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Forecasting technological progress potential based on the complexity of product knowledge

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ABSTRACT

Investing in R&D for a product employing new technologies is a challenging issue for companies and governments alike, especially at the critical juncture of deciding the degree of resource allocation, if any. Decision-makers generally rely either on historical data or intuitive prediction to gauge the rate of improvement and level of R&D spending to achieve the desired improvement. This paper introduces a systematic way of forecasting the endogenous progress potential of a product based on the complexity of its knowledge structure. The knowledge structure represents knowledge associated with the product's core technology and the configuration of the components and sub-systems supporting the core technology. Topological properties of complex networks are applied to assess the knowledge complexity of a product relative to its class. Analyses of the complexity of knowledge structures for a set of energy harvesting devices confirm that node degree and clustering coefficient provide distinguishing topological properties whereas community size and membership number do not clearly differentiate the knowledge structure complexity. We discuss the implications of these findings on forecasting progress potential.

1. Introduction

A central concern in R&D investment in product innovations employing new or untested technology is the necessary level of resource allocation to grow the stock of knowledge [1,2]. A model of the intrinsic improvability of a product would allow decision makers to forecast a product's endogenous rate of improvement, or progress potential, which would inform their decisions on the appropriate level of research budget and the time span for the stock of knowledge to accumulate [3]. Similarly, companies or governments aiming to allocate investments across a number of potential product innovations, all of which appear attractive, may prefer to invest in those that have a higher likelihood of faster progress. We contrast this problem of forecasting the endogenous progress potential of a product based on its intrinsic improvability with forecasting the diffusion of product innovation [4,5], which generally focuses on exogenous, market-driven factors, or forecasting the general growth of knowledge about technologies through environmental scanning, for which bibliometrics and Delphi have played a key role [6,7].

The extent to which a product and its core technology respond to investment and improve has been quantified by progress functions [8] and 'learning curves' or 'experience curves'. Progress functions measure the result of companies gaining experience and making improvements to production, which is assessed by data on cumulative volume of production and unit cost. Despite subtle differences in the definition of progress functions and learning curves or experience curves [8], they all rest on the same principle: the cost of production decreases as individuals, companies, or industries 'learn by doing'. The precise nature of the relation between the inherent

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difficulty in 'learning by doing' posed by a specific technology and cumulative volume of production is not yet fully understood, though. In the energy sector, for example, experience curves only weakly explain the change in cumulative volume of production, with the endogenous factor of technical barriers being more significant [9]. Two other causal factors downplayed in progress functions are the intrinsic degree of difficulty in 'learning' about a technology at a component level and the degree of architectural complexity in configuring parts and sub-systems around the technology into a commercial product. Understanding how the intrinsic complexities in the design and underlying technology of a product affect growing the stock of knowledge, and hence the progress potential of a product, would be a powerful tool for investors and policy-makers to forecast the progress potential of new products at the early stages of technological development.

To address this question, we bring engineering design to the problem of forecasting technological improvement by exploring a seldom-cited link, which is the knowledge that is embodied in the design of a product. When we mean design, we refer to both the componentry of the core technologies and the configuration of the parts and sub-systems of a product, that is, the product architecture. Significant knowledge is embodied in the components of the product and in the way that they fit together. One way in which a number of academic studies have connected technological improvement and design is through the modularity of product architecture. A highly modular product architecture has been shown to decrease the time to design the product [10], support end-user innovation [11], and facilitate the establishment of product platforms and families [12,13] among other benefits that increase the rate of innovation [14]. Architectural modularity turns out to be an important way to link the design of a product to its progress potential. McNerney et al. [15] developed an intriguing model showing that the progress potential of a product is driven by a power law with exponent $b = 1 / (\gamma d^*)$, where γ is the intrinsic difficulty of finding a better component and d^* is the maximum design complexity of the product. The maximum design complexity of the product is determined by the component that has the most influence on other components, such that it is not possible to alter that component without simultaneously altering the other dependent components. Through simulation on synthetic data, they showed a correspondence between their model and reported rates of progress.

A notable caveat to this perspective is the work by Henderson and Clark [16], who studied the relationships between architectural knowledge as embodied in the product architecture and the capability of companies to implement architectural innovation. They showed that simply modularizing the physical architecture of a product does not then mean that knowledge underlying the product has also been modularized. Brusoni and Prencipe [17] emphasize the point "that product modularization does not derive from, nor bring about, knowledge modularization". When there is a correspondence between architectural and knowledge modularity, Ethiraj et al. [18] showed that an increase in physical product modularity decreased the cognitive complexity of the product, leading to easier and quicker imitation by competitors. In essence, they point toward the main thrust of this article: the complexity of the knowledge structure underlying a product influences the dynamics of progress. The questions are, how complex and complex relative to what?

Modeling progress according to architectural modularity alone downplays the inherent difficulty in producing new knowledge relevant to the product and the knowledge dependencies between interacting components and systems. When it comes to product innovation, knowledge is both a requisite of innovation and a barrier to innovation. It is a barrier to innovation because the process of acquiring and transforming knowledge input into innovation output is costly and requires coordination. Previously, scholars have examined the problem of the complexity of the coordination in relation to the complexity of the task structure [19,20] or product architecture [21]. Much less is known, though, how the complexity of the knowledge structure may affect the cost of transforming the knowledge into an innovation, with the exception of the study by Dollinger [22], who demonstrated that increasing complexity of information requires more boundary spanning across knowledge domains by individuals so as to produce cohesive strategic plans.

