Model granularity and related concepts

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MODEL GRANULARITY AND RELATED CONCEPTS

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1. Introduction

Models are of fundamental importance in many contexts of science, economics, engineering and other disciplines. Indeed, most product development is nowadays almost unthinkable without the assistance of modelling and simulation. Models can help to tackle the considerable complexity and interconnectedness exhibited by design projects in domains like aircraft and automotive industries. It can be argued that in many cases engineers interact more closely with various kinds of models than with the actual products and consequently base many decisions on the former. It is therefore crucial to understand how the models' properties may impact their behaviour and thereby influence such decisions. This article focuses on an important attribute of models – their granularity – specifically in conceptual or computational rather than physical models. The aims of the paper are to clarify terminology, to contribute to the understanding of the various facets of model granularity and to provide a reference point for further discussion about the topic.

By their very nature, models are abstract representations of their target system, the part of reality they choose to capture, created for a specific purpose [Frigg 2003]. Depending on how and to what extent the target system is abstracted the emerging model comprises a certain level of granularity. The term granularity is used here to describe, broadly speaking, the level of detail in the description of various aspects of the target system. Granularity was chosen as a focus as it refers to a property of the model itself rather than its construction or output. It thus provides a point of reference for reviewing and relating other similar notions. Recent studies have shown that granularity plays a crucial role in all aspects of modelling and impacts analysis [Chiriac et al. 2011]. However, relatively little research targets the understanding of phenomena related to model granularity in general and even less in engineering design. Extending the search to other relevant domains yields more results. Still, such discussions often remain on a more theoretical level and are distributed across a number of different disciplines, making them less accessible for modelling and simulation practitioners or designers with little expertise in modelling. This highlights the need for a theoretical approach that captures and synthesises the various aspects of model granularity and shows their pertinence for engineering design.

In this article, a range of theoretical definitions of granularity and related concepts from various communities are collected and discussed with respect to their relevance for engineering design. Modelling and the role of abstraction are explored more generally and theoretically before focusing on the implications for engineering design. Section 2 discusses the relationship between model and target system, the role of abstraction in modelling and the resulting importance of model granularity. Section 3 provides a range of definitions for granularity and related concepts from different disciplines, discusses them briefly and reflects on the use of terminology across domains. Section 4 points out why model granularity matters for engineering design and indicatively presents some approaches before Section 5 discusses the research and draws conclusions.

2. Background

Modelling has been described as ‘the purposeful process of abstracting and theorizing about a system, and capturing the resulting concepts and relations in a conceptual model’ [Tolk and Turnitsa 2012]. While the emphasis on conceptual models might not seem appropriate in all contexts, there are a number of insights that can be drawn from this definition. Firstly, it highlights that the purpose is central to modelling activities. Secondly, it states that modelling is a matter of abstracting and based on theory. Thirdly, the goal is to capture both concepts and relations, or dependencies, in the emerging model. This article focuses on one aspect of modelling, granularity, which relates to all three insights and should not be discussed without a brief introduction of theoretical concepts from the wider field of modelling and simulation.

A large number of theoretical contributions about models and modelling can be found in the Philosophy of Science community. The concepts and vocabulary of this more mature discipline can be useful to discuss models in general and provide a basis for approaching granularity. The structuralism view of modelling interprets models as structures (entities and their relations) which represent their target system [Frigg 2003]. Morrison and Morgan [1999] adopt a wider perspective by describing models as mediators, autonomous agents who function as instruments of investigation. Knuuttila [2005] extends this perspective by describing models as epistemic artefacts, which provide us with knowledge in many other ways than just abstract representation. The model as an artefact does not in itself constitute a representation, which also includes an intentional relation, connecting the artefact with the target system. This implies that the model could be detached from this relation and therefore allow for different interpretations and thus different representations.

It can be argued that the relationship between target system and models used in engineering, and in particular engineering design, differs from what can be encountered in the sciences. While scientific models usually aim to represent some real target system, often with the goal of isomorphism or similarity, engineers can be thought of as actively intervening with the world [Boon and Knuuttila 2009]. This hints at some of the challenges encountered when describing the relationship between model and target system in engineering design. Boon and Knuuttila [2009] advocate a pragmatic account of models as epistemic tools rather than representations of a real target system. Godfrey-Smith [2006] states that modellers often perceive themselves to be describing imaginary objects and systems, which resonates with the use of models for design. They are less straightforward in some respects given the less clearly defined target system and the resulting importance of purpose, scope and choices regarding model granularity.

