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Criteria and Heuristics for Business Process Model Decomposition: Review and Comparative Evaluation

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Abstract. It is generally agreed that large process models should be decomposed into subprocesses in order to enhance understandability and maintainability. Accordingly, a number of process decomposition criteria and heuristics have been proposed in the literature. This paper presents a review of the field revealing distinct classes of criteria and heuristics. The study raises the question of how different decomposition heuristics affect process model understandability and maintainability. To address this question, an experiment is conducted where two different heuristics, one based on breakpoints and the other on data objects, were used to create decompose a flat process model. The results of the experiment show that, although there are minor differences, the heuristics cause very similar results in regards to understandability and maintainability as measured by various process model metrics.

Keywords: *Process modeling, Decomposition, Process model metrics*

1. Introduction

Business process models are used for many purposes, ranging from internal communication and knowledge management, to process improvement and information systems requirements engineering (Becker et al. 2009). Given this multifunctional character, process models need to be captured in a way that facilitates understanding by a variety of stakeholders. In this respect, it is generally accepted that large process models should be decomposed into smaller subprocesses.

While the benefits of such process decomposition are acknowledged (Johannsen and Leist 2012), there is far less consensus as to how a given process model should be decomposed (Reijers et al. 2011). Instead, several guidelines and goodness criteria for process decomposition co-exist and there is a lack of evidential comparison of their relative merits. For instance, some authors propose that the goodness of a decomposition should be assessed using size (Wolter and Schaad 2007; Mendling et al. 2010), while others suggest transposing modularization criteria from information systems (Reijers and Vanderfeesten 2004; Johannsen and Leist 2012). Other studies propose to decompose processes based on data (Ivanović et al. 2010) or adopt a role-based decomposition approach (Khalaf and Leymann 2006). Despite the plethora of available approaches, it has been stated decomposition is more an art than it is a science (Burton-Jones and Meso 2004).

In this setting, this paper addresses two research questions: (1) "*How can process models be decomposed?*" and (2) "*How do different decomposition approaches affect a process model in terms of metrics associated with maintainability and understandability?*" The first question is addressed via a literature review and classification of process model decomposition approaches. The second question is addressed via a controlled experiment. Specifically, two representative decomposition heuristics are used to decompose a real-life flat process model. Then, we compare the resulting set of decomposed process models using a range of maintainability and understandability metrics.

The rest of the paper is structured as follows. Section 2 presents a literature review on process decomposition, a categorization of proposed heuristics and a discussion of observations made. Next, Section 3 introduces and discusses the results from the experiment where different heuristics are applied and compared. Finally, Section 4 concludes the paper and outlines future work.

2. Literature Review

In this Section, we present a literature review aimed at inventorying and classifying existing decomposition approaches to address the research question of "*how can process models be decomposed?*" We also identify metrics used to assess process model understandability and maintainability as basis for our second research question "*How do different decomposition approaches affect a process model in terms of metrics associated with maintainability and understandability?*"

2.1 Search Process

The literature search process was based on the principles of (Kitchenham 2004). We submitted queries to Google Scholar (which encompasses relevant databases such as ACM DL and IEEE Xplore), using three different queries (conducted October 2014). These three queries had one of the following keywords "process model", "process modeling" and "workflow" in combination with all of the following terms; "modularization", "decomposition", "subprocess", "fragment", "abstraction", "refactoring", "hierarchy". The first 400 hits of each of the three queries (1600 hits in total) were examined.

In the first round of filtering, based on title only, we eliminated duplicates and papers that were clearly off-topic. After this iteration, the list shortened to 250 candidate papers. We then proceeded with an inspection of the abstract and the introduction of each paper to eliminate papers that did not deal with process modeling. For instance, many papers deal with decomposition or modularization of information systems or software code but had no significant relation to process models. We also eliminated papers that did not propose specific approaches to process decomposition but instead dealt with another topic and referred to process decomposition as a separate issue. At the end, we obtained 72[1] relevant publications.

An initial analysis of these 72 publications revealed two distinct categories. On the one hand, one subset of publications (55 papers) provided prescriptive methods or guidelines for decomposing a given process model into subprocess. The other subset of the publications (17 papers) proposed *criteria* and associated *metrics* to assess the "goodness" of a given decomposition without prescribing how a process model should be decomposed in order to achieve a suitable level of goodness. Herein, we use the term *decomposition heuristics* to refer to approaches in the first category and *decomposition criteria* to refer to the second category. Below we discuss each category in turn.

