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Project dynamics and emergent complexity

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Abstract This paper presents a theoretical analysis of project dynamics and emergent complexity in new product development (NPD) projects subjected to the management concept of concurrent engineering. To provide a comprehensive study, the complexity frameworks, theories and measures that have been developed in organizational theory, systematic engineering design and basic scientific research are reviewed. For the evaluation of emergent complexity in NPD projects, an information-theory quantity—termed "effective measure complexity" (EMC)—is selected from a variety of measures, because it can be derived from first principles and therefore has high construct validity. Furthermore, it can be calculated efficiently from dynamic generative models or purely from historical data, without intervening models. The EMC measures the mutual information between the infinite past and future histories of a stochastic process. According to this principle, it is particularly interesting to evaluate the time-dependent complexity in NPD and to uncover the relevant interactions. To obtain analytical results, a model-driven approach is taken and a vector autoregression (VAR) model of cooperative work is formulated. The formulated VAR model provided the foundation for the calculation of a closed-form solution of the EMC in the original state space. This solution can be used to analyze and optimize complexity based on the model's independent parameters. Moreover, a transformation into the spectral basis is carried out to obtain more expressive solutions in matrix form. The matrix form allows identification of the surprisingly few essential parameters and calculation of two lower complexity bounds. The essential parameters include the eigenvalues of the work transformation matrix of the VAR model and the correlations between components of performance fluctuations.

Keywords Emergent complexity · New product development · Cooperative work · Project dynamics · Vector autoregression model · Effective measure complexity

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1 Introduction

In times of economic instability, successful development of innovative products and effective management of new product development (NPD) projects are particularly important for gaining competitive advantage. To shorten time-to-market and lower development/production costs, NPD projects are often subjected to concurrent engineering (CE). In their landmark report, Winner et al. (1988) define CE as the systematic approach to the integrated, concurrent design of products and work processes, including manufacture and support. This organizational concept is intended to cause the developers, from the outset, to consider all elements of the product life cycle from concept design to disposal, including quality, cost, schedule, and end user requirements. A good example is a vehicle development project in the automotive industry. In the late development stage, such a project involves dozens of CE teams. The CE teams are usually structured according to the subsystems of the product to be developed (e.g. car body, powertrain, chassis frame, etc.) and are coordinated by system-integration and management teams. The needs, functional requirements and concepts are discussed and "orchestrated" by the subject-matter experts in regular CE team meetings and mapped onto design parameters in a highly cooperative work process.

NPD projects can show very informative but also complex and difficult-to-manage patterns of organizational dynamics. The patterns emerge from cooperative work that is not only fundamentally iterative, with analysis, synthesis and decision-making stages, but also tightly coupled through the product structure with many interfaces between modules. Iterations occur frequently because of the availability of new or updated information about geometric entities, topological entities etc. As a consequence, the development tasks are both highly variable and strongly dependent on each other and on elements of "surprise" in the form of seemingly erratic evolutionary events that occur. These phenomena are typical of complex systems, as stressed by Shalizi (2006) and Nicolis and Nicolis (2007). In that sense, NPD projects with long-range spatiotemporal coordination structures can be regarded as one of the most authentic prototypes of complex organizational systems. They serve as inspiration for raising new issues and stimulate applied and basic scientific research. One important source of variability is the human factor. The manifold project states usually create a demand for mental resources that exceeds the deliberative capacity of any developer, and many assumptions about design ranges or physical functions have to be made. This inevitable level of "ignorance" leads to unpredictable performance fluctuations. The performance fluctuations in conjunction with tight coordination structures often render the project difficult to anticipate, because the evolution toward a stable development solution can differ significantly from the expected (unperturbed) process (Huberman and Wilkinson 2005). Depending on the kind and intensity of cooperative relationships, some of the CE teams can enter multiple cycles of revisions, which demand unplanned effort as well as long delays. Moreover, the simultaneous revision cycles can be reinforced, and a fatal pattern of organizational dynamics termed "design churns" (Yassine et al. 2003) or "problem-solving oscillations" (Mihm et al. 2003; Mihm and Loch 2006) can emerge. In this case, the progress of the project irregularly oscillates between being on, ahead of, or behind schedule.

This phenomenon was analyzed in detail by Terwiesch et al. (2002) and Yassine et al. (2003) for the automotive industry. According to the literature review of Mihm and Loch (2006), the design churn effect occurs across different domains.

Design churns are an intriguing example of emergent (self-generated) complexity in NPD projects, which can lead to disastrous results. The emergence is strong in the sense that patterns can only be reliably forecasted from the observation of the past of each particular instance of task processing and with a large body of knowledge of prior history (Chalmers 2002). A deeper understanding of the interrelationships between performance variability and project dynamics is needed to cope with emergent complexity, together with new methods for quantitative complexity evaluation. The goal of this paper is therefore twofold: first, to introduce a complexity measure that is underpinned by a rigorous theory of basic scientific research (Grassberger 1986) and enables quantifying strong emergence in an open organizational system in terms of mutual information that is communicated from the infinite past to the infinite future. Second, it aims to present a stochastic model of cooperative work in NPD that is based on the theory of vector-autoregressive processes and to use this generative model to obtain analytical complexity results. The challenge is that even if the breakdown structure of the tasks, their rate of processing and the laws of interaction are given, it is difficult to anticipate the performance of the whole project. The complexity-theory approach builds on our previous work on project modeling and simulation (Schlick et al. 2007, 2008, 2009, 2011, 2012; Tackenberg et al. 2009, 2010) and differs from the abovementioned studies in the way that closed-form solutions of different strengths are formulated, which can be used for identifying and controlling the essential complexity-driving variables.

The paper is organized as follows. In Sect. 2, frameworks, theories and measures that have been developed in organizational theory, systematic engineering design and basic scientific research to evaluate complexity in new product development (and comparable open organizational systems) are reviewed. An information-theory quantity—termed the "effective measure complexity" (EMC)—is analyzed in detail because of its outstanding construct validity and computational merits for the evaluation of emergent complexity in NPD projects. In Sect. 3, the foundations for deterministic and stochastic modeling of cooperative work in NPD projects are laid, and the corresponding state equations are formulated and explained. The stochastic model explicitly allows calculation of the EMC. Moreover, a transformation into the spectral basis is performed to uncover the essential mechanisms of concurrent task processing. Closed-form complexity solutions in the original state-space coordinates and the spectral basis are derived and discussed in detail in Sect. 4. Lower bounds are put on the EMC at the end of this section. Section 5 covers the main conclusions of the paper and gives an outlook for future research.

2 Evaluation of complexity in new product development

The term "complexity" stems from the Latin word "complexitas", meaning comprehensive or inclusive. In current language usage, it is the opposite of simplicity, but this interpretation does not appear to be underpinned by any explicit concept. Various disciplines have studied the concepts and principles of complexity in basic and applied scientific research. Several frameworks, theories and measures have been developed, depending on differing views of complexity among disciplines. An objective evaluation of structural and dynamic complexity in NPD would benefit system designers and managers, because it would enable them to compare and optimize different systems in analytical and experimental studies. To obtain a comprehensive view of organizational, product and process elements and their interactions in the product development environment, a thorough review of the notion of complexity has to start by organizational theory. The literature on organizational theory demonstrates that the complexity of NPD projects results from different sources and the consideration of the underlying organizational factors and their interrelationships is important for successful project management (Kim and Wilemon 2009). However, we hypothesize that factor-based approaches are not sufficient to evaluate emergent complexity in open organizational systems with tightly coupled work processes and therefore the complexity theories and measures of basic scientific research must also be taken into account (cf. Amaral and Uzzi 2007). They can provide deep and consistent insights into emergent phenomena of systems and dynamic complexity of cooperation. Selected measures can also be used to optimize project organizational design (Schlick et al. 2009). The formalized measures build upon our intuition that a system is complex if it is difficult to describe and predict efficiently. A comprehensive overview of this concept including detailed descriptions and illustrations can be found in Shalizi (2006), Prokopenko et al. (2007) and Nicolis and Nicolis (2007). For effective complexity management in NPD, the product-oriented measures from theories of systematic engineering design are also relevant. Seminal work in this field has been done by Suh (2005) on the basis of information-theoretic quantities. These quantities are also the foundation of statistical complexity measures from basic scientific research, which means that Suh's complexity theory and recent extensions of it (see Summers and Shah 2010) must be discussed in the light of the latest theoretical developments. Moreover, the literature that has been published around the Design Structure Matrix (Steward 1981) as a dependency modeling technique has to be considered. This literature also provides a firm foundation for mathematical modeling of cooperative work in NPD projects. In general, we try to restrict our analyses to mature scientific theories because of their objectivity and construct validity.

2.1 Approaches from organizational theory

According to Murmann (1994) and Griffin (1997) complexity in the product development environment is determined by the number of (different) parts in the product and the number of embodied product functions. Kim and Wilemon (2003) developed a complexity assessment template covering these and other important "sources". The first source in their assessment template is "technological complexity", which can be divided into "component integration" and "technological newness". The second source is the "market (environmental) complexity" that results from the sensitivity of the project's attributes to market changes. "Development complexity" is the third source and is generated when different design decisions and components have to be integrated, qualified suppliers have to be found and supply chain relationships have to be managed. The fourth source is "marketing complexity" resulting from the problems of bringing the product to market. "Organizational complexity" is the fifth source because projects usually require intensive cooperation and involve many areas of the firm. In large-scale engineering projects other companies are also involved. Their coordination leads to "intraorganizational complexity", the sixth source. In order to validate and prioritize complexity sources, Kim and Wilemon (2009) carried out an extensive empirical investigation. An analysis of exploratory field interviews with 32 project leaders and team members showed that technological challenges, product concept/customer requirement ambiguities and organizational complexity are major issues promoting complexity in NPD. The perceived dominant source was technological challenges, since about half of the respondents noted technological difficulties encountered in attempting to develop a product using an unproven technique or process.

Hölttä-Otto and Magee (2006) developed a project complexity framework based on the seminal work of Summers and Shah (2003). They identified three dimensions: the product itself (artifact), the project mission (design problem), and the tasks required to develop the product (process). The key indicators for each of these complexities are size, interactions and stretch (solvability). They conducted interviews in five divisions of large corporations competing in different industries in the North American market. The results show that the effort estimation is primarily based on the scale and the stretch of the project and, surprisingly, not on subsystem interactions. Tatikonda and Rosenthal (2000) focus on the task-dimension and relate project complexity to the nature, quantity and magnitude of the organizational subtasks and subtasks interactions required by a project.