The importance of abstraction for modelling and simulation is discussed in a variety of fields, ranging from discrete-event simulation [Zeigler et al. 2000] to artificial intelligence [Saitta and Zucker 2013]. In many accounts abstraction is seen as the crucial step in representing the real-world target system in a (conceptual) model (e.g. [Frantz 1995]). This process results in a particular level of abstraction of the developed model, which can be reached in two ways: bottom-up and top-down. Bottom-up generally consists of aggregating elements of the target system, which leads to a more abstract description. For instance, a number of specific tasks could be aggregated to describe the overall activity. On the other hand, top-down approaches involve decomposition of a more abstract description into smaller more concrete parts. For instance, a car could be decomposed into engine, transmission, body etc.; and an engine into crankshaft, pistons, cylinder heads etc. Depending on the context, the purpose and the data available both bottom-up and top-down approaches can be employed in modelling. Depending on how, or to what degree, the target system is abstracted a model emerges with a certain level of abstraction and, related to this, granularity. Multiple levels can be derived, often with an underlying hierarchical structure, as discussed in disciplines like complex systems design [Alfaris et al. 2010] and process modelling [Eshuis and Grefen 2008]. This can provide a range of benefits but also poses a range of challenges like ensuring and maintaining consistency across abstraction levels [Smirnov et al. 2012], choosing appropriate levels [Eshuis and Grefen 2008] and abstraction techniques [Frantz 1995] as well as factoring in the impact the different levels can have on analysis [Chiriac et al. 2011]. While it is easy to imagine hierarchical systems as tree structures, it is worth noting that this is a special case and such systems are more akin to general lattice structures (e.g. [Alexander 1965]).

3. Towards defining granularity and related concepts

3.1 Collecting definitions of relevant terms

With a few exceptions the topic of model granularity has only received limited attention in the engineering design literature. Nevertheless, a number of explicit approaches towards the topic and related issues relevant to model granularity exist both in engineering design and other disciplines. In particular, discussions around topics like model abstraction, aggregation, decomposition, complexity, clustering and hierarchies are useful when approaching model granularity. Table 1 assembles a range of definitions for relevant terms, collected from various fields. The definitions for a specific term are ordered to reflect the relevance attributed to them by the authors.

Table 1. Definitions for relevant terms

Term	Definition
Abstraction	'Abstraction of a process will inevitably involve a reduction in model components and interactions, along with the reduction in behavioral complexity of the model when simulated' [Fishwick 1988, p.18] 'A concept a is more abstract than the members b_i of a family $B=\{b_1, b_2, \ldots\}$ of concepts, where $b_i \neq a$ for all i, iff (A1) For a to apply it is necessary that at least one member of B applies. (A2) On any given occasion, the fact that b_i, say, applies is what the applying of a at the same occasion consists in.' [Frigg 2003, p.52] 'First, a concept that is abstract relative to another more concrete set of descriptions never applies unless one of the more concrete descriptions also applies. These are the descriptions that can be used to 'fit out' the abstract description on any given occasion. Second, satisfying the associated concrete description that applies on a particular occasion is what satisfying the abstract description consists in on that occasion.' [Cartwright 1999, p.39] 'A level of abstraction (LoA) is a finite but non-empty set of observables. No order is assigned to the observables, which are expected to be the building blocks in a theory characterised by their very definition.' [Floridi 2008, p.309] More definitions of abstraction can be found in [Saitta and Zucker 2013]
Accuracy	'The degree to which a parameter or variable or set of parameters or variables within a model or simulation conform exactly to reality or to some chosen standard or referent.' [Gross 1999, p.4] 'The accuracy of a model marks how closely the model's predictions match the world's behavior.' [Weld 1992, p.285]
Aggregation	'aggregation refers to the conceptual task of processing a set of modeling artifacts/concepts at some level of abstraction and generating a set of "higher level" modeling artifacts/concepts that are useful for decision making. The aggregated model artifacts contain a smaller quantity of information and often manifest themselves as a summary of the information contained at the lower level of abstraction.' [Benjamin et al. 1998, p.392] 'Aggregation is performed by grouping together variables and relations into subsystems, and by redescribing the entire system in terms of these subsystems and their interactions.' [Iwasaki and Simon 1994] 'Aggregation implies that insignificant elements of a process model are aggregated with other elements. In contrast to elimination, aggregation allows preserving information about the abstracted element in the model.' [Polyvyanyy et al. 2008, p.330] 'Is-member-of-mapping' [Erens et al. 1994, p.23]. 'The term "aggregation" can conceptually be considered as a subset of "abstraction"' [Fishwick 1988, p.18]