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[1] The list of publications can be accessed at http://sep.cs.ut.ee/Main/ProcessDecomposition

2.2 Decomposition Heuristics

From the 55 publications dealing with decomposition heuristics, we found as expected, papers proposing “manual” methods or guidelines for process model decomposition. In addition, we found decomposition heuristics being employed in other related contexts such as refactoring. These are summarized and presented below.

A process model can be decomposed based on “milestones” in the process. For instance, when decomposing existing EPC models (Davis 2001), decomposition is based on points in the process where there are (1) limited connection to other parts of the process, (2) connected events, (3) limited use of loops and (4) a common distinct theme (such as order fulfillment). Another method (Sharp and McDermott 2009) adopt a similar approach where they seek to decompose a process at those points where significant milestones in the overall process are achieved. They are usually points of interest in terms of process measurement. In (Milani et al. 2013), the authors propose aligning the decomposition along variants and milestones.

Others (Ivanović et al. 2010) propose fragmenting a workflow based on data objects by looking at what and how many data inputs an activity has and which other activities share the same data objects. In (de Leoni et al. 2014) the authors utilize data objects in combination with “single entry single exit” (SESE) as basis for decomposition heuristics. These approaches postulate that if many activities use the same data objects, they are related and thus belong in one process fragment.

Another set of approaches, as introduced in (Kim et al. 2005; Khalaf and Leymann 2006) propose that each stakeholder model their own separate processes that then is included as parts of a larger process model. The same idea permeates an approach presented in (Eberle et al. 2009) who consider that process knowledge is fragmented at the local levels (building blocks for a larger process model). As such, each local expert will model their fragment (subprocess) that is subsequently put together with other fragments. Subject-oriented BPM (S-BPM) also sets the subject of the process in focus where decomposition captures the activities performed by a specific role (Turetken and Demirors 2011).

Yet another basis for decomposition is to consider the goal or the output of the process such as in goal modeling (Pohl 2010). In the context of business process modeling, several approaches (Antón et al. 1994; Kueng and Kawalek 1997), determine the decomposition of a business process based on goals and sub-goals. Specifically, elements in the process (e.g. activities) are clustered based on the goals/sub-goals they intend to achieve, and the resulting clusters are mapped to separate subprocesses.

Another set of modeling approaches focus on the iterative characteristics of process fragments, specifically prevalent in product development processes. Product development processes concern the process of transforming a technical solution to a product that can be sold to customers (Westerberg et al. 1997) and often include several iterations of sections of the process. For instance, in (Rogers 1990; Kusiak and Wang 1993; Eppinger et al. 1994; Li and Moon 2012; León et al. 2013) decomposition is based on sequential, parallel or cyclical behavior of process fragments. As such, fragments exhibiting iterative characteristics are clustered together as one subprocess.

Business Process Model Abstraction (BPMA) methods apply techniques on detailed process models for the purpose of generating generalized versions (Polyvyanyy et al. 2010). Therefore BPMA techniques collect and cluster a certain set of atomic activities or subprocesses and represent them with one aggregated subprocess by using selection criteria. The criteria used can be roles (resources), activity frequency or activity completion time, (Smirnov et al. 2012), structural aspects of a process model (Polyvyanyy et al. 2009) or semantic aspects (Sadiq and Governatori 2010; Smirnov et al. 2010). Once the perspective is chosen, the process models are transformed (decomposed) accordingly.

Process model refactoring improves understandability and maintainability of process models by changing them (e.g. decompose) without affecting their execution semantics (Dijkman et al. 2011). Although refactoring entails many techniques, some result in decomposition of activities and subprocesses. These are e.g. redundancy in process models (repetition of the same fragments), which are extracted and put as a subprocess. Another example is lazy process models (subprocesses containing few activities) and techniques aiming at addressing frequently occurring deviations from the main process. These can be managed by representing them with one or more “generalizing” subprocesses (Weber et al. 2011).