We thus make one important correction and contribution to studies aiming to forecast the progress potential of products: the fundamental factor in the progress potential of a product is not the complexity of the product architecture, but rather the complexity of the underlying knowledge structure for the product. Our main hypothesis is that progress potential is bounded by the degree of complexity (or simplicity) of the underlying knowledge structure of a product, which represents both knowledge associated with the product's core technology and the configuration of the parts and sub-systems around the core technology to produce a commercially viable product. The challenge lays in understanding the differentials in underlying knowledge structures for products. Which characteristics of knowledge structures distinguish the complexity of products and how can the complexity of product knowledge structures be assessed to ascertain progress potential?

This paper explores the hypothesis that a relationship exists between product knowledge structure and the product's progress potential. We describe an approach based on complex network theory and tensor analysis. The complexity of the knowledge structure for a product is compared to products within its class in a form of outside-view reference class forecasting [23]. We present three hypotheses to test which topological properties distinguish the complexity of products and examine these topological properties for a set of products. Our first hypothesis tests the degree of connectivity between knowledge elements associated with a product. The second hypothesis tests the relative sizes of modules of knowledge elements. The third hypothesis tests the links between knowledge elements to elements outside of its knowledge module. Each of the hypotheses is based on a set of arguments relating to challenges associated with producing new stock of knowledge as the knowledge structure complexity increases. We illustrate our approach on a set of energy conversion devices employing various core technologies including piezoelectric, wind, wave, and solar to find evidence to support our principle hypothesis that a relationship exists between the complexity of product knowledge structures and the rate of progress.

We find that the topological properties of node degree and clustering coefficient distinguish the knowledge structure complexity of products, whereas there is insufficient difference in community sizes and community degree. That is, there is support for the first hypothesis but insufficient support for the second and third hypotheses in our data set. We find that piezoelectric technologies have product knowledge structures with the lowest node degree and clustering coefficient. The similarity in knowledge structure complexity based on node degree and clustering coefficient for wind and solar energy harvester devices follows the observed learning rates for wind power and solar photovoltaic panels [24]. This correspondence and the statistically significant difference in node degree and clustering coefficient between products employing piezoelectric technologies and other products lead us to conjecture that piezoelectric-based energy harvesting products will likely progress the fastest. Wind and solar products will progress at approximately the same rates and slower than piezoelectric. Hybrid technologies combining wind and solar will progress the slowest.

2. Forecasting method

2.1. Knowledge representation

In this section, we develop a means to model the knowledge underlying a product. In the field of engineering design, one of the most accepted methods for modeling a product in a component and architecture independent manner is from the perspective of the product's function, in other words, what it is intended to do. Conceptualizing a product in terms of its intended functions is considered a knowledge-oriented view of engineering design. Functional representations of products include the Function–Behavior–Structure (FBS) ontology [25], the design matrix [26], and functional modeling [27,28]. In this paper, we will utilize the functional model because of its ontological rigor. A functional model identifies the intended purpose behind a product, typically using a standardized and economical (exhaustive but mutually exclusive) set of function-related terminology such as the functional basis [28]. More formally, function is the operation on a flow, or the manner in which an input is transformed into an output [29], as depicted in Fig. 1 for a piezoelectric component (adapted from [30]).

The functional modeling approach provides 'structural' data about the knowledge underlying a product, because the functions (e.g., convert, transmit) describe the intended reason behind the existence of the product, and the flows (e.g., human energy, mechanical energy, electrical energy) connect the functions to produce the full set of functional requirements for the product [31]. Further, because a functional model can rely on a controlled vocabulary (ontology) of function and flow with the functional basis [28], it describes product knowledge in an objective and uniform manner.

The functional model lends itself to mathematical representation in matrix form since all that is required to produce the knowledge representation is to answer the question: Does a product implement a given function on a given flow? If the answer to this question is 'Yes', then it can be said that a product contains a flow that is operated on by a number of functions. Matrix **A** in Eq. (1) models the structure of the knowledge about the product because it provides a mapping between m functions and n flows, where $a_{i,j} = 1$ if function i operates on flow j and 0 otherwise.

$$\overset{\mathbf{A}}{\begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix}} \tag{1}$$

Alternatively, we can represent matrix **A** as a bi-partite network G. Each type-1 node in G is a function and each type-2 node is a flow. A homomorphism exists between the representation of G and matrix **A**. Matrix **A** is an adjacency matrix of network G:

$$\mathbf{A}_{ij} = \begin{cases} 0 & \text{if an edge exists between nodes } i \text{ and } j \\ 1 & \text{otherwise} \end{cases}. \tag{2}$$

A typical functional model will contain a variety of functions, possibly repeated, operating on a set of flows. If functional models represent a set of products achieving a similar primary function, such as generating electricity, then the set of knowledge structures becomes a reference class against which the complexity of a specific knowledge structure can be compared. In the next section, we turn to the details of making this relative comparison of knowledge complexity.

