Applying data mining technique to disassembly sequence planning: a method to assess effective disassembly time of industrial products

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Design for end-of-life and design for disassembly are enabling design strategies for the implementation of business models based on the circular economy paradigm. The paper presents a method for calculating the effective disassembly sequence and time for industrial products. Five steps support designers in defining liaisons and related properties and precedence among components with the aim to calculate the best disassembly sequence and time. The effective disassembly time is computed considering the actual conditions of a product and its components (e.g., deformation, rust, and wear) using corrective factors. This aspect represents the main contribution to the state of the art in the field of design for disassembly. The corrective factors are derived from a specific data mining process, based on the observation of real de-manufacturing activities. The proposed approach has been used for calculating the disassembly times of target components in a washing machine and in a coffee machine. The case studies highlight the method reliability of both: definition of time-effective disassembly sequences and assessment of effective disassembly times. In particular, a comparison of experimental tests shows a maximum deviation of -6% for the electric motor of the washing machine and -3% for the water pump of the coffee machine.

Keywords: Design for disassembly, Disassembly planning, Data mining, Estimated disassembly time, De-manufacturing, Target disassembly.

1 Introduction

Circular economy (CE) is today considered a new business model oriented to increase economic opportunities against resource shortages and waste. Industries and enterprises are supporting the CE perspective by adopting closed-loop life cycle models for the development of new products and services. Recycling, remanufacturing and reusing represent possible scenarios in dealing with this new paradigm.

In this context, product disassembly plays a critical role. Disassembly can be defined as a systematic method for separating a product into its constituent parts, components and subassemblies (Mitrouchev et al. 2015). Disassembly processes are classified into the following categories: (i) complete product dismantling and (ii) selective disassembly of target components (Lambert and Gupta 2008). In particular, selective disassembly is mostly adopted for maintenance/service and for recovery of product components during de-manufacturing operations (Yi et al. 2008).

Product disassembly generally occurs in the last part of the product life cycle, but it originates in the preliminary phases of product design. The analytical assessment of product disassemblability is a key aspect in implementing design for disassembly (DfD) strategies. This analysis is characterized by the definition of elementary activities required to remove components from a product and the definition of best disassembly sequences for each target component. In the design scenario, a metric is necessary to solve the disassembly sequence planning (DSP) problem and thus to compare design alternatives.

The paper proposes a method to solve the DSP problem of complex assemblies using effective disassembly time as a metric for the final assessment. The method is developed according to well-known theories and techniques in this field, and it is grounded on an innovative procedure to calculate the effective disassembly time. In particular, the main novelty proposed by this study is the use of data mining (DM) techniques to define corrective factors used to calculate the effective disassembly time. These factors mainly depend on the liaison features, disassembly tools and the overall condition of the product at the moment of disassembly (wear and rust). Disassembly times have been sampled by the direct observation of de-manufacturing activities at dismantling centres and opportunely clustered and elaborated to obtain standard disassembly times and corrective factors. A specific repository (called Liaison_DB) has been developed to collect all relevant data.

The possibility of achieving a reliable estimation of the effective disassembly time for each sequence and target component represents the main contribution to the state of the art in the field of DfD. The time-based method can be used by designers and engineers during product development to conceive the correct product architecture or to choose the most appropriate joining methods. The aim is to improve the disassemblability of specific parts, thus favouring the implementation of closed-loop strategies (e.g., remanufacturing).

The paper is structured as follows. Firstly, an overview of the state of the art in design for disassembly methods is given, highlighting the limitations of current methods. Secondly, the method and the related algorithms are presented, including the data mining approach for the classification of disassembly information stored in the Liaison_DB repository. Lastly, the paper presents the analysis of two different household appliances (washing machine and coffee machine). The proposed examples demonstrate the usefulness and effectiveness of the proposed approach in real contexts not only for the assessment of the time-effective disassembly sequence but also in the disassembly time estimations' reliability.

2 Research background

Design for disassembly studies began in the early 1990s when environmental concerns related to the disposal of industrial products became a new world challenge (Dewhurst 1993). The literature base is particularly broad due to the multi-disciplinary nature of this topic, including DfD rules and guidelines, DSP, disassembly optimization algorithms, and materials/components recovery (Santochi et al. 2002; Lambert and Gupta 2016). From the perspective of product development (design phase), DSP is considered as a fundamental task to judge the component or subassembly accessibility, as well as the disassembly paths, which give a quantitative measurement of product disassemblability (Favi et al. 2012b). Despite that the final goal of a DfD design project is the minimization of the disassembly time and cost, several objective functions are considered by researchers, such as the shortest disassembly path (minimum number of disassembly operations), minimum number of components to remove, and maximum recycling ratio (Yi et al. 2008).

2.1 DSP methods

Several research activities focus on the development of algorithms and procedures to find the best disassembly sequence for target components in an industrial product. Two main categories of DSP methods can be defined: (i) exact methods (EM) and (ii) heuristic/metaheuristic methods (HM).

Research works based on EM guarantee finding the global optimum in a disassembly problem. Product architecture is first investigated as the basis for the definition of exact disassembly algorithms (Dewhurst 1993; Ong and Wong 1999). Other exact algorithms have been defined based on the *branch-and-bound* concept (Gungor and Gupta 1998; Gungor and Gupta 2001; Zhang and Zhang 2010), as well as the *wave propagation* model (Srinivasan et al. 1997; Mascle and Balasoiu 2003). Most of the mentioned methods aim to find the global optimum in the complete disassembly planning, which is not the goal of selective disassembly. In addition, EM are time-consuming and of limited feasibility when the number of product components or sub-assemblies increases, because of the combinational nature of the problem.

