# A Platform to Support the Product Servitization

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***Abstract*—Nowadays manufacturers are forced to shift from their traditional product-manufacturing paradigm to the goods-services continuum by providing integrated combination of products and services. The adoption of service-based strategies is the natural consequence of the higher pressure that these companies are facing in the global markets especially due to the presence of competitors which operate in low wage region. By betting on services, or more specifically, on servitization manufacturing companies are moving up the value chain in order to move the competition from costs to sophistication and innovation. The proliferation of new emerging technologies and paradigms together with a wider dissemination of information technology (IT) can significantly improve the capability of manufacturing companies to infuse services in their own products. The authors present a knowledge-based and data-driven platform that can support the design and development of Product Extended by Services (PESs) solutions.**

***Keywords—Product-Services System; Servitization; Service-Oriented Architecture; Ambient Intelligence; Context Awareness; Data Mining***

## I. Introduction

In the pursuit of competitiveness, European manufacturing companies are required to create value by designing and producing the so called products of the future that satisfy an heightened costumer awareness and needs, improve their own operational efficiency and effectiveness while enabling market expansion in Europe and abroad [1]. As a response to this need, manufacturing companies are increasingly shifting from pure manufacturing and delivering of physical product to the provisioning of sophisticated integrated solutions where physical products are enhanced by functions and services [2]. This business trend can be designed as servitization that means the process of creating value in products and goods by adding services. The term was initially coined by Vandermerewe & Rada [3], and now is widely recognized and adopted to identify a specific competitive manufacturing strategy as pointed in [4]. The integration of products and services offers innovative and sophisticated solutions that are distinctive and, above all, easier to defend from competition based in lower cost economies [4]. The trend in servitization is confirmed in [5], where it is claimed that European manufacturing industries of today are under high pressure in the global market due to: 1) the presence of competitors which operate in regions with low-wage and are absolving very fast the available technologies; 2) and to the need to keep pace with science-based innovation processes and products that are creating new markets and new business. The fierce competition for key markets share between manufacturing companies are boosting the search for innovation in both processes and products in order to enable the paradigm migration from cost-oriented to High-Adding-Value (HAV) manufacturing (see Fig. 1). Therefore, the key to competitiveness passes through the capability to provide innovative products, i.e. to provide products that encompasses components, consumer goods and capital goods while extending them with services.

Considering this baseline the research challenge addressed by this work is:

*"Which tools and methodology should be implemented and included in manufacturing companies to enable the extensions of products by services for global markets?"*.

## II. Contribution to Cyber-Physical Systems

As stated in [1] and [6], the provisioning of both products and associated services according to the Product-Service System (PSS) approach will incredibly benefit from an increased product/process intelligence and an overall manufacturing enterprise infrastructure to support both the Product Lifecycle Management (PLM) and Service Lifecycle Management (SLM) integration. Current trends and developments in emerging technologies, such as Internet of Things (IoT), service-oriented, high-performance and distributed computing combined with the increasing advances in manufacturing technologies – embedded control and monitoring systems are radically changing the way product and processes are designed to cope with additional features, improved monitoring and performance – could potentially trigger a new generation of systems which main capabilities relies on local on-device distributed intelligence empowered by global accessibility over the cloud.

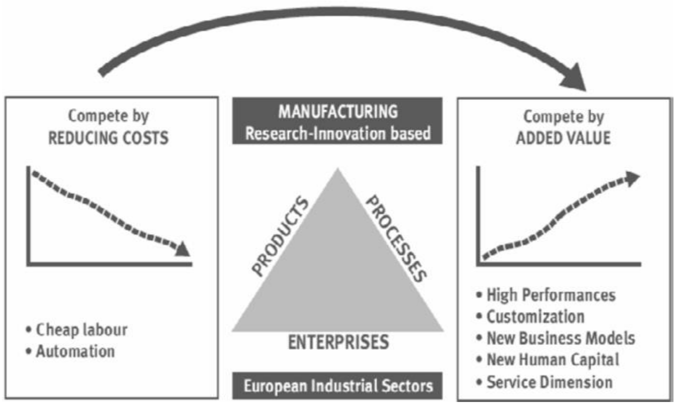


Fig. 1. Competition Shift from reducing costs to High-Added-Value (HAV) [5]

Current work benefits from the CPS research domain that in turn relies on on-device functionalities for monitoring, controlling, optimizing and adapting physical entities, as well as, in-cloud functionalities for delivering advanced features. However, the usage of embedded mechatronics components that combine the physical part with new technologies such as innovative materials, nanotechnologies, and information and communication technology is a necessary but not sufficient condition to allow data extraction from the environment and data processing. As a matter of fact to fully implement the PLM approach, it is necessary to have a totally integrated manufacturing information system for integrating people, data, processes, and business systems and providing product information for manufacturing companies and their extended enterprise , as they are presented in [7]. The combination of smart embedded systems together with a SOA-based infrastructure will allow the extraction of knowledge from products while enabling a fast response in the most different conditions and the design, development and provisioning of services and/or enhanced functionalities associated to these products. In this scenario current work provides such SOA-based infrastructure to fully exploit the capabilities of cyber-physical systems.