2.2. Quantifying the complexity of the knowledge structure

To motivate our approach to quantify the complexity of the knowledge structure, we consider the issue of independence and dependence in the knowledge structure, along with two associated boundary conditions. At one boundary condition lies a truly decoupled design. Matrix **A** is fully diagonal with network G containing independent pairs of a single type-1 node connected to exactly one type-2 node. Each function operates on exactly one flow. Modularity exists in a perfect form in this matrix, as modular functions do not affect other functions and flows. In a perfectly modular knowledge structure, what is known about one aspect of a design neither affects nor influences knowledge about another aspect of the design. For example, to know how the LCD screen of a cell phone works, I do not also need to know

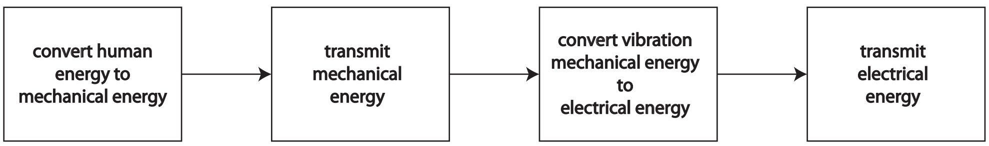

Fig. 1. Functional model of a piezoelectric component.

how the Li-ion battery works, except for its power output, and knowledge of these two aspects of the cell phone is essentially independent. At the other boundary condition lies a truly coupled design. That is, matrix **A** is fully filled, with network *G* containing all type-1 nodes connected to all other type-2 nodes. Each function operates on all flows, which in turn affects all other functions. Modularity does not exist at all in this matrix; no function can be altered without affecting any other function or flow.

In general, matrix **A** is neither perfectly diagonal nor fully filled because the knowledge structure for a product involves a complex set of interactions between the functions and flows. Returning to the example of the cell phone, knowledge about a touch screen requires knowledge of both capacitive sensing and liquid crystal display technology. Algebraic properties of matrix **A** or equivalently the topological properties of network *G* can characterize the degree of complex coupling in the knowledge structure.

The field of complex networks has developed a number of techniques and metrics to characterize the complexity of networks in terms of their topological properties [32]. The specific topological property of interest is the modular organization of the complex network including the number of modules, the number of levels of hierarchical organization, and node properties at the various levels of modular organization of the network. In Section 3, we will explain the relevance of modularity in the knowledge structure to progress potential. We first explain how we identify modularity in the knowledge structures.

A module is a tightly clustered or interacting subset of nodes in the network that has much sparser interaction with the rest of the network. By definition, a module has more intra-module edges than inter-module edges. If there is modular organization in the network, many nodes in modules will have common neighbors. This will result in many columns in the adjacency matrix of the network having the same or similar entries, resulting in redundancy of information. Thus, the number of modules will always be much lower than the rank of matrix **A**. In contrast, if there is no modular organization in the network, e.g., there is perfect independence in the adjacency matrix, then the number of modules will be exactly the rank of matrix **A**. If there are modules, what this means is that there is mathematical redundancy in the adjacency matrix, because there are linearly dependent rows or columns, and a lower dimensional basis for those vectors exists.

In previous work, we have proven that the Eigenvalue or Singular Value Decomposition (EVD/SVD) provides an efficient way to detect the modular organization and levels of hierarchical modular organization of complex networks by analyzing the eigenvalue/singular value spectra of their adjacency matrices [33,34]. We summarize the key findings herein. The eigenvalue (for networks having a single type of node) or singular value (for networks having two types of nodes) spectra provide sufficient information both to identify the optimal number of modules in the network and to identify which nodes belong to which modules, including their possible overlap into multiple modules. First, the eigenvalue/singular value spectra correspond to the modularity structure of the network. The number of largest eigenvalues/singular values well separated from the tail of the trailing ones exactly describes the optimal number of modules in the network. If the network has a hierarchical modular organization, the largest singular values have a stepped pattern of decrease, i.e., clusters of similar singular values followed by a large gap followed by another such cluster, and so on. The number of such gaps describes the number of hierarchical levels and the number of singular values of similar magnitude at each step describes the number of modules within that level. Second, a least squares approximation of the network's adjacency matrix generated by truncating the eigenvalue/singular value matrix and their associated eigenvectors at the optimal degree of modularity *k* has the net effect of translating positions of nodes into a continuous real-valued space where previously the positions of nodes were in a binary space. By clustering nodes in space using a simple algorithm such as k-means clustering with a distance-based metric, the modules in the network can be readily identified. One other important consequence of the least squares approximation is that nodes that were previously modeled as not having an edge relation, or conversely nodes that were modeled as having an edge relation, may have their edge relations strengthened (i.e., $\mathbf{A}_{ij} = 0 \Rightarrow \mathbf{A}_{ij} > 0$) or weakened depending upon the statistical pattern of edge relations across the entire network. The strengthening or weakening of edge relations reveals additional or decreased latent complexity that was previously unaccounted for in the original network model. This is an essential outcome for assessing the actual complexity of networks (knowledge structures).

To make the relative comparisons of knowledge complexity, we must take one more analytical step. Up to this point, we have been discussing the knowledge structure for products based upon single, independent network representations. Topological signatures of complexity for each knowledge structure without reference to a class would not provide us meaningful information, however. In other words, we still need an answer to the question of complexity relative to what. Our approach is to compare the knowledge structure of a product to a reference class. To perform this comparison, we draw upon the main pillars of reference class forecasting [35] and outside-view similarity-based forecasting [23,36], which are: 1) to generate forecasts from an unbiased class of similar projects; and 2) draw on statistical relations between the target and the reference class. Based upon these principles, we combine the knowledge structure for a set of similar products, where similarity is determined by the primary function of the product rather than the technology employed by the product, into a single knowledge structure consisting of all of the products. The 'stacked' functional models result in a tensor representation of order 3: product × function × flow. A tensor is a matrix with dimensionality greater than 2. Consistent with accepted notation, tensors will be represented with boldface Euler capitals, e.g., $\mathcal{A}$. Tensor $\mathcal{A}$ is a knowledge representation for a class of products. By embedding the knowledge structure for a product into a tensor representation for the knowledge structure of the class, we can compute the statistical pattern of cross-relations (i.e., similarities) of knowledge shared by all of the products in the class using the Higher-Order Singular Value Decomposition (HOSVD) tensor decomposition. The HOSVD is a generalization of the singular value decomposition [37]. The HOSVD decomposes a tensor $\mathbb{A}$ into a core tensor $\mathbb{C}$ (equivalent to the matrix of singular values **S**) and a set of matrices **B** (equivalent to the left and right singular vectors **U** and **V**) along each mode of **A**. Computing the HOSVD of an order N tensor is equivalent to the computation of N different matrix SVDs, one for each n-mode matrix unfolding of the tensor $\mathbb{A}$ [37]. The consequence of this homomorphism between SVD and HOSVD is that concepts about identifying the modularity of complex networks apply equivalently to networks described as two-dimensional matrices and order N tensors. Findings on the number of modules and levels of organization apply to the singular value spectra of tensors due to the homomorphism of SVD and HOSVD. The significance of this generalization is that we thus have a unified method to characterize both the degree of modularity (how many modules) and hierarchical modularity (how many modules at different levels of organization of the knowledge structure) in multi-dimensional knowledge structures.

