Measuring the Complexity of DMN Decision Models

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Abstract. Complexity impairs the maintainability and understandability of conceptual models. Complexity metrics have been used in software engineering and business process management (BPM) to capture the degree of complexity of conceptual models. A vast array of metrics has been proposed for processes in BPM. The recent introduction of the Decision Model and Notation (DMN) standard provides opportunities to shift towards the Separation of Concerns paradigm when it comes to modelling processes and decisions. However, unlike for processes, no studies exist that address the representational complexity of DMN decision models. In this paper, we provide a first set of ten complexity metrics for the decision requirements level of the DMN standard by gathering insights from the process modelling and software engineering fields. Additionally, we offer a discussion on the evolution of those metrics and we provide directions for future research on DMN compexity.

Keywords. Decision Modelling, Decision Model and Notation, DMN, Complexity, Complexity Metrics

1 Introduction

Decision modelling has seen a surge in scientific literature, as illustrated by the vast body of recent work on DMN [1–7]. DMN consists of two levels. Firstly, the decision requirement level in the form of a Decision Requirement Diagram (DRD) is used to portray the requirements of decisions and the dependencies between the different constructs in the decision model. Secondly, the decision logic level is used to specify the underlying decision logic, usually in the form of decision tables. The standard also provides an expression language FEEL (Friendly Enough Expression Language), as well as boxed expressions and decision tables for the notation of the decision logic. In DMN rectangles are used to depict decisions, corner-cut rectangles for business knowledge models, and ovals to represent data input. The arrows represent information requirements (from data or decisions). DMN aims at providing a clear and simple representation of decisions in a declarative form and offers no decision resolution mechanism

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of its own. Rather, the invoking context, e.g. a business process, is responsible for ensuring a correct invocation and enactment of the decision, as well as ensuring data processing and the storage and propagation of data and decision outcomes throughout the process. This makes DMN particularly interesting for a *Service-Oriented Architecture*, as DMN is independent of the applications and the invoking context. That way, DMN is able to capitalise on the benefits that are inherent to service-orientation in terms of maintainability, scalability, understandability, and flexibility both for modelling and mining decisions.

Complexity metrics have been adopted in the BPM field for process model complexity and applied on for instance the Business Process Model and Notation (BPMN) standard [8]. Despite the adoption of the DMN standard in the BPM field, a discussion on DMN model complexity is still lacking in literature. This paper aims at addressing that research gap and at proposing a set of metrics for the decision requirements level of the DMN standard.

This paper is structured as follows. In Section 2, relevant works on complexity are provided, as well as a running example that will be used throughout the paper. Section 3 provides a first set of ten DRD metrics for DMN models, while Section 4 outlines a discussion on the evolution of the proposed metrics. Section 5 provides an initial empirical evaluation of the metrics. In Section 6 a research agenda for DMN model complexity is contributed. Finally, Section 7 provides the conclusions.

2 Related Work and Running Example

In this section we provide an overview of related work for DMN, complexity metrics in the BPM field, and complexity assessments to the DMN standard in particular. Additionally, we provide a running example which will be used to illustrate the proposed complexity metrics in the subsequent sections.

2.1 Related Work

Recent BPM literature moves towards accommodating decision management into the paradigms of The Separation of Concerns (SoC) [3, 9, 10] and and Service-Oriented Architecture (SOA) [6], by externalising decisions and encapsulating them into separate decision models, hence implementing decisions as externalised services. Literature proposes several conceptual decision service platforms and frameworks [6, 11, 12] and industry has adopted this trend, as several decision service systems have appeared, e.g. SAP Decision Service Management [13]. This externalisation of decisions from processes provides a plethora of advantages regarding maintainability and flexibility of both process and decision models [3, 6, 10, 14–17].

A plethora of works on software complexity metrics exists [18–20]. Additionally, software metrics have been transformed and applied on processes and workflow nets in a vast array of studies [21–27]. Most of these studies focus on the BPMN standard. A systematic literature review of process metrics is provided in [28], where the authors identify and discuss 65 process metrics found in BPM literature.