## III. Related Areas and Supporting Concepts

### A. Product-Services System

As stated in [8], the first formal definition of PSS has been given by Goedkoop in [9] that identifies its three fundamental elements: i) Product; ii) Service; and iii) System. During the years several definitions for PSS have been given. For instance in [10] a PSS is defined as; “a system of products, services, networks of players and supporting infrastructure that continuously strives to be competitive, satisfy customer needs and have a lower environmental impact than traditional business models”. In [11] PSS is “an innovation strategy, shifting the business focus from designing (and selling) physical products only, to designing (and selling) a system of products and services which are jointly capable of fulfilling specific client demands”. Although the different definitions given all of them adding some elements to the core definition given by Goedkoop. Despite the particular definition of PSS, all the authors in the literature agree in thinking on PSS as a manufacturing business model and/or strategy for manufacturing companies pursuing competitiveness, customer satisfaction as well as sustainable development [12].

### B. Cloud Manufacturing

Cloud Manufacturing (CMfg) is a new paradigm where manufacturing resources and capabilities are virtualized as services available in the cloud to users. This concept was firstly proposed by [13] with the intent to transform the manufacturing business into a new paradigm where manufacturing resources (i.e. physical devices, machines, products, processes, etc.) are transformed into cloud entities. This transformation is also called virtualization and enables for full sharing and circulation of virtualized resources that are capable of providing fundamental information about their own status. This information can potentially be used for local and global optimisation of the whole lifecycle of manufacturing.

### C. Service-Oriented Architecture

Service-Oriented Architecture (SOA) paradigm has emerged and rapidly grown as a standard solution for publishing and accessing information in an increasingly Internet-ubiquitous world. SOA defines an architectural model aiming to enhance efficiency, interoperability, agility and productivity of an enterprise by positioning services as the building blocks through which solution logic is represented in support of realization of strategic goals [14]. The existence of Web Services technology has enabled and stimulated the implementation and development of SOAs. The application of SOA and Web Services in the context of manufacturing layer is still scarce, since a set of persisting technical challenges exists as pointed in [15]. SOA and Web Service are considered promising techniques for integrating all the existing layers within a manufacturing enterprise spacing from business to the physical process. The capability of encapsulating functions and tools as services through standard interfaces and protocols, enables their access and usage by clients without the need to know and control their specific implementations. All these aspects promote the SOA paradigm and its most used implementing technology (Web Services) as the de-facto standards for fast, secure and, above all, easy integration of any new functionality within existing software solutions while electing them as one of the pillars for implementing the CMfg paradigma as also confirmed in [16].

### D. Service Composition

Services are the building block of a SOA, they provide simple interactions between client and server provider. However, sometimes atomic services need to be straightforwardly combined and/or assembled in order to generate more complex ones rising the service abstraction as referred by [17]. In this scenario as argued in [18], the term service composition is referred to the process of developing a composite service. Moreover, a composite service can be defined as the service that is obtained by the composition of the functionalities of several simplest services. Currently in the domain of SOA-based systems, two main approaches can be used for the service composition, namely [19]: orchestration and choreography. As stated in [20], although there is an available assortment of standards for web services orchestration, the most employed are consistently Web Services Business Process Execution Language (BPEL) [21] and Business Process Modelling Notation (BPMN) [22]. Actually the latter is becoming wider popular than the former as also confirmed by several solutions that adopt it [23].