The HOSVD, like the SVD, changes the values of the cells in the tensor depending upon their original statistical pattern of cross-relations when the tensor is re-represented in a truncated lower-dimensional space. If the knowledge structure for a product is similar to the class, then the values in the cells (their node positions in a continuous real-valued 3D space) of the 'slice' of the tensor representing the product will become similar in value to the values for the class during the tensor decomposition process. Changes to values in the tensor following the HOSVD decomposition have the effect of altering the topological properties of the network representing the knowledge for the product so that it is more similar to the topological properties of the class. The same effects happen in reverse. As the knowledge structure for the product differs from the class, the values in the cells of the 'slice' of the tensor diverge from the class. The consequence is that the topological properties of the network representing the knowledge for the product also diverge from the class. In short, by combining the knowledge structures into a single tensor, and then computing the HOSVD of the tensor, we can compare knowledge structures of products relative to their class in a single computation.

The only remaining step is to derive hypotheses linking topological properties of a network representing a knowledge structure and its complexity to progress potential. We develop these hypotheses in the next section.

3. Hypotheses on complexity and progress potential

If the essence of innovation is the production and integration of knowledge in a new way, these knowledge-oriented activities will entail a cost influenced by the complexity of the knowledge structure. Topological properties associated with the modular organization of complex networks are proposed to explain the influence of the complexity of knowledge structure on progress potential. We propose three hypotheses based on the complex network topological properties of node degree, clustering coefficient, community size, and node overlap in the knowledge structure of products.

Hypothesis 1. Progress potential increases as the node degree decreases and as clustering coefficient decreases.

A complex network consists of components that interact and that are interdependent to some degree. The degree of decomposability of the network into modules that have weak interactions between them but strong interactions within them [38] is partially determined by the degree of interconnectedness of the nodes. At one extreme is a fully connected complex network, in which every node is connected by an edge to every other node; this network is not decomposable, and there is only a single community. At the other extreme are fully independent nodes. Knowledge structures that are decomposable into modules can enable the creation of modular organizational units to handle the associated knowledge creation activities [39]. The complex network features of Node Degree (ND) and Clustering Coefficient (CC) capture this degree of interconnectedness of nodes. In a knowledge structure, each edge represents a dependency between knowledge (nodes). The ND is the number of edges (links) per node and is one of the most fundamental features of a complex network, as illustrated in Fig. 2. The CC measures the probability that two nodes connected to some other node are themselves connected; that is, the CC measures the density of knowledge clusters in terms of the number of actual "triangles" compared to the number that is theoretically possible. High values of CC indicate that there are dense knowledge dependencies in the knowledge structure.

Hypothesis 2. Progress potential increases as the module sizes approach equilibrium.

The module size is the number of nodes in a module, as illustrated in Fig. 3. If a given knowledge structure partitions into a few large modules and then many small ones as opposed to modules of approximately the same size (equilibrium), this means that there is an imbalance in the type and amount of knowledge located within these modules. This imbalance introduces a coordination problem for companies in knowledge sharing and transfer. The difference in type and amount of domain-specific knowledge within each module increases the effort to share the knowledge [40]. Knowledge sharing activities require more effort from the smaller knowledge community because it takes more time for the smaller community to absorb knowledge transmitted by the larger community [41]. This view leads us to hypothesize that products having knowledge structures containing disproportionately sized modules will progress more slowly than products having knowledge structures containing similarly sized modules. We measure this imbalance through the complex network feature of community degree. The community degree is the probability p_k of finding a module with size k in the knowledge structure. A cumulative distribution plot of the community degree would identify the extent to which modules have a similar size. A convex shape means that there are a few modules of large size whereas a concave shape means that there are many modules of similar size.

Hypothesis 3. Progress potential increases as the number of modules with which a node shares an edge decreases.