Unlike for processes and BPMN, few works on complexity metrics for DMN models exist. In [29], the meta model complexity of the DMN modelling method is assessed according to the theory specified by [30]. Additionally, an explorative study of the notational aspects of DMN was conducted in [31]. In this study the authors focus on the cognitive analysis of the DMN notation in the light of theories on effective visual design. Hence, DMN complexity was assessed on a meta model level, i.e. the theoretical complexity of the modelling method as a whole, and on the cognitive visual level. However, no works on the complexity of DMN decision models are present in literature. In the following sections, we propose a set of complexity metrics for the DRD level of DMN.

2.2 Running Example

Figure 1 provides a running example of a DRD model that will be used in the coming section to illustrate the complexity metrics. The DRD represents an event selection decision based on the preferred location and the food and drinks that are offered, while taking into consideration the season, the number of guests, whether children are allowed, the sleeping facilities, and the budget. The value of every proposed metric will be calculated for this DRD.

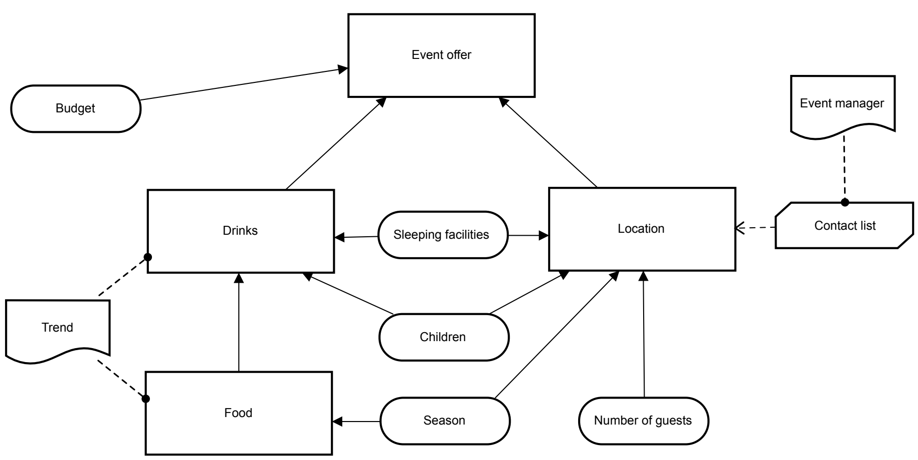

Fig. 1: DRD running example.

3 DRD Metrics

In this section we provide a set of ten DRD metrics that are capable of representing graph complexity in analogy with business process or software engineering literature. For every metric, a brief explanation is provided. Additionally, we calculate the value of every proposed metric for the running example provided in Figure 1. An overview of the metrics and the metric values for the running example is given in Table 1. Later on, we will discuss the evolution of the metrics and validate them through an exploratory survey.

3.1 Number of Decisions (NOD)

As proposed by [23], BPMN complexity can be measured by counting the number of activities. They called this metric *number of activities* (NOA), which is a summation of all activity elements in the model. A similar metric can be worked out for DMN, counting the number of decision nodes in the DRD model instead of counting the activities, thus arriving to the metric of *number of decisions* (NOD). Applied to the running example of Figure 1, the NOD is 4. As the models grow larger, they tend to have more decision elements. Thus, this metric will go up if a decision element is added to the model, indicating that the model has become more complex according to this metric. Given that DMN is a standard for modelling decisions, we assume that the number of decisions that are modelled within one DRD model will be indicative of the complexity of the model. However, note that the granularity of the DRD will play a crucial role as well, as one decision node can possibly be decomposed into a number of decision nodes each containing a portion of the underlying decision logic. Therefore, it will be of paramount importance to develop complexity metrics for the logic layer of DMN as well to capture these changes in granularity of the DRD model.