A recent literature review and own empirical work about elements contributing to complexity in large engineering projects was published by Bosch-Rekveldt et al. (2011). The analysis of the literature sources and 18 semi-structured interviews in which six completed projects were studied in depth led to the development of the TOE framework. The framework covers 50 different elements, which are grouped into three main categories: "technical complexity" (T), "organizational complexity" and "environmental complexity" (E). Additional subcategories of TOE are defined on a lower level: "goals", "scope", tasks", "experience", "size", "resources", "project team", "trust", "stakeholders", "location", "market conditions", and "risks", showing that organizational and environmental complexity are more often linked with softer, qualitative aspects. Interestingly, Bosch-Rekveldt et al. (2011) distinguish between project complexity and project management (or managerial) complexity. Project management complexity is seen as a subset of project complexity. Various normative organizing principles to cope with managerial complexity can be found in the standard literature on project management (e.g. Shtub et al. 2006; Kerzner 2009). If, for instance, managerial complexity is low, project management within the classic functional organizational units of the company is usually most efficient and cross-functional project organization types can create unnecessary overhead. However, if coordination needs between functional, spatial and temporal boundaries are high, a matrix organization is often a better practice allowing development projects to be staffed with specialists from throughout the organization (Shtub et al. 2006). For large engineering projects with a long duration a pure project organization is often the preferred type in industry as the project is cared for full-temporally by a team that is fully responsible for the entire extent. Specific sources of managerial complexity and their impact on performance were also examined in the literature, e.g. communication across functional boundaries (Carlile 2002), cross-boundary coordination (Kellogg et al. 2006), spatial and temporal boundaries in globally distributed projects (Cummings et al. 2009) and the effects of a misalignment in the geographic configuration of globally distributed teams (O'Leary and Mortensen 2010). Maylor et al. (2008) developed an integrative model of perceived managerial complexity in project-based operations. Based on a multistage empirical study elements of complexity were identified and classified under the dimensions of "mission", "organization", "delivery", "stakeholder", and "team".

The literature review shows that there is a large variety of nomenclatures and definitions for the sources of complexity in NPD projects. However, the underlying factors have not yet been integrated into a single objective and valid framework. According to Lebcir (2011) there is an urgent need for a new, non-confusing, and comprehensive framework that is derived from the extensive body of knowledge. He suggests a framework in which "project complexity" is decomposed into "product complexity" and "innovation". Product complexity refers to structural complexity (see Sect. 2.3) and is determined by "product size" in terms of the number of elements (components, parts, sub-systems, functions) in the product and "product interconnectivity", representing the level of linkages between elements. On the other hand, innovation refers to "product newness" and "project uncertainty". Product newness represents the degree of redesign of the product compared to previous generations of the same or similar product. Project uncertainty represents the fact that methods and capabilities are often not clearly defined at the starting point of a project. The results of a dynamic simulation indicate that an increase in uncertainty has a significant impact on the development time. The other factors tend to increase development time as they increase, but their impact is not significantly different in projects involving medium or high levels of these factors.

The complexity templates and frameworks from organization theory are especially beneficial for project management because they help to focus managerial intervention on empirically validated performance-shaping factors. It must be criticized, though, that without a quantitative theory of emergent complexity it is almost impossible to identify the essential variables and their interrelationships. Furthermore, it is very difficult to consolidate them into one consistent complexity metric. In the literature very few authors, such as Mihm et al. (2003, 2010), Rivkin and Siggelkow (2003, 2007), Braha and Bar-Yam (2007) build upon quantitative scientific concepts for the analysis of complex organizational systems. Mihm et al. (2003) present analytical results from random matrix theory predicting that the larger the project, as measured by components or interdependencies, the more likely are problem-solving oscillations and the more severe they become—failure rates grow exponentially. In the work of Rivkin and Siggelkow (2003, 2007) the famous biological evolution theory of Kauffman and the NK model are used for studying organizations as systems of interacting decisions. Different interaction patterns such as block diagonal, hierarchical, scale-free, and so on are integrated into a simulation model to identify local optima. The results show that by holding the total number of interactions among decisions fixed, a shift in the pattern can alter the number of local optima by more than an order of magnitude. In a similar fashion Mihm et al. (2010) use a statistical model and Monte-Carlo experiments to explore the effect of an organizational hierarchy on search solution stability, quality and speed. Their results show that assigning a lead function "anchoring" a solution speeds up problem solving, local solution choice should be delegated to the lowest hierarchical level and organizational structure matters little at the middle management level, but it matters at the "front line"—front-line groups should be kept small. Braha and Bar-Yam (2007) examine the statistical properties of networks of people engaged in distributed development and discuss their significance. The autoregression models of cooperative work in NPD that will be introduced in the next section (Eqs. (17) and (24)) are quite closely related to their dynamical model. However, there are important differences: the autoregression models are defined over a continuous range of state values and can therefore represent different kinds of cooperation relationships as well as precedence relations (e.g. overlapping); each task is nonequally influenced by other tasks; and finally, correlations ρ_{ij} between performance fluctuations among tasks i and j can be captured.

2.2 Approaches from basic scientific research

2.2.1 Algorithmic complexity

Historically, the most important approach from basic scientific research is algorithmic complexity, dating to the great mathematicians Kolmogorov, Solomonoff and Chaitin (Chaitin 1987; Li and Vitanyi 1997). Considering an information processing system, the complexity of the intricate mechanisms can be evaluated using output signals and symbols that are communicated to an intelligent observer. In that sense, complexity is manifested to an observer through the complicated way in which events unfold in time and organize in state space. If the output is symbolic, it can be concatenated in the form of strings and may be sequentially stored in a computer file. The symbols are typically chosen from a predefined alphabet $\mathcal{X}$. If the output is not symbolic, it can be encoded with methods of symbolic dynamics (Lind and Marcus 1995; Nicolis and Nicolis 2007). The central idea of Kolmogorov, Solomonoff and Chaitin is that a generated string is "complex" if it is difficult for the observer to describe. The observer can describe the string by writing a computer program that reproduces it. The difficulty of description is measured by the length of the computer program on a Universal Turing Machine U. If x is a binary string, the algorithmic complexity of x, termed $K_U(x)$, is the length of the shortest program with respect to U that will print x and then halt. According to Chaitin (1987) an additional requirement is that the string x has to be encoded by a prefix code $d(x)$. The complete definition is:

$$K_U(x) = \min\left\{\left|d(p)\right| : U(p) = x\right\}. \tag{1}$$

In that sense, $K_U(x)$ is a measure of the computational resources needed to specify the string x in the language of U. According to this concept, a simple periodic work process whose activities (labeled by discrete events) are processed in strict cycles, like in an assembly line, is not complex because we can store a sample of the period and write a program that repeatedly outputs it. At the opposite end of the complexity range, a random work process without a purposefully designed organization cannot be described in any meaningful way except by storing every feature. This is due to the mere fact that we cannot identify any persisting structure to utilize for a shorter description. It is obvious that the algorithmic complexity is not a good measure for emergent complexity in NPD projects, because it is maximal in the case of a completely randomized task processing. It usually cannot uncover the important long-range temporal coordination structures either. An additional conceptual weakness is that it aims for an exact description of observations. Many of the details of any configuration are just random fluctuations (noise). It is impossible to identify regularities from noise that generalize to other data sets from the same system; to assess complexity, the underlying rules must be in focus and separated from noise (Shalizi 2006). Therefore, a statistical representation is necessary.

2.2.2 Stochastic complexity

The most prominent statistical complexity measure is Rissanen's (1989, 2007) stochastic complexity. To clarify the concept, it is assumed that we have carried out a comprehensive longitudinal study of cooperative work in an NPD project and have drawn a large sample of work processes. Single work process observations in a specific project phase were labeled by discrete events and stored in a string $x_0^{\mathcal{T}} = (x_{j(0)}, x_{j(1)}, \ldots, x_{j(\mathcal{T})})$ $(x_{j(\tau)} \in \mathcal{X}, j(\tau) \in \{1, \ldots, |\mathcal{X}|\}, \tau = 0, 1, \ldots, \mathcal{T})$, indicating the history of task processing across an interval $\mathcal{T}$. Labeling converts the relevant features into discrete events such as rapidly or slowly declining work remaining (see Sect. 3). The index $j(\tau)$ can be interpreted as a pointer to event $x_{j(\tau)}$ observed at process instant τ. The analysis of all work process observations in the project phase allows the formation of a joint probability mass function $P(X_0, \ldots, X_{\mathcal{T}})$. It is assumed that we can uncover the essential dynamical dependency structures and represent the probability mass function efficiently using a discrete state model (e.g. a first-order Markov chain). We denote the parameters of the model by the tuple θ (probabilities of initial state, transition probabilities etc.). The model assigns a certain probability

$$P(X_0 = x_{j(0)}, \ldots, X_{\mathcal{T}} = x_{j(\mathcal{T})} | \theta), \tag{2}$$

to the data. The discrete state variables $(X_0, \ldots, X_{\mathcal{T}} | \theta)$ form a one-dimensional random process representing an ensemble of histories that can be explained in light of the model. The above likelihood function can be transformed into a loss function L representing the information content:

$$\begin{aligned} L\left[\theta, x_0^{\mathcal{T}}\right] &:= \log_2 \frac{1}{P(X_0 = x_{j(0)}, \ldots, X_{\mathcal{T}} = x_{j(\mathcal{T})} | \theta)} \\ &= -\log_2 P(X_0 = x_{j(0)}, \ldots, X_{\mathcal{T}} = x_{j(\mathcal{T})} | \theta). \end{aligned} \tag{3}$$

According to information theory, minimizing the loss can also be thought of as minimizing the encoded length of the sequence. However, we do not have a complete description; we have an encoded version of the data, but we have not specified what the encoding scheme, i.e. the model itself, is (Shalizi 2006). Thus, the total description length DL can be divided into two parts,

$$DL\left[x_0^{\mathcal{T}}, \theta, \Theta\right] = L\left[\theta, x_0^{\mathcal{T}}\right] + D[\theta, \Theta],$$

where $D[\theta, \Theta]$ is the number of bits needed to specify θ from among the set of all feasible models in class Θ (e.g. class of Markov chains of order n). The model represents the part of the description, which can be generalized, whilst $L[\theta, x_0^{\mathcal{T}}]$ includes the noisy part that does not generalize to other data sets. If $D[\theta, \Theta]$ assigns short code words to simple models, we have the desired tradeoff: we can reduce the part of the data that looks like noise only by using a more elaborate model. The minimum description length (MDL) principle of Rissanen (1989, 2007) allows the selection of the model that minimizes the total description length:

$$\theta_{MDL} := \arg\min_{\theta} DL\big[x_0^{\mathcal{T}}, \theta, \Theta\big].$$

The stochastic complexity C_{SC} of $x_0^{\mathcal{T}}$ given the model class Θ is simply the MDL:

$$C_{SC}\big[x_0^{\mathcal{T}}, \theta\big] := \min_{\theta} DL\big[x_0^{\mathcal{T}}, \theta, \Theta\big]. \tag{4}$$

Under mild conditions for the process in the class Θ, as we provide more data, θ_{MDL} will converge to the model in Θ that minimizes the generalization error. Regarded as a principle of model selection, MDL has proved very successful (Grünwald 2007). Nevertheless, a part of this success comes from tuning the model-coding term $D[\theta, \Theta]$ so that models that do not generalize well turn out to have long descriptions. This is not illegitimate, but it relies on the intuition and knowledge of the model builder. Whatever its merits as a model selection method, stochastic complexity is not a good metric of emergent complexity in NPD projects for three reasons (sensu Shalizi 2006): (1) The dependence on the model-encoding scheme, which is difficult to formulate in a valid form. (2) The log-likelihood term, $L[\theta, x_0^{\mathcal{T}}]$, can be decomposed into additional parts, one of which is related to the entropy rate of the information-generating work processes (h_μ, Eq. (13)) and so it reflects their intrinsic unpredictability, not their complexity. (3) The need to specify some particular dynamic model and to formally represent this specification. This is necessarily part of the model development process but seems to have no significance from a theoretical point of view. For instance, an NPD project does not need to represent its organization; it just has it.