Organizational boundaries of companies are often based upon around distinct units of knowledge and expertise [42],

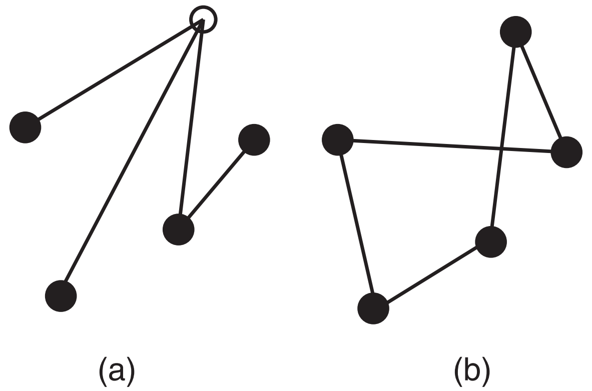

Fig. 2. Node degree. The node having no fill in (a) has the highest node degree of 3 whereas the other nodes have a node degree of 1 or 2. All nodes in (b) have the same node degree, 2.

that is, the knowledge required to deliver a product. These organizational units produce specialized knowledge, and, moreover, produce specific framings of their knowledge as a means for solving the innovation problem [43]. In order to transfer knowledge between organizational units, the strength of ties, network cohesion, and network range of the organization must be increased [44]. In a knowledge-sharing network, the number of edges that connect a node (i.e., an individual) to other modules (i.e., another organizational unit) represents the degree of knowledge transfer. However, in a product knowledge structure, the situation is reversed. The more edges that connect a node to other modules, the more knowledge sharing that is required across communities regardless of the organization having the characteristics or knowledge transfer mechanisms to facilitate the knowledge sharing and creation across boundaries [45]. In a product knowledge structure, as the number of edges with which a node shares with other modules increases, so do the requirements for knowledge transfer and sharing [40]. This creates a context wherein knowledge creation across boundaries is more challenging, and, therefore, the progress potential is likely to decrease.

Typically, a node is said to be overlapping a module if it can belong in multiple communities [46]. Jun et al. [47] propose that a node could be considered as overlapping multiple modules if it shares edges between two non-overlapping modules, in which case it is considered a boundary node, as shown in Fig. 3. We apply the definition by Jun et al. [47] as it provides a less conservative definition of overlap than that of Palla et al. [46]. We define the membership number of a node as the number of edges from a node within a module to other nodes in other modules. We can again plot the cumulative distribution function of membership number as the probability p_k of finding a node with membership number k to illustrate the extent to which nodes in the knowledge structure contain edges to nodes outside of their respective modules.

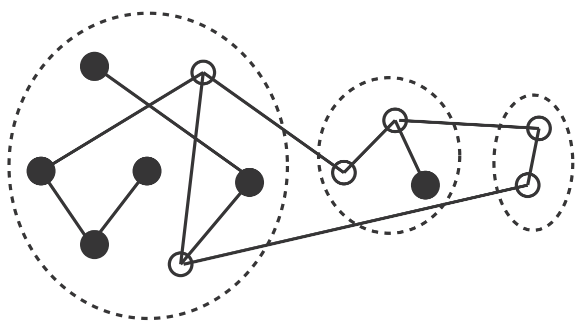

Fig. 3. Module size and membership number. This figure shows three modules having an imbalance in sizes, and six boundary nodes (no fill), nodes within a module that share edges with nodes in other modules.

4. Results of analysis of energy harvesting devices

In these empirical experiments, we study the complexity of the knowledge structure of a data set of energy harvesting products provided by Weaver et al. [30]. We studied an externally developed data set so as to minimize selection bias by the researchers. Weaver et al. [30] produced this data set to investigate the innovation potential of these products, specifically, how 'concepts' from one product might be incorporated into other products. Originally, the functional models were represented in a two-dimensional matrix with the rows being products ($i = 39$) and the columns representing both function ($k = 21$) and flow ($j = 16$). Their two-dimensional matrix is a tabular representation of a functional model as shown in Fig. 1. This representation was converted into a three-dimensional (order-3) tensor $\mathtt{A}$ by 'stacking' the functional models, where $\mathtt{A}_1$ is product, $\mathtt{A}_2$ is flow and $\mathtt{A}_3$ is function. The value $\mathtt{A}_{ijk} = 1$ if product i uses flow j in function k. Some sample data is shown in Table 1.

Second, we identified the modular organization of the tensor as the number of modules and number of levels of hierarchical modular organization in the tensor. The levels of hierarchy are determined by the singular value indices at which a large gap exists in the values between the kth and kth + 1 singular values [34]. This step change is calculated as $\varepsilon = \frac{k_i - k_{i+1}}{k_i}$. For the analyses shown in this paper, we set $\varepsilon = 0.01$, but the conclusions are robust for values of ε between 0.01 and 0.05. However, we note here that optimal or robust values of ε will, in general, result from the data itself. If there is a very pronounced community structure or hierarchical community structure, the gaps between singular values will be very pronounced, and ε will be higher. For example, a network with 4 communities of 16 nodes each, with all 16 nodes of a single community fully connected to each other,

Table 1
Sample data for energy harvesting devices. E = energy; ME = mechanical energy; rot = rotational; trans = translational. A value of 1 in a table cell means that, e.g., the product Wing Wave Generator can "import" "rotational mechanical energy" and then "transfer" the "rotational mechanical energy".

Product	Import			Transfer		
	Human E	Rot ME	Trans ME	Human E	Rot ME	Trans ME
Perpetuum	0	0	0	0	0	0
Nova Energy Turbine	0	1	1	0	1	1
Wing Wave Generator	0	1	0	0	1	0
Micropelt STM-PEM	0	0	0	0	0	0

but to no other community, will show the highest $\varepsilon = 1$. If there is a weak community structure or hierarchical community structure, the gaps between the singular values will be smaller and the whole spectrum will be smoother, resulting in lower ε values. In our data set, we identified 5 levels of hierarchy and corresponding sets of singular value indices, or k-indices, representing the number of modules at each level of hierarchy along each of the 3 tensor modes: (7, 3, 4); (11, 8, 8); (13, 11, 11); (13, 13, 14); and, (13, 13, 16). Using these k-indices as levels of modular organization of the tensor, we compare the complexity of the knowledge structure of individual products to the class.