In process architecture, decomposition is found either in the form of aggregation (“part-of relation” - process is decomposed into fully contained subprocesses) or generalization (“is-a relation” - process is decomposed into variants representing alternative ways of performing the process) (Muehlen et al. 2010). For instance, in (Muehlen et al. 2010) milestone and stakeholder based decomposition heuristics is proposed. In (Malinova et al. 2013), the authors found that practitioners decompose their process models based on number of elements (size), complexity or stakeholders. Similarly in (Dijkman et al. 2014), five different principles for decomposition are elicited. These are (1) goal-oriented, (2) function-based, (3) reference model-based (adapting an industry reference model), (4) object-based, and, finally, (5) based on business units.

Finally, methods to “parse” a process model into a hierarchy of (SESE) fragments (Vanhatalo et al. 2009; Huang et al. 2014) have been used to decompose process models. Changes in such fragments are locally confined and thus the fragments are independent of each other. These properties allow for fragments to be extracted as a separate subprocesses, thus providing a basis for automated process model decomposition (Uba et al. 2011). For instance label similarity based on SESE extraction techniques has been applied to determine which activities should be gathered in one subprocess (Reijers et al. 2011). This automated decomposition method is based on the assumption that nodes with similar labels (excluding control nodes) are more likely to belong to the same subprocess than those with different labels (measured e.g. via string-edit distance).

When examining the various approaches and their underlying foundation for decomposing process models, we found that the approaches could be categorized based on their common denominator (underlying principle for decomposing). Our analysis distinguished 6 classes of decomposition heuristics based on the following underlying principles; breakpoints, data objects, roles, repetition, sharing and structuredness (cf. Table 1).

Table 1: Decomposition Heuristics

Decomposition Heuristics	*References*
Breakpoints	(Antón et al. 1994; Kueng and Kawalek 1997; Smith and Morrow 1999; Davis 2001; Sharp and McDermott 2009; Muehlen et al. 2010; Milani et al. 2013; Dijkman et al. 2014)
Data Objects	(Ivanović et al. 2010; Conforti et al. 2014; de Leoni et al. 2014; Dijkman et al. 2014)
Role	(Pimmler and Eppinger 1994; Kim et al. 2005; Khalaf and Leymann 2006; Eberle et al. 2009; Muehlen et al. 2010; Turetken and Demirors 2011; Smirnov et al. 2012; Malinova et al. 2013; Dijkman et al. 2014)
Shared Processes	(Rogers 1990; Kusiak and Wang 1993; Eppinger et al. 1994; Weber et al. 2011)
Repetition	(Dijkman et al. 2011; Uba et al. 2011; Weber et al. 2011; Li and Moon 2012; León et al. 2013)
Structuredness	(Sadiq and Governatori 2010; Smirnov et al. 2010; Reijers et al. 2011; Huang et al. 2014)

The common denominator of approaches subsumed by *breakpoints* is their reliance on milestones or breakpoints of the process. In these methods, decomposition is made at points representing natural phases of the business process in its path to fulfill an objective. For instance, heuristics based on goal-decomposition (Antón et al. 1994; Kueng and Kawalek 1997) cut the process at points where sub-goals are achieved. Similarly other authors (Davis 2001; Sharp and McDermott 2009; Muehlen et al. 2010) propose to decompose at points where two subprocesses have distinct themes and therefore constitute different milestones or separate functions in the process. Breakpoints are also used for decomposition in the context of reference process models, for example in the MIT process handbook (Malone et al. 1993).

Object-based heuristics assume that activities sharing common objects belong together and thus should be in one subprocess. These approaches consider the objects as primary driver for decomposition decisions.

Role based heuristics ground their decomposition decisions on "who" is performing the activities (Pimmler and Eppinger 1994; Muehlen et al. 2010; Smirnov et al. 2012). These approaches are applied to collaborative process modeling where different organizations or business units contribute with their own fragments as proposed by (Kim et al. 2005; Eberle et al. 2009), or when modeling for outsourcing purposes (Khalaf and Leymann 2006).

Shared processes subsume approaches, such as (Dijkman et al. 2011; Uba et al. 2011; Weber et al. 2011) that seek to reduce redundancy by modeling process fragments that are called upon multiple times in different parts of a process, a one sub-process.

Repetition-based heuristics, on the other hand, consider the frequency of activities as basis for decomposition. For instance, some (Rogers 1990; Kusiak and Wang 1993; Eppinger et al. 1994) propose separating sets of activities that are repeated more often (cyclical) from those that are sequential or parallel. Another example is the generalization of frequently occurring instance and variant changes into a separate subprocess (Weber et al. 2011).