3.2 Number of Elements (NOE)

The *number of elements* (NOE) is the sum of all building blocks of the DRD. Hence, NOE takes into account all elements of the DRD rather than only the decision nodes, as is the case in the NOD metric. More specifically:

$$\begin{aligned} NOE = {} & \#decisions + \#inputs + \#knowledgesources \\ & + \#businessknowledgemodels + \#informationrequirements \\ & + \#knowledgerequirements + \#authorityrequirements \end{aligned}$$

Applied to the running example model in Figure 1, the NOE is 27. The larger the DRD model, the higher NOE will be. This is self-explanatory, as DRD models are solely made up out of these elements.

3.3 Number of Basic Elements (NOBE)

The most basic elements of a DRD model are decisions nodes, input nodes, and information requirements. They form the spine of a DRD model. Therefore, the *number of basic elements* (NOBE) probably is a good metric. NOBE can be calculated as follows:

$NOBE = \#decisions + \#inputs + \#informationrequirements$

Applied to the running example in Figure 1, the NOBE is 20. Clearly, the NOBE metric will be higher as basic elements are added to the DRD model.

3.4 Total Number of Data Objects (TNDO)

As discussed in [28], the *total number of data objects* (TNDO) represents all data objects in the BPMN diagram. For a DRD, data objects are represented by all input data objects present in the model. The running example in Figure 1 has 5 input data elements, hence the TNDO is 5.

Similar to the explanation of NOD and NODIR, bigger models tend to have more input data elements. By adding a data input element to a model, the TNDO metric will grow.

3.5 Sequentiality (SEQ)

As pointed out by [28], the sequentiality (SEQ) of BPMN is equal to one minus the percentage of nodes with no more than one incoming and outgoing arrow. In other terms: the percentage of nodes that have more than one successor or predecessor. This metric can be used in the same way for the nodes of a DRD. Sequentiality is expressed as a number between one and zero. If the DRD looks more like a sequence rather than a parallell network, the value of the sequentiality metric will be low. This corresponds with a less complex model, and vice versa. Applying this to the running example in Figure 1, we get the formula

$SEQ = 1 - 4/12 = 0.6667$.

Models with a lot of single-path sequences will have a low complexity value. Also note that sequentiality in DMN will be greatly impacted by leaf elements since DRD models usually have multiple input data elements, thus increasing the SEQ metric.

3.6 Longest Path (LP)

Unlike BPMN, a DRD model does not allow loops. Therefore, the *longest path* (LP) can be measured unambiguously. Calculating the longest path of a DRD graph, which in essence is a directed acyclic graph (DAG), is done by topologically sorting the graph [32]. In the running example of Figure 1, the LP of 4 is found. This is the length of the path going from *Season* to *Event offer* through *Food* and *Drinks*. It is not possible to find a longer path in the model. Typically, the longest path and the sequentiality metrics of a DRD will oppose in value. When a model is more sequential, it will have a low complexity according to the *sequentiality* metric. However, the model will typically have longer paths and thus higher complexity according to the *longest path* metric. This proves the importance of using multiple complexity metrics to assess DRD model complexity from different perspectives.

As DRD models are getting bigger and more arcs, i.e. requirements in the DRD graph, are introduced, the value of LP will indicate a high complexity.

3.7 Average Vertex Degree (AVD)

The *average vertex degree* (AVD) [33] is calculated as the average of all incoming and outgoing connections across all nodes of the DRD. This can be applied directly to DRD graphs. The bigger the AVD, the more complex the model. Applying this to the running example in Figure 1, we get the following result:

$AVD = (1 + 3 + 1 + 5 + 2 + 6 + 2 + 2 + 2 + 3 + 2 + 1)/12 = 2.5$

The average vertex degree heavily relies on the number of connections between DRD model elements. In other terms, the more the decision requirements diagram resembles a strongly connected network, the more complex it is. Additionally, it might be interesting to look at the modular behaviour of the DRD model trough fan-in and fan-out metrics that are heavily dependent on the average vertex degree.