We begin by performing a test of internal validity. Given the data set, we expect that similar types of products would appear in the same module along mode-1 (the product mode). That is, all the products grouped by Weaver et al. [30] as thermal products should appear in the same module. Indeed, a comparison of the modules in mode-1 with the classification by Weaver et al. [30] shows a high-degree of correspondence. Table 2 shows the accuracy (the fraction of products that should appear in the module) and precision (the fraction of products in a cluster that are relevant) of the clustering of products into modules along mode-1. In the results shown in Table 2, the original categories of inductive and piezoelectric vibration were combined and the categories of wind, solar and hybrid were combined before making the accuracy and precision calculations. The rationale behind combining some of the categories is that piezoelectric products are found in both the inductive and piezoelectric vibration categories, and the products in the hybrid category combine both wind and solar technologies, so they are equally similar to products in the wind or solar categories alone. Accuracy and precision levels above 80%, generally regarded as thresholds for automated clustering, show that the method is able to cluster the products into appropriate communities of products sharing similar modes of input for energy harvesting and technologies for converting the energy.

We now turn our attention to the comparison of the topological properties of each individual product to the class. For each product, which is represented by a 'horizontal' slice of the tensor, we calculated the metrics associated with each of the hypotheses at each level of hierarchical organization of the tensor, that is, for each set of k-indices stated previously. Each horizontal slice of the tensor represents the knowledge relation between the flow and the function for each product calculated at each level of hierarchical organization of the knowledge structure for the class. In order to convert the matrix for each slice into a network according to Eq. (2), we set an edge threshold value. An edge is wired between nodes in a 'slice' if the value in a cell is greater than or equal to the threshold.

Table 2
Product cluster accuracy and precision.

Cluster name	Accuracy	Precision
Inductive and piezoelectric vibration	100%	100%
Wind, solar and hybrid	100%	93.75%
Ocean	100%	100%
Thermal	100%	80%

To test Hypothesis 1, we calculated the topological properties of node degree and clustering coefficient across all k-indices. For threshold values greater than 0.6, for some products (Innowattech piezoelectric vibration harvester and transparent film on window solar panels) at the lowest level of hierarchical organization, k-index (7, 3, 4), no edges could be established between nodes. This is a numerical artifact of the weak knowledge relation between function and flow for some products. To enable a comparison of node degree and clustering coefficient across all products, we set the threshold ceiling at 0.6. We test Hypothesis 1 in two ways: by technology and by individual product. Table 3 shows the descriptive statistics for ND and CC calculated at the various levels of hierarchical organization of the knowledge structure for the products and grouped by underlying technology as categorized by Weaver et al. [30].

There is a statistically significant difference in average node degree and clustering coefficient between the technologies. The one-way, between-technologies analysis of variance revealed an effect of technology on node degree, $F\ (6,\ 188) = 22.351$, $p < .001$, $M\ S_{error} = 1.896$, $\alpha = .05$, and on clustering coefficient, $F\,(6,\ 188) = 29.458$, $p < .001$, $M\ S_{error} = .007$, $\alpha = .05$. The choice of technology has a statistically significant difference in node degree and clustering coefficient for product knowledge structures. A Welch test of means confirmed that there is a statistically significant difference in the means at the $\alpha = 0.05$ level. Post-hoc comparisons using the Tukey HSD test indicated that the mean value of the node degree and clustering coefficient for the hybrid technologies was statistically higher than all of the other technologies. With respect to hybrid products, combining technologies makes the knowledge about the products more complex, as would be expected. The technology with the lowest node degree, piezoelectric vibration, is statistically significantly lower than all the other technologies except ocean at the $\alpha = 0.05$ level. The technology with the lowest clustering coefficient, piezoelectric vibration, is statistically significantly lower than all of the other technologies at the $\alpha = 0.05$ level. In summary, we find support for Hypothesis 1. The statistically significant difference in average node degree and clustering coefficient distinguishes products having a higher knowledge structure complexity.

To compare the knowledge complexity of individual products, we calculated the node degree and clustering coefficient for all products at the various k-indices and edge thresholds to check the robustness of the results. Figs. 4 and 5 show the variation of average node degree and clustering coefficient, respectively, by edge threshold for all of the products at k-index (7, 3, 4) due to space limitations. The purpose of these graphs is to identify the product(s) having a knowledge structure with the lowest node degree and clustering coefficient. This determination entails identifying the products corresponding to the lines having the lowest, non-zero node degree or clustering coefficient at the highest edge threshold. Identifying the product having the lowest non-zero node degree or clustering coefficient at increasing edge thresholds sets a conservative rule, as it requires a stronger connection between knowledge elements. Consistent with the previous results at the technology level, the product having the lowest node degree and clustering coefficient is the Innowattech piezoelectric energy harvester. The three products with consistently lower node degree

Table 3
Topological properties of products by technology (IV = inductive vibration; PV = piezoelectric vibration).