### *E. Ambient Intelligence and Context Awareness*

Ambient Intelligence (AmI) is about sensitive and thus adaptive electronic environments that actively interact with people to fulfill their needs [24]. However, as pointed in [25], people are still far from being immersed in the envisioned scenarios because of two main factors, namely: digital divide, and security and privacy threats. Even if AmI research has not generated the expected result some concepts and principles that are relevant whenever it is necessary to support human in complex and intricate tasks. AmI is strictly related to the design and development of context awareness applications as confirmed in [26]: *"Ambient intelligence a new paradigm of information and communication technologies […] to realize context-aware environments that are sensitive and responsive to the presence of people"*. Context awareness is widely applied in modern ICT solutions for developing pervasive computing applications that are characterized by flexibility, adaptability and are capable of acting autonomously [27]. As exposed in [28], a system is context-aware if it can extract, interpret and use context information to adapt its functionalities and behaviour to the current context. The development of such kind of applications is inherently complex since typically context information is gathered from a variety of sources that differ in quality of information they produce and are usually failure prone [29]. According to [27], the complexity of engineering context-aware applications can be reduced solely using infrastructure capable of gathering, managing and provisioning context information to the applications that require it.

### *F. Data Mining in Manufacturing*

The process of extracting/discovering knowledge from large quantities of data is also known as data mining (DM) [30], [31]. DM can be defined as the process that starting from apparently unstructured data tries to extract knowledge and/or unknown interesting patterns [32]. During this process machine learning algorithms are used.The discovered knowledge can be used for classification tasks, modeling tasks, and to make prediction about future evolution of the analyzed variables. As stated in [33], the application of data mining techniques is quiet old. As a matter of fact, DM has been used and successfully applied in several areas like banking, insurance, fraud detection, telecommunication data etc. for future strategy and planning [34]. However, there are areas where these techniques are not exhaustively explored such as manufacturing. In this scenario, the current proliferation of new technologies and paradigms and the consequent trends in connectivity (cars, home appliance, etc) is pushing the data availability to another level unreached before while empowering the possibility to collect data from products/processes during their lifecycle. The analysis of this data by using data mining techniques is the basis for gaining competitive advantage.

## IV. Research Contribution and Innovation

The research motivation behind this work relates with the strategic objective of allowing the manufacturing companies to enter in a continuous process of upgrading their products along their life cycle in the direction of the Product Service System (PSS) model. A PSS is a function-oriented business model aimed at offering products enriched by services. In this scenario the opportunities to extend products (PES) can be enormously facilitated by the wider dissemination of intelligent devices and, thus, the proliferation of cyber-physical systems. However, these aspects alone are not sufficient if a comprehensive ICT infrastructure – to allow to fully take advantage of intelligent and connected devices – is not provided. Therefore, in line with the research question mentioned in section 1, the research statement that supports the current research work is:

*"The extensions of products by services can be facilitated if a service-oriented cloud-based platform that provides a set of tools and services to support the data extraction, collection and analysis is available"*

Thereby the presence of an ICT supporting environment is a necessary condition to enable and boost the extension of product and processes by services as also presented in [35]–[37], . Such technical environment is aimed at a lower level to gather information from any available resource (product/process) and at a higher level to provide novel mechanisms (such as AmI monitoring, context extraction, data mining and more in general data analysis) in a unified approach to facilitate the extraction of useful knowledge from data. Finally, the presence of the referred technical environment is only the key enabler for extension of products/processes by services and requires to be supported by a strong methodology for driving the users of ProSEco in the complex process of acquiring necessary data related to product/processes and how to transform such "raw data" in valuable and relevant knowledge that in turn will be used as foundation for the creation of new services associated to the selected product/process.

## V. The ProSEco Architecture

The overall aim of the ProSEco project is to implement a novel Cloud-enabled and extensible platform for collaborative design of product/production processes extended by services. To do this a SOA-based software architecture – that describes the ProSEco solution/system and its internal components/modules – has been designed and implemented during the project (see Fig. 2).

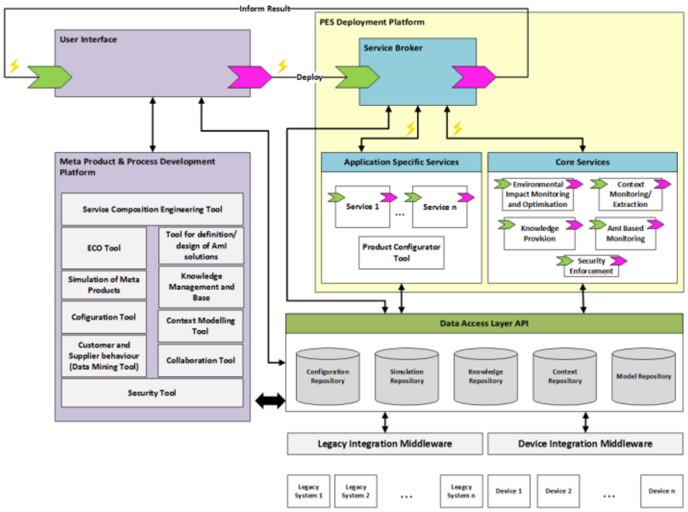


Fig. 2. Collaborative Environment for Product-services design and deployment of PES [48]