2.2.3 Effective measure complexity and forecast complexity

Motivated by weaknesses such as these, the physicist Peter Grassberger (1986) developed a highly satisfactory complexity theory whereby complexity is the amount of information required for optimal prediction. In general, there is a limit to the accuracy of any prediction of a given system set by the characteristics of itself, e.g. free will of decision makers, limited precision of measurement etc. Suppose we have a model that is maximally predictive, i.e. its predictions are at the theoretical limit of accuracy. Prediction is always a matter of mapping inputs to outputs. In our application context, the inputs might be work process observations labeled by discrete events, and the output could be the future course of the project. However, the entire past is usually not relevant for making good predictions. In fact, if the task processing is strictly periodic, one only needs to know which of the ϕ phases the work process is in. For a completely randomized work process with independent and identically distributed (iid) state variables, the past is completely irrelevant for predicting the future.

Because of this "memorylessness", the clever, evidence-based estimates of an experienced project manager on average do not outperform naive guesses of the outcome based on means. If we ask how much information about the past is relevant in these two extreme cases, the correct answers are $\log_2(\phi)$ and 0, respectively. It is intuitive that these cases are of low complexity, and more informative dynamics "somewhere in between" must be assigned high complexity values.

When dealing with a Markovian model such as the vector autoregression model that will be formulated in Sect. 3.2, only the present state of work remaining is relevant (Eq. (17)), so the amount of information needed for optimal prediction is just equal to the amount of information needed to specify the current state. More formally, any predictor g will translate the one-dimensional infinite past $x_{-\infty}^{-1}$ into an effective state $s = g[x_{-\infty}^{-1}]$ and then make its prediction on the basis of s. The amount of information required to specify the effective state in case of discrete-type random variables (or discretized continuous-type random variables) can be expressed by Shannon's information entropy $H[S]$ (Cover and Thomas 1991). It is defined for a discrete-type random variable X with values in the alphabet $\mathcal{X}$ as

$$H[X] := -\sum_{x\in\mathcal{X}} P(X = x)\log_2 P(X = x). \tag{5}$$

$H[.]$ measures in [bits] the amount of freedom of choice in the associated decision process. If we focus on the set $\mathcal{M}$ of maximally predictive models, we can define what Grassberger called "the true measure complexity" C_μ of the process as the minimal amount of information needed for optimal prediction:

$$C_\mu := \min_{g\in\mathcal{M}} H\big[g\big[X_{-\infty}^{-1}\big]\big]. \tag{6}$$

$X_{-\infty}^{-1}$ denotes the infinite, one-dimensional sequence of random variables $\ldots X_{-3}X_{-2}X_{-1}$ representing the past of the process. Unfortunately, Grassberger provided no procedure for finding the maximally predictive models. However, he did draw the following conclusion. A basic result of information theory, called "the data-processing inequality", says that for any pair of random variables A and B the mutual information follows the rule:

$$I[A, B] \geq I\big[g[A], B\big]$$

The mutual information $I[.,.]$ measures the amount of information that can be obtained about one random variable by observing another and can be equivalently expressed through the entropy $H[.]$ as

$$\begin{aligned} I[A, B] &= H[A] - H[A|B] \\ &= H[A] + H[B] - H[A, B] \\ &= I[B, A]. \end{aligned}$$

According to the data-processing inequality, it is impossible to extract more information from samples by processing than was in the samples to begin with. Since the state of the predictor is a function of the past, it follows that

$$I\big[X_{-\infty}^{-1}, X_0^{\infty}\big] \geq I\big[g\big[X_{-\infty}^{-1}\big], X_0^{\infty}\big],$$

where X_0^∞ represents infinite future (including the present state). Presumably, for optimal predictors, the two information values are equal and the predictor's state is just as informative as the original data. Otherwise, the model would be missing potential predictive power. Another basic inequality is that $H[A] \geq I[A, B]$, i.e. no variable contains more information about another than it does about itself. Even for the maximally predictive models, $H[X_{-\infty}^{-1}] \geq I[X_{-\infty}^{-1}, X_0^\infty]$. Grassberger called the latter quantity $I[X_{-\infty}^{-1}, X_0^\infty]$—the mutual information between the past and the future—the Effective Measure Complexity (EMC):

$$\mathrm{EMC} := I\big[X_{-\infty}^{-1}, X_0^\infty\big]. \tag{7}$$

Shalizi and Crutchfield (2001) proved that the true measure complexity gives an upper bound:

$$C_\mu \geq \mathrm{EMC}.$$

In terms of a communication channel, EMC is the effective information transmission rate of the process. The units are bits. C_μ is the memory stored in that channel. Hence, the inequality above means that the memory needed to carry out an optimal prediction of the future cannot be less than the information that is transmitted from the past $X_{-\infty}^{-1}$ to the future X_0^∞ (by storing it in the present).

Another key invariant of stochastic processes that was discovered much earlier is Shannon's source entropy rate:

$$h_\mu := \lim_{\eta \to \infty} \frac{H[X^{n=\eta}]}{\eta}. \tag{8}$$

This limit exists for all stationary processes. The source entropy rate is the intrinsic randomness that cannot be reduced, even after considering statistics over longer and longer blocks of generating variables. The unit of h_μ is bits/symbol. In the above definition the variable $H[X^n]$ is the information entropy of length-n blocks X^n. In the following, we will use the shorthand notation $H(n)$ to represent this kind of entropy, which is also termed Shannon block entropy (Grassberger 1986). For discrete-type random variables it is defined as

$$H(n) := H\big[X^n\big] = -\sum_{x^n \in \mathcal{X}^n} P\big(X^n = x^n\big) \log_2 P\big(X^n = x^n\big), \tag{9}$$

with

$$H(0) := 0. \tag{10}$$

The sums in the above equation run over all possible blocks of length n. The entropy rate h_μ can also be defined on the basis of the two-point slope $h_\mu(n)$ of the block entropy $H(n)$. If the block length n is varied, the two-point slope is simply

$$h_\mu(n) := H(n) - H(n-1), \tag{11}$$

with

$$h_\mu(0) := \log_2 |\mathcal{X}|. \tag{12}$$

$h_\mu(n)$ can be regarded as a dynamic entropy representing the entropy gain. $h_\mu(n)$ can also be expressed as conditional entropy (cf. Eq. (30))

$$h_\mu(n) := H\big[X_n | X^{n-1}\big].$$

In the limit of infinitely long blocks, it is equal to the source entropy rate

$$h_\mu = \lim_{\eta \to \infty} h_\mu(n = \eta). \tag{13}$$

According to Crutchfield and Feldman (2003) each difference $h_\mu(n) - h_\mu$ represents the difference between the entropy rate conditioned on n measurements and the entropy rate conditioned on an infinite number of measurements. In that sense, it estimates the information-carrying capacity in blocks in which the difference is not actually random but arises from correlations. The differences can be used to define a universal learning curve $\Lambda(n)$ (Bialek et al. 2001) as

$$\Lambda(n) := h_\mu(n) - h_\mu, \quad n \geq 1. \tag{14}$$

The EMC is the discrete integral of $\Lambda(n)$ with respect to the block length n, which controls the speed of convergence of the dynamic entropy to its limit (Crutchfield et al. 2010):

$$\mathrm{EMC} := \sum_{n=1}^{\infty} \Lambda(n). \tag{15}$$

In the sense of a learning curve, the EMC evaluates the apparent randomness at small block length n that can be "explained away" by considering correlations among blocks with increasing length.

As already mentioned, the EMC is zero for an iid process. According to Bialek et al. (2001), it is positive in all other cases and grows with time less rapidly than a linear function (subextensive). The EMC may either stay finite or grow infinitely with time. If it stays finite, no matter how long we observe the past of a process, we gain only a finite amount of information about the future. This holds true, for instance, for the cited periodic processes after the period ϕ has been identified. A longer period results in larger complexity values and $\mathrm{EMC} = \log_2(\phi)$. For some irregular processes, the best predictions may depend only on the immediate past, e.g. in our Markovian model or generally when evaluating a system far away from phase transitions or symmetry breaking. In these cases, the EMC is also small and is bound by the logarithm of the number of accessible states. Systems with more accessible states and larger memories are assigned larger complexity values. On the other hand, if the EMC diverges and optimal predictions are influenced by events in the arbitrarily distant past, then the rate of growth may be slow (logarithmic) or fast (sublinear power).

The mutual information between the infinite past and future histories of a stochastic process has been considered in many contexts. It is termed, for example, excess entropy **E** (Crutchfield and Feldman 2003; Ellison et al. 2009; Crutchfield et al. 2010), predictive information I_{pred} (Bialek et al. 2001), stored information (Shaw 1984) or simply complexity (Arnold 1996; Li 1991). Rissanen (1996, 2007) also refers to the part of stochastic complexity required for coding model parameters as model complexity.

2.3 Complexity measures from theories of systematic engineering design

The most prominent complexity theory in the field of systematic engineering design has been developed by Suh (2005) on the basis of his famous axiomatic design theory. His theory aims at providing a systematic way of designing large-scale systems.

He defines complexity in the functional domain and measures uncertainty through information-theory quantities. In this view, the product to be developed and the problem to solve the design issues are coupled through functional requirements (FRs) and design parameters (DPs). Two axioms are proposed, the independence and the information axioms. The independence axiom states that the FRs should be maintained by the developers independently of one another. When there are two or more FRs, the design solution must be such that each of the FRs can be satisfied without affecting any of the other FRs. This means that a correct set of DPs is to be chosen so as to satisfy the FRs and maintain their independence. If the independence can be maintained for all FRs, the design is "uncoupled" and a theoretically optimal solution. Once the FRs are established, the next step is the conceptualization process, which occurs during the mapping process going from the functional to the physical domain. The conceptualization process may produce several designs, all of which may be satisfactory in terms of the independence axiom. Even for the same task defined by a set of m FRs ($FR_1, \ldots, FR_m$), it is likely that different developers will come up with different designs, because there are many acceptable solutions. The information axiom provides a guideline in selecting the best design among those. The metric being used is the information content I_i for a given FR_i ($1 \leq i \leq m$). The information content is defined on the basis of the probability p_i of satisfying FR_i:

$$I_i := \log_2 \frac{1}{p_i} = -\log_2 p_i .$$

In the general case of m FRs, the information content I_{sys} for the entire system is

$$I_{sys} := -\log_2 P\left(X^m\right),$$

where $P(X^m)$ denotes the joint probability that all m FRs are satisfied. When all FRs are independent the information content I_{sys} can be decomposed into independent summands $-\log_2 p_i$. When not all FRs are statistically independent, there holds

$$I_{sys} = -\sum_{i=1}^{m} \log_2 p_{i|\{j\}} \quad \text{for } \{j\} = \{1, \ldots, i-1\}.$$

The term $p_{i|\{j\}}$ denotes the conditional probability of satisfying FR_i given that all other interrelated $\{FR_j\}_{j=1,\ldots,i-1}$ are also satisfied. The information axiom states that the best design is the one with the smallest I_{sys}, because the least amount of information is required to achieve the design goals. The probability of success p_i can be determined by the intersection of the design range defined to satisfy the FRs and the ability of the system to produce the part within the specified range. It can be calculated by specifying the design range (r) for the FR and by determining the system range (sr) that the proposed design can provide to satisfy the FR. The lower bound of the specified design range for functional requirement FR_i is denoted by $r^l[FR_i]$, and the upper bound by $r^u[FR_i]$. The system range can be modeled by a probability density function (*pdf*, Papoulis and Pillai 2002). The system *pdf* is denoted by $f_{sys}[FR_i]$. The overlap between the design and system ranges is called "the common range" (cr), and this is the only range where the FR is satisfied. Consequently, the area A_{cr} under the system *pdf* within the common range is the design's probability of achieving the specified goal. The information content I_i can be expressed as

$$I_i = -\log_2 A_{cr} = -\log_2 \int_{r^l[FR_i]}^{r^u[FR_i]} f_{sys}[FR_i] dFR_i.$$