3.8 Coefficient of Network Complexity (CNC)

The *coefficient of network complexity* (CNC) was proposed to measure the degree of complexity of a critical pass network [34]. It was adapted by [23] to measure the degree of complexity in processes by dividing the number of arcs by the number of the activities, splits and joins in the BPMN diagrams. It is possible to have identical values of the coefficient of network complexity for different models but with different comprehensibility due to a different set of used node types. This metric can be adopted for the DMN standard by focusing on the nodes and arcs in the decision requirements diagram. Applying this to the running example in Figure 1 gives the following result:

$CNC = 15/12 = 1.25$

Clearly, if an arc is added to the DRD graph, the CNC value will increase because of the increasing effect on the numerator.

3.9 Knot Count (KC)

In decision models, some components, more specifically requirement associations, may be forced to cross each other. This is captured in the *knot count* (KC) metric. Each occurrence of a crossing is expressed as a knot and each knot occurrence in a DRD means an increase in the complexity of understanding the model. Unlike the metrics used by [18] which focused on counting the knots created by the crossing of only arrows, counting all requirement relation crossings regardless of their types is suggested for DMN adoption. The higher the knot count value, the higher the complexity assumed. The running model in Figure 1 does not have knot occurrences, and hence has a knot count value of 0.

As more arcs and nodes are introduced in the DRD model, the more difficult it becomes to avoid crossing arcs, i.e. knots. This will thus likely result in a higher knot count.

3.10 Cyclomatic Complexity (CC)

In [23] the adaptation of McCabes *cyclomatic complexity* (CC) metric [35] for process is proposed. According to [19], this is one of the most widely used complexity metrics. The cyclomatic complexity formula for non-strongly connected graphs, such as a DRD graph, is the number of edges (E) minus the number of nodes (N) plus two times the number of connected components. Since a decision requirements diagram is one connected component, the formula can be reduced to the following calculation for the running example in Figure 1:

$CC = E - N + 2 = 15 - 12 + 2 = 5$

Thus, larger models, especially those that contain many arcs, are likely to have a higher CC value.

Metric	Value
Number of decisions (NOD)	4
Number of elements (NOE)	27
Number of basic elements (NOBE)	20
Total number of Data Objects (TNDO)	5
Sequentiality (SEQ)	0.6667
Longest Path (LP)	4
Average Vertrex Degree (AVD)	2.5
Coefficient of Network Complexity (CNC)	1.25
Knot Count (KC)	0
Cyclomatic Complexity (CC)	5

Table 1: DRD metrics as calculated for the running example in Figure 1.

4 Expected Evolution of the Metrics

In this section we concisely discuss the evolution of the metric values when a certain element is added to the DRD model. We limit our discussion to adding arc requirements and decision nodes to the DRD model respectively. When a decision requirements diagram gets larger in terms of number of elements, most metrics will indicate that the representational complexity of the decision model has increased. Model size is what most of the proposed metrics rely on. NOD, NOE, NOBE, and TNDO are simple count metrics that grow larger as relevant elements are added to the model. The remaining metrics, i.e. SEQ, LP, AVD, CNC, KC, and CC, are also indirectly dependent on the number of DRD elements. Here too, adding an element to the DRD model is likely to result in an increase in complexity metric values. Note that all metrics have a lower value when indicating simpler models and a higher value when indicating more complex DRD models.

4.1 Requirement Arcs

The following metrics all rely on the number of arcs in the model, i.e. information requirements, authority requirements, and knowledge requirements. When a requirement is added to a DRD model:

- NOE increases since it is the summation of all elements.
- NOBE increases if that arc is an information requirement.
- LP is not affected or can increase, depending on whether the added arc results in a longer or another longest path.
- AVD will definitely increase because the new connection will always positively impact exactly two model elements, which in turn increases the overall average vertex degree.
- CNC will increase given the increasing effect on the numerator in the formula.
- KC can never decrease as the new arc can either cross existing arcs or not.
- CC will increase given the increasing effect on the first term in the formula.