The ProSEco solution/system is constituted by two main platform the Meta Product & Process Development platform and the PES Deployment platform. Both the platforms relay on a backbone infrastructure that enables the development, provisioning, and deployment of Product Extensions Services (PES) solutions around the products and their production processes. In particular the Meta Product & Process Development platform provides all the necessary mechanisms to allow the users (PES designers) of the ProSEco system/solution to design/configure their own PES associated to a certain product/process as well as to simulate the meta product offerings in dynamic business ecosystem in order to explore and test the effects of alternative offering designs. In this case a set of engineering tools are provided and are used during these activities. Therefore, the main purpose of the engineering tools could be categorized as in Fig.3. Tools such as simulation of meta-products and user behavior analysis can be used by the industry partners to test the market viability of a new product as well as gathering intelligence from user behavior data to un-derstand how their designs could be further enhanced to be eco-friendly as well as customer friendly. Tools such as context modeling, design of AMI solutions, security and service configuration could be used by the partners to design PES to provide better meta-products and services. On the other hand, tools such as knowledge management, eco-design rules and metrics using LCA techniques and collabo-ration environments provide the industry partners with capabilities to manage their knowledge share their knowledge and collaborate with range of partners to design innovative PES.

On the other hand, the PES Deployment platform provides all the necessary mechanisms to assure the execution of a PES. In this scenario, several core software modules/functionalities are provided to allow the extraction/gathering of data from the environment, the processing/analysis of the extracted data and the provisioning of the results to the user (the data generated by the ProSEco solution/system is the basis for competitive advantage). According to Fig. 2 the PES Deployment platform is constituted by the following modules:

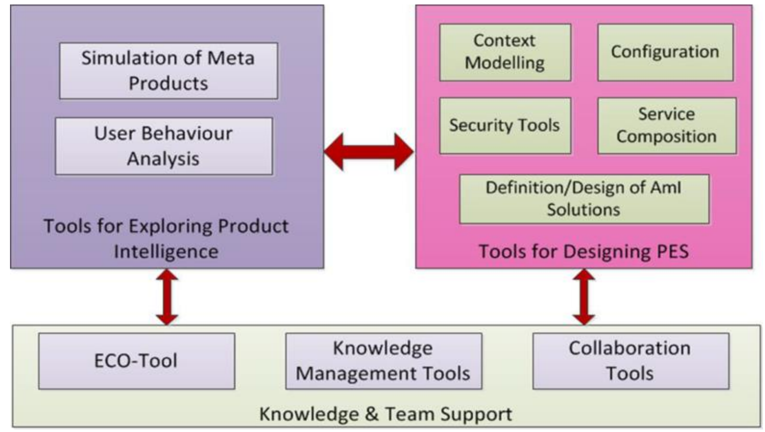


Fig. 3. Categorisation of Engineering tools [48]

- *Service Broker*;
- *Application Specific & Core Services*
- *Data Access Layer*;
- *Integration Layer;*
- *and Security Enforcement.*

Finally, the PES Collaborative Development platform provides the tools for configuring all the necessary elements of the PES Deployment platform whenever a new PES solution needs to be implemented. More details about the components of the ProSEco solution/system can be found in [38] and in [39].

### A. Service Broker

The *Service Broker* module/component is responsible to execute a PES solution designed by using the Meta Product & Process Development platform. It is responsible to identify the application specifc and core services that compose a PES solution and to orchestrate them according to what has been specified in the the Meta Product & Process Development platform and in particular by the service composition engineering tool.

### B. Application Specific & Core Services

The *Application Specific & Core Services* are atomic functionalities that are provided by the ProSEco system and can be used for designing PES solutions. The *Application Specifc Services* represent functionalities that are specific for the particular application scenario. On the other hand the *Core Services* represent core functionality that are generic enough to be used and applied in all the application scenarios. Therefore, a PES solution is basically composed by a set of linked *Application Specific & Core Services* and their configurations.

### C. Data Access Layer

The *Data Access Layer* is responsible to separate the business logic from the knowledge storage. This layer is intended to handle every access (read and/or write) to the repositories. Furthermore, it is responsible to store all the knowledge generated during the ProSEco system runtime and provide this knowledge to other external applications/systems that want use it. In such a way, it facilitates the smoothly integration of the ProSEco system in already existent and deployed IT solution inside a manufacturing company.