The final class of heuristics for decomposition is based on the *structuredness* of the process models, i.e. using SESE fragments as a basis for identifying candidate subprocesses (Sadiq and Governatori 2010; Smirnov et al. 2010; Uba et al. 2011; Reijers et al. 2011).

2.3 Decomposition Criteria

In this Section we review metrics associated with process model decomposition rather than specific decomposition heuristics.

It has been shown that larger process models tend to hamper understandability (Reijers and Mendling 2011) and increase the probability of making errors (Mendling et al. 2007). On this basis, “good” subprocesses are neither to small nor overly large (Weber et al. 2011). For instance, the IDEF0 method propose 4 – 6 activities (Muehlen et al. 2010) while some state 5-15 (Kock and McQueen 1996), or 5-7 (Sharp and McDermott 2009) activities per process model. Others propose limiting number of elements to less than 50 (Mendling et al. 2007) or 31 nodes (Rosa et al. 2012). Another study (Cardoso and Mendling 2006) propose considering other size related metrics including number of specific elements such as activities and control-flow elements, or number of activities, joins, and splits in a process model.

Complexity (as various ratios of process model elements) is reversely correlated with understandability and increase probability for errors (Cardoso and Mendling 2006). For measuring complexity, the CFC (aggregated number of branches from all split constructs of a process model) metrics (Cardoso 2005) and HPC (measuring length, volume and difficulty of a process model) metrics (Cardoso and Mendling 2006) have been proposed. Other complexity metric are CNC (number of arcs divided by nodes) (Latva-Koivisto 2001) and CI (number of node reductions required bring a process model to one node). Density (relation between nodes and arcs) of a process model is also an approximation of its complexity. A high density value indicates a more complex process model and is negatively related to understandability (Vanderfeesten et al. 2008a; Dumas et al. 2012). Coupling metrics, as inspired by software engineering, have been transposed to process models such as “density metrics” (Mendling 2006), “cross-connectivity metric” (Vanderfeesten et al. 2008a), “connectedness” (Reijers et al. 2011), “weighted coupling metric” (Vanderfeesten et al. 2007), “process coupling” (Reijers and Vanderfeesten 2004; Vanderfeesten et al. 2008b) and adaptation of coupling metrics for eEPC models (Braunnagel et al. 2014). A common feature of these metrics is that they look at the connectedness of control-flow elements in a subprocess. Therefore, when a collection of nodes are seen as connected to each other, they are more likely to be related and should belong to the same subprocess. Cohesion is closely related to the notion of coupling. Cohesion refers to how much the sub-elements of a given subprocess, are internally connected. Cohesion measure such as "functional", "event" and "logical connectors" are proposed in (Daneva et al. 1996). A cohesion metrics has also been developed based on the "steps" composing an activity and their associated data objects (Reijers 2003; Reijers and Vanderfeesten 2004; Vanderfeesten et al. 2008b).

Our observation distinguished 3 main classes of metrics for decomposition based on the following underlying principles; size, coupling and cohesion and complexity (cf. Table 2).

Table 2: Metrics for Decomposing

Process Model Metrics	*References*
Size	(Kock and McQueen 1996; Cardoso and Mendling 2006; Sharp and McDermott 2009; Muehlen et al. 2010)
Coupling and Cohesion	(Daneva et al. 1996; Reijers 2003; Reijers and Vanderfeesten 2004; Mendling 2006; Vanderfeesten et al. 2007; Vanderfeesten et al. 2008a; Vanderfeesten et al. 2008b; Reijers et al. 2011; Braunnagel et al. 2014)
Complexity	(Latva-Koivisto 2001; Cardoso 2005; Cardoso and Mendling 2006)

2.4 Discussion

We note that some decomposition heuristics can be applied surgically, i.e. on sections of process models that exhibit specific patterns. The "repetition", "shared processes" and "role based" heuristics are possible to implement on process fragments if and only if certain conditions are fulfilled. For instance "repetition" and "shared processes" heuristics are only applicable to process fragments that exhibit such patterns. Likewise, "role based" heuristics offer guidelines for cases with several stakeholders but cannot be applied when for instance, the process of one stakeholder is large and is in need of further decomposing. As such, these heuristics do not provide enough support to be generally applied on a set of process models but rather function as complementary to other heuristics. The "breakpoint", "data object" and "structuredness" heuristics on the other hand, can be applied generally on process models, as they are not dependent upon certain conditions being fulfilled.