4.2 Decision Nodes

The following metrics all rely on the number of decision nodes in the model. When a decision node is added to a DRD model:

- NOD increases by definition.
- NOE increases since it is the summation of all elements.
- NOBE increases since a decision node is a basic element
- LP is either not affected or it is likely to increase, depending on whether the added decision node results in a longer or another longest path.
- CC stays unchanged or decreases. While the formula suggests that CC would increase, this is not the case in reality. When a decision node is added, at least one edge is added as well to connect the node to the rest of the graph.

5 Empirical Evaluation

An exploratory survey was held during the master's course of *Knowledge Management and Business Intelligence* at KU Leuven. Students were presented with 11 DRD models ranging from simple to complex in an arbitrary order. The students were asked to indicate on a visual analogue scale how complex they perceived each of the DRD models to be. In total 22 students with previous knowledge about DMN took part in the survey.

To detect how well the proposed metrics describe the perceived complexity as indicated by the survey, the metric values were compared to the survey results. This was done by calculating the correlation and the sum of squared differences (SSD) of the metric values for all the DRD models and the survey averages. In order to calculate a valid sum of squared differences, the metric values were first scaled to a range from zero to ten, i.e. reflecting the complexity range of the visual analogue scale of the survey.

Initial results are presented in Table 2. For all the 11 tested DRD models, the metric value of all 10 proposed metrics are calculated and included in the table. Higher (lower) values of the metrics represent a higher (lower) degree of complexity. The final two rows of the table give the average degree of complexity as indicated by the students in the survey on the visual analogue scale (on a scale of 10) and the standard deviation of the complexity as indicated in the survey. The final two columns in Table 2 depict the correlation and the sum of squared differences (SSD) of the metric values and the survey results respectively.

By examining the sum of squared differences we can conclude that basic metrics such as Number of Elements (NOE), Number of Decisions (NOD), and Total Number of Data Objects (TNDO) measure the perceived complexity quite well, indicated by the low values in SSD. Additionally, the Cyclomatic Complexity (CC) also showcases a low SSD, indicating that the popular CC metric might be a good measure for DRD model complexity as well.

6 Future Work

In future work, we will expand the set of DRD metrics to include other metrics from the software engineering and BPM fields. Additionally note that DMN contains two levels: the DRD and the decision logic level, usually specified in the form of decision tables. Thus, we plan to constitute a set of complexity metrics for the decision tables by capitalising on complexity metrics of database tables. Furthermore, we will look into combining DRD and decision table metrics into aggregated and holisitc complexity metrics, thus denoting the complexity of the entire DMN decision model.

Next to this theoretical metric discourse on DMN complexity, we will look into additional empirical validation for the proposed metrics through additional surveys. Finally, inquiries into the complexity of integrated process and decision models will be conducted, by combining and integrating complexity metrics of DMN decision models and BPMN process models.

7 Conclusion

This paper provides a first discussion on complexity metrics for individual DMN decision models. Ten complexity metrics for decision requirement graphs were proposed and illustrated on a running example. Furthermore, metric evolution was discussed and an agenda for future inquiry into DMN decision model complexity was suggested. The emphasis was put on expanding the body of metrics to the decision logic level of DMN and later on combining the metrics of both the logic level and the requirements level into aggregate metrics for the DMN model as a whole. Finally, a survey was set up to empirically evaluate the proposed complexity metrics and initial results revealed that the simple metrics were the most suitable for capturing DRD complexity.