Suh (2005) calls a design complex when its probability of success is low and hence the information content I_{sys} required to satisfy the FRs is high. To govern the design process toward more robust systems, he formulates an additional complexity axiom, which says "reduce the complexity of a system" (Suh 2005). The metric is the information content according to the above equation. In that sense Suh ties the notion of complexity to the design range for the FRs—the tighter the design range, the more difficult it becomes to satisfy the FRs. An uncoupled design is likely to be least complex. However, the complexity of a decoupled design can be high because of so-called "imaginary complexity" if we do not understand the system. It is not really complex, but it appears to be so because of our "ignorance". According to Suh (2005) complexity can also be a function of time if the system range changes over time. Two types of time-dependent complexity are distinguished: combinatorial and periodic complexity. Time-dependent combinatorial complexity is defined as the complexity that increases as a function of time because of a continued expansion in the number of possible combinations of FRs and DPs. Periodic complexity is defined as the complexity that only exists in a finite time period, resulting in a finite and limited number of probable combinations. If a system is subject to combinatorial complexity, Suh (2005) hypothesizes that the uncertainty of future outcomes continues to grow over time, and as a result, the system cannot have long-term stability. In the case of systems with periodic complexity, he presumes that the system is deterministic and can renew itself over each period. Under this premise a reliable system must be periodic. A systematically designed system should have small time-independent real and imaginary complexity and no time-dependent combinatorial complexity. If the system range must change as a function of time, the developer should introduce time-dependent periodic complexity.

Although Suh's complexity theory is grounded in axiomatic design theory and has been successfully applied in different domains, our criticism is that product and design problems are evaluated irrespective of the work processes, which are needed to decompose the FRs and DPs. The decomposition is a highly cooperative process that must be taken into account to satisfy all specified FRs on time and to avoid cycles of continuing revisions. Furthermore, the fact that Suh uses the information content I_{sys} directly as a complexity measure can be subject to criticism. I_{sys} is a simple additive measure that only represents the encoded length of the design in terms of binary design decisions. It does not take into account the encoding scheme. However, both parts of the description of a design are important because the description can always be simplified by formulating more complicated design rules, more complex standard components or interfaces (cf. Sect. 2.2.2). Finally, Suh (2005) does not define specific measures for time-dependent complexity.

El-Haik and Yang (1999) have extended Suh's theory by representing the imaginary part of complexity through the differential entropy (Sect. 4) associated with the joint *pdf* of FRs with three components of variability, vulnerability and correlation.

These components evaluate the product design according to the vector of DPs (see Summers and Shah 2010). Although this approach is able to assess the mapping from the FRs to the DPs, an analysis of the topological structure of the Design Structure Matrix (Browning 2001, see discussion below) and the variability of the design parameters do not take into account the dynamics of concurrent development processes in terms of a Work Transformation Matrix (WTM, Sect. 3.1). An alternative view introduced by Braha and Maimon (1998) suggests that complexity is a fundamental characteristic of the information content within either the product or the process. They introduce two measures that quantify either the structural representation of the information or the functional probability of achieving the specified requirements. The measures are able to compare products and processes at different levels of abstraction. The process is nominally defined as mapping between the product and problem, where the coupling determines process complexity. The size of the process is defined as the summation over the number of instances of operators (relationships) and operands (entities). A process instance is a sequence of the instances of operands and operators. The average information content of sequences can be evaluated on the basis of the block entropy (Eq. (9)). As the design takes on different types of representations through the development stages, the average information contained changes. Braha and Maimon (1998) suggest that the ratio of the amount of average information content between the initial and current states is a measure of the current abstraction level. The effort required to move between abstraction levels is inversely proportional to this ratio. The proportionality constant is the information content of the current state. Summers and Shah (2010) follow these lines of thought and propose a process size complexity measure that includes the vocabulary of the specific representation for the problem, the product, the development process and the four operators available for sequencing the states of the design evolution. The measure is defined as

$$\begin{aligned} &Cx_{size\_process} \\ &\quad := \left(M^o + C^o + P_{op}\right) \ln |idv + ddv + dr + mg + a_{op} + e_{op} + s_{op} + r_{op}|. \end{aligned}$$

The size of the vocabulary is represented by the total number of possible primitive modules (M^o), possible relations between these modules (C^o) and possible operators and operands (P_{op}). The additional parameters denote the variables whose values are controlled by the designer (*idv*), are derived from the independent design parameters, other dependent variables and design relations (*ddv*), are constraints that dictate the association between the other design variables (*dr*), are used to determine how well the current design configuration meets the goals (*mg*) plus the four operators available for sequencing the states. Although the concepts based on information contents are appealing, the fact that the development process is only analyzed on different hierarchical description levels, not on the basis of an explicit state-space model of cooperative work opens it to criticism, because it does not take into account dynamic entropies in the sense of Grassberger's theory. Furthermore, in real design problems, it is difficult to identify all operators and operands in advance and to specify valid sequences leading from one level of abstraction to the next.

In addition to methods for measuring characteristics of the design based on information-theoretic quantities, a large body of literature has been published around the Design Structure Matrix (Steward 1981) as a dependency modeling technique supporting complexity management by focusing attention on the elements of a system and the dependencies through which they are related. Recent surveys can be found in the textbooks of Lindemann et al. (2009) or Eppinger and Browning (2012). Browning (2001) distinguishes two basic DSMs types: static and time-based. Static DSMs represent either product components, development tasks or teams in an organization existing simultaneously. Time-based DSMs either represent dynamic activities indicating precedence relationships or design parameters that change as a function of time. Product- or team-related static DSMs are usually analyzed for structural characteristics or by clustering algorithms (e.g. Rogers et al. 2006), while time-based DSMs are typically used to optimize workflows based on sequencing, tearing and banding algorithms (e.g. Gebala and Eppinger 1991; Maurer 2007). Kreimeyer et al. (2008) reviews and discusses a comprehensive set of metrics that can be applied to assess the structure of engineering design processes encoded by DSMs (and other forms). The vast majority of work on complexity management with static DSMs focuses on the concept of modularity in identifying product-related cluster structures (see Baldwin and Clark 2000). This work has been very influential in academia and industry. An important limitation, however, is a purely static view of the product structure and, consequently, of the task structure and the interactions among them. Task processing on different time scales corresponding to different autonomous task processing rates of developers cannot be represented. Recent publications also indicate that technical dependencies in product families tend to be volatile and therefore coordination needs among development tasks can evolve over time (e.g. Cataldo et al. 2006, 2008; Sosa 2008). When those evolving coordination needs are not adequately managed, significant misalignments of organizational structure and product architecture can occur that have a negative effect on product quality (Gokpinar et al. 2010). An effective method for dealing with volatility of dependencies is to use models with different static task-based DSMs (see Sects. 3.1 and 3.2) for different phases of the project where no task is theoretically processed independently of the others. Furthermore, at the transition points between phases additional task-mapping matrices can be specified. By doing so, the number of tasks as well as the kind and intensity of coordination needs can be adapted.

Another limitation of the concept of product modularity is that the organizational patterns of a development project (e.g. communication links, team co-membership) not necessarily mirror the technical dependency structures (Sosa et al. 2004). The literature review of Colver and Baldwin (2010) shows that the “mirroring hypothesis” was supported in only 69 % of the cases. Support for the hypothesis was strongest in the within-firm sample, less strong in the across-firm sample, and relatively weak in the open collaborative sample. In that sense, static task-based DSMs represent dependency structures in their own right. They must be related to product components or development teams through additional multiple domain mapping matrices (Danilovic and Browning 2007) and cannot be substituted by the traditional modeling elements.

An approach for measuring structural complexity based on component-based DSMs that is formally similar to our dynamic dependency analysis in the spectral basis (see Sects. 3.3 and 4.2) has been introduced by Sinha and de Weck (2009). The parameters of their metric C are related to the complexity of each component in the product (α_i) and the complexity of each connection between a pair of components (β_{ij}). Moreover, a scaling factor γ is introduced. The definition is (Denman et al. 2011):

$$C := \sum_{i=1}^{n} \alpha_i + \left(\sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} A_{ij} \right) \gamma E(A)$$

The scaling factor γ is taken as $1/n$ and used to map the n different components onto a comparable scale. The matrix A is the component-based DSM of the product. The underlying concept of the metric is that in order to develop the individual components, a non-zero complexity is involved. This complexity can vary across components and is represented by the α_i's. Similar arguments hold true for the complexity of each connection. If there are multiple types of connection between two components (energy flow, material flow, control action flow etc.), large beta coefficients are assigned since it would require more effort to implement them compared to a simpler (univariate) connection. An important aspect is the correlation among the α_i's and β_i's that can vary depending on the kind of product. For large-scale mechanical systems, the β_i's are often much smaller than the α_i's. However, in micro or nanoscale systems it can be the opposite, because it is often much more difficult to develop the interfaces. Finally, the term $E(A)$ represents the graph energy of the DSM. For the calculation a binary encoding scheme is used (i.e. an adjacency matrix). The graph energy is defined as the sum of the singular values σ_i of the orthogonal vectors:

$$E(A) := \sum_{i=1}^{n} \sigma_i,$$

where

$$A = U \Sigma_A V^{\mathrm{T}}$$
$$\Sigma_A = \mathrm{diag}[\sigma_i].$$

The graph energy is invariant under isomorphic transformations (Weyuker 1988) and therefore highly objective. Summers and Shah (2010) developed a coupling measure based on graphical models in which the tasks are nodes of a graph and connected through variable dependency. This measure requires a formal representation that is based on undirected graphs, which seem to not be expressive enough for project management and consequently will not be considered in the following.

The information-theory and dependency-structure-based complexity metrics from theories of systematic engineering design are undoubtedly beneficial in facilitating studies that require the use of equivalent but different design problems and in comparing computer-aided design automation tools. However, they do not stress the dynamic nature of cooperation in NPD projects and cannot be derived from first principles. Therefore, we will bring the EMC into focus in the following sections according to Grassberger's seminal theoretical work (1986). EMC is able to evaluate self-generated complexity and can be calculated efficiently either from generative models or from field data, without intervening models. If the work processes are represented by a generative model in a specific class but with unknown parameters, we can derive closed-form solutions of different strength, as will be shown in Sects. 4.1 and 4.2

for first order vector autoregression models (cf. Eqs. (38) and (45)). Corresponding deterministic and stochastic formulations will be developed in the next section.

