participants to guarantee the coverage and reliability, thus the system must always maintain a minimum number of active participants with budget constraint [34]. Individuals may feel reluctant to participate and share their sensing knowledge due to the risk (e.g. data privacy) or cost (e.g. data transmission, energy consumption) raised thereafter [22]. Therefore, it is quite challenging that certain incentive mechanisms should be provided to motivate user participation while maintaining the cost-efficiency and data quality. Based on a holistic literature review, the incentive mechanisms can be classified based on: *form of rewards*, i.e. monetary (e.g. reverse auction [35]), services (e.g. social welfare [36]), or entertainment approach (e.g. game [33]); *target object*, i.e. customer-centric (e.g. user fairness [37]) or platform-centric (e.g. service provider benefits [38]); and *level of participation*, i.e. opportunistic (e.g. urban sensing [39]) or participatory (e.g. route planning [31]). One can refer to Tanev *et al.* [22] and Zhang *et al.* [28] for more details. Meanwhile, recent works are not only looking at stimulating user participation, but also sensing quality issues and dynamic changes of budget settings [40], and the overall consideration of all MCS participants, including data collectors, service providers, and service consumers, to join the networks [41].

As pointed out by Shu *et al.* [42], scarcely any works consider the potentials of MCS application in industrial spaces by leveraging both static sensing nodes with high reliability (e.g. service records derived) and MCS with high mobility into a hybrid concern. Meanwhile, few works report on a cost-effective and reliable data collection and information fusion manner for the Smart PSS design.

III. HYBRID CROWD SENSING DRIVEN SMART PSS DESIGN

Aiming to fill the research gaps, the evolvement of IT-driven PSS paradigms towards Smart PSS is first depicted below. Owing to the unique characteristics of Smart PSS, a hybrid crowd sensing approach is hence proposed to support its value co-creation process.

A. FROM PSS TO SMART PSS

Figure 1 outlines the IT-driven PSS evolvement process ever since its first coined in 1999 by Goedkoop [43]. Three phases, i.e. *conventional PSS (1999 -)*, *IoT-enabled PSS (2010 -)* and *Smart PSS (2015 -)* [12], are reasonably categized respectively by its first adopting the new waves of IT innovation, and further assessed based on their smart- and connected-ness.

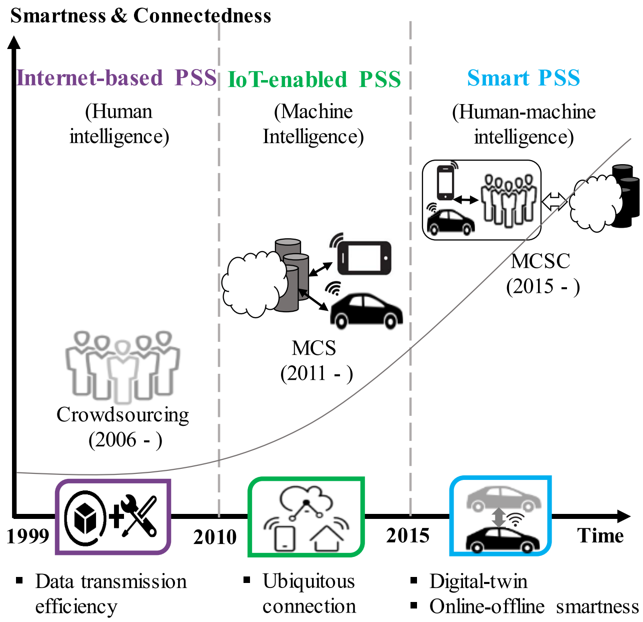


FIGURE 1. IT-driven PSS evolvement with data-driven mechanisms.

The *conventional PSS* benefits from the wide spread of Internet implementation as the first wave of IT innovation in 2000, many e-commerce platforms and online forums enabled an open environment by leveraging the massive human intelligence. In this phase, the major concern of IT-driven value creation lies in the efficient delivery of data/information (e.g. 3G/4G) with little intelligence. *Crowdsourcing* [44], as the practice of obtaining needed services or content by soliciting contributions from a crowd of people, especially from an online community, is a typical way for user-generated design innovation. A well-known example is LEGO Ideas [45], which empowers user's active participation for LEGO bricks design.