On the other side, research works based on HM were developed proposing the use of *genetic algorithms* (Galantucci et al. 2004; Kongar and Gupta 2006; Giudice and Fargione 2007; Hui et al. 2008; Tseng et al. 2009; Kheder et al. 2017; Meng et al. 2016) or *Petri nets* (Tiwari et al. 2002; Rai et al. 2012; Kuo 2013) to determine the optimal disassembly sequence of a given product. Another way to reduce the complexity of the DSP problem and its representation consists of using simplification methods, such as graphs and matrices. Diagrams and graphs, such as *AND/OR diagrams* (Kara et al. 2005), *Precedence graphs* (Johnson and Wang 1998; Lambert and Gupta 2008), *Connection graphs* (Dong at al. 2006) and *Extended process graphs* (Lambert 2007), were used to represent the DSP problem. Likewise, *Transition matrices* (Lambert 2003; Kang et al.

2010), *Precedence matrices* (Tang et al. 2002) and *Interference matrices* (Ong and Wong 1999) allow to mathematically solve the mentioned representations. Heuristic and simplified methods seem beneficial in terms of computational time, as they search the best sequence without analysing all the possible alternatives. However, exact, heuristic and simplified approaches aim to solve the disassembly problem using the number of disassembly operations or the number of components to remove as an objective function. A literature analysis of DSP methods highlights a lack of information concerning the estimation of disassembly time. The developed methods consider disassembly time as a known input for the final assessment of DSP without exploring the way to quantify and to formalize this input.

2.2 Disassembly time estimation methods

A large set of equations and methods to estimate the assembly time considering the liaison features were developed in the past, starting from the representation of the product architecture (Boothroyd et al. 2010; Mathieson et al. 2013). However, disassembly is not the reverse process of assembly, and the assessment of disassembly time can be drastically different compared with the assembly time of a specific component (Lambert and Gupta 2016; Wang et al. 2017).

Disassembly time depends on several factors, such as component shape, size and weight, joining elements, joining directions, disassembly tools, and equipment (Kondo et al. 2003). It is influenced by the product work load (life cycle stress), working environment, chemical and physical degradation (ageing), deformation, cleanliness, material type, and coating/painting process (Yi et al. 2003). The condition of the product and its constituent components could be uncertain when disassembly occurs, and this kind of information needs to be processed systematically in order to develop any realistic and credible disassembly plan (Zhu and Roy 2015). With such hypotheses, the disassembly time of target components cannot be assessed using the assembly information; however, the evaluation is generally performed at the de-manufacturing centres (Favi et al. 2016). This is the main issue to face if designers want to use disassembly time data when the product is conceived (Favi et al. 2012a). On the other hand, a large amount of information is currently available at dismantling centres, and this information can be sorted and clustered by using DM techniques, with the aim of specifying a disassembly time associated to a specific disassembly task or liaison. DM allows extracting valid, previously unknown, comprehensible information from large databases (Fayyad et al. 1996; Nettleton 2014). DM has been used in design-for-X (Braha 2001) applications, such as design for manufacturing (Bae and Jinhwa 2011) and design for assembly (Kretschmer et al. 2017). The application of DM techniques in DfD has not yet been investigated, and it requires an initial collection and classification of de-manufacturing operations.

A possible classification for mechanical connections and part interfaces was proposed (Matsumoto et al. 2009; Jeandin and Muscle 2016). Whilst the proposed classifications can be considered as the basis for the development of a complete characterization of assembly/disassembly liaisons, they have some limitations. Firstly, they are incomplete and do not propose an effective disassembly time for each specific category or item. Secondly, they do not consider the ageing effect caused by the product lifecycle in terms of corrosion and parts deformation. Lastly, they are based on a theoretical framework and not on experimental measurements and data processing. Some of these limitations have been recently addressed by Mandolini et al., (2018), who proposed a time-based disassembly method, including a preliminary classification of disassembly times for standard assembly components (screws, nuts, etc.) and corrective factors considering life cycle conditions (ageing, deformations, etc.). However, the way of retrieving and clustering disassembly times is not mentioned and argued. This study wants to overcome the state of the art on this topic by proposing a method for estimating the “effective” disassembly time, based on observation/classification/elaboration of data gathered from real de-manufacturing activities.

3 Materials and methods

The objective of the proposed method is to calculate the disassembly time by using an exact DSP approach and a structured repository (called *Liason_DB*) of knowledge about elementary disassembly tasks. Section 3.1 describes the steps required for assessing the time-based disassembly sequences starting from the identification of the target components as well as the effective disassembly time. The complete description of the method can be found in Mandolini et al. (2018), while only a summary and a demonstrative example are reported in the present paper. Section 3.2 presents the full details of the data mining approach followed for establishing the corrective factors used for estimating the disassembly time of a single disassembly operation. This contribution represents the main novelty of this study.

3.1 Proposed disassembly time calculation method

Figure 1 depicts the steps foreseen by the proposed method, which are described in detail in the next five subsections.