Table 2: Survey results and analysis

Metric	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Cor	SSD
NOD	2.00	2.00	5.00	4.00	7.00	4.00	8.00	7.00	5.00	5.00	11.00	-0.09	106.65
NOE	9.00	16.00	17.00	27.00	29.00	27.00	46.00	42.00	28.00	37.00	33.00	0.20	129.88
NOBE	9.00	8.00	13.00	20.00	29.00	20.00	43.00	21.00	20.00	29.00	40.00	0.01	122.56
TNDO	3.00	2.00	2.00	5.00	4.00	5.00	14.00	2.00	3.00	9.00	4.00	0.05	92.49
SEQ	0.40	0.50	0.22	0.67	0.82	0.67	0.43	0.58	0.58	0.33	0.55	0.14	133.42
LP	3.00	3.00	3.00	4.00	6.00	4.00	5.00	6.00	5.00	5.00	7.00	0.07	146.87
AVD	1.60	1.89	1.78	2.50	3.45	2.50	2.09	2.42	2.67	2.11	3.10	-0.03	157.74
CNC	0.80	1.00	0.89	1.25	1.73	1.25	1.04	1.16	1.33	1.06	1.52	-0.06	156.03
KC	0.00	0.00	0.00	0.00	8.00	3.00	1.00	4.00	0.00	0.00	28.00	0.10	169.32
CC	1.00	2.00	1.00	4.00	13.00	5.00	3.00	7.00	6.00	3.00	8.00	-0.12	113.63
Survey AVG	3.5364	3.7182	1.6182	4.0409	1.2286	7.1909	2.8909	4.8909	3.4136	4.9318	4.5636		
STDEV	2.2311	1.9549	1.1636	1.7928	1.7373	2.0672	1.7949	1.5405	1.5388	2.3204	1.9182		

References

1. OMG: Decision Model and Notation 1.1 (2016)
2. Horita, F.E., de Albuquerque, J.P., Marchezini, V., Mendiondo, E.M.: Bridging the gap between decision-making and emerging big data sources: an application of a model-based framework to disaster management in brazil. Decision Support Systems **97** (2017) 12–22
3. Hasić, F., De Smedt, J., Vanthienen, J.: Augmenting processes with decision intelligence: Principles for integrated modelling. Decision Support Systems **107** (2018) 1 – 12
4. Estrada-Torres, B., del Río-Ortega, A., Resinas, M., Ruiz-Cortés, A.: On the relationships between decision management and performance measurement. In: International Conference on Advanced Information Systems Engineering, Springer (2018) 311–326
5. De Smedt, J., Hasić, F., Vanthienen, J.: Towards a holistic discovery of decisions in process-aware information systems. In: Business Process Management. Lecture Notes in Business Information Processing, Springer (2017)
6. Hasić, F., De Smedt, J., Vanthienen, J.: A service-oriented architecture design of decision-aware information systems: Decision as a service. In: On the Move to Meaningful Internet Systems. Lecture Notes in Computer Science, Springer (2017)
7. Calvanese, D., Dumas, M., lari Laurson, Maggi, F.M., Montali, M., Teinemaa, I.: Semantics, analysis and simplification of dmn decision tables. Information Systems (2018)
8. OMG: Business process model and notation (BPMN) 2.0 (2011)
9. Campos, J., Richetti, P., Baião, F.A., Santoro, F.M.: Discovering business rules in knowledge-intensive processes through decision mining: an experimental study. In: International Conference on Business Process Management, Springer (2017) 556–567
10. Hasić, F., Devadder, L., Dochez, M., Hanot, J., De Smedt, J., Vanthienen, J.: Challenges in refactoring processes to include decision modelling. In: Business Process Management Workshops. LNBIP, Springer (2017)
11. Zarghami, A., Sapkota, B., Eslami, M.Z., van Sinderen, M.: Decision as a service: Separating decision-making from application process logic. In: EDOC, IEEE Computer Society (2012) 103–112
12. Mircea, M., Ghilic-Micu, B., Stoica, M.: An agile architecture framework that leverages the strengths of business intelligence, decision management and service orientation. Business Intelligence-Solution for Business Development (2011)
13. SAP: Sap decision service management. http://www.sap.com/pc/tech/business-process-management/software/decision-service-management/index.html
14. Biard, T., Le Mauff, A., Bigand, M., Bourey, J.P.: Separation of decision modeling from business process modeling using new decision model and notation(dmn) for automating operational decision-making. In: Working Conference on Virtual Enterprises, Springer (2015) 489–496
15. van der Aa, H., Leopold, H., Batoulis, K., Weske, M., Reijers, H.A.: Integrated process and decision modeling for data-driven processes. In: Business Process Management Workshops. Volume 256 of LNBIP., Springer (2015) 405–417
16. Hasić, F., De Smedt, J., Vanthienen, J.: An Illustration of Five Principles for Integrated Process and Decision Modelling (5PDM). Technical report, KU Leuven (2017)