The *IoT-enabled PSS* is triggered by the ubiquitous connectivity of billions of mobile devices, vehicles, etc. with the emerging concept of IoT [46]. Sensing data are collected and interchanged among the networked devices, which interact with real ''things'' such as sensors, actuators and RFID, to realize value generation in the Internet with more intelligence. In this phase, the major concern is the machine intelligence for value co-creation. MCS [29], as a typical approach, leverages large-scale smart mobile devices to fulfill various sensing tasks for design innovation. A typical example is the traffic route selection of Google Maps based on GPS in the mobile phones.

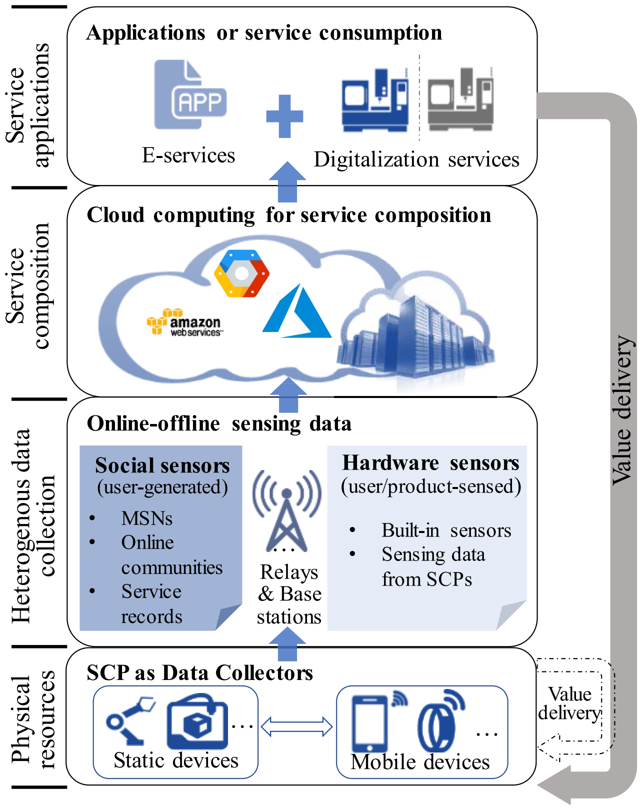


FIGURE 2. Hybrid crowd sensing driven smart PSS design framework.

The emerging *Smart PSS* is enabled by the prevailing adoption of SCPs [5], digital-servitization [47] and the state-of-the-art artificial intelligence (AI) techniques [48]. SCP changes the way value created by embedding IT into the product itself. Hence, it occupies the offline smartness, which can self adaptive to the context by leveraging the embedded systems. Meanwhile, as the tool and medium, SCP communicates with others, and massive user-generated data can be obtianed through MSNs, adapted at a component and system level autonomously based on intelligent algorithms and big data [19], which represents the online smartness [49]. In such context, levels of smartness and connectedness follows the 5C principles defined in [16], and both human and machine intelligence (e.g. MCSC) should be considered integrally to be well-adapted for Smart PSS design.

B. HYBRID CROWD SENSING-BASED SMART PSS DESIGN FRAMEWORK

The proposed hybrid crowd sensing is defined as "*a community sensing paradigm leveraging both the high reliability and performance of static devices and the large-scale, cost-effective mobile devices in a smart, connected environment*". Following this definition, its conceptual framework for manufacturer/service provider-user value co-creation is proposed, as shown in Figure 2. It mainly consists of four layers, i.e. *physical resource layer*, *hierarchical data collection layer*, *service composition layer*, and *service application layer*, conducted in a platform-based data-driven manner.

Physical resource layer, consists of various SCPs, including both mobile devices (e.g. smart phones, wearables, etc.) and static sensing devices (e.g. machine tool equipped with RFID tags). Each device is assigned with a universal unique identifier (UUID) for easy identification and retrieval. Both serve as the main data collectors, and different stakeholders (e.g. manufacturer, service provider and customer) participated in the sensing task with massive user-generated (e.g. service record) and product-sensed (e.g. failure mode) data in a connected environment. For cases, industrial devices (e.g. assembly line) can communicate with mobile devices (e.g. smart phones) through specific communication protocols (e.g. OPC Unified Architecture) so that information can be otherwise collected by the mobile devices alone as the wireless terminals.