Furthermore, we note that the heuristics do not provide sufficient criteria for determining which fragment of the process model to include as a separate subprocess. A heuristic might offer necessary criteria (statements on how to decompose) but not sufficient criteria (statements determining which process fragments to include in a subprocess). For instance, "structuredness" provides necessary criteria (SESE blocks) but not sufficient criteria for determining which SESE fragment to use (usually there are many such fragments in a subprocess). It is possible to set threshold values that assists as a "guide" for determining which activities to include in a subprocess but such strategies are not sufficently refined yet (Reijers et al. 2011). In similar manner, "breakpoint" and "data object" provide necessary but not sufficient criteria. For instance the breakpoint heuristics do not give enough guidance for identifying "milestone steps" in a process. Similarly, data object heuristics lack proper guidance for determining when a set of activities shares the same set of data objects. As such, there are currently no heuristics that provide both necessary and sufficient criteria for process model decomposition. However, in contrast to "structuredness", breakpoint and data object heuristics, while not offering sufficient criteria, can be applied by relying on the knowledge of the domain experts and should, intuitively, produce process models that better reflect the actual business processes. It should be noted that the data object heuristics not only requires that the data objects be modeled but that they are captured in a consistent manner across the process models. Otherwise it would be very difficult, if not impossible to apply this heuristics.

We also note that the heuristics for decomposition are highly inspired by conceptual modeling while metrics for assessing decompositions are direct transposition of metrics from programming and software design to process models (Cardoso and Mendling 2006; Muketha and Ghani 2010). For instance, coupling and cohesion metrics are inspired by Wand and Weber (Johannsen and Leist 2012), size from lines of code (LOC) (Cardoso and Mendling 2006), modularity from information flow by Henry and Kafura (Cardoso and Mendling 2006) and complexity from McCabe's cyclomatic complexity metrics (Muketha and Ghani 2010). As such, decomposition heuristics and metrics have emerged quite independently of each other as separate streams of research. In the literature on process model metrics, there are no substantiated claims that a certain metric is more suited for use together with a certain decomposition heuristics.

3. Controlled Experiment

In this Section we analyze the second research question on "*how do different decomposition heuristics affect a process model in terms of metrics associated with maintainability and understandability?*" To answer it we performed an experiment.

Subjects: The experiment was conducted in April 2015 with second year master students of a BPM course. The population consisted of 36 (voluntary) students who were in their third month of a course on business process management. As such, they had gained the required background and familiarity required for reading, understanding and working with process models. Each student was randomly assigned to one of two groups (decomposition based on data object or breakpoint heuristics).

Objects: The flat process model used as input comes from the operations of mid-sized European bank managing fixed income products. The process model used had been modeled for documentation purposes by a team of consultants. This model is flat i.e. no decomposition has been made. It begins with a start event and continues until the end of the process (including data objects)[2].

Factor and Factor Levels: The main factor in this experiment is the heuristics used to decompose the process model. As such, the same process model is given to two groups of students to be decomposed according to a pre-determined heuristics.

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[2] The flat process model can be accessed at http://sep.cs.ut.ee/Main/ProcessDecomposition

Response Variable: The response variable used was the process model metrics of the decomposed process models (size, cohesion, complexity and density).

Hypothesis Formulations: The goal of the experiment is to investigate if the different decomposition heuristics (data object and breakpoint) cause any significant differences on size, cohesion, complexity and density metrics. As two different heuristics are applied, we expect the resulting models to exhibit differences in process model metrics. Accordingly, the following hypotheses are formulated.

- Hypothesis: Different decomposition heuristics (data object and breakpoint) cause significant differences in size, cohesion, complexity and density metrics.
- Alternative hypothesis: Different decomposition heuristics (data object and breakpoint) do not cause significant differences in size, cohesion, complexity and density metrics.