### D. Integration Layer

The *Integration layer* comprises the Legacy Integration Middleware and the Device integration Middleware. The former provides wrapper services to integrate legacy systems into the ProSEco architecture. The latter provides an infrastructure to integrate AmI and other devices (intelligent devices) into the platform.

### E. Security Enforcement

The *Security Enforcement* module/component is responsible for controlling the access to the system as well as guaranteeing the integrity and confidentiality of data, and the availability of the system to perform its primary functionality.

## VI. Application Scenario

To validate the current proposal, four business cases from four industrial partners drove the current research work. Each business case is constituted by several application scenarios extracted form concrete/typical situations allowing experimental validation of the ProSEco platform in order to assure that the proposed solution and cloud-based infrastructure as well as the methodology is generic enough and valid to be applied in distinct industrial environments. Thereby, the objective is to use the developed solution to exploit cyber physical features of modern products and processes for extending them by generating services.

In this paper the focus was put over one of the existing application scenarios to validate current infrastructure supported by early test results.

### A. Modelling of the Consumer Behavior

The purpose of the application scenario from Electrolux grounds on the continuous monitoring of the home appliances as a necessary condition to enable the modelling of the consumer behaviour during the home appliance lifecycle (see Fig. 4).

The monitoring process is done in completely anonymous way, without collecting sensitive data, to guarantee the full respect of privacy. In this context, Electrolux intends to deeply use the ProSEco solution for studying advanced post sale services for its customers.

In particular Electrolux plans to apply the ProSEco ICT infrastructure and the entire set of engineering tools for extracting and collecting data from the home appliances during their normal use, with the purpose of analyzing them to collect information capable to improve the User-(i.e. misuse or not efficient use of the home appliance) and, in general, the product performances. The possibility of running this type of User-behaviour analysis, based on a large scale, with different level of clustering (e.g. ethnographic, age-based …) can provide a big amount of feedbacks that was not possible to collect with simple physical products.

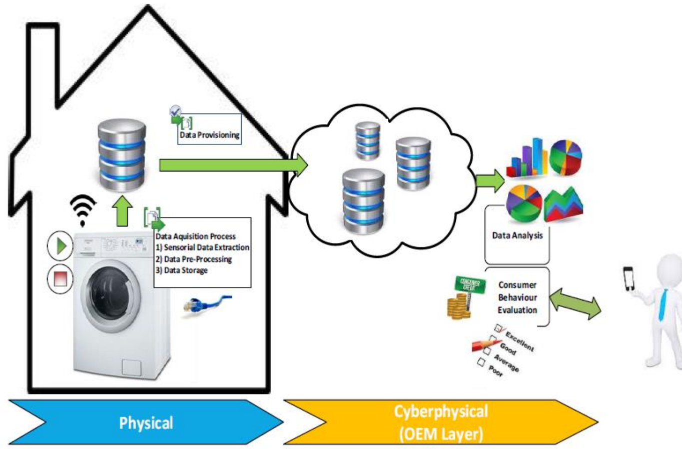


Fig. 4. The concept of the consumer behaviour application scenario

The following functionalities provided by the ProSEco solution are planned to be used during this application scenario:

1) *Meta Product & Process Development platform:*

*a) AmI Monitoring Engineering Tool: to configure the sensorial information to be extracted from the home appliance;*

*b) Context Modelling Engineering Tool: to model the contextual information to be used for extracting and identifying current context from sensorial data;*

*c) Data Mining Engineering Tool: to define the data source and the machine learning algorithm to be applied.*

2) *PES Deployment Platform & Service Composition:*

*a) AmI Monitoring Core Service: to extract and collect sensorial data from the environment;*

*b) Context Extraction Core Service: to extract the context from sensorial data;*

*c) Data Mining Core Service: to analyze the data provided by sensors plus the context enrichment with the goal of modelling the behavior of the consumers.*

### B. Preliminary Experimental Results

To validate the fitness of the proposed approach offline data about some home appliances – provided by Electrolux – has been used. The data has been recorded over several months from 85 refrigerators installed to some pilot customers in the US. The data is stored as a pair (Timestamp, Door_Close), from which atomic information has been derived, such as day of the week (DW), Date and Hour, as depicted in Table I.

A preliminary inspection of the data, described in depth in [49], shows that the values are consistent (e.g. the number of records with Door_Close = TRUE is equal with the number of records with Door_Close = FALSE). Therefore for the experiments only half of the record may be needed in most of the cases.