Heterogenous data collection layer includes both user-generated online data (e.g. ratings, text feedback) from MSN and/or online communities as social sensors and user-/product-sensed offline data (e.g. location, acceleration, pressure) from built-in sensors and/or sensing data from other connected devices as hardware sensors. Meanwhile, other reliable existing data sources (e.g. product-service information, service records, etc.) should be considered as well. In return, the service providers should give certain incentives to the effective contributors. The wireless data sensed can be submitted to data collectors via access to macro base stations (MBSs) or submitted through little access points (LAPs), such as micro base stations and relay stations from nearby data collectors deployed by manufacturer/service providers [41]. The LAPs work as the middleware to not only receive data, but also pre-process it (e.g. filtering, cleaning) before submission to the data collectors. Nevertheless, due to the limited sensing coverage of LAPs, large-scale mobile devices can also act as temporary relay stations for relaying data collected to the LAPs.

Service composition layer, is responsible for generating novel service concepts, and managing encapsulated services based on request. It is mainly composed by the intelligent system platform established based on the state-of-the-art cloud computing, knowledge-based systems (KBS) and AI techniques. Cloud computing enables ubiquitous access to a shared pool of configurable system resources and higher-level services of end users in a "pay-per-use" business model [50]. It has the advantages of agility, scalability, high-performance computing, social media support, ubiquitous access multi-tenant etc. [51], where service providers/manufacturers in the Smart PSS can achieve abundant design information without capital investment in the IT infrastructure. Meanwhile, by leveraging KBS and AI techniques, valuable knowledge can be extracted, and further analysed from the big data.

Service application layer includes both e-services and digitalization service for uses' applications (i.e. service consumers). E-services stands for the ones that has little dependent with the product itself, e.g. the mobile APP for weather forecasting or industrial news subscriptions. Meanwhile, digitalization services represent the ones that are largely dependent, e.g. smart maintenance services of the product. In the Smart PSS context, these smart services as add-on values, are delivered to the customers by embedding them in the SCPs in an interconnected manner. Hence, the design of Smart PSS can be conducted in a circular manner with sustainability concerns.

IV. PROPOSED SYSTEMATIC PROCESS VIA HYBRID CROWD SENSING FOR SMART PSS DESIGN

Based on the above conceptual framework, to ensure the successful implementation of hybrid crowd sensing for Smart PSS design, as an explorative study, this section introduces a novel systematic process, including *user participation incentive mechanism*, *data collection and transformation*, *reliable information fusion* and its *cost-sensitive decision making*. It is also claimed that this research follows the data privacy regulations, e.g. GDPR (general data privacy regulation), where no personal data is collected, is proposed to ensure users' awareness and consent to the data collected. Nevertheless, the cyber security issues or user data permission process is beyond the scope of this research, and hence not discussed here.

A. USER PARTICIPATION INCENTIVES

To motivate massive users' participation to elicit useful requirement information and to fulfil the sensing task, monetary or service-based incentive mechanism should be provided. In this work, a monetary approach is provided based on the teaching cost [52] and rewarding cost depicted in the Table 1.

TABLE 1. Cost matrix for user participation.

User/service provider action	I	$\sim I$
a	λ_{aa}	λ_{ar}
p	λ_{pp}	λ_{pp}
r	λ_{ra}	λ_{rr}

Where *a, p, r* stands for the design action determined by the service provider, viz. accept, pending and reject, respectively. Meanwhile, I or $\sim I$ stands for the user's action to conduct the design or not. $\lambda \in \{\lambda_{aa}, \lambda_{rr}, \lambda_{ar}, \lambda_{ra}, \lambda_{pp}\}$ stands for the cost/reward given to the users as incentives. Generally, only when user's action matches with service provider's, will a reward be given, viz. λ_{aa} or λ_{rr}. However, in the three-way based incentive model, the pending situations will result in a teaching cost, viz. λ_{pp} to acknowledge the users giving pending feedback, however, the reward will be much less than λ_{aa} or λ_{rr} since service providers need more accurate responses. Also, the misclassification will result in no rewards, i.e. λ_{ra} or λ_{ar}.

B. DATA COLLECTION AND TRANSFORMATION

The heterogeneous data collected, including user-generated data, product sensed data and other existing data sources contain various formats, including numerical data (e.g. distance, temperature) or non-numerical data (e.g. text, audio, video). For the former one, to deal with the high variety of discrete numbers, specific ranges should be pre-defined by service providers to categorize them into different classes. For example, in Table 2, the distance by GPS varied from 1.65 km to 58.09 km can be further classified into very short (VS) (<10 km), short (S) (10 km – 20 km), medium (M) (20 km – 50 km) and long (L) (50 – 100 km). Meanwhile, for the latter one, specific semantics should be extracted and again categorized based on the information fusion techniques. One may refer to [53] for more details. For example, the image can be extracted by the RGB value, x-axis dimension and y-axis dimension, and categorized into the set of {coloured, black and white}. Hence, the heterogeneous data will be fused into a consistent manner with pre-defined classes for further three-way based decision-making process.