Enter Figure 1 here

3.1.1 1st step – Detection of target components from the general assembly

The approach begins by defining the target components of the disassembly analysis. Target components are single components or assemblies (group of components). A target component can be established according to its compliance with the maintenance/service plan during the use phase or compliance with EoL regulations/directives. Furthermore, the definition of the target component can be influenced by the reusing, remanufacturing or recycling strategies of a company, deployed for developing new business models.

3.1.2 2nd step – Analysis of the virtual product model

The second step of the method aims to analyse the product structure starting from the virtual model with its geometrical presentation using a CAD model or without it using the bill of materials (BOM). The following information can be extracted analysing the virtual model: quantity and name of components, general arrangement and physical obstructions among components and subassemblies, and geometrical features of components and subassemblies (e.g., dimensions, weights, materials, cutting edges, holes, and tapered geometry).

3.1.3 3rd step – 'Level' matrix and liaison types

The third step aims to define the disassembly levels, precedence relations and liaisons among components and subassemblies. Starting from the component list, extrapolated during the 2nd step of the method, the 'level' matrix template is initialized (NxN square matrix, where N is the total number of components). Liaison and joining elements (e.g. screws, rivets, and connectors) do not contribute to the definition of the 'level' matrix.

3.1.3.1 Definition of 'level' matrix and disassembly levels

The approach leads with the *disassembly level* concept, defined as '*the level in which one or more components/subassemblies connected to other components/subassemblies can be disassembled without any physical obstruction*.' By defining the disassembly levels of a product, it is possible to reduce the number of feasible paths for the selected target component, avoiding time-consuming calculations of non-optimum disassembly sequences (i.e., sequences with higher disassembly time).

The 'level' matrix development is performed considering two hypotheses.

- *Hypothesis #1*: If *component A* obstructs one or more components (e.g., *component B*) that are in relation only with *component A*, and in case *component A* is removed at *level n*, the other components (e.g., *component B*) are free to be removed at *level n+1.*
- *Hypothesis #2*: If *component C* obstructs *component B* and *component B* obstructs *component A*, then *component A* is free to be removed after *component B* (direct precedence) and *component C* (inherited precedence).

According to the first hypothesis, *level 0* contains all the components that can be disassembled from the general assembly, without any precedence. The components belonging to *level n* can be removed only after removing one or more components of *level n-1*. The method does not foresee the assignment of the level for all of the components because the procedure can be stopped when all of the target components have been reached.

Figure 2 shows a 3D representation of a simple example (gear reducer) used to explain the application of such rules and the related definition of disassembly levels and 'level' matrix.

Enter Figure 2 here

In this example, the gear reducer is composed of twelve components:

① - Housing

② - Worm Gear

③ - High speed shaft

④ - Roller bearing 1

⑤ - Roller bearing 2

⑥ - Motor adaptor

⑦ - Slow speed shaft

⑧ - Retaining plate 1

⑨ - Roller bearing 3

⑩ - Roller bearing 4

⑪ - Bearing cap

⑫ - Retaining plate 2

Figure 3 shows disassembly levels and those components or sub-assemblies that can be removed in each level for the gear reducer example.

Enter Figure 3 here

The identified precedence relations among the product components are used to fill the ‘level’ matrix template. In the ‘level’ matrix, each cell identifies the relation between two components/subassemblies of the general assembly. The cells of the matrix are filled using two possible values as follows:

- ‘1’ for those components in the column that require disassembly before the component in the row being analysed;
- ‘0’ for all other cases.

For example, if *component A* is not related to *component B*, the cell in row A and column B is set to ‘0’ (as well the cell in row B and column A). If *component A* must be removed after *component C*, the cell in row A and column C is set to ‘1’.

An example of a ‘level’ matrix for the gear reducer is proposed in Figure 4. The ‘level’ matrix can be easily read by following each row. For instance, component ⑦ in the matrix in Figure 4 can be removed after the disassembly of two components positioned in level 2 (components ⑨ and ⑩), as well as the two components inherited from level 0 (components ⑧ and ⑫). On the other hand, component ⑤ can be removed after the disassembly of only one component (component ⑥) that is positioned at level 0. An important consideration is that the sum of the items in each row identifies the number of components/subassemblies to remove before reaching the target component. This sum is called 'disassembly depth'.

Enter Figure 4 here

3.1.3.2 Definition of liaison types

The assignment of liaisons types between components is another task of the third step. A *liaison* is defined as '*the type of connection (mechanical and electrical) between two components that can be removed by a specific disassembly operation*'.

This step leverages a comprehensive database (Liaison_DB) containing the typical liaisons (assembly connections) that are properly classified and characterized with the relative standard disassembly times (Favi et al. 2016). Liaisons are classified in classes (e.g., screwed liaisons and electrical liaisons) and types (e.g., screw, threaded rod, and nut). An example of this classification for the 'screw' liaison type of a 'threaded' liaison class is illustrated in Table 1.

Enter Table 1 here

Each liaison type, which refers to a disassembly task, has a specific standard disassembly time. This value refers to a liaison in standard conditions (length, diameter, and tool) and undamaged. The last assumption is important because the purpose of selective disassembly is to recover components without destroying them. For instance, the standard condition for a screw refers to a new screw (not used or damaged) with a hexagonal notch head, a length of 20 mm or less, a diameter between 4 mm and 12 mm and disassembled with a pneumatic screwdriver. In this case, the standard disassembly time (4 seconds) equals the assembly time.