17. Figl, K., Mendling, J., Tokdemir, G., Vanthienen, J.: What we know and what we do not know about dmn. Enterprise Modelling and Information Systems Architectures (2018)
18. Woodward, M.R., Hennell, M.A., Hedley, D.: A measure of control flow complexity in program text. IEEE Transactions on Software Engineering (1) (1979) 45–50
19. Sharma, A., Kumar, R., Grover, P.: Empirical evaluation and critical review of complexity metrics for software components. Proceedings of the 6th WSEAS Int. Con. on SE, Parallel and and disributed systems (2007) 24–29
20. Queiroz, R., Passos, L., Valente, M.T., Hunsen, C., Apel, S., Czarnecki, K.: The shape of feature code: an analysis of twenty c-preprocessor-based systems. Software & Systems Modeling **16**(1) (2017) 77–96
21. Kluza, K., Nalepa, G.J., Lisiecki, J.: Square complexity metrics for business process models. In: Advances in Business ICT. Springer (2014) 89–107
22. Gruhn, V., Laue, R.: Adopting the cognitive complexity measure for business process models. In: Cognitive Informatics, 2006. ICCI 2006. 5th IEEE International Conference on. Volume 1., IEEE (2006) 236–241
23. Cardoso, J., Mendling, J., Neumann, G., Reijers, H.A.: A discourse on complexity of process models. In: International Conference on Business Process Management, Springer (2006) 117–128
24. Kluza, K.: Measuring complexity of business process models integrated with rules. In: International Conference on Artificial Intelligence and Soft Computing, Springer (2015) 649–659
25. Sánchez-González, L., García, F., Mendling, J., Ruiz, F., Piattini, M.: Prediction of business process model quality based on structural metrics. In: International Conference on Conceptual Modeling, Springer (2010) 458–463
26. Lassen, K.B., van der Aalst, W.M.: Complexity metrics for workflow nets. Information and Software Technology **51**(3) (2009) 610–626
27. Gruhn, V., Laue, R.: Complexity metrics for business process models. In: 9th international conference on business information systems (BIS 2006). Volume 85., Citeseer (2006) 1–12
28. Polančič, G., Cegnar, B.: Complexity metrics for process models–a systematic literature review. Computer Standards & Interfaces **51** (2017) 104–117
29. Hasić, F., De Smedt, J., Vanthienen, J.: Towards assessing the theoretical complexity of the decision model and notation (dmn). In: Enterprise, Business-Process and Information Systems Modeling. Springer International Publishing (2017)
30. Rossi, M., Brinkkemper, S.: Complexity metrics for systems development methods and techniques. Information Systems **21**(2) (1996) 209–227
31. Dangarska, Z., Figl, K., Mendling, J.: An explorative analysis of the notational characteristics of the decision model and notation (dmn). In: Enterprise Distributed Object Computing Workshop (EDOCW), 2016 IEEE 20th International, IEEE (2016) 1–9
32. Kahn, A.B.: Topological sorting of large networks. Communications of the ACM **5**(11) (1962) 558–562
33. Cardoso, J.: Business process quality metrics: Log-based complexity of workflow patterns. In: OTM Confederated International Conferences" On the Move to Meaningful Internet Systems", Springer (2007) 427–434
34. Kaimann, R.A.: Coefficient of network complexity. Management Science **21**(2) (1974) 172–177
35. McCabe, T.J.: A complexity measure. IEEE Transactions on software Engineering (4) (1976) 308–320

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