TABLE 2. Water dispenser maintenance service records.

Product Type	Failure mode*	User rating	Distance by GPS (km)	Maintenance cost (SGD)	Service provider action
A	CM	5	3.17 (VS)	13 (very low)	Yes
A	CM	5	1.65 (VS)	19 (very low)	No
A	TDS	1	2.24 (VS)	46 (medium)	Yes
A	HM	5	5.54 (VS)	26 (low)	No
A	M	4	58.09 (L)	85 (high)	No
…	…	…	…	…	…
A	E	2	4.27 (VS)	22 (low)	Yes
A	HM	1	25.19 (M)	35 (low)	Yes
A	FV	4	18.85 (S)	9 (very low)	No

C. INFORMATION FUSION BY 4-TUPLE INFORMATION TABLE

The design in the hybrid crowd sensing environment can be structured as a 4-tuple information table:

$$T = (U, A, V, f), \tag{1}$$

where $U = \{x_1, x_2, \ldots, x_{|U|}\}$ is a nonempty finite set of design records, as the universe. $A = \{a_1, a_2, \ldots, a_{|A|}\}$ is a nonempty finite set of attributes and $\forall a \in \{M_H, M_S, S, DI\}$, where M_H is the set of MCS hardware sensing attributes (e.g. GPS location), M_S is the set of MCS social sensor data (e.g. user rating), S is the set of static sensing data (e.g. failure mode), as shown in Table 2. They together form the conditional attributes. While *DI* is the set of design decisions made by service providers, as the decision attributes. $A = M_H \cup M_S \cup S \cup DI$, and $M_H \cap M_S \cap S \cap DI = \emptyset$. V_a is a nonempty set of values for an attribute $a \in$ A. $f: U \times A \rightarrow V$ is an information function, where $f(x_i, a_l) = v_{il} (i = 1, 2, \ldots, |U|, l = 1, 2, \ldots, |A|)$ denotes the attribute value of object x_i under a_l.

D. RELIABLE INFORMATION FUSION

Three-way decision theory [54] is an extension of decision-theoretic rough set approach based on the rough set theory [55], to deal with situations where three possible decisions exist. It has been widely adopted in various applications, such as movie recommendation, filtering spam email, to name a few. It has the unique advantages of scalability, i.e. computing the thresholds of boundary region with flexibility. Therefore, it can be adapted in the hybrid crowd sensing environment for Smart PSS design, to enable information fusion in a structured manner.

In this study, after the data have been transformed into a consistent manner, the indiscernibility relation of the subset of attributes $A_S \in A$ can be defined as [54]:

$$IND(A_S, V) = \{(x, y) \in A_S^2 | \forall a \in V, f(x) = f(y)\}, \quad (2)$$

where two objects x and y are indiscernible with respect to A_S if and only if they have the same value on every attribute in A_S, and for simplicity, the equivalence class of x $\in A_S$ is denoted by [x] in this work where

$$[x] = \{y \in A_S | (x, y) \in IND(A_S, V)\} \quad (3)$$

The partitioning of As induced by V is represented as:

$$As/V = \{s_1, s_2, \ldots, s_N\}, \quad (4)$$

where $\forall s \in As/V$ is an equivalence class, and $\forall(s_i, s_j) \in As/V$, $s_i \cap s_j = \emptyset$, and hence, $P(s)$ represents the probability that a design action is needed (i.e. $f(y)$ = Y) according to the condition attributes:

$$P(s) = |\{y \in A_S | f(y) = Y\}|/|A_S| \quad (5)$$

For example, the first two rows in Table 2 have the same set of condition attributes and values, while they result in different classes in the decision (1 Y, 1 N), hence, the probability of its service action is 50%. Then, the expected cost associated with taking different actions can be written as following equations:

$$C_{aa} = \lambda_{aa} P(x|I) + \lambda_{ar} P(x| \sim I) \quad (6)$$
$$C_{pp} = \lambda_{pp} P(x|I) + \lambda_{pp} P(x| \sim I) \quad (7)$$
$$C_{rr} = \lambda_{ra} P(x|I) + \lambda_{rr} P(x| \sim I), \quad (8)$$

where $P(x|I)$ is the conditional probability of the object x in the condition I. According to Bayesian decision procedure, one can find the minimum-cost decision rules can be written as:

$$\text{If } C_{aa} < C_{pp} \text{ and } C_{aa} < C_{rr}, \quad \text{decide } x \in \text{ Accept} \quad (9)$$
$$\text{If } C_{pp} < C_{aa} \text{ and } C_{pp} < C_{rr}, \quad \text{decide } x \in \text{ Pending} \quad (10)$$
$$\text{If } C_{rr} < C_{aa} \text{ and } C_{rr} < C_{pp}, \quad \text{decide } x \in \text{ Reject} \quad (11)$$