3 Models of cooperative work in new product development projects

3.1 Deterministic formulation

To analyze the interrelationships between project dynamics and emergent complexity explicitly, mathematical models of cooperative work had to be formulated. We start by formulating a deterministic continuous-state, discrete time model. The model is based on the seminal work of Smith and Eppinger (1997), according to whom the time evolution of a NPD project with p concurrent but interacting tasks can be expressed as

$$x_t = A_0 \cdot x_{t-1} \quad (t \geq 1). \tag{16}$$

The p-dimensional state vector x_t represents the work remaining for all tasks at time step t. The amount of work remaining can be measured by the time left to finalize a specific design, the number of engineering drawings requiring completion before the design is released, or the number of open issues that need to be addressed/resolved before design release (Yassine et al. 2003). The $p \times p$ matrix $A_0 = (a_{ij})$ is a dynamical operator for the iteration over all tasks, also called the "work transformation matrix" (WTM). According to Browning's taxonomy in the previous section, the WTM is a static task-based DSM covering all parallel development tasks. Continuing feedback/feed-forward loops are modeled by the off-diagonal elements. The WTM enables the project manager to model, visualize and evaluate the dynamic dependencies among development tasks and to derive suggestions for reorganization. The task-centered approach is motivated by the work of Tatikonda and Rosenthal (2000), who relate project complexity to the nature, quantity and magnitude of organizational subtasks and subtask interactions. Given a distinct phase of an NPD project, it is assumed that the WTM does not vary with time.

In this paper, we use the improved WTM concept of Yassine et al. (2003) and Huberman and Wilkinson (2005). Hence, the diagonal entries a_{ii} $(i = 1 \ldots p)$ account for different productivity levels of developers and are defined as autonomous task-processing rates. This is in contrast to the original WTM model of Smith and Eppinger (1997) in which tasks are processed at the same rate. The a_{ii}'s indicate the part of the work left incomplete after an iteration over task i and therefore must be nonnegative real numbers ($a_{ii} \in \mathbb{R}^+$). The off-diagonal entries a_{ij} $(i \neq j)$ model the coupling among tasks and indicate the intensity and nature of cooperative relationships. Depending on their value, they have different meanings: (1) if $a_{ij} = 0$, work carried out on task j has no direct effect on task i; (2) if $a_{ij} > 0$, work on task j slows down the processing of task i, and one unit of work on task j at time step t generates a_{ij} units of extra work on task i at step $t + 1$; (3) if $a_{ij} < 0$, work on task j accelerates the processing of task i, and one unit of work on task j reduces the work on task i by a_{ij} units at time step $t + 1$. The only limitation on the use of negative entries is that negative values of work remaining in the state vector x_t are not allowed. In practice, many off-diagonal elements must be expected to be larger than zero, because NPD projects usually require intensive cooperation, leading to additional work. This paper only considers project phases in which subgroups of interacting tasks must be processed in parallel. That means that no task in the subgroup is theoretically processed independently of the others, because input about modules or components under development by other tasks is required regularly. This assumption does not limit the generality of the approach. In NPD projects in which work is broken down into non-overlapping stages, the analysis holds for each stage.

The time instant $t = 0$ usually indicates the beginning of a phase. It is often assumed that all parallel tasks are initially 0 % complete, and so the initial state is $x_0 = [1, \ldots, 1]^{\mathrm{T}}$. However, one can also assign nonnegative values smaller than one to vector components of x_0. By doing so, it is possible to model overlapping tasks (see Schlick et al. 2008, 2012). Moreover, if an NPD project undergoes major reorganization, one can define separate initial states and WTMs.

From the theory of linear systems it is known that the rate and nature of convergence of the modeled NPD project are determined by the eigenmodes of A_0. Following Smith and Eppinger (1997), we use the term "design mode" $\varphi_i = (\lambda_i(A_0), \vartheta_i(A_0))$ to refer to an eigenvalue $\lambda_i(A_0)$ inherent to A_0 along with its eigenvector $\vartheta_i(A_0)$ $(1 \le i \le p)$. In that sense, each design mode φ_i has both temporal (eigenvalue) and structure-organizational (eigenvector) characteristics. According to Luenberger (1979), the work remaining converges to the zero vector, if and only if the modulus of all eigenvalues $\lambda_i(A_0)$ is less than 1: that is, $\forall i$: $|\lambda_i(A_0)| < 1$. In this case, the project is asymptotically stable. We follow the convention of listing the eigenvalues in order of decreasing magnitude ($|\lambda_1(A_0)| \ge |\lambda_2(A_0)| \ge \cdots$). The equation $|\lambda_1(A_0)| = 1$ for the first design mode φ_1 with the dominant (i.e. greatest-magnitude) eigenvalue determines the stability bound of the project. If the project is not asymptotically stable and $|\lambda_1(A_0)| > 1$, a redesign of tasks is necessary, because the work remaining increases beyond all given limits. Unfortunately, even if the modeled project is asymptotically stable, theoretically an infinite number of iterations are necessary to reach the state where zero work remains for all tasks. Therefore, the project manager has to specify an additional stopping criterion $\delta \in [0; 1]$, e.g. at most five percent for all tasks. According to Huberman and Wilkinson (2005), the zero vector represents a theoretical optimal solution, and the values of the state vector are an abstract measure of the amount of work left before a solution is optimal.

3.2 Stochastic formulation in original state space

In their seminal paper on performance variability and project dynamics, Huberman and Wilkinson (2005) showed how to model NPD projects as open organizational systems based on stochastic processes theory. An open organizational system is a system in which humans continuously interact with each other and with their work environment. These interactions usually take the form of goal-directed information exchange within and through the system boundary and lead to a kind of self-organization, since patterns can emerge that convey new properties, such as oscillations. In the work presented here, we follow the basic ideas of Huberman and Wilkinson and formulate a model as a linear stochastic difference equation. However, we do not incorporate "multiplicative noise" to represent performance variability as Huberman and Wilkinson did, but rather assume that the effects of performance fluctuations are cumulative. Our model generalizes the deterministic state Eq. (16) to a stochastic process $\{X_t\}$ generated by

$$X_t = A_0 \cdot X_{t-1} + \varepsilon_t. \tag{17}$$

The random variable $X_t \in [0; 1]^p$ represents the measured (or estimated) work remaining at time step t. A_0 is the cited WTM. The variable ε_t is used to model performance fluctuations (noise). In NPD projects there are many performance-shaping factors. Although we do not know their exact number or distribution, the central limit theorem tells us that, to a large degree, the sum of independently and identically distributed factors can be represented by a Gaussian distribution $\mathcal{N}(x; \mu, C)$ with location $\mu = E[x]$ and covariance $C = E[(\mu - x) \cdot (\mu - x)^{\mathrm{T}}]$. The covariance matrix C is a square matrix of size p, whose entry $C_{[[i,j]]}$ in the i, j position is the covariance between the i-th element $x^{(i)}$ and the j-th element $x^{(j)}$ of the random vector X, that is

$$C_{[[i,j]]} = \mathrm{Cov}\big[x^{(i)}, x^{(j)}\big] = E\big[\big(\mu^{(i)} - x^{(i)}\big)\big(\mu^{(j)} - x^{(j)}\big)\big].$$

C is symmetric by definition and also positive-semidefinite (Lancaster and Tismenetsky 1985). The diagonal elements $C_{[[i,i]]}$ represent the scalar-valued variances

$$c_{ii}^2 = \mathrm{Var}\big[x^{(i)}\big] = E\big[\big(\mu^{(i)} - x^{(i)}\big)^2\big]. \tag{18}$$

c_{ii} is the standard deviation. The off-diagonal elements $C_{[[i,j]]}$ represent the scalar-valued covariances

$$\rho_{ij} c_{ii} c_{jj} = \rho_{ij} \sqrt{\mathrm{Var}\big[x^{(i)}\big]\mathrm{Var}\big[x^{(j)}\big]} \quad (i \neq j), \tag{19}$$

where the first factor is Pearson's famous product-moment coefficient

$$\rho_{ij} := \mathrm{Corr}\big[x^{(i)}, x^{(j)}\big] = \frac{\mathrm{Cov}\big[x^{(i)}, x^{(j)}\big]}{\sqrt{\mathrm{Var}\big[x^{(i)}\big]\mathrm{Var}\big[x^{(j)}\big]}}. \tag{20}$$

The correlation ρ_{ij} is $+1$ in the case of a perfect positive linear relationship and -1 in the case of a perfect negative linear relationship. It has values between -1 and 1 in all other cases, indicating the degree of linear dependence between the variables. We assume that the fluctuations have no systematic component and that $\mu = (0\,0\,\ldots\,0)^{\mathrm{T}}$. We put no restrictions on the covariance matrix C. Hence, ε_t is represented by the Gaussian *pdf*

$$f[x] = \mathcal{N}(x; 0, C) = \frac{1}{(2\pi)^{p/2}(\mathrm{Det}[C])^{1/2}} \mathrm{Exp}\left[-\frac{1}{2} x^{\mathrm{T}} \cdot C^{-1} \cdot x\right] \tag{21}$$

(see e.g. Puri 2010). If $C = \{\sigma^2\} \cdot I_p$, we speak of isotropic noise. The factor $\sigma^2 \in \mathbb{R}^+$ represents the scalar variance.

It is not difficult to see that the process can be decomposed into a deterministic and stochastic part as

$$X_t = A_0^t \cdot x_0 + \sum_{v=1}^{t} A_0^{t-v} \cdot \varepsilon_v, \quad t \geq 1.$$

The first summand represents the means of the work remaining $E[X_t, \mathcal{N}(x; 0, C)] = A_0^t \cdot x_0$, which evolve unperturbed. The second summand represents the performance fluctuations, which are independent of the work remaining. Despite this independency, the correlations between performance fluctuations among tasks i and j, defined as ρ_{ij} above, can have a strong effect on the time evolution of the project. To reinforce the correlations, the covariance matrix C must have nonzero off-diagonal entries: in other words, the noise must be nonisotropic. Depending on the structure of the WTM A_0, the correlations ρ_{ij} can significantly excite the design modes and lead to unexpected effects of emergent complexity, such as the cited problem-solving oscillations in the preasymptotic range of development projects (Mihm and Loch 2006; Schlick et al. 2008). We will return to the excitation of design modes in Sects. 4 and 5.

3.3 Stochastic formulation in spectral basis

In order to identify the essential independent parameters (Sect. 4.2), it is useful to work in the spectral basis (Neumair and Schneider 2001). To carry out the transformation of the state-space coordinates, the WTM A_0 is diagonalized through an eigendecomposition as

$$A_0 = S \cdot \Lambda_S \cdot S^{-1}, \tag{22}$$

where

$$\Lambda_S = \mathrm{diag}\big[\lambda_i(A_0)\big] \quad 1 \le i \le p. \tag{23}$$

The eigenvectors $\vartheta_i(A_0) = S_{:i}$ of the design modes φ_i of A_0 are the column vectors of S $(i = 1 \dots p)$. Because A_0 must not be symmetric, the eigenvectors are in general not mutually orthogonal, and their entries can be complex numbers. The diagonal matrix Λ_S stores the ordered eigenvalues $\lambda_i(A_0)$ along the principal diagonal. In the spectral basis, the dynamic model from Eq. (17) can be expressed by the state vector X_t and the fluctuation vector ε_t as simple linear combinations:

$$X_t = S \cdot X_t',$$
$$\varepsilon_t = S \cdot \varepsilon_t'.$$

For the initial state,

$$x_0 = S \cdot x_0'.$$

The coefficient vectors are defined as:

$$X_t' = \big\{X_t'^{(1)}, \dots, X_t'^{(p)}\big\}^{\mathrm{T}}$$
$$\varepsilon_t' = \big\{\varepsilon_t'^{(1)}, \dots, \varepsilon_t'^{(p)}\big\}^{\mathrm{T}}.$$

We obtain the transformed dynamic model for the coefficient vectors as:

$$X_t' = \Lambda_S \cdot X_{t-1}' + \varepsilon_t' \tag{24}$$

with

$$\varepsilon_t' = \mathcal{N}(x; 0, C') \tag{25}$$

and

$$C' = S^{-1} \cdot C \cdot \left(\left[S^{\mathrm{T}}\right]^{*}\right)^{-1}. \tag{26}$$

C' is also positive-semidefinite. The '*' symbol in the above equation represents the conjugate matrix.