Clustering	‘The foremost objective [of clustering] is to maximize interactions between elements within clusters (chunks) while minimizing interactions between clusters.’ [Browning 2001, p.294] ‘Clustering produces modules, i.e., it produces an ordering such that elements or parameters that are coupled or have higher degree of interaction within them as compared with the rest are sorted out in groups.’ [Alfaris et al. 2010, p.6] ‘The objective of the clustering analysis is to detect subsets that possess many internal dependencies between nodes of a cluster subset and as few dependencies as possible to or from the external nodes of the structure.’ [Maurer 2007]
Complexity	‘the overall complexity of the model is taken here to be a combination of three elements: the number of components, the pattern of the connections (which components are related), and the nature of the connections (the complexity of the calculations determining the relationships).’ [Brooks and Tobias 1996, p.6] ‘Complexity is that property of a model which makes it difficult to formulate its overall behaviour in a given language, even when given reasonably complete information about its atomic components and their inter-relations.’ [Edmonds 1999, p.72] ‘Roughly, by a complex system I mean one made up of a large number of parts that interact in a nonsimple way.’ ‘complexity frequently takes the form of hierarchy’ [Simon 1962, p.468] ‘A complex system is literally one in which there are multiple interactions between many different components’ [Rind 1999, p.105]
Decomposition	‘Decomposition or Dis-aggregation refers to the conceptual task of taking a model artifact/concept at some level of abstraction and developing a set of modeling artifacts/concepts that contain more information about the model.’ [Benjamin et al. 1998, p.392] ‘the act of breaking a large problem into a set of smaller problems or elements’ [Alfaris et al. 2010, p.2] ‘Has-member-mapping’ [Erens et al. 1994, p.23]. ‘granulation involves decomposition of whole into parts; organization involves integration of parts into whole’ [Zadeh 1997, p.111].
Fidelity	‘Fidelity of a simulation is the accuracy of the representation when compared to the real world system represented. A simulation is said to have fidelity if it accurately corresponds to or represents the item or experience it was created to emulate: How realistic does the simulation react?’ [Tolk 2012, p.17] ‘The degree to which a model or simulation reproduces the state and behavior of a real world object or the perception of a real world object, feature, condition, or chosen standard in a measurable or perceivable manner; a measure of the realism of a model or simulation; faithfulness. Fidelity should generally be described with respect to the measures, standards or perceptions used in assessing or stating it.’ [Gross 1999, p.3]
Granularity	‘The term level of granularity […] is used to describe the “grain size” i.e., the size and the detail of the system elements after system decomposition.’ [Chiriac et al. 2011, p.1] ‘The granularity of a subset of a universal set depends on its size. A subset should have a lower granularity than its supersets. The granularity of a partition depends on both the number of the blocks in the partition and the sizes of the blocks. A partition should have a lower granularity than its coarsening partitions.’ [Yao and Zhao 2012, p.12] ‘extent to which an object or model is broken down into smaller elements’ [Hehenberger 2014, p.188] ‘The depth of the architecture hierarchy of components, modules and subassemblies defines its level of detailed description or granularity’ [AlGeddawy and ElMaraghy 2013, p.151] ‘Node granularity is the number of undecomposable tasks in process model nodes. The bigger the node granularity is, the more abstract this node is, and there are more tasks in this node.’ [Ding et al. 2012, p.492]