However, the conditions of the liaison (worn, rusted, and deformed) and the tools used to perform the disassembly task influence the effective disassembly time. Indeed, if the product service life is particularly long and perhaps also in a severe working environment, rust and oxides formation, and wear deposition can increase the disassembly difficulties and subsequently the time necessary for the specific activity (e.g., unscrewing). Each deviation from the standard condition must be addressed while calculating the effective disassembly time. Variation in geometrical features (screw length, screw diameter, and screw head type) and variation in assembly/disassembly tools available during the disassembly operations (manual screwdriver and Allen key) are typical examples of corrective factors to be considered. These values are used to adjust the standard disassembly times and thereby obtaining the effective disassembly times, according to equation (1):

$$Te = Ts \cdot \prod_k CF_k \tag{1}$$

where

- Te is the effective disassembly time,
- Ts is the standard disassembly time, and
- CF_k is the corrective factor for the *k-th* liaison property related to the chosen de-manufacturing conditions.

A complete example of the corrective factors defined for the screw liaison types and features is proposed in the Table 1 (the procedure for calculating corrective factors is available in section 3.2). An example of a rusted screw is reported below to better understand the influence of corrective factors. For this liaison type, the parameters are as follows:

- Standard disassembly time (*Ts*) = 4 [s]
- Liaison properties:

  - ✓ Head type: cylindrical with notch → CF_1 = 1
  - ✓ Length: > 20 mm, < 40 mm → CF_2 = 1.1
  - ✓ Diameter: < 4 mm → CF_3 = 1.2
  - ✓ Wear: partially worn / rusted → CF_4 = 1.3
  - ✓ Deformation: not deformed → CF_5 = 1
  - ✓ Tool: spanner → CF_6 = 1.2

- Effective disassembly time (*Te*) = $Ts * CF_1 * CF_2 * CF_3 * CF_4 * CF_5 * CF_6$ = 8.24 [s]

The deviation between the standard and the effective disassembly times justifies the importance of defining corrective factors for each type of liaison. This is an essential feature of the proposed approach for guaranteeing a high reliability in the time estimation.

3.1.4 4th step – Calculation of feasible disassembly sequences

Disassembly 'level' matrix and disassembly levels are the two mathematical models required for the definition of feasible disassembly sequences. The fourth step is based on the following hypothesis:

- *Hypothesis #3*: Considering a generic level *n*, only components belonging to the same level (*n*) or to the subsequent level (*n+1*) are considered for the calculation of the feasible disassembly sequences. After the removal of a component at level *n*, the removal of components which belong to level *n-1* is not considered in the calculation.

This rule allows discarding some sequences from the combinatorial calculation, thus permitting a drastic reduction of the computational time, while keeping the quality and the accuracy of the result.

As reported in Figure 3, the disassembly levels for the gear reducer example are the following:

- Level 0: components ⑥, ⑧, ⑪ and ⑫;
- Level 1: components ④ and ⑤ and sub-assembly ②⑦⑨⑩;
- Level 2: components ①, ③, ⑨ and ⑩;
- Level 3: components ② and ⑦.

The knowledge of the disassembly levels allows calculating the feasible disassembly sequences to reach each target component. Three feasible disassembly sequences for the gear reducer, considering ③ as the target component are reported here below:

- ⑧ → ⑪ → ④ → ⑥ → ⑤ → ⑫ → ③
- ⑧ → ⑫ → ⑪ → ⑥ → ④ → ⑤ → ③
- ⑥ → ⑤ → ⑪ → ④ → ⑫ → ⑧ → ③

In the previous list, each arrow identifies a disassembly operation, i.e., the process to disassemble one component, by removing all the liaisons that link the analysed component with the rest of the assembly. The effective disassembly time for each operation consists in summing the disassembly time for all the liaisons of a component. The disassembly time for each feasible sequence is then calculated as the sum of the different disassembly operations involved in a specific disassembly sequence (equation 2).

$$Seq\_i_{Tx} = \sum_m Op\_m_{Tx} \qquad (2)$$

where

- Seq_i_{Tx} is the disassembly time of the *i-th* sequence to reach the target component *Tx*, and
- Op_m is the disassembly time of the *m-th* operation belonging to the Seq_i_{Tx} sequence.

3.1.5 5th step – Calculation of the best disassembly sequence

The fifth step aims to find the disassembly sequence with the lowest time. It is important to notice that, for complex products, the shortest path (i.e., minimum number of disassembly operations) is not always the best way to reach the target (i.e., minimum disassembly time).

The mathematical model used for determining the best disassembly sequence is a pairwise comparison among the feasible disassembly sequences, realized step by step during the calculation of each feasible disassembly sequence (equation 3).

$$BDS_{Tx} = \min(Seq\_1_{Tx}, Seq\_2_{Tx}, Seq\_3_{Tx}, \dots\ Seq\_i_{Tx}, \dots\ Seq\_n_{Tx}) \tag{3}$$

where

- BDS_{Tx} is the Best Disassembly Sequence for the target component *Tx*,
- Seq_i_{Tx} is the *i-th* feasible disassembly sequence for the target component *Tx*, and
- *n* is the overall number of feasible disassembly sequences for the target component *Tx*.