In the literature the stochastic process that is generated by the state equations (17) and (24) is termed a vector autoregressive process of order 1, abbreviated as VAR(1). Neumair and Schneider (2001), Lütkepohl (2005) and others developed efficient methods to estimate the parameters, spectral information and confidence regions. These methods were used to validate the model against data from an industrial company (see Schlick et al. 2008, 2012).

4 Model-based evaluation of emergent complexity

The main problem that has to be addressed is that Grassberger (1986) defined the EMC on the basis of information-theoretic variables with discrete states and did not generalize it to continuous-state processes. However, Bialek et al. (2001), de Cock (2002), Bialek (2003), and Ellison et al. (2009) pioneered the generalization, and we can build upon their results to evaluate emergent complexity in NPD projects. Their analyses show that we must primarily consider the differential block entropy (Eq. (29)) and not the Shannon block entropy (Eq. (9)) as a basic quantity. The differential entropy extends the fundamental idea of Shannon's information entropy as a universal measure of uncertainty about a discrete-type random variable with known probability mass function to a continuous-type variable with given *pdf*. According to Eq. (9) the entropy of a discrete-type random variable X is always positive and can be used as a measure of average surprisal about X. This is slightly different for a continuous-type variable, whose entropy can take any value from $-\infty$ to ∞ and is only used to measure changes in uncertainty. For instance, the differential entropy of a continuous random variable X that is uniformly distributed from 0 to a (and whose *pdf* is therefore $f[x] = 1/a$ from 0 to a, and 0 elsewhere) is $\log_2 a$. For $a < 1$ the differential entropy is negative and can get arbitrarily small as a approaches 0. An additional subtlety is that the continuous entropy can be negative or positive depending on the coordinate system. This also holds true for the differential block entropy (Eq. (29)). However, it can be proven that the EMC calculated on the basis of dynamic differential entropies (Eq. (33)) is always positive and may exist even in cases where the block entropies diverge. Under the assumption of an underlying VAR(1) model, for instance, a closed-form solution for the EMC can be derived that is simply a ratio of determinants of covariance matrices (cf. Eqs. (38) and (41)), which in most case studies can be interpreted similarly to discrete-state processes. Furthermore, it can be proven that EMC is invariant under arbitrary reparameterizations based on smooth and uniquely invertible maps (Kraskov et al. 2004). The theoretical analyses of Bialek et al. (2001) and other researchers show that the generalized measure is an objective and valid quantity for evaluating emergent complexity.

To obtain analytical results, it is assumed that the VAR(1) process is strict-sense stationary (Puri 2010) and therefore all its statistical properties are invariant to a time-shift. Let $f[x_{t+1}, \ldots, x_{t+n}]$ ($t \in \mathbb{Z}, n \in \mathbb{N}$) be the joint *pdf* of the block of random vectors $(X_{t+1}, \ldots, X_{t+n})$, and let $f[x_{t+n}|x_{t+1}, \ldots, x_{t+n-1}]$ be the conditional density of vector X_{t+n} given vectors $X_{t+1}, \ldots, X_{t+n-1}$. Hence,

$$\begin{aligned} & f[x_{t+1}, \ldots, x_{t+n}] = f[x_{t+1+\tau}, \ldots, x_{t+n+\tau}] \\ & f[x_{t+n}|x_{t+1}, \ldots, x_{t+n-1}] \\ & \quad = f[x_{t+n+\tau}|x_{t+1+\tau}, \ldots, x_{t+n-1+\tau}] \quad (t \in \mathbb{Z},\ n \in \mathbb{N},\ \tau \geq 0). \end{aligned}$$

Furthermore, we assume that ergodicity holds. Due to the strict-sense stationary behavior we can use the index υ to denote the time structure. Hence, $f[x_{\upsilon+1}, \ldots, x_{\upsilon+n}]$ denotes the joint *pdf* and $f[x_{\upsilon+n}|x_{\upsilon+1}, \ldots, x_{\upsilon+n-1}]$ denotes the conditional density of the process in the steady state. The conditional density is given by (cf. Billingsley 1995):

$$f[x_\upsilon|x_{\upsilon-m}, \ldots, x_{\upsilon-1}] := \frac{f[x_{\upsilon-m}, \ldots, x_{\upsilon-1}, x_\upsilon]}{f[x_{\upsilon-m}, \ldots, x_{\upsilon-1}]}.$$

Since the considered VAR(1) process is a Markov process, the conditional density simplifies to

$$f[x_{\upsilon+n}|x_{\upsilon+1}, \ldots, x_{\upsilon+n-1}] = f[x_{\upsilon+n}|x_{\upsilon+n-1}] = \frac{f[x_{\upsilon+n-1}, x_{\upsilon+n}]}{f[x_{\upsilon+n-1}]}, \tag{27}$$

and the strict stationarity condition implies (Brockwell and Davis 1987)

$$f[x_{\upsilon+n}|x_{\upsilon+n-1}] = f[x_\upsilon|x_{\upsilon-1}] = f[x_2|x_1] \quad \text{and} \quad f[x_{\upsilon+n-1}] = f[x_\upsilon] = f[x_1] \quad \forall \upsilon \geq 2. \tag{28}$$

Let the differential block entropy of the process (cf. Eq. (9)) be

$$H(n) := -\int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_1, \ldots, x_n] \log_2 f[x_1, \ldots, x_n]\, dx_1 \ldots\, dx_n. \tag{29}$$

To compute the EMC for the introduced VAR(1) process in the steady state, observe first that

$$\begin{aligned} H(n) &= -\int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_1, \ldots, x_n] \cdot \log_2 f[x_1, \ldots, x_n] dx_1 \ldots dx_n \\ &= -\int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_n|x_1, \ldots, x_{n-1}] \cdot f[x_1, \ldots, x_{n-1}] \\ &\quad \cdot \log_2\big(f[x_n|x_1, \ldots, x_{n-1}] \cdot f[x_1, \ldots, x_{n-1}]\big) dx_1 \ldots dx_n \\ &= -\int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_n|x_1, \ldots, x_{n-1}] \cdot f[x_1, \ldots, x_{n-1}] \\ &\quad \cdot \log_2 f[x_n|x_1, \ldots, x_{n-1}] dx_1 \ldots dx_n \\ &\quad - \int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_n|x_1, \ldots, x_{n-1}] \cdot f[x_1, \ldots, x_{n-1}] \\ &\quad \cdot \log_2 f[x_1, \ldots, x_{n-1}] dx_1 \ldots dx_n \\ &= -\int_{\mathbb{R}^p} \cdots \int_{\mathbb{R}^p} f[x_1, \ldots, x_{n-1}] \\ &\quad \cdot \left(\int_{\mathbb{R}^p} f[x_n|x_1, \ldots, x_{n-1}] \cdot \log_2 f[x_n|x_1, \ldots, x_{n-1}] dx_n\right) dx_1 \ldots dx_{n-1} \end{aligned}$$

$$-\int_{\mathbb{R}^p}\cdots\int_{\mathbb{R}^p} f[x_1,\ldots,x_{n-1}]\cdot\log_2 f[x_1,\ldots,x_{n-1}]$$
$$\cdot\left(\int_{\mathbb{R}^p} f[x_n|x_1,\ldots,x_{n-1}]dx_n\right)dx_1\ldots dx_{n-1}. \tag{30}$$

According to the definition of a *pdf*, the inner integral in the second summand of the above equation equals 1. Hence,

$$\begin{aligned}H(n) = &-\int_{\mathbb{R}^p}\cdots\int_{\mathbb{R}^p} f[x_1,\ldots,x_{n-1}]\\ &\cdot\left(\int_{\mathbb{R}^p} f[x_n|x_1,\ldots,x_{n-1}]\cdot\log_2 f[x_n|x_1,\ldots,x_{n-1}]dx_n\right)dx_1\ldots dx_{n-1}\\ &+H(n-1),\end{aligned}$$

which implies that

$$\begin{aligned}h_\mu(n) = &\int_{\mathbb{R}^p}\cdots\int_{\mathbb{R}^p} f[x_1,\ldots,x_{n-1}]\\ &\cdot\left(\int_{\mathbb{R}^p} f[x_n|x_1,\ldots,x_{n-1}]\cdot\ \log_2 f[x_n|x_1,\ldots,x_{n-1}]dx_n\right)dx_1\ldots dx_{n-1}.\end{aligned}$$

In view of the Markov property, the above equation can be expressed as

$$\begin{aligned}h_\mu(n) = &-\int_{\mathbb{R}^p} f[x_{n-1}]\left(\int_{\mathbb{R}^p} f[x_n|x_{n-1}]\cdot\ \log_2 f[x_n|x_{n-1}]dx_n\right)dx_{n-1},\\ &\forall\, n\geq 2.\end{aligned} \tag{31}$$

It follows that the entropy rate h_μ is equal to the dynamic entropy $h_\mu(n)$ for block length $n=2$ and that larger block lengths do not change the rate, that is

$$h_\mu =\ h_\mu(2) = h_\mu(3) = \cdots. \tag{32}$$

Given the steady-state condition, we conclude that

$$h_\mu = -\int_{\mathbb{R}^p} f[x_1]\left(\int_{\mathbb{R}^p} f[x_2|x_1]\cdot\ \log_2 f[x_2|x_1]dx_2\right)dx_1.$$

Based on Eq. (15), we obtain the generalized solution:

$$\begin{aligned}\mathrm{EMC} &= h_\mu(1) - h_\mu\\ &= H(1) - h_\mu(2)\\ &= -\int_{\mathbb{R}^p} f[x_1]\log_2 f[x_1]dx_1\\ &\quad+\int_{\mathbb{R}^p}\int_{\mathbb{R}^p} f[x_2|x_1]\log_2 f[x_2|x_1]dx_2 f[x_1]dx_1.\end{aligned} \tag{33}$$

4.1 Closed-form solution in original state space

To calculate EMC on the basis of the above-generalized solution in the coordinates of the original state space $\mathbb{R}^p$, we must find the *pdf* of the stochastic process in the steady state. Let the p-dimensional random vector X_1 be normally distributed with location $\mu_1 = A_0 \cdot x_0$ and covariance $\Sigma_1 = C$ (Eqs. (17) and (21)), that is $X_1 = \mathcal{N}(x; A_0 \cdot x_0, C)$. Starting with this random vector the project evolves according to state Eq. (17). Due to the strictly stationary behavior for $t \to \infty$ a joint probability density is formed that is invariant under shifting the origin. In steady state we must have for the locus

$$\mu = A_0 \cdot \mu + E[\varepsilon_t] = A_0 \cdot \mu \tag{34}$$

and for the variance

$$\Sigma = A_0 \cdot \Sigma \cdot A_0^{\mathrm{T}} + \mathrm{Var}[\varepsilon_t] = A_0 \cdot \Sigma \cdot A_0^{\mathrm{T}} + C. \tag{35}$$