To simplify the rules and follow the incentive mechanism, some constrains are added below:

$$P(x|I) + P(x| \sim I) = 1 \quad (12)$$
$$\lambda_{aa}, \lambda_{rr} \geq \lambda_{pp} > 0, \quad \text{and } \lambda_{ra} = \lambda_{ar} = 0 \quad (13)$$
$$0 < C_L \leq C_U < 1 \quad (14)$$

The C_L and C_U are the lower and upper threshold of the pending region, where probabilities below C_L are in the reject region, ones above C_L are in the accept region, and ones in-between in the pending region, respectively. The threshold values of C_L and C_U can be further calculated as:

$$C_U = \frac{\lambda_{rr} - \lambda_{pp}}{(\lambda_{rr} - \lambda_{pp}) + (\lambda_{pp} - \lambda_{ra})} = \frac{\lambda_{rr} - \lambda_{pp}}{\lambda_{rr}} \quad (15)$$
$$C_L = \frac{\lambda_{pp} - \lambda_{ar}}{(\lambda_{pp} - \lambda_{ar}) + (\lambda_{aa} - \lambda_{pp})} = \frac{\lambda_{pp}}{\lambda_{aa}} \quad (16)$$

Hence, the equations can be denoted as:

$$\lambda_{rr} = \frac{1}{1 - C_U} = \lambda_{pp} \quad (17)$$
$$\lambda_{aa} = \frac{1}{C_L} = \lambda_{pp} \quad (18)$$

Finally, classification decision rules are obtained as:

$$\text{If } P(x|I) > C_U, \quad \text{decide } x \in \text{ Accept} \quad (19)$$
$$\text{If } C_L \leq P(x|I) \leq C_U, \quad \text{decide } x \in \text{ Pending} \quad (20)$$
$$\text{If } P(x|I) \leq C_L, \quad \text{decide } x \in \text{ Reject} \quad (21)$$

E. COST-SENSITIVE DECISION MAKING

From the above equations, one can obtain the total and average cost for user participation as follows:

$$T_c = \lambda_{aa} R_{aa} + \lambda_{pp} R_{pp} + \lambda_{rr} R_{rr}, \quad (22)$$

where R_{aa}, R_{rr} are the total numbers of users who provide the accurate feedback to design action in the accept region and reject region, respectively, and R_{pp} stand for the total numbers of users providing pending reviews.

To maintain the minimum active participation while not exceeding budget, random forest approach is adopted in this research, to predict DI and compute Tc and number of people rewarded based on the three-way incentive model. To test its performance, the total dataset is randomly divided into a training set and testing set to conduct the learning process.

Step 1 (Construction of Random Decision Tree): In the training set, decision-tree learners build a tree by recursively partitioning the data, as depicted in Algorithm I. These trees are merged together to form a random forest.

Step 2 (Design Action Result Prediction): Each random decision-tree produces a prediction result, i.e. $P(s)$, based on the conditional/decision attributes and values. By leveraging theses probabilities, one can obtain the P in the three-way model, as shown in Algorithm II.

Step 3 (Computation of Total Cost and Number of People Rewarded): The pre-defined threshold C_L and C_U are leveraged to compare with the value P to classify different categories based on Eqs. (19-21). Then, both the total number of people rewarded and the cost can be calculated by the cost matrix and Eq. (22), as shown in Algorithm III.