3.2 Data mining process for calculating corrective factors

The corrective factors used for calculating the effective disassembly time have been defined using a DM approach. As highlighted in the literature, information extracted from data mining processes can be used as knowledge patterns and rules to propose possible suggestions and solutions during product design and product development process (e.g., knowledge-based systems, rules and guidelines for design-for-X). In this case, the process for defining the corrective factors for calculating the effective disassembly times have been defined in accordance to the Fayyad et al. (1996) approach, based on five steps, hereafter described.

3.2.1 Definition of the Business Objectives

This step defines a Data Mining project by setting the motivation, benefits and the business objectives.

a. *Motivation*: define corrective factors for calculating the time for disassembly operations starting from the time for standard conditions. The corrective factors have to consider the liaison conditions at the time of dismantling or during maintenance operations.

b. *Benefits*: support designers in developing products easy to disassemble and make them aware about difficulties in de-manufacturing.

c. *Business objective*: increase competitiveness of products to foster the implementation of the circular economy and/or product service system (e.g., take-back systems).

3.2.2 Data preparation

This step aims to define the source of data and information. Listed below are the activities required in this step.

a. *Parameters to analyse*: definition of the parameters that could affect the disassembly time. Such parameters have been classified in three levels: base parameters (e.g., operating environment, deformation, and weight), liaison class-related parameters (e.g., wear) and liaison type-related parameters (e.g., head type, length, diameter, and unscrewing tool).

b. *Selection of product categories to analyse*: identification of products to be used for gathering disassembly time (mainly mechatronic products in this work).

c. *Classification of the products to disassemble*: the products have been classified for decoupling the relationship among base, liaison class and liaison type parameters. For example, the type-related parameters of a screw have been evaluated primarily considering products that are not worn out, used in a clean and dry environment and not deformed.;

d. *Selection and training of dismantlers and maintainers*: identification of dismantling centres and maintainers for this kind of product. General training about the method to use for collecting data.

e. *Definition of disassembly procedures*: definition of templates used by dismantlers and maintainers for classifying and characterising liaisons and collecting disassembly times. Definition of equipment used for disassembling products. Definition of documentation used by dismantlers for establishing the value for the analysed parameters (e.g., what is the meaning of 'not deformed', 'partially deformed' and 'deformed' for the parameter 'deformation'?).

f. *Disassembly time gathering*: collection of disassembly times and liaisons parameters for the following data analysis. Direct observation/video recording of dismantling operators' activities have been used to collect relevant knowledge about liaisons (duration of each disassembly task, needs of special tools, difficulties of the disassembly or extraction operation).

Spreadsheets have been used to collect conditions and disassembly times for the components and products analysed.

3.2.3 Data analysis

This step aims to define the most common types of data analysis for data mining, which are listed below for the scope of this work.

a. *Clustering of the parameters*: parameters can be classified in two categories, discrete (e.g., screw head type, screwing type) and continuous (e.g., screw length, screw diameter). The first typology of parameters are clustered by definition. Indeed, regulations, unifications or equipment often define predetermined values (e.g., hexagonal head for screws). Continuous or semi-continuous parameters should be clustered for a correct data modelling. The adopted clustering algorithm is the '*k-means*' whose aim is to partition *n* observations into *k* clusters and in which each observation belongs to the cluster with the nearest mean, thereby serving as a prototype of the cluster. The '*elbow*' method was then used to define the optimal number of clusters for each parameter. The elbow method considers the relation between the total within-cluster sum of squares (WSS) and the number of clusters. The optimal number is defined so that adding another cluster does not much improve the total WSS. Figure 5 shows the WSS for the screw diameters clustering process.

Enter Figure 5 here

The number of clusters has been defined for a WSS reduction of 10%. Figure 6 presents the results of the screw head diameter clustering process. The clustering process is performed on the corrective factors for isolating the contribution of the analysed parameter on the disassembly time.

Enter Figure 6 here

b. *Selection of the parameters that influence the disassembly time*. A parameter influences the disassembly time under the following conditions:

   i. The coefficient of determination (R^2) between disassembly time and the investigated parameter is greater than 0.8. A coefficient of determination below this threshold means a poor correlation between the observed parameter and the disassembly time.

   ii. There exist two or more clusters (disassembly time vs parameter) whose mean values (disassembly time for each cluster) deviate no more than 5% from the average disassembly times measured for each value of the observed parameter (e.g., screw head diameter).

3.2.4 Modelling

This step aims to extract patterns from the source data and present results in a user-readable manner.

a. *Analysis of the disassembly times for defining the corrective factors for each parameter*. The definition of the corrective factors for each parameter is performed considering a parameter at a time. Listed below are the six data modelling process steps for determining the corrective factors for the screw head type (Figure 7).

   i. *STEP A*: Plot the average disassembly times measured for specific combinations of disassembly parameters related to a specific liaisons type or class (i.e., unscrewing tool, screw length, screw diameter and screw head type). The table consists of n rows (e.g., cylindrical with hexagonal notch and hexagonal) as the number of clusters for the parameter to be investigated (i.e., screw head type).

ii. *STEP B*: Calculation of the average disassembly time for the combination of the other parameters characterizing the liaison. This value defines the impact of the other parameters on the disassembly time.

iii. *STEP C*: Normalization of the disassembly time measured for each combination of parameters with the average disassembly times previously calculated (Step B). This is the first definition of corrective factor.

iv. *STEP D*: Average the previous calculated corrective factors (Step C) for each cluster of the parameter under investigation (i.e., screw head type). This is necessary for evaluating an average behaviour of the corrective factor for the analysed parameter.

v. *STEP E*: Assessment of the minimum corrective factor among the factors previously calculated (Step D). The minimum corrective factor refers to the optimal disassembly condition for a specific parameter (a screw with a notched cylindrical head is more easily disassemble than the other head types, as seen in Figure 7). This is required for normalizing the same factors.