It follows from Eq. (34) that μ must be an eigenvector corresponding to the eigenvalue 1 of A_0. Clearly, if the modeled project is asymptotically stable, no such eigenvector can exist. Hence, the only vector that satisfies this equation is the zero vector, indicating that there is no remaining work. Let $\lambda_1(A_0), \ldots, \lambda_p(A_0)$ be the eigenvalues of WTM A_0 ordered by magnitude. If $|\lambda_1(A_0)| < 1$, the solution of Eq. (35) can be written as (Lancaster and Tismenetsky 1985):

$$\Sigma = \sum_{k=0}^{\infty} A_0^k \cdot C \cdot \left(A_0^{\mathrm{T}}\right)^k. \tag{36}$$

It follows from the definition of the differential entropy of a Gaussian distribution with *pdf* according to Eq. (21) (e.g. Cover and Thomas 1991) that the first summand in Eq. (33) is

$$-\int_{\mathbb{R}^p} f[x_1] \log_2 f[x_1] dx_1 = \log_2\left((2\pi)^{p/2}\sqrt{\mathrm{Det}[\Sigma]}\right) + \frac{p}{2}.$$

For the calculation of the second summand, the following insight is helpful. Given vector x_1 in steady state, the distribution of X_2 is a normal distribution with location $A_0 \cdot x_1$ and covariance C. Hence, the inner integral of the second summand in Eq. (33) is equal to minus the differential entropy of that distribution. It follows that the second summand is simply

$$\int_{\mathbb{R}^p} \left(\log_2\left(\frac{1}{(2\pi)^{p/2}\sqrt{\mathrm{Det}[C]}}\right) - \frac{p}{2}\right) f[x_1] dx_1.$$

As we are integrating with respect to a *pdf*, the above term is equal to

$$\log_2\left(\frac{1}{(2\pi)^{p/2}\sqrt{\mathrm{Det}[C]}}\right) - \frac{p}{2}.$$

It follows for the VAR project model that

$$\begin{aligned}
\mathrm{EMC} &= \log_2\left((2\pi)^{p/2}\sqrt{\mathrm{Det}[\Sigma]}\right) + \frac{p}{2} + \log_2\left(\frac{1}{(2\pi)^{p/2}\sqrt{\mathrm{Det}[C]}}\right) - \frac{p}{2} \\
&= \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[\Sigma]}{\mathrm{Det}[C]}\right) = \frac{1}{2}\log_2\left(\mathrm{Det}[\Sigma]\right) - \frac{1}{2}\log_2\left(\mathrm{Det}[C]\right) \\
&= \frac{1}{2}\log_2 \mathrm{Det}\left[\Sigma \cdot C^{-1}\right].
\end{aligned} \tag{37}$$

According to the above equation, the EMC can be decomposed additively into dynamic and pure-noise parts. The dynamic part represents the differential entropy during steady-state operation. If the noise is isotropic, the dynamic part completely decouples from the noise (Ay et al. 2010). Substituting Eq. (36) in Eq. (37), we obtain the desired first closed-form solution as

$$\mathrm{EMC} = \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[\sum_{k=0}^{\infty} A_0^k \cdot C \cdot (A_0^{\mathrm{T}})^k]}{\mathrm{Det}[C]}\right). \tag{38}$$

The covariance matrices above are positive-semidefinite. Under the assumption that they are of full rank, the determinants are positive, and the range of the EMC is $[0, +\infty]$.

4.2 Closed-form solutions in the spectral basis

In this section, we calculate an additional solution in which the dependence of the EMC on the anisotropy of the noise is made explicit. This solution is much easier to interpret, and to derive it we work in the spectral basis (cf. Eq. (22)). According to Neumair and Schneider (2001), the steady-state covariance matrix Σ' in the spectral basis can be calculated based on the transformed covariance matrix of the performance fluctuations $C' = S^{-1} \cdot C \cdot ([S^{\mathrm{T}}]^*)^{-1}$ (Eq. (26)) as

$$\Sigma' = \begin{pmatrix} \frac{c_{11}'^2}{1-\lambda_1\overline{\lambda_1}} & \frac{\rho_{12}' c_{11}' c_{22}'}{1-\lambda_1\overline{\lambda_2}} & \cdots \\ \frac{\rho_{12}' c_{11}' c_{22}'}{1-\lambda_2\overline{\lambda_1}} & \frac{c_{22}'^2}{1-\lambda_2\overline{\lambda_2}} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}. \tag{39}$$

The ρ_{ij}''s are the transformed correlation coefficients (cf. Eq. (20)). The $c_{ii}'^2$'s (cf. Eq. (18)) and $\rho_{ij}' c_{ii}' c_{jj}'$'s (cf. Eq. (19)) are scalar-valued variance and covariance components of C':

$$C' = \begin{pmatrix} c_{11}'^2 & \rho_{12}' c_{11}' c_{22}' & \cdots \\ \rho_{12}' c_{11}' c_{22}' & c_{22}'^2 & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}. \tag{40}$$

The transformation into the spectral basis is a linear transformation and therefore does not change the mutual information. Hence, the functional form of the closed-form solution from Eq. (37) holds, and the EMC can be expressed as the variance ratio (de Cock 2002):

$$\mathrm{EMC} = \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[\Sigma']}{\mathrm{Det}[C']}\right) = \frac{1}{2}\log_2 \mathrm{Det}\left[\Sigma' \cdot C'^{-1}\right]. \tag{41}$$

The basis transformation does not change the positive-definiteness of the covariance matrices. Under the assumption that the matrices are of full rank, the determinants are positive. The determinant $\mathrm{Det}[\Sigma']$ of the covariance matrix Σ' can be regarded as a generalized variance of the stationary process in the spectral basis, while $\mathrm{Det}[C']$ represents the generalized variance of the prediction error. The variance ratio can be interpreted as the (entropy lost and) information gained when the modeled project is in the steady state, and the state is observed by the project manager with predefined "error bars", which cannot be under-run because of the inherent prediction error. The inverse C'^{-1} is the so-called "precision matrix".

An important finding is that the scalar-valued variance components of the noise part do not contribute to emergent complexity. This follows from the definition of a determinant. The calculated determinants of Σ' and C' just give rise to the occurrence of the factor $\prod_{i=1}^{p} c_{ii}'^2$, which cancels out:

$$\mathrm{Det}\big[\Sigma' \cdot C'^{-1}\big] = \mathrm{Det}[\Sigma'] \cdot \mathrm{Det}\big[C'^{-1}\big] = \frac{\mathrm{Det}[\Sigma']}{\mathrm{Det}[C']}.$$

Hence, we can also calculate with the "normalized" covariance matrices Σ'_N and C'_N:

$$\Sigma'_N = \begin{pmatrix} \frac{1}{1-|\lambda_1|^2} & \frac{\rho'_{12}}{1-\lambda_1\overline{\lambda_2}} & \cdots \\ \frac{\rho'_{12}}{1-\lambda_2\overline{\lambda_1}} & \frac{1}{1-|\lambda_2|^2} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}, \tag{42}$$

$$C'_N = \begin{pmatrix} 1 & \rho'_{12} & \cdots \\ \rho'_{12} & 1 & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}. \tag{43}$$

According to Shannon's classic findings about the capacity of a Gaussian channel (Cover and Thomas 1991), the normalized covariance matrix Σ'_N can be decomposed into summands as follows:

$$\Sigma'_N = C'_N + \begin{pmatrix} \frac{|\lambda_1|^2}{1-|\lambda_1|^2} & \rho'_{12}\frac{\lambda_1\overline{\lambda_2}}{1-\lambda_1\overline{\lambda_2}} & \cdots \\ \rho'_{12}\frac{\lambda_2\overline{\lambda_1}}{1-\lambda_2\overline{\lambda_1}} & \frac{|\lambda_2|^2}{1-|\lambda_2|^2} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}. \tag{44}$$

The second summand in the above equation is defined as Σ''_N. We obtain an expressive closed-form solution based on the signal-to-noise ratio $\mathrm{SNR} := \Sigma''_N \cdot C_N'^{-1}$:

$$\mathrm{EMC} = \frac{1}{2}\log_2 \mathrm{Det}\big[I_p + \Sigma''_N \cdot C_N'^{-1}\big]. \tag{45}$$

The SNR can be interpreted as the ratio of the effective variance Σ''_N of the signal (work remaining) in the spectral basis that is generated by cooperative work and the effective variance C'_N of the performance fluctuations. The performance fluctuations "drive" the development processes to a certain extent and can be reinforced through the structural organization of the project. The effective fluctuations are in the same units as the input x_t. This is called "referring the noise to the input" and is a standard method in physics for characterizing detectors, amplifiers and other devices (Bialek 2003). The obtained closed-form solution has at most only $(p^2 - p)/2 + p = p(p+1)/2$ independent parameters and not a maximum of approximately $p^2 + (p^2 - p)/2 + p = p(3p+1)/2$ parameters, which are encoded in the WTM A_0 and the covariance matrix C. Hence, through a transformation into the spectral basis we can identify the essential parameters influencing emergent complexity and reduce the dimensionality of the problem in many cases by the factor

$(3p+1)/(p+1)$. The essential parameters are also easy to interpret. The eigenvalues $\lambda_i(A_0)$ represent the essential temporal dependencies of the modeled project in terms of effective productivity rates on linearly independent scales determined by the eigenvectors $\vartheta_i(A_0)$ $(i = 1 \ldots p)$. The effective productivity rates depend only on the design modes φ_i and therefore reflect the project's organizational design. The lower the effective productivity rates because of slow task processing or strong task couplings, the less the design modes are "damped", and hence the larger the complexity. On the other hand, the correlations ρ'_{ij} model the essential dependencies between the unpredictable performance fluctuations that can give rise to an excitation of the design modes and their interactions. This excitation can compensate for the damping factors. The ρ'_{ij}'s scale linearly with the variances along each independent direction of the fluctuations: the larger the variances, the larger the correlations and the stronger the excitation. However, the scale factors are determined not only by a linear interference between design modes φ_i and φ_j caused by cooperation but by the weighted interference with corresponding eigenvectors of the covariance matrix of the fluctuations. In other words, the emergent complexity of the modeled NPD project does not simply come from the least-damped design mode $\varphi_1 = (\lambda_1(A_0), \vartheta_1(A_0))$ because this mode may not be sufficiently excited, but rather is caused by a complete interference between all design and "fluctuation" modes. Emergent complexity in the sense of Grassberger's theory is a holistic property of the organization and usually cannot be reduced to a single property of the project organizational design. This is a truly nonreductionist approach.