Algorithm 1 Construct Random Decision Trees

```
Input: Training dataset (D_T), Condition attributes
       (A_C), Probability (P), Design action (DI)
Output: A Random Decision Tree (CNode)
Output: New Random Tree
1:  P = P(D_T); // probability of the training set D_T based
    on Eq. (5)
2:  DI = DI(P);
3:  CNode = NewRandomTree (D_T, A_C, DI);
4:  found = false; // Randomly select A_C and split (Line 6
    - 13)
5:  For (a ∈ A_C)
6:      A_C = A_C − {a};
7:      If (InformationGain (a) > 0) then
8:          found =true;
9:          break;
10:     End If
11: End For
12: If If (not found) then
13:     CNode.children = Null;
14:     return CNode;
15: End If
16: CNode.splittingAttribute = a; // Construct random
    tree (Line18 - 26)
17: Na = number of attribute values of a;
18: CNode.children = newbulidRandomTree [Na]
19: For (i = 1 to Na)
20:     D_T(i) = {a ∈ D_T|a(x) = i}
21:     DI = DI(D_T(i));
22:     CNode.children [i] = bulidRandomTree (D_T(i),
        A_C, DI);
23: End For
24: return CNode
```

Algorithm 2 Design Action Prediction Based on Random Decision Tree

```
Output: Current node (CNode), Test dataset (D_t)
Output: DI Prediction Result (Pt)
Output: PredictionbyRandomDecisionTree
        (PRDT)
1: a = CNode.splittingAttribute;
2: j = a(D_t) ;
3: If (CNode.children = NULL) then
4:         return CNode.DI;
5: Else if (CNode.children [j] = NULL) then
6:         return CNode.DI;
7: Else
8:         return PRDT (CNode.children [j], D_t);
9: End if
```

V. CASE STUDY

To demonstrate the feasibility and advantage of the proposed approach, smart maintenance service design, as a typical kind of Smart PSS solution design is adopted, and a case study on a smart water dispenser product (SWD) made by company X is chosen. Unlike most existing companies undertaking maintenance services in a ''on call''-based manner with service records documented manually, company X aims to obtain cost-effective reliable data sources from end users through APP and potentially automate the service recommendation process by leveraging existing datasets (i.e. service records). The end-product SWD, as the static sensing node, is equipped with several embedded sensors to detect water pressure (207-827kPa), water temperature (0.6°-48.0°C), flow rate (1.39-1.89Lpm), flow volume threshold (800 L), total dissolved solids (TDS) (<40 etc. as the S). It can communicate with smart mobile phones with specific APP installed via Bluetooth module to monitor its real-time conditions for failure mode detection. Meanwhile, users can contribute their social sensing data (i.e. M_S), e.g. comments and ratings, and real-time MCS data, e.g. GPS and images (i.e. M_H), to the online community authorized by the manufacturer/service provider. Following such manner, the SWD maintenance service can be performed in a user-centric and cost-effective manner with wide coverage, and the descriptive architecture of its hybrid crowd sensing network is shown in Figure 3. For simplicity, as partially shown in Table 2, a total of 7045 service design action (i.e. *DI*) records (.csv file in the supplementary materials) of product A is analyzed in this research. The initial cost of λ_{pp} is set as 10 SGD, while the records are transformed into pre-defined categories as follows: *failure mode* (flow volume exceeded (FV); general electrical problem (E); TDS > 40; heater malfunction (HM); general mechanical problem (M); cooling malfunction (CM)); *user rating*(rating scale 1-5) ({1, 2} (not acceptable); 3 (pending); {4, 5} (acceptable)), *distance by GPS* (service zones) (very short (<10 km); short (10 – 25 km); medium (25 – 50 km); long (> 50 km)). *Maintenance cost* (very low (<20 SGD); low (20-40 SGD); medium (40 – 60 SGD); high (60 – 100 SGD); very high (>100 SGD)). In this study, *failure mode* is calculated by the microprocessor in the existing SWD based on the abnormal signals detected from the sensors, *user-rating* is pre-defined in a 5-point rating scale, and *distance by GPS* is measured based on the distance between the location of the mobile device and the actual service provider. The data analytics and visualization process are run in the *Jupyter* notebook web application written by Python 3 programming language. The authors exploit several existing libraries, such as *pandas* and *numpy* to do the data mining, data cleaning and extract useful information. The data visualization is achieved by *seaborn* and *matplotlib*, and the random forest model is retrieved from *sciki-learn*.