						95% confidence interval for mean			
		N	Mean	Std. dev.	Std. error	Lower bound	Upper bound	Minimum	Maximum
ND	IV	45	5.512	1.082	0.161	5.187	5.837	3.500	7.500
	PV	30	4.203	1.474	0.269	3.653	4.753	0.667	6.056
	Wind	30	6.029	1.071	0.195	5.629	6.429	3.308	7.438
	Ocean	15	5.450	1.552	0.401	4.590	6.309	2.300	7.625
	Solar	30	6.219	1.641	0.300	5.606	6.832	1.875	8.667
	Thermal	25	6.078	1.451	0.290	5.479	6.677	4.800	8.944
	Hybrid	20	8.672	1.563	0.349	7.941	9.404	5.429	10.579
	Total	195	5.891	1.774	0.127	5.640	6.141	0.667	10.579
CC	IV	45	0.324	0.063	0.009	0.305	0.343	0.232	0.464
	PV	30	0.256	0.096	0.017	0.220	0.291	0.000	0.360
	Wind	30	0.422	0.065	0.012	0.398	0.446	0.246	0.497
	Ocean	15	0.392	0.142	0.037	0.313	0.470	0.083	0.542
	Solar	30	0.352	0.101	0.018	0.314	0.390	0.000	0.515
	Thermal	25	0.355	0.083	0.017	0.320	0.389	0.242	0.503
	Hybrid	20	0.556	0.054	0.012	0.531	0.581	0.374	0.632
	Total	195	0.366	0.117	0.008	0.349	0.382	0.000	0.632

and clustering coefficient, at edge threshold values where comparisons can be made, are the Innowattech, transparent film on window, and Columbia Power Manta Buoy. Tukey HSD tests confirm that the node degree and clustering coefficient for the Innowattech and transparent film on window are significantly lower than all other products. For the Columbia Power Manta Buoy, its node degree is similar only to the Perpetuum Free Standing Harvester (FSH/C) electromagnetic-energy harvester, and its clustering coefficient is statistically similar only to the Micropelt STM-PEM (STMicroelectronics and Micropelt) thermal electrical energy harvesting and solid-state thin-film battery. The Innowattech product has a statistically significant lower node degree and clustering coefficient than all other products except for the Columbia Power Manta Buoy and the transparent film on window solar panel.

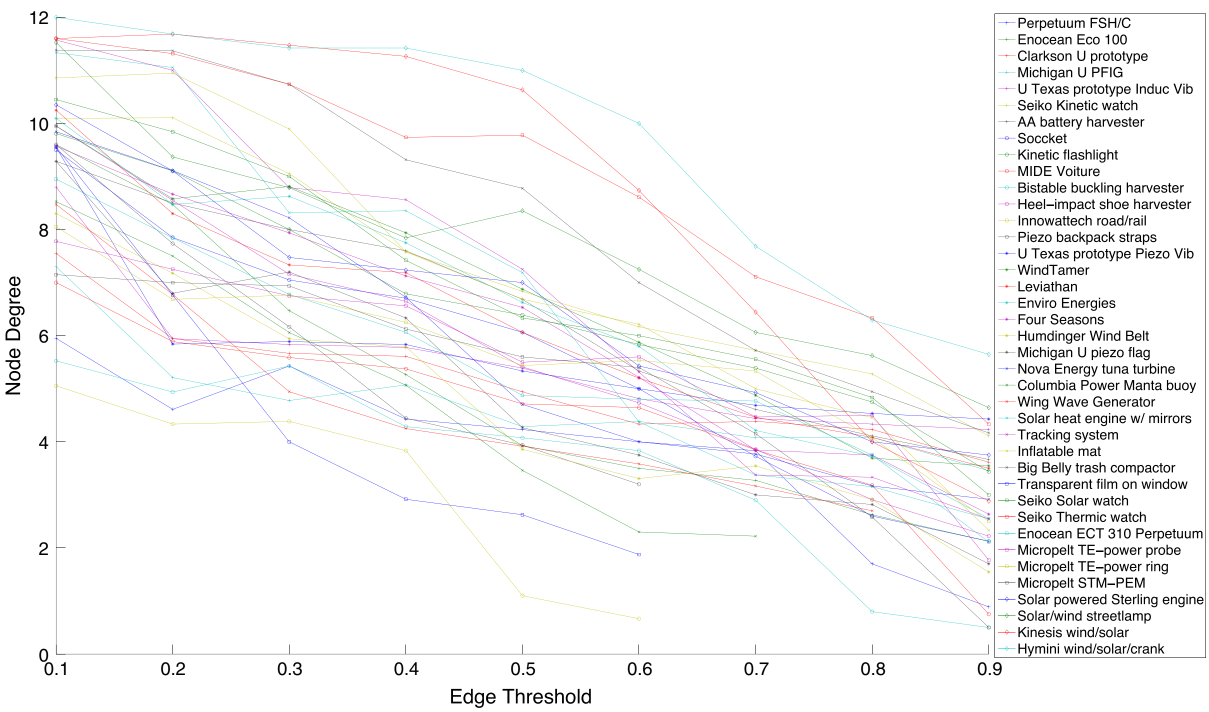

Fig. 4. Node degree of knowledge structures for energy harvesting products.