STEP F: Calculation of the normalized corrective factors based on the easiest to disassemble screw head type (Figure 8Figure 7. Data modelling process for calculating the corrective factors.

vi. Figure 8).

b. *Analysis of the distribution fitting for the corrective factors*: validation of the corrective factors previously calculated (Figure 9).

Enter Figure 7 here

Enter Figure 8 here

Enter Figure 9 here

3.2.5 Deployment

At this stage, the normalized corrective factors previously calculated are ready to be deployed within the formulas for calculating the effective disassembly time (equation 1).

4 Test cases and results discussion

Two household appliances (Figure 10) have been used to test different aspects of the proposed approach. Section 4.1 reports the complete analysis of an old washing machine (Figure 10 A) with the aim to verify the effectiveness of the method in calculating the feasible disassembly sequences, estimating the relative disassembly times and identifying the best disassembly paths for the selected target components. Section 4.2 reports the reliability analysis of disassembly time estimation with respect to real de-manufacturing operations and involves the same model of washing machine (Figure 10 A) and a new model of coffee machine (Figure 10 B).

Enter Figure 10 here

4.1 Testing of the method effectiveness: the washing machine case study

The analysed product is an old washing machine with a lifecycle of more than 15 years. Its intensive use in wet environments caused the formation of rust in the external cabinet and in several screws and fasteners (Figure 10 A). A step-by-step procedure is presented to show how the approach can be practically implemented.

The *Detection of Target Components from the general assembly* (1st step of the method) have been carried out to choose the targets of the disassemblability analysis, according to specific EoL or maintenance aims. The following Table 2 reports the five target components considered for the analyses, together with the motivations that justify the choice.

Enter Table 2 here

The *Analysis of the Virtual product Model* (2nd step of the method) allowed to extrapolate the list of the 20 components/subassemblies composing the washing machine. Those components have been labelled, by using a letter from A to T, and successively used to initialize the 20x20 'level' matrix template.

The *'Level' Matrix, Disassembly Levels and Liaison Type* (3rd step of the method) is characterized by two tasks. The first task (*Definition of Level Matrix and Disassembly Levels*) is related to the setting of the precedence relations among the 20 product components that allow filling the 20X20 'level' matrix (Figure 11 A). An interesting piece of information can be easily derived from this matrix: values reported in the right-hand column represent the disassembly depth of each component/subassembly (i.e., minimum number of disassembly operations before removing the component). For instance, in the case of the analysed washing machine, the component D (Electric motor) has a disassembly depth of 13 that means it has to give precedence (direct or inherited) to 13 other components/subassemblies (the 13 components with a '1' in the relative column). In addition, components B and T (highlighted in green in Figure 11 A) have a disassembly depth equal to 0, which means they can be disassembled first and belong to level '0'. Therefore, all the disassembly sequences necessarily begin with one of those level 0 components. Considering the washing machine example, the Wood panel (component F) that belongs to level ‘1’ has to give precedence to both the components of level ‘0’ (TOP back cover and Back cover); thus, its disassembly can be performed after the disassembly of the components B and T.

The second task (*Definition of Liaison Type*) regards the definition of liaisons between components, which can be performed concurrently with the definition of precedence relations (first task of the 3rd step of the method) in order to reduce the method’s implementation time with real products. The table contained in the Appendix (Mandolini et al., 2018) reports the complete set of the defined precedence relations, liaisons between components and related features and conditions to reach the Electric motor of the analysed washing machine.

Using the defined disassembly precedencies contained in the disassembly ‘level’ matrix (Figure 11), the 4th step of the method (*Calculation of Feasible Disassembly Sequences*) can be performed to generate the disassembly paths for the chosen target components (Table 2). The iterative process for the sequence generation begins considering the initial input information previously extrapolated from the ‘level’ matrix: all the disassembly sequences have to start with components B or T. For instance, starting with the disassembly of the TOP back cover (component B), the complete washing machine ‘level’ matrix can be reduced (Figure 11 B) by eliminating the row and column corresponding to component B and updating the disassembly depth values (calculated by summing the ‘1’ in each row). After the TOP back cover disassembly, the only component/subassembly candidate to be disassembled is the Back cover (component T) that has disassembly depth equal to ‘0’ (in the reduced ‘level’ matrix, Figure 11 B). The disassembly of component T (2nd disassembly operation) releases the Wood panel (component F) that, after the second reduction of the ‘level’ matrix, has disassembly depth equal to ‘0’ (Figure 11 C). Following this procedure, all the feasible disassembly sequences that respect the precedence constraints can be derived.