The objective was to feed the ProSEco solution/system with the provided data in order to test and understand the capability of the system to find patterns and correlation between the data extracted and the behavior of the consumer.

TABLE I. A SNAPSHOT OF THE DATA SOURCE AND FORMAT USED DURING THE EXPERIMENT

| **Data extracted from home appliance** | | | | |
|---|---|---|---|---|
| ***Timestamp*** | ***DW*** | ***Date*** | ***Hour*** | ***Door_Close*** |
| ***15.11.2013 00:28*** | ***6*** | ***15.11.2013*** | ***0*** | ***TRUE*** |
| ***15.11.2013 00:28*** | ***6*** | ***15.11.2013*** | ***0*** | ***FALSE*** |
| ***15.11.2013 01:11*** | ***6*** | ***15.11.2013*** | ***1*** | ***TRUE*** |
| ***15.11.2013 01:11*** | ***6*** | ***15.11.2013*** | ***1*** | ***FALSE*** |
| ***15.11.2013 01:40*** | ***6*** | ***15.11.2013*** | ***1*** | ***TRUE*** |
| ***15.11.2013 01:41*** | ***6*** | ***15.11.2013*** | ***1*** | ***FALSE*** |
| ***15.11.2013 01:44*** | ***6*** | ***15.11.2013*** | ***1*** | ***TRUE*** |

For starting to explore the data, some preliminary analysis has been carried out and the results are depicted in the three chart of Fig. 5, Fig. 6, and Fig. 7.