Granulation	'Granulation of a universe involves the decomposition of the universe into families of subsets, or the clustering of elements into groups. It leads to a collection of granules, with a granule being a clump of points (objects) drawn together by indistinguishability, similarity, proximity or functionality [Zadeh 1997]. Granulation may produce either a single-level flat structure or a multi-level hierarchical structure [Yao 2001a].' [Yao 2003, p.287]
Hierarchy	'By a hierarchic system, or hierarchy, I mean a system that is composed of interrelated subsystems, each of the latter being, in turn, hierarchic in structure until we reach some lowest level of elementary subsystem' [Simon 1962, p.468] 'Every object is a hierarchy of components, the large ones specifiying the pattern of distribution of smaller ones, the small ones themselves, though at first sight more clearly piecelike, in fact again patterns specifying arrangement and distributions of still smaller components.' [Alexander 1964, p.130] 'our primary measure is "hierarchy," defined as the degree to which transactions in the network flow in one direction, from "upstream" to "downstream."' [Luo et al. 2012, p.2]
Modularity	'A fully modular architecture is one with clear clusters of elements, and where the relationships between the elements within an assembly are hidden to the elements outside the assembly. This incorporates the notion that a module not only contains elements, but also contains a higher density of relationships between those elements than to elements outside the module.' [Yu et al. 2007, p.91] 'A module is tightly coupled within and loosely connected to the rest of the system.' [Chiriac et al. 2011, p.1] 'Modularity refers to products, processes, and resources that fulfill various functions through the combination of distinct building blocks.' [Kusiak 2002]
Precision	'1. The quality or state of being clearly depicted, definite, measured or calculated. 2. A quality associated with the spread of data obtained in repetitions of an experiment as measured by variance; the lower the variance, the higher the precision. 3. A measure of how meticulously or rigorously computational processes are described or performed by a model or simulation.' [Gross 1999, p.4]
Resolution	'The resolution of a model or a simulation is the degree of detail and precision used in the representation of real world aspects in a model or simulation. Resolution means the fineness of detail that can be represented or distinguished in an image: How much detail do I observe?' [Tolk 2012, p.17] '1. The degree of detail used to represent aspects of the real world or a specified standard or referent by a model or simulation. 2. Separation or reduction of something into its constituent parts; granularity.' [Gross 1999, p.5] 'Resolution refers to the precision of the model's output, for example, a qualitative model has lower resolution than a quantitative description.' [Weld 1992, p.257]
Scope	'By the scope of a model, we denote the range of phenomena that the model describes. A model has greater scope than another if it describes strictly more of the world.' [Weld 1992, p.284]

3.2 Relating model granularity to related concepts

The term abstraction is mostly used in a more conceptual manner [Cartwright 1999], for instance when describing modelling activities or resulting levels of abstraction (e.g. [Fishwick 1988]). Abstraction is a fundamental part of most modelling endeavours [Frigg 2003], leads to a particular level of abstraction of a model and thereby drives its granularity. This article focuses on the description of model granularity as it is more suited to describe the resulting model itself. However, the notion of (levels of) abstraction [Floridi 2008], [Saitta and Zucker 2013] remains very relevant and it can be said that abstraction in the modelling process determines model granularity.

Model resolution is very closely linked with model granularity and is in many cases used to describe similar ideas. It is often associated with the amount of detail a model includes to represent its target system [Tolk 2012]. Resolution is perhaps the closest related concept to granularity given that both are directly proportional – a high resolution requires a fine granulation.

Aggregation and decomposition are often referred to as the two opposite directions of constructing models. Aggregation is a bottom-up approach where elements of a model are grouped together and described on a higher level of abstraction [Iwasaki and Simon 1994]. Aggregation generally results in more coarse grained models. Decomposition denotes a top-down approach where system elements are broken into a set of smaller entities or sub-systems [Alfaris et al. 2010]. Decomposition generally leads to more fine grained models. For both concepts a range of drivers and approaches exist that are employed depending on context and purpose of the model.

Complexity can refer to the target system's properties that will have to be represented in some way in the model. Capturing a more complex system, comprising multiple components interacting in non-simple ways [Simon 1962], may require a more detailed, fine-grained model. Complexity can also refer to the model itself, describing either the number of elements and their connectedness or the difficulty to understand and work with them [Edmonds 1999]. In many cases a larger, more fine grained model will also be considered more complex.

The organisation of complex systems is often characterised as multi-level hierarchies with of systems and sub-systems [Simon 1962], [Alexander 1964], [Ladyman et al. 2013]. Depending on the chosen approach, aggregation or decomposition both lead to hierarchical structures, which strongly influence the resulting model granularity. Similarly, models that offer different levels of granularity are often based on a hierarchical structure – of data or model architecture.

Clustering aims to group elements of a model that are strongly interconnected into clusters, while minimising the connectivity outside of the clusters [Browning 2001]. Models can be clustered on multiple levels, resulting in hierarchical structures. A model can be aggregated through clustering, thereby transforming it to a more coarse grained instance. The size and number of clusters depend on the granularity of the original model and the desired granularity of the clustered model.