This original dataset is repeated 20 times with random partitioning (i.e. 20 × cross-validation) to separate them into the training set (50%) as chosen, and testing set (50%) as the remaining based on Algorithm I. Then, based on Eqs. (2-3), 558 equivalence classes are derived out of the 7405 records,

Algorithm 3 Computation of Total Cost and Number of People Rewarded

Input: Dataset of condition attributes and values (D_a), Thresholds (C_U, C_L), Cost for Pending (C_p), *DI* Prediction Result (*Pt*), Number of people rewarded ($Num = 0$)
Output: Total Cost (T_c), *Num*

N = merge D_a and Pt together;
ClassofDesignInnovation(N) using Eq. (19-21);
Define an empty list L_1;
For *($i \in C_U$)*
  Calculate rewards using Eq. (17);
  Define an empty list L_2
  For *($j \in C_L$):*
    Calculate awards using Eqs. (18);
    If ClassofUserAction(N_{ij}) ==ClassofDesignInnovation(N_{ij})
      then Num ++;
      Calculate T_c using Eqs. (22);
      add T_c to a list L_2;
  End For
  add list L_2 to list L_1;
End For
Convert list L_1 to dataframe;
return T_c, *Num* and corresponding C_U, C_L

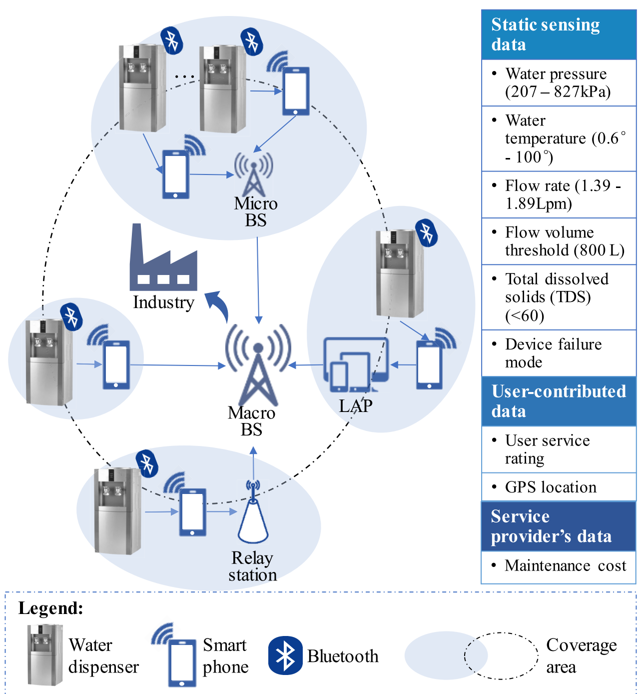
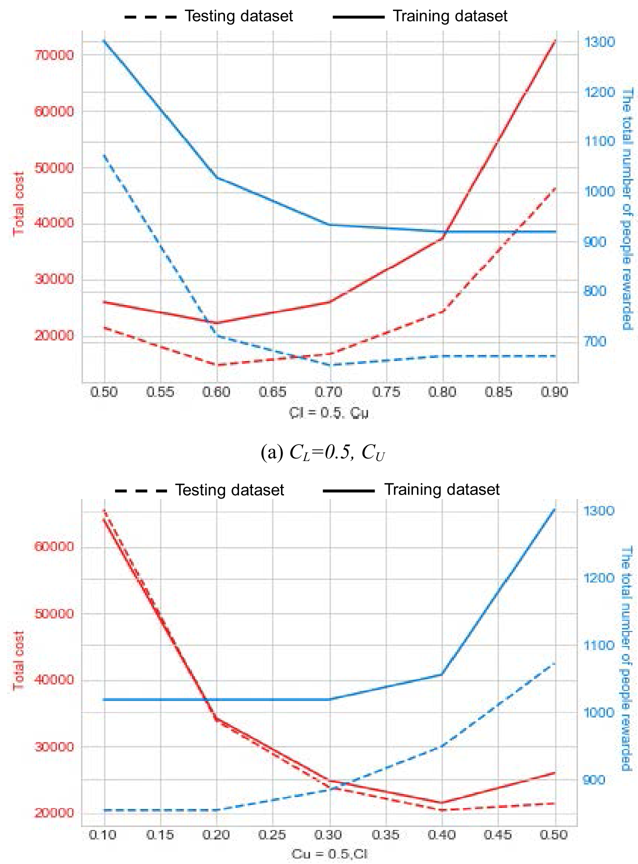


FIGURE 3. General architecture of water dispenser maintenance data collection in a hybrid crowd sensing network.

however, many of them only have 1 or 2 service record, which is not convincing for determining the probability (P). Therefore, the authors set a threshold value of 10 to filter the ones below it, and 273 equivalence classes out of 5655 records are selected based on Algorithm II. Then, by utilizing Eq. (5), $P(s)$ of each class can be calculated to be compared with the C_L and C_U. The ones bigger than C_U are put into the accept region, in-between C_L and C_U in the pending region, and smaller than C_L in the reject region, respectively, based on Eqs. (19-21). Hence, according to Eq. (22) and Algorithm III, the average total cost (in red) and number of people rewarded (in blue) with different combination of C_L and C_U (interval of 0.05) is depicted in the line chart of Figure 4 (a) $C_L = 0.5$, and (b) $C_U = 0.5$, by calculating both the training (solid line) and testing dataset (dashed line), repeating 20 times. One should notice that the situations where $C_U = 0$, or $C_L = 1$ are not considered since they did not even exist according to Eqs. (17-18).