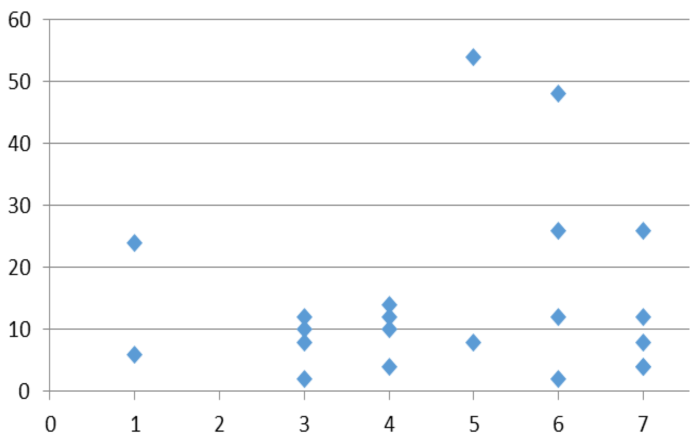

Fig. 5. Results of the preliminary analysis: DW vs Hours of openings

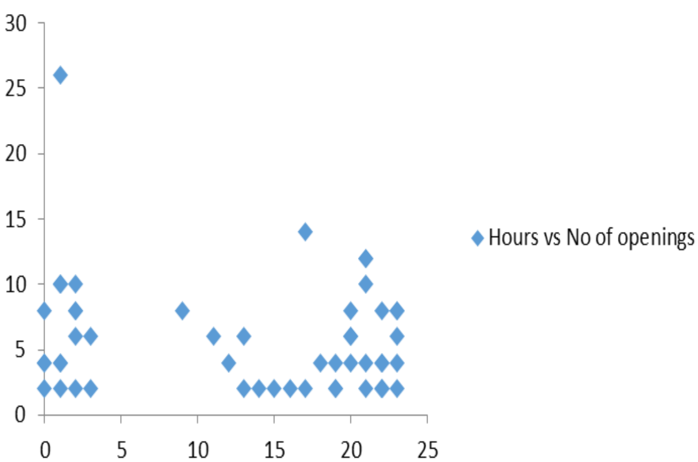


Fig. 6. Results of the preliminary analysis: Hours vs No of openings

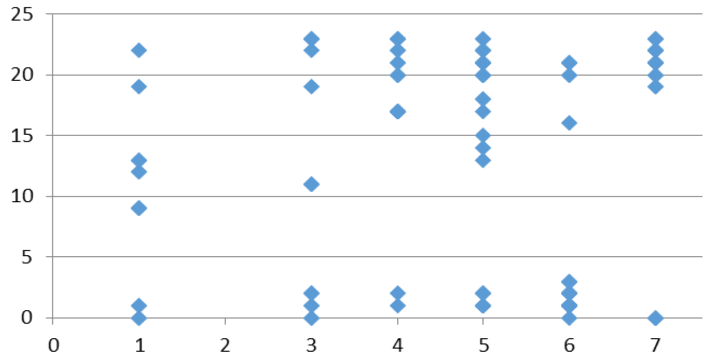

Fig. 7. Results of the preliminary analysis: DW vs No of openings

The chart of the Fig. 5 draws the number of opening vs. the days of the week (1 = Monday… 7 = Sunday). The statistical correlation factor is 0.1097, which shows that there is no significant statistical correlation between the two. But that does not mean that the two data sets are not related in some other way. For instance, it is obvious that on Tuesday the oven is not used at all. The chart of the Fig. 6 displays the number of openings vs. the hours of the day. For relevance of the data, the time consists only of hours, not of minutes, this is all events between 2:00 and 2:59 are recorded on the hour 2. The correlation factor is -0.202 which says that there is no significant statistical correlation (although more than in the previous case – DW vs. number of openings). However, some conclusions can be drawn, such as that the oven is used over the night and is idle from 4:00 to 9:00. The chart of Fig. 7 represents the days of the week ((1 = Monday,…, 7 = Sunday)) vs. the hours of openings. Like in the previous chart, the time contains only the hours, not the minutes. The correlation factor is 0.0247, which means that there is no statistical relation between the two data sets. However, a close look at the plot shows that:

- The oven is not used on Tuesdays;
- The over is not used from 4:00 – to 9:00;
- The time when the oven starts being used goes later over the week:
  - on Mondays, the oven starts working around 9:00;
  - Tuesdays are off;
  - on Wednesdays: starts around 11:00;
  - on Thursdays: starts around 17:00;
  - on Fridays: starts around 13:00;
  - on Saturdays: starts around 16:00;
  - on Sundays: starts around 19:00.

## C. Data Mining Results

The previous section shows obvious relationships between openings and days (of the week). However, the next step is to find them out. To do that three sets of experiments have been carried out, namely:

- determining the number of openings per day;
- determining the next hour when the appliance is opened;
- and determining the interval when the appliance is not used at all.

The experiments have been conducted by using the RapidMiner[1] data mining tool. The applied methodology is similar to the one reported in [50].

*1) Determining the number of openings per day*

This experiment aims to determine how many times the appliance is opened based on the number of openings in the previous days. This would be a good statistical indicator about the usage of the appliance itself. The time window varies from 1 day to 5 days, but only the best results are reported here. The final results of the experiment are summarized in Table II.

*2) Determining the next hour whene the appliance is opened*

This experiment is intended to determine when the appliance is used again, having the previous openings. This is a difficult task as no clear distribution of the usage can be found over the days (see Fig. 5,6 and 7). However, if possible, this is the best indicator. The results are summarized in Table III.

*3) Determining the next hour whene the appliance is opened*

As can be seen in Fig. 3, there is a band over the week when the device is not used at all. The process described here aims to find the bandwidth (minimum and maximum hour). The best results are summarized in Table IV.

TABLE II. ACCUREACY OF THE DATA MINING ALGORITHM FOR DETERMINING THE NUMBER OF USAGES

| **Experiment 1** | | |
|---|---|---|
| **Algorithm** | **Configuration** | **Accuracy** |
| Local Polynomial Regression | Window size = 4<br>Degree = 5<br>Ridge factor = $10^{-6}$<br>Numerical measure = Manhattan distance<br>Neighborhood type = Relative number<br>Relative size = 0.1<br>Smoothing kernel = Gaussian | 45.7% |
| Support vector machine (SVM) | Window size = 7<br>Kernel type = polynomial<br>Kernel degree = 10<br>Kernel cache = 200<br>C = 0<br>Convergence epsilon = 0.01 | 54.3% |
| Neural networks (multi-layer perceptron) | Window size = 7<br>Hidden layers = 0<br>Training cycles = 500<br>Learning rate = 0.5<br>Momentum = 0.3 | 56.8% |

TABLE III. ACCURACY OF THE DATA MINING ALGORITHM FOR DETERMINING THE NEXT OPENING HOUR

| **Experiment 2** | | |
|---|---|---|
| **Algorithm** | **Configuration** | **Accuracy** |
| Local Polynomial Regression | Window size = 5<br>Degree = 2<br>Ridge factor = 10-9<br>Numerical measure = Euclidean distance<br>Neighborhood type = minimum distance<br>Distance = 10<br>Minimum distance = 20<br>Smoothing kernel = exponential | 20.8% |
| k-Nearest Neighbor | Window size = 10<br>k = 5<br>Numerical measure = Bregman divergency<br>Divergence = generalized divergence | 17.0% |