Experimental Design: Both groups received an (1) introduction to the experiment, (2) explanation of the concepts of process model decomposition, (3) overview of the flat process model and (4) practical instructions such as submission format. The only difference in the given introductions was the decomposition heuristics. Each group was only introduced to the heuristics they were assigned to. The students were randomly assigned to one of the two groups. The students were given 6 days to decompose the flat process model. In addition to the decomposition task, they also answered questions regarding the extent of their previous experience with process models and ratings of difficulty of the experiment.

The submitted sets of sub-processes were analyzed to ensure that they were complete. Submissions requiring interpretation (such as to which sub-process an activity should belong) were discarded. At the end of the filtering, 25 valid submissions remained. Of these, 14 had applied data object heuristics and 11 had applied breakpoint heuristics. For each valid submission, the number of sub-processes, size (number of activities and nodes per sub-process), cohesion, CNC and density of all sub-processes were calculated. The average of these values were calculated for the whole set of sub-processes of each submission and used as value for the whole set of decomposed process models. For instance, if a student had decomposed the flat process model into 10 different sub-processes, the values of each of the ten sub-processes was first calculated. Then the average value of each metric for all the 10 sub-processes was calculated and used in the data analysis presented below[3].

The two groups were similar in terms of prior experience with process models and familiarity with BPMN. For instance, both groups had created or edited about 7,5 (7,64 for breakpoint and 7,43 for data object) process models during the past year. These process models had an average size of 18 activities (18,64 for breakpoint and 18,79 for data object). In response to questions regarding familiarity and confidence in understanding and using BPMN, both groups stated on average that they ‘somewhat agree’ (on a 7-step scale of ‘strongly agree’, ‘agree’, ‘somewhat agree’, ‘neutral’, somewhat disagree’, ‘disagree’, and ‘strongly disagree’). Test conducted to verify their statistical significance (t-test and Mann-Whitney test) showed that the averages of both groups were similar with 95 % confidence[4].

3.2 Findings

The decomposed process models were analyzed in terms of number of sub-processes, size (as measured by number of activities and nodes), cohesion, CNC and density. For each set of decomposed process model, the average of the above metrics were calculated. The average values of these metrics are shown in Table 3 below.

Table 3: Average Value of Metrics

Heuristics	No of Sub-processes	Size (Activities)	Size (Nodes)	Cohesion	CNC	Density
BreakPoint	16.73	6.48	12.46	0.26	1.01	0.15
DataObject	15.14	5.34	10.08	0.38	0.96	0.15

In order to determine if the average values of both groups are similar (with statistical confidence), the two-sample t-test (for normal distributed samples) or

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[3] The values for the experiment can be accessed at http://sep.cs.ut.ee/Main/ProcessDecomposition

[4] The statistical analysis can be accessed at http://sep.cs.ut.ee/Main/ProcessDecomposition

Mann-Whitney test (for non-normal distributed samples) was conducted. In order to determine which of these tests should be applied, the Shapiro-Wilk test (results shown in Table 4) of normality was conducted.

Table 4: Shapiro-Wilk test determining if the data is normally distributed.

Heuristics	No of Sub-processes	Size (Activities)	Size (Nodes)	Cohesion	CNC	Density
BreakPoint	0.990	0.000	0.000	0.953	0.124	0.859
DataObject	0.454	0.001	0.008	0.323	0.004	0.006

The Shapiro-Wilk test shows that the two-sample t-test can be applied on 'number of sub-processes' and 'cohesion' as the p-value for both sets is above 0.05. For the other metrics, which are not normally distributed, Mann-Whitney test is conducted to determine if there are significant differences in the averages of the two sets.

The results show that there is not enough evidence to support the hypothesis that the values of the two sets, in regards to 'average no of sub-processes', 'average size (activities)', 'average size (nodes)', 'average CNC', and 'average density' are significantly different as the p-value is above 0.05 (cf. Table 5). As such, it can be inferred that the average values of the two sets (BreakPoint and DataOjbect) are similar. However, as the p-value for 'average cohesion' is below 0.05 (cf. Table 5), it can be stated with 95 % confidence that their averages differ. This is expected as data object heuristics base decomposition on the cohesion of the activities. Any other results would have been surprising.

Table 5: P-value of two-sample t-tests and Mann-Whitney tests.