Model accuracy can describe the degree to which the model constructs or its output conforms to reality [Gross 1999]. Similarly, precision can describe both a quality of the model itself as well as the results that are obtained from it [Gross 1999]. Both accuracy and precision may depend on the granularity of the model as describing certain aspects of reality requires a larger amount of detail. However, a fine granular model is not automatically accurate/precise and and accurate/precise model does not necessarily have to be fine grained.

Similar to accuracy and precision, the notion of model fidelity also relates to granularity. Fidelity refers to the extent to which state or behaviour of a real world system is reproduced by a model or simulation [Gross 1999]. Fidelity describes the capability of a model to represent the real world whereas granularity describes properties of a model, which result from the modelling process and may influence the model's fidelity.

Finally, granularity refers to a property of the model itself and is characterised more or less formally, depending on the discipline. Mathematical definitions are based on set theory and consider cardinality and size of subsets [Yao and Zhao 2012]. In engineering design, the size and detail of model elements determine its granularity, which is commonly understood to result from (hierarchical) decomposition [Chiriac et al. 2011], [AlGeddawy and ElMaraghy 2013]. We refer to the granularity of a model as a manifestation of the level of detail in which it represents its target system. In particular, granularity may be used to describe the size and information content of model elements as well as the nature of dependency between model elements. Granularity can also relate to the resolution of output obtained through analysis based on a model.

3.3 Use of terminology in different communities

Modelling communities differ in their use of terminology to describe granularity and related concepts. In many cases similar meanings are associated to particular terms but their use is not consistent across domains and or even within the engineering design domain. Having an overview of the use of terminology and conceptualisation of granularity across disciplines can help to build a substantial understanding of the topic and enables a wider discussion. A brief summary across the main

communities discussing models is presented here to point readers in the direction of relevant literature, without aiming to provide an exhaustive review.
In the engineering design community many of the concepts presented in Table 1 are used, depending on the modelling domain. For product models, aggregation and decomposition as well as hierarchy are important concepts relating to their construction. Clustering and modularity are mostly used for analysis and granularity has recently been used to describe the level of detail a model offers. Fidelity is an important concept especially in analysis task like various applications of FE methods. The wider modelling and simulation community refers to a model's accuracy, precision, resolution or fidelity when describing its attributes but also reasons about abstraction. In philosophy and related disciplines discussions are usually more high level and include reflections on the nature of abstraction, complexity or more generally how models represent their target systems. Complexity Science focuses on the notion of complexity, mostly of the target system, but also includes discussions of other aspects related to model properties. Graph and network theory also often refer to complexity but include concepts like hierarchy and clustering. In the field of Artificial Intelligence researchers have focused on the role of hierarchies and abstraction but also include complexity and other terms. Other disciplines of computer science like granular computing or fuzzy logic discuss granularity more specifically.

4. Relevance for design community

4.1 Importance of model granularity in engineering design

In many respects, the discussion of model granularity in the field of engineering design resonates with modelling and simulation in other domains. However, models for design differ from models for analysis in that the target system might not physically (or even conceptually) exist in its final state when the model is being developed. So, the choice of model granularity has implications beyond the performance of the model itself as it can also influence the target system. For instance, product model granularity can influence modularisation of system architectures [Chiriac et al. 2011] or sequencing of integration tasks [Eppinger et al. 2014]. Also, process models have to account for the fact that product development processes are multi-disciplinary, interdependent, parallel and iterative [Browning et al. 2006] and can exhibit considerable uncertainty [Wynn et al. 2011]. Depending on the modelling approach, this complexity can lead to uneven model granularity, for instance to capture parts of interest in more detail while capturing the rest of the system on a more abstract level [Tilstra et al. 2012]. Another particularity of modelling in engineering design is the distinction between product and process modelling, which are often handled separately but can also be integrated (see e.g. [Eckert et al. 2015]). In either case, granularity choices in one domain of modelling can influence the other and models within one domain each other. For example, the granularity of a product model can influence design process simulation and task sequencing [Maier et al. 2014, 2015].
It can be argued that due to the 'to be' nature of models in the field of design their properties also have an increased impact on the real world, which highlights the importance of understanding their implications. The granularity of a model, like its scope, is one of those properties that should be scrutinised in order to derive reliable insights [Chiriac et al. 2011], [AlGeddawy and ElMaraghy 2013]. Especially in dependency-type, structural models, which play a big role in product development [Browning 2015], problem decomposition or partitioning are highly important [Alfaris et al. 2010].