4.3 Lower bounds on EMC

To calculate the lower bounds on EMC we can make use of Oppenheim's inequality (see Horn and Johnson 1985). Let M and N be positive-semidefinite matrices and let $M \circ N$ be the entry-wise product of these matrices (so-called "Hadamard product"). The Hadamard product of two positive-semidefinite matrices is again positive-semidefinite. Furthermore, if M and N are positive-semidefinite, then the following equality based on Oppenheim holds:

$$\mathrm{Det}[M \circ N] \geq \left(\prod_{i=1}^{p} M_{[[i,i]]}\right) \mathrm{Det}[N].$$

Let $M = (M_{[[i,j]]}) = (1/(1 - \lambda_i(A_0)\overline{\lambda_\mathrm{j}(A_0)}))$ be a Cauchy matrix $(1 \leq i, j \leq p)$. The entries along the principal diagonal of this matrix represent the "damping factor" $1 - |\lambda_i|^2$ of design mode φ_i, and the off-diagonal entries $1 - \lambda_i \overline{\lambda_i}$ are the damping factors between the interacting modes φ_i and φ_j. We follow the convention that the eigenvalues are ordered in decreasing magnitude in rows. Let $N = C'_N$ be the normalized covariance matrix of the noise, as defined in Eq. (43). Then the normalized covariance matrix of the signal Σ'_N from Eq. (42) can be written as the Hadamard product $\Sigma'_N = M \circ C'_N$. According to Oppenheim's inequality, the following inequality holds:

$$\begin{aligned}\mathrm{EMC} &= \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[\Sigma'_N]}{\mathrm{Det}[C'_N]}\right) = \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[M \circ C'_N]}{\mathrm{Det}[C'_N]}\right)\\ &\geq \frac{1}{2}\log_2\left(\frac{(\prod_{i=1}^{p} M_{[[i,i]]})\mathrm{Det}[C'_N]}{\mathrm{Det}[C'_N]}\right)\\ &= \frac{1}{2}\log_2\left(\prod_{i=1}^{p}\frac{1}{1-|\lambda_i|^2}\right)\\ &= -\frac{1}{2}\sum_{i=1}^{p}\log_2\bigl(1-|\lambda_i|^2\bigr). \end{aligned} \tag{46}$$

The lower bound according to the above equation shows that emergent complexity can be kept to a minimum, if the variances of the performance fluctuations are equalized by purposeful interventions of the project manager and correlations between vector components are suppressed. Next, because of the commutativity of the Hadamard product, it holds that

$$\begin{aligned}\mathrm{EMC} &= \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[\Sigma'_N]}{\mathrm{Det}[C'_N]}\right) = \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[C'_N \circ M]}{\mathrm{Det}[C'_N]}\right)\\ &\geq \frac{1}{2}\log_2\left(\frac{(\prod_{i=1}^{p} C'_{N[[i,i]]})\mathrm{Det}[M]}{\mathrm{Det}[C'_N]}\right)\\ &= \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[M]}{\mathrm{Det}[C'_N]}\right). \end{aligned}$$

The determinant of the Cauchy matrix M in the numerator can be written as (Krattenthaler 2005)

$$\mathrm{Det}[M] = \mathrm{Det}\begin{bmatrix} \frac{1}{1-|\lambda_1|^2} & \frac{1}{1-\lambda_1\overline{\lambda_2}} & \cdots \\ \frac{1}{1-\lambda_2\overline{\lambda_1}} & \frac{1}{1-|\lambda_2|^2} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} = \frac{\prod_{i<j}^{p}(\lambda_i-\lambda_j)(\overline{\lambda_{\mathrm{i}}}-\overline{\lambda_{\mathrm{j}}})}{\prod_{i,j}^{p}(1-\lambda_i\overline{\lambda_{\mathrm{j}}})}.$$

Hence,

$$\begin{aligned}\mathrm{EMC} &= \frac{1}{2}\log_2\left(\frac{\mathrm{Det}[C'_N \circ M]}{\mathrm{Det}[C'_N]}\right)\\ &\geq \frac{1}{2}\log_2\left(\frac{\prod_{i<j}^{p}(\lambda_i-\lambda_j)(\overline{\lambda_{\mathrm{i}}}-\overline{\lambda_{\mathrm{j}}})}{\prod_{i,j}^{p}(1-\lambda_i\overline{\lambda_{\mathrm{j}}})\mathrm{Det}[C'_N]}\right)\\ &= \frac{1}{2}\left(\sum_{i<j}^{p}\bigl(\log_2(\lambda_i-\lambda_j)+\log_2(\overline{\lambda_{\mathrm{i}}}-\overline{\lambda_{\mathrm{j}}})\bigr)\right.\\ &\qquad \left. -\sum_{i,j}^{p}\log_2(1-\lambda_i\overline{\lambda_{\mathrm{j}}}) - \log_2\mathrm{Det}\bigl[C'_N\bigr]\right). \end{aligned} \tag{47}$$

The additional lower bound on the EMC in the above equation is only defined for a dynamical operator A_0 with distinct eigenvalues. Under this assumption, a particularly interesting property of the bound is that it includes not only the damping factors

$(1-\lambda_i\overline{\lambda_i})$ inherent to the dynamical operator A_0 (as does the bound in Eq. (46)) but also the differences between eigenvalues $(\lambda_i-\lambda_j)$ and their complex conjugates $(\overline{\lambda_i}-\overline{\lambda_j})$. We can draw the conclusion that under certain circumstances, differences among effective productivity rates (represented by the λ_i's) stimulate emergent complexity in NPD. Conversely, small complexity scores are assigned if the effective productivity rates are similar. Numerical analyses have shown that the lower bound defined in Eq. (46) is tighter when the eigenvalues of the dynamical operator A_0 are of similar magnitudes.

5 Conclusions and outlook

This paper introduced vector autoregression models of cooperative work in NPD projects that are subjected to concurrent engineering. The models are based on the seminal work of Smith and Eppinger (1997) and Yassine et al. (2003) on deterministic project dynamics and also consider the important developments by Huberman and Wilkinson (2005) toward the theory of stochastic processes. The models can capture typical patterns of project dynamics in open organizational systems and explain "problem-solving oscillations" (Mihm et al. 2003) with few assumptions about the problem-solving processes. According to the deterministic and stochastic parts of the state equations, the irregular oscillations between being on, ahead of, and behind schedule can be interpreted as excited performance fluctuations (Schlick et al. 2008). The excitation can occur because of the multiple interrelationships between the design modes φ_i of the work transformation matrix A_0 and the effective variance C'_N of performance fluctuations. These mechanisms were uncovered explicitly in the spectral basis (Eq. (45) in conjunction with Eqs. (42), (43) and (44)).

Moreover, an information-theory complexity metric termed effective measure complexity (EMC) was introduced, and closed-form solutions were calculated. These solutions are beneficial for evaluating emergence in terms of mutual information communicated from the infinite past to the infinite future. The measure goes back to Grassberger (1986), whose seminal work in theoretical physics has been completely overlooked in organization theory and engineering management literature. His theory allowed us to derive the EMC of the specified class of models from first principles and to find closed-form solutions with different strengths. The results are given in Eqs. (38) and (45). Furthermore, we were able to calculate lower bounds (Eqs. (46) and (47)). It is important to point out that Grassberger's theory is not limited to a specific class of project models. If the data are generated by a project in a specific class but with unknown parameters, we can calculate the EMC explicitly, as we did. It is also possible, however, to evaluate the complexity of projects that fall outside the conventional models.

The EMC has several favorable properties: (1) It is small for projects in which tasks can be processed independently without cooperation and it assigns larger complexity values to intuitively more complex projects with the same dominant eigenvalue of the work transformation matrix but a stronger task coupling. The importance of the nature, quantity and magnitude of organizational subtasks and subtask interactions is also pointed out in the theoretical and empirical analyses of Tatikonda and Rosenthal (2000). Interestingly, the empirical studies of Hölttä-Otto and Magee (2006) show that estimation of effort in NPD projects is primarily based on the scale and stretch of the project and not on interactions. This is due to the fact that the balancing or reinforcing effects of concurrent interactions are very difficult to anticipate for project managers. In that sense, the measure can contribute to more reliable effort estimation. The dependencies between tasks were also mentioned as complexity-contributing elements in four out of six cases in the empirical analysis of Bosch-Rekveldt et al. (2011). Summers and Shah (2010) consider "complexity as coupling" as one of three main aspects of design complexity. (2) The measure tends to assign larger complexity values to projects with more tasks if the intensity of co-operative relationships is similar, and therefore it is sensitive to the cardinality of the project. This property follows, for instance, from the lower bound in Eq. (46). The complexity-reinforcing effects of the "size" of a project are also stressed in Mihm et al. (2003), Mihm and Loch (2006), Huberman and Wilkinson (2005), Suh (2005), Hölttä-Otto and Magee (2006), Summers and Shah (2010), and Bosch-Rekveldt et al. (2011). Alternatively, one can divide EMC by the dimension p of the state space and compare projects with different cardinalities. (3) The measure can evaluate both weak and strong emergence in an uncertain product development environment. According to Chalmers (2002) weak emergence means that there is in principle no choice of outcome. It can be anticipated without detailed inspection of particular instances of task processing. Given the state equation, there are entirely reproducible features of its subsequent evolution that inevitably emerge over time. In light of our approach, a good technique for the evaluation of weak emergence is the eigenvalue analysis of the WTM. It is obvious that the EMC indicates the same bound of asymptotic stability as does a classic eigenvalue analysis by assigning infinite complexity values: if the dominant eigenvalue has modulus less than 1, the infinite sum in Eq. (38) converges, and the project will converge toward the asymptote of "no remaining work"; on the other hand, if the dominant eigenvalue has modulus greater than 1, the sum diverges, and the work remaining grows over all given limits. The emergence of complexity is termed strong if the patterns of project dynamics can only be reliably forecast from the observation of the past of each particular instance of task processing and with relevant knowledge of prior history (Chalmers 2002). In the management literature this phenomenon is also known as "path dependence" (Maylor et al. 2008). Relevant information about the prior history is extracted through the predictive information according to Eq. (45). This formula—in conjunction with the formulation of the normalized work transformation and fluctuation matrices—allows a holistic excitation analysis of the design modes under uncertainty. The importance of the factor "uncertainty" in the scope and methods of a project in conjunction with "stability of project environment" is also pointed out in the TOE framework of Bosch-Rekveldt et al. (2011). The information axiom of Suh (2005) addresses both size and uncertainty. The simulation study of Lebcir (2011) shows that development time significantly increases when project uncertainty is changed from low to reference level. (4) The measure is independent of the basis in which the state vectors are represented. It is invariant under arbitrary reparameterizations based on smooth and uniquely invertible maps (Kraskov et al. 2004) and therefore is independent of the subjective choice of the measurement instrument of the project manager. To the best of our knowledge, this fundamental objectiveness is a unique property that other metrics do not possess.

The task-based approach to evaluating emergent complexity in NPD in conjunction with the developed state-space models will need to be worked out in more detail in the future. A first step in that direction would be to compute the EMC of the project model developed by Huberman and Wilkinson (2005), which incorporates multiplicative instead of additive noise (cf. Eq. (17)). Their model is interesting not only because it can reproduce critical effects of both large groups and long delays with few parameters, but also because of its reasonable assumption that the autonomous task-processing rates and the task coupling are subject to random influences. However, to the best of our knowledge, the Huberman–Wilkinson model has not been supported by empirical evidence, and it is an open question whether it has a higher validity than our VAR(1) approach, which has been validated in an industrial case study (Schlick et al. 2008, 2012). A theoretically and practically very promising extension of the dynamic project model is to formulate a periodic vector autoregressive (PVAR) stochastic process (Ursu and Duchesne 2008). A PVAR process can capture the dynamics of short cyclic processing of component-level design information within the development teams as well as long-range "seasonal" effects. A seasonal effect is common in large-scale CE projects and is caused by the periodic information release policy of system-level design information across teams. A deterministic model able to simulate this kind of task processing was developed by Yassine et al. (2003). A corresponding stochastic model has been formulated recently (see Schlick et al. 2011). A PVAR model offers a compact representation as a VAR process, as we have formulated in Eq. (17). Hence, the closed-form solutions and bounds can be applied directly. In the long run, we aim to conduct an external validation study with experienced project managers in industry. It is hypothesized that the EMC is a conceptually valid complexity variable and that it has the potential to capture the implicit knowledge of project managers based on the process dimension in NPD (Summers and Shah 2010). In general, this complexity measure provides valuable information enabling the project manager and CE teams to better organize their work and to improve coordination.

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