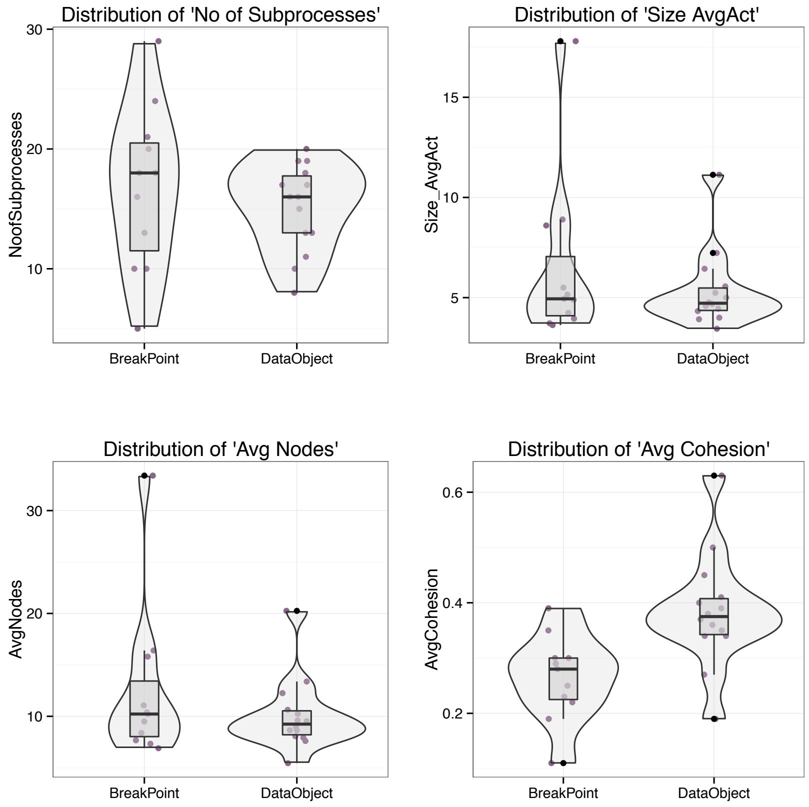
	Test	P-Value
Average No of Sub-processes	Two-sample t-test	0.502
Average Size (Activities)	Mann-Whitney test	0.809
Average Size (Nodes)	Mann-Whitney test	0.687
Average Cohesion	Two-sample t-test	0.004
Average CNC	Mann-Whitney test	0.309
Average Density	Mann-Whitney test	0.689

The violin plot and boxplot of the metrics, as shown in Figure 1 visually express the same results. An interesting observation is that the standard deviations of all metrics in breakpoint heuristics are noticeably higher than for data object heuristics.

Table 6: Standard Deviation

Heuristics	No of Sub-processes	Size (Activities)	Size (Nodes)	Cohesion	CNC	Density
BreakPoint	6.92	4.16	7.63	0.08	0.12	0.06
DataObject	3.65	1.94	3.53	0.10	0.06	0.04

For instance, as can be seen from Table 6, the standard deviation of breakpoint set is often about twice as high as for data object heuristics (with the exception of cohesion). Furthermore, the heights of the boxplots in Figure 1 (encompassing 50 % of the data) for breakpoint heuristics are larger as compared to the data object heuristics. As such, it indicates that following data object heuristics result in more consistency in regards to number of sub-processes, size, complexity and density. In other words, breakpoint heuristics allow more interpretation as to where the breakpoints are in the flat process model when decomposing.