4.2 Existing approaches dealing with model granularity

Despite the apparent importance of model granularity in the field of engineering design relatively few research contributions address the topic directly. Indeed it is often assumed that some appropriate level will be determined without considering the sensitivity of the results [Chiriac et al. 2011]. There are, however, a number of approaches that directly deal with issues surrounding model granularity. Some examples are briefly introduced here. Further approaches could be said to deal with the topic more or less directly, like clustering and modularisation. A detailed review of these would go beyond the scope of this article. Chiriac et al. [2011] focus on how model granularity affects the degree of modularity of a product. They conclude that architectural analysis can be distorted by the level of granularity of its components and advise caution when decomposing a system for analysis tasks. Cladistics is a classification method that hierarchically groups entities into discrete sets and subsets [ElMaraghy et al. 2008]. It has been used in the field of engineering design, among other things to determine an optimum granularity level for architecture models of modular products [AlGeddawy and ElMaraghy 2013]. This approach uses component-based DSMs and yields a hierarchical clustering, which can be visualised in a cladogram. For each level of this clustering a modularity index is calculated, which enables choosing the best modularity configuration and its respective granularity. Tilstra et al. [2012] present the High Definition Design Structure Matrix (HDDSM), which employs a hierarchical modelling method to include higher levels of detail where needed. The approach builds upon DSM research and allows modular construction and assembly of highly detailed models and sub-models, facilitating the distribution of modelling tasks. The authors note the potential for analysis on different levels of detail with the potential of including strategic clustering.

The presented approaches show that model granularity has received increasing attention in engineering design. However, the majority focuses on a particular purpose or issue and largely omits the wider challenges of model granularity. Also, because the contributions differ in their use of terminology, comparisons and attempts to synthesise them are complicated. A clearer view of how granularity can be described and how related challenges and mitigating approaches can be categorised could advance the necessary understanding of the field and spark further, necessary discourse on the topic.

5. Discussion and conclusion

This article gives an overview over the terminology used to describe granularity and related concepts across a range of disciplines. It also provides a list of definitions for relevant terms, making them explicit and providing a reference point for further discussions and research in the area. It is shown how different communities use terminology to describe similar or related concepts, which should facilitate interdisciplinary advances towards model granularity. The relevance for engineering design is summarised along with presenting some approaches dealing with granularity in the domain. This provides a basis for further investigation of the topic and highlights its importance for engineers and designers working with models on a regular basis.

While the article provides a range of definitions, these only constitute examples the authors selected as relevant. Further definitions can be found in the literature in various fields. However, the presented selection is representative of the most common perceptions in communities concerned with modelling of any form. For full coverage, a very extensive literature review would be necessary due to the interdisciplinarity and the scope of this research. Granularity was selected as the main theme of the article. Other relevant concepts are presented and could be selected to describe the phenomena that are associated with a wider definition of granularity in this article. The term granularity was found to have the potential to synthesise many of the related concepts by describing a property of the model itself, rather than its construction. This terminology also allows including or referring to other mentioned concepts more consistently. Empirical data on the perception of practitioners is not included in this article. An interview study conducted by the authors suggests that the notion of granularity is widely accepted and understood and in many cases a direct consideration. Further empirical studies could help to determine the challenges encountered and help supply more targeted support. This research should be seen as a step towards a more comprehensive study of the nature of model granularity. As this is an extensive field that requires including a range of so far only loosely connected domains, further, more detailed characterisation of model granularity is necessary to for a thorough investigation of the topic.

The terminology and definitions presented in this article offer a basis for further discussion and research in the field of model granularity. This can be seen as a step towards establishing a common vocabulary and understanding, informing researchers and practitioners with the aim of promoting the importance of reflecting on modelling granularity. Integrating perspectives from various disciplines is necessary due the limited attention the topic has received in engineering design so far. This provides directions for further investigation and motivates multidisciplinary research and knowledge transfer. Understanding model granularity is very important for engineers constantly making decisions based on models. The theoretical contribution of this article marks a step in establishing the relatively abstract topic of model granularity on the research agenda with the objective of assisting both researchers and practitioners. Further work is required to obtain more comprehensive and formalised knowledge of the characteristics of granularity as well as the associated challenges and ways of alleviating them. Providing a concrete overview of granularity levels and their respective influence on engineering design decisions could provide more direct guidance for practitioners when selecting a level of granularity. Additional research into the sensitivity of models and approaches to determine suitable levels of granularity is required to derive relevant recommendations for modellers. Finally, empirical investigation could reveal how related challenges are addressed in practice to date and what can be done to improve this.

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