Enter Figure 11 here

In parallel, by considering the data stored in the Liaison_DB (i.e., standard disassembly time for liaisons, liaison conditions, corrective factors, and disassembly tools), it is possible to calculate the disassembly time and thereby step-by-step discard the non-optimum paths. This is the 5th step of the method (*Calculation of the Best Disassembly Sequence*) that allows to derive the best disassembly sequence for each target component previously identified. As an example, Table 3 reports the best disassembly sequence calculated for the Electric motor, together with the details of the disassembly operations and removed liaisons. By evaluating the output results, it is possible to establish the most critical disassembly operation that is related to the disassembly of the Electro-mec Assembly (operation #10) in this case and in particular, to the presence of 30 electric plugs. If used during the product design process, the method appears to be useful in improving product maintenance/EoL performance.

Enter Table 3 here

4.2 Testing of the method reliability: manual disassembly of the washing machine and coffee machine

The old washing machine model previously introduced (Figure 10 A) and a new coffee machine for domestic applications (Figure 10 B) have been used to test the reliability of the disassembly times estimated through the proposed method and database. In the case of the coffee machine, the selective disassembly aims to reach the following target components:

- Water pump, which could be maintained/substituted during the product lifecycle, and has to be separated at EoL and then potentially remanufactured;
- Electronic board, to treat separately at EoL;
- Boiler, which is important for maintenance reasons (i.e., possible substitution during the useful life).

As was done for the washing machine case study, the time-based disassembly method has been applied for the target components of the coffee machine to estimate disassembly time. Since the approach implementation procedure is the same one illustrated in the context of the washing machine case study (section 4.1), the step-by step analysis is not detailed in the case of the coffee machine and only the final results are reported (Table 4).

Non-destructive manual disassembly operations have been carried out in collaboration with an authorized WEEE dismantling centre for both appliances, to measure the disassembly time of real de-manufacturing operations. A skilled operator, equipped with a full-range of tools (e.g., electric screwdrivers, keys, Allen keys, and pliers) and knowledge of the disassembly sequences to follow for each target component, simulated the real disassembly procedures. During this task, disassembly times are measured one step after another with a stopwatch, and every step is documented to provide detailed feedback on each disassembly operation in terms of time, observed difficulties and notes. Table 4 reports a summary of the obtained results for each target component of both the washing machine and the coffee machine.

Analysing the estimation errors, the gap between the measured and estimated times is in the range 4-10% for all the disassembled target components. The experimental times are systematically higher than the estimated ones, as reported in Table 4. Figure 12 reports, in greater detail, the cumulative disassembly time graph and the step-by-step comparison between the estimated and measured times for the washing machine electric motor (graph on the top) and for the coffee machine water pump (graph on the bottom).

Enter Table 4 here

Enter Figure 12 here

The observed errors for the single disassembly operations are lower than ±15%, which can be considered an acceptable error during the design process. Indeed, the proposed method does not intend to provide an extremely precise estimation of the disassembly time. It mainly aims to guide the decision-making during design activities (e.g., identification of product criticalities and setting a redesign strategy to improve product EoL performance). In both the cases in Figure 12, the graphs of the estimated and measured cumulative disassembly times have a comparable shape and a comparable slope in the most critical point (e.g., disassembly of the Electro-mec Ass. in the washing machine), indicating that the method can be considered sufficiently reliable to support the identification of criticalities and re-design activities.

A reason for the observed inaccuracies is very likely the difficulty to model the heterogeneous wear conditions of components/liaisons through a limited set of corrective factors. This is confirmed by the higher estimation errors observed in the case of the washing machine that was disassembled after 15 years of use, while for the new coffee machine, errors for single operations are lower than ±8%. Moreover, the corrective factors do not account factors related to the operator, such as his/her skills (i.e. experience in disassembling specific products or target components acquired with training courses or experience) and the working environment (i.e. physical ergonomics of the operator when interacting with the product). The lack of such factors represents a limitation of the proposed approach that contributes in underestimating the disassembly times of the target components. Another source of error in the method is related to the prediction of accessibility problems due to component obstruction, product re-orientation or the use of large disassembly tools.

5 Conclusions and future research

The paper presents a method to calculate the effective time for the selective disassembly of target components of industrial products. The approach considers the effective conditions of a product and its components (e.g., deformation, rust, and wear) using corrective factors. This is the main contribution to the state of the art of design for disassembly. The corrective factors are derived from a specific data mining process, based on the observation of real de-manufacturing activities. The knowledge (i.e., experience of de-manufacturing centres), gathered and elaborated through a data mining process, is stored within a specific database, called *Liaison_DB*. Such a result, once implemented by a software tool, can be directly used by designers for calculating the disassembly times of target components and verify compliance with target values. Moreover, by analysing the cumulative disassembly time graph (Figure 12), designers can identify the most critical disassembly operation (namely that one with the highest slope).

The work presented by the authors has been tested with two different household appliances: a washing machine and a coffee machine. The case studies highlighted the reliability of the method for calculating the corrective factors through the data mining approach. The deviations between the estimated disassembly times and the actual ones for the single operations range from -13% to 15% for the washing machine and from -8% to 2% for the coffee machine. The errors in estimating the disassembly time for the selected target components are -6% for the electric motor of the washing machine and -3% for the water pump of the coffee machine. The case studies also highlighted the adaptability of the method to different product families and different conditions of use. Another feature of this approach is the upgradability, because the *Liaison_DB* can be considered as a data structure for storing liaisons and relative properties/factors that can be updated by analysing new product types.