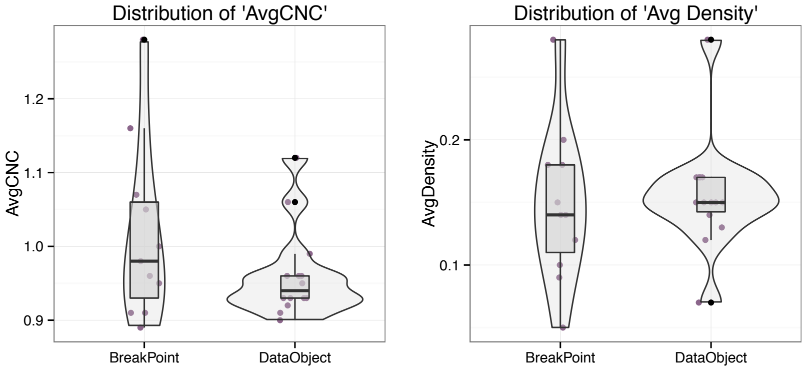


Figure 1: Violin Plot and Boxplot of the Metrics

The participants also answered a questionnaire that included 4 questions regarding degree of difficulties on (Q1) understanding the flat process model, (Q2) difficulty in identifying logical breakpoints or common data objects, (Q3) difficulty in determining which activities should belong to one sub-process and (Q4) difficulty in applying the heuristics when decomposing the flat process model. The responses were given on a scale between 1 and 5 (‘very simple’, ‘simple’, ‘neutral’, ‘rather difficult’ and ‘very difficult’). In order to detect any dissimilarity between the responses given by those who applied breakpoint as compared to data object, Fisher’s Exact test was conducted (cf. Table 7).

Table 7: Fisher's Exact Test

	Q1	**Q2**	**Q3**	**Q4**
Fisher’s Exact Test (p-value)	0.5844	0.6006	0.1882	0.3661

A closer look at the results for Q3 and Q4 (cf. Table 8) show that there is a slight overweight of 4 (rather difficult) for both questions from those who applied data object heuristics.

Table 8: Distribution of Responses for Q3 and Q4.

Scale	**1**	**2**	**3**	**4**	**5**	**Total**
Q3 – How easy or hard was it to determine which activities should be in one sub-process model?						
Breakpoint	0.00	0.27	0.55	0.18	0.00	**1.00**
DataObject	0.00	0.14	0.29	0.57	0.00	**1.00**

Q4- How easy or hard was it to apply the breakpoint/data object approach when decomposing the large flat process model?						
Breakpoint	0.00	0.27	0.46	0.27	0.00	**1.00**
DataObject	0.00	0.29	0.21	0.50	0.00	**1.00**

The Fisher's Exact test indicate that for Q1 and Q2, the responses given by the two groups are similar (high p-value). However, for Q3 and Q4 (in particular for Q3) there seems to be indications that it was more difficult to determine which activities should belong to one sub-process (Q3) and applying data object heuristics when decomposing a flat process model (Q4).

3.4 Threats to Validity

The sample size and one flat process model to be decomposed is not adequate to draw conclusions about the effects of different heuristics on understandability and maintainability. Due to this, our discussion in the previous section is indicative and based on observations rather than statements or conclusions. Other experiments are required to make the findings more conclusive. Another threat to validity comes from the use of size and complexity metrics as proxy for understandability and maintainability. Understandability of process models entail more than metrics such as cognitive factors, perceived understandability and layout. This limitation is shared with several other studies (Dumas et al. 2012). Finally it should be noted that the experiment was conducted with students and as such, they are novice modelers. However, their level of expertise was uniform, i.e. no expert modelers participated.

4. Conclusion

The benefits of process model decomposition for increased comprehensibility and maintainability are widely recognized, however, the question of how to decompose a process model is not as clearly agreed upon. In fact, some argue that it is more an art rather than science. Nevertheless a variety of approaches have been proposed. In light of the proposed approaches, we examined how a process model can be decomposed and how different decomposition heuristics affect the process models.

Our survey showed (as discussed in Section 2.3) that three heuristics (repetition, shared processes and role based) do not require certain conditions to be fulfilled. Applying these heuristics would not produce enough candidates for subprocesses, as sections of process models that do not fulfill the required conditions would not be fragmented to subprocesses. These heuristics are therefore useful as complementary to other heuristics. On the other hand, three heuristics (breakpoint, data object and structuredness) provide necessary but not sufficient criteria for decomposition. These heuristics can be generally applied for process model decomposition but fall short in determining which process fragments to model as a subprocess.

We examined how the different heuristics (the breakpoint and data object-based) affect understandability and maintainability of process models by conducting an experiment. Using quantitative metrics as approximation of understandability, the experiment showed that the two heuristics are similar in terms of understandability and complexity. Therefore choosing heuristics could be influenced by factors such as type of stakeholders involved or the level of details captured in the models.

However, understandability of process models is not restricted do its metrics only. Therefore, exploring the effect of decomposition on cognitive understandability is a relevant and important direction for future work. We also observed that the research on decomposition of process models has been conducted independently of goodness criteria and associated metrics. As such, little, if any, research has been conducted on the correlation between type of processes and metrics. Hence, it is important to conduct further empirical studies on the relation between decomposition heuristics and understandability and maintainability metrics.

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