TABLE IV. ACCURACY OF THE DATA MINING ALGIRITHM FOR DETERMINIG THE BANDWITH OF THE NON USAGE HUORS

| **Experiment 3** | | |
|---|---|---|
| **Algorithm** | **Configuration** | **Accuracy** |
| Local Polynomial Regression | Window size = 7<br>Degree = 2<br>Ridge factor = 1<br>Numerical measure = Correlation similarity<br>Neighborhood type = relative number<br>Relative size = 0.5<br>Smoothing kernel = Gaussian | 68.8% |
| Neural networks (multi-layer perceptron) | Window size = 7<br>Hidden layers = 0<br>Training cycles = 500<br>Lear Momentum = 0.2ning rate = 0.6 | 62.5% |
| Support vector machine (SVM) | Window size = 7<br>Kernel type = polynomial<br>Kernel degree = 15<br>Kernel cache = 200<br>C = 0<br>Convergence epsilon = 0.001 | 68.8% |
| Evolutionary SVM | Window size = 7<br>Kernel type = dot<br>C = 0<br>Epsilon = 0.1 | 56.2% |
| k-Nearest Neighbor | Window size = 1<br>k = 15<br>Numerical measure = Correlation similarity | 68.2% |

*4) Wrap-up*

Finally, comparing the three experiments it is obvious that the most difficult task is the determination of the next opening hour. is the most difficult task and the reason is because of the hazardous distribution of the usage over the days, respectively over the week. Predicting the number of openings per day leads to unsatisfactory results. An accuracy of 56.8% is just a little more than 50%. However, finding the bandwidth brings to the best results (68.8%) and this is just a starting point for further research. A summary of the results is presented in Table V.

[1] https://rapidminer.com/

TABLE V. SUMMARY OF THE APPROACHES USED DURING THE THREE EXPERIMENTS

| Summary of the Experiments | | | |
|---|---|---|---|
| **Approch** | **Number of worthy algorithms** | **Best Accuracy** | **Average Accuracy** |
| determining the number of openings per day | 3 | 56.8% | 52.3% |
| determining the next hour when the appliance is opened | 2 | 20.8% | 18.9% |
| determining the interval when the appliance is not used at all | 5 | 68.8% | 64.9% |

## VII. CONCLUSIONS

Current work presents the first implementations of a supporting infrastructure to design PES solutions following the PSS strategy. The proposed solution addresses the extraction and collection of relevant data about the product, the enrichment of data with context and the analysis of the enriched data by suing data mining techniques and statistics. Thereby result of such analysis provide the basis for the implementation of highly personalized advanced services (i.e. maintenance services, post sell, etc.).

The application scenario shows the potential of the proposed solution. The data recorded from the field refrigerators is consistent and relevant, although there is no significant statistical correlation between the datasets compared. However, some heuristics can be drawn, such as:

- The oven is not used on Tuesdays;
- The over is not used at all from 4:00 – to 9:00;
- The time when the oven starts being used goes later over the week.

The data processed covers only seven weeks, which is a reasonable interval for a preliminary analysis. However, for a very thorough research, the data should be gathered over a longer period. Further research will focus also on the utilization of real connected appliances as data source (see Fig. 8). In this case high complexity of data acquisition and real-time data analysis algorithms will be addressed in further research to “fully” utilize the opportunities offered by the proposed solution. In particular, the research presented in this paper is focusing on using the data extracted from home appliances for analyzing and modelling the consumer behavior. However, this is not the only purpose of the proposed research. The next step will be the extraction and analysis of the data to model the behavior of the hardware components installed on the home appliance in order to predict failures and to gather fundamental knowledge that allows the paradigm shift from run-to-failure maintenance to the proactive maintenance strategy. Finally, as future works the proposed reaserch will follow two main paths the *consumer behavior* and the *component behavior* where data mining processes will be adapted and configured for the specific objective of the analysis.

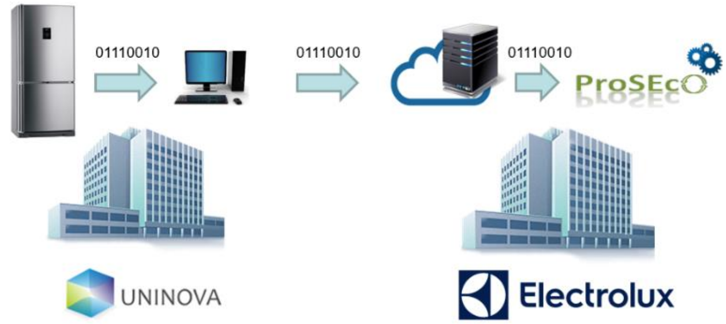


Fig. 8. New experimental setup for further research

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