The critical analysis of the proposed method highlights two main limitations. Corrective factors are calculated using a data mining approach by considering just a parameter at a time. Even if the estimated disassembly times are close to the actual ones, for considering mutual dependency of the corrective factors, the data mining method should consider more than a parameter at a time when calculating a corrective factor. Moreover, the two case studies, carried out involving only one operator per product, cannot indicate the dependency between the operator skill and the disassembly time. A broader campaign of experimentation (more products and operators) will be required for this aim.

Future research should be focused on seeking a strategy for combining heuristic and exact methods for disassembly time calculation. First, exact methods, whose use does not imply any preliminary activity, should be used during the product embodiment design phase, with the aim to develop a database of disassembly analyses. Second, such a repository will represent the basic knowledge to be used during the product conceptual design. This integrated approach will make the product disassemblability evaluation feasible during conceptual and embodiment design. Finally, the development of a dedicated software tool, powered with algorithms for automatically recognizing precedence, liaisons and disassembly levels, will be an effective enabling strategy. with the aim to foster the adoption of the presented method and *Liaison_DB* in real design departments.

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Table 1: Corrective factors for a screw liaison type (Mandolini et al., 2018)

Liaison class	**Liaison type**	**Standard disassembly time [s]**	**Liaison property**	**Liaison corrective factors**
Threaded	Screw	4	Wear	Completely worn / rusted = 2 Partially worn / rusted = 1.3 Not worn / rusted = 1
			Deformation	Deformed = 2 Not deformed = 1
			Head type	Hexagonal = 1.2 Hexagonal with notch = 1 Cylindrical = 1.2 Cylindrical with notch = 1 Cylindrical with hex notch = 1.1
			Length	$L \leq 20$ mm = 1 20 mm $< L \leq 40$ mm = 1.1 $L > 40$ mm = 1.2
			Diameter	$D \leq 4$ mm = 1.2 4 mm $< D \leq 12$ mm = 1 $D > 12$ mm = 1.2
			Tool	Screw gun = 1 Spanner = 1.2 Screwdriver = 1.4

Table 2: Target components for the analyzed washing machine

Target Componen t	**Relevant features**	**Motivation for selective disassembly**			
		Legislatio n	**Maintenanc e**	**Remanufacturin g**	**Material Recover y**
Capacitor	Potential failures Potential presence of hazardous substances and materials	X	X		
Water pump	Potential failures Potential use as second-hand component	X	X	X	
Electric motor	Potential failures Potential use as second-hand component	X	X	X	
Heating element	Potential failures		X		
Drum	Economic convenienc e for the recovery of				X

	stainless steel				

Table 3: Operations and disassembly time for the Electric motor component

Operation N°	**Removed component**	**Removed liaisons**	**Estimated disassembly time [s]**
1	TOP back cover	3 screws	14.4
2	Back cover	6 screws	28.8
3	Wood panel	2 guides	9.8
4	TOP guide DX	2 screws	9.6
5	TOP guide SX	2 screws	9.6
6	Concrete weight 1	2 screws	13.8
7	TOP front cover	2 screws	9.6
		1 snap-fit	2.2
8	Control Panel Assembly	3 screws	14.4
9	Detergent box	3 pins	16.6
		3 screws	14.4
		1 snap-fit	2.4
10	Electro-mec Assembly	30 electric plugs	120
		6 screws	28
11	Electric wires	26 electric plugs	67.6
		1 pin	6.5
12	Cabinet	3 pins	18
		3 snap-fits	6.8
		1 nut	4.8
13	Motor support	1 nut	4.4
14	Electric motor	2 screws	11.5
		1 guide	3.2
		Total	416.4

Table 4: Estimated disassembly time vs. Measured disassembly times for the target components of washing machine and coffee machine

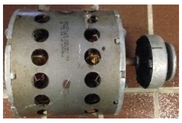
Product	Target component	Estimated disassembly time [s]	Measured disassembly time [s]	Error [%]
Washing machine	Capacitor 	45	48	-6.3
	Water pump 	51	57	-10.5
	Electric motor 	416	443	-6.1
	Heating element 	420	466	-9.9
	Drum 	466	496	-6.0
Coffee machine	Water pump 	227	234	-3.0
	Electronic board 	429	444	-3.4
	Boiler	598	624	-4.2

Figure 1. Workflow of the proposed DSP approach.

Figure 2. Exploded view of the gear reducer example.

Figure 3. Disassembly levels for the gear reducer example.

Figure 4. Disassembly ‘level’ matrix for the gear reducer example.

Figure 5. Within-cluster sum of square (WSS) for screw diameter clustering. The red circle indicates the optimal number of clusters (elbow method).

Figure 6. Screw diameter clustering (k-means algorithm).

Figure 7. Data modelling process for calculating the corrective factors.

Figure 8. Corrective factors for screw head type (cluster view). Within brackets the normalized corrective factors.

Figure 9. Distribution fitting analysis for the corrective factors.

Figure 10. (A) Analysed washing machine and (B) coffee machine models.

Figure 11. ‘Level’ matrices for the washing machine: (A) initial matrix, (B) reduced matrix after the disassembly of component B, (C) reduced matrix after the disassembly of component B and T.

Figure 12. Cumulative disassembly time graph for the washing machine electric motor and for the coffee machine water pump.