(a) C_L=0.5, C_U

(b) C_U=0.5, C_L

FIGURE 4. Total cost and number of people rewarded in the training dataset and testing dataset: (a) $C_L = 0.5$; (b) $C_u = 0.5$.

From Figure 4, one can find that the minimum total cost lies in where $(C_L, C_U) = (0.5, 0.6)$, while the maximum users get awarded lies in $(C_L, C_U) = (0.5, 0.5)$. Meanwhile, the line chart of training and testing set in Figure 4 matches well, which proves the accuracy of design decisions made and award given. Hence, companies can determine the incentive strategy to half the incentive with pending reviews provided to users to achieve reliable data sources with minimum cost.

Moreover, according to the systematic hybrid crowd sensing process, another point is to discover whether the future design action prediction can be made based on the reliable conditions given. In this experiment, 50%, 60%, 70%, 80% and 90% of the original dataset were randomly chosen as the training set, with the remaining as the testing set. The testing result can be found in Table 3, where the accuracy is determined based on the value of precision (i.e. accuracy) and recall (i.e. sensitivity). One can find that 80% or more of training dataset can result in prediction result with high accuracy, which indicates that the dataset is somewhat robust. Moreover, the approach itself is proven reliable for information fusion, and intelligent to predict design actions without further human intervention.

TABLE 3. Prediction accuracy result.

Percentage of training dataset	Precision (%)	Recall (%)
50%	76	83
60%	81	85
70%	82	84
80%	95	95
90%	90	91

VI. CONCLUSION

The state-of-the-art ICT and AI techniques have enabled a prevailing *servitization* paradigm, i.e. Smart PSS. SCP, as the media and tool for data collection and smart service generation, serves as the key to flourish the companies by offering a novel data-driven co-creation manner. In such context, massive user-generated and product-sensed data can be obtained by the manufacturers/service providers upon users' consent, and further leveraged to create novel applications to the users. This work introduces a hybrid crowd sensing approach with a systematic solution design process for industrial Smart PSS solution design. The main contributions can be summarized into two aspects:

1) *A hybrid crowd sensing paradigm* by combining the prevailing MCS techniques with reliable static sensing nodes in the smart, connected environment for industrial value co-creation in a cost-effective manner. With the ever-increasing computation and communication capabilities of the end mobile devices, bandwidth and latency may be less problematic, but rather the interfaces and tools people utilizing to communicate/collaborate with machines. Hence, the proposed paradigm has several advantages compared to the existing crowd sensing or static sensing approach alone, including: (1) high coverage with reliability concerns, and (2) easy access with better user experience.

2) *The proposed architecture and systematic process for Smart PSS solution design* enables the scalability of active participants selection, and the reliability of data sources and its information fusion for smart decision making. A 4-tuple information table was introduced to organize both user-generated and product-sensed information as per service record in an event-based manner. Meanwhile, a cost-sensitive learning approach was further proposed to facilitate the company to: (1) decide how much incentives to provide to users with reliable data sources and minimum cost, and (2) utilize existing reliable data sources to potentially automate their future maintenance services.

To validate the feasibility and effectiveness of the proposed approach, a case study of a smart water dispenser maintenance service design was illustrated. The result shows that the proposed hybrid crowd sensing approach can be a promising manner to enable design innovation in the Smart PSS context cost-effectively. Nevertheless, this work, as an explorative study, still restricts its scope by only looking at a systematic process to realize the proposed hybrid crowd sensing approach, rather than a detailed comparison with other existing machine learning approaches. Other aspects, such as (1) AI techniques to support heterogeneous knowledge representation and reasoning with computational efficiency; (2) cloud-edge computing architecture for improved hybrid crowd sensing implementation; and (3) in-context user experience and data privacy can be further studied in-depth.

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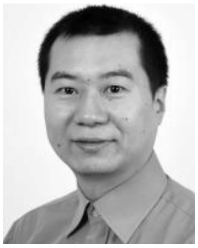

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