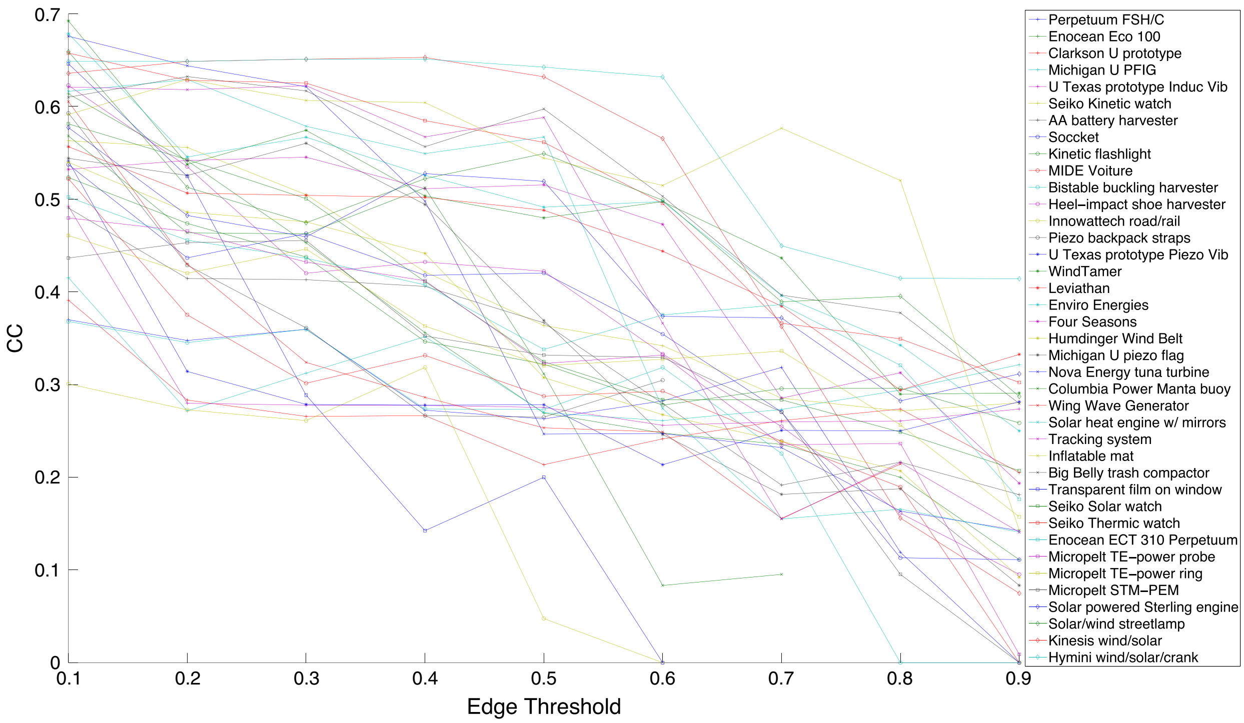

Fig. 5. Clustering coefficient of knowledge structures for energy harvesting devices.

To test Hypothesis 2 and Hypothesis 3, we calculated the module sizes and membership number of nodes. Fig. 6 shows the cumulative distribution for community degree and membership number for all of the products by technology. As before, these graphs were produced by calculating the module size and membership number for all of the products at the edge threshold level of 0.6 for all *k*-indices. In this way we find as many modules as possible in each knowledge structure so that we produce more observations of module size and membership number. The graphs do not provide a differential prediction of progress potential because the distributions follow a similar shape. As the results are similar when we plot community degree and membership number by product, we do not show these graphs. These results imply that community degree and membership number for product knowledge structures may in general follow similar cumulative distributions. In summary, we do not find sufficient differential in community degree and membership number between these products to support using Hypothesis 2 and Hypothesis 3 to gauge knowledge structure complexity and progress potential.

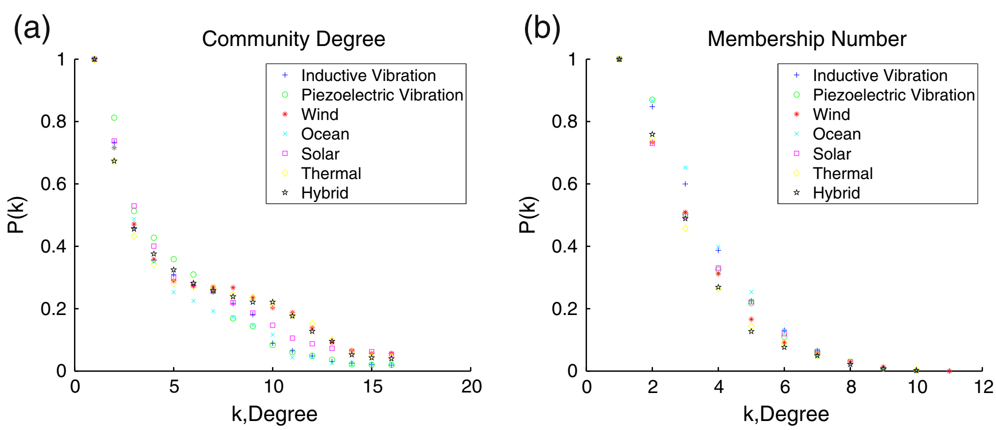

Fig. 6. Community degree and membership number for energy harvesting devices by technology.

5. Discussion

Studies estimating the rate of progress of energy generation technologies using experience curves have, of course, contributed much to thinking about policy decisions related to energy technology [24]. However, as some researchers are starting to identify, the theoretical mechanism underlying experience curves, which is learning by experience, weakly accounts for actual progress [9,48]. What remains largely missing is the study of the influence of knowledge underlying a product and its core technology on the learning rate. The knowledge structure of a product has important implications on how companies organize themselves to create the required knowledge. Put simply, the structure of knowledge has affordances, which lend themselves to certain organizational forms to enable learning-by-experience activities including knowledge production, transfer, integration, and absorption. Our methodology complements existing forecasting methods to estimate progress when companies (or industries) have scant historical data, and, thus, the use of experience curves is not practical, or when a technology is simply not mature enough to have any certainty in the factors appearing in calculations such as the Levelized Cost of Energy (LCOE).

From a management of technological innovation perspective, our methodology aims to answer the following question: the likelihood of progress under the assumption that investing resources into a technology would yield progress. This question could be asked in at least two circumstances. Companies may be given a choice of alternatives in which they can invest resources. They may wish to know into which product (and its associated technology) should investment be made because it is likely to progress faster and thus become commercially viable faster. In another circumstance, a company or a government may have already decided that it will invest in a range of products and must allocate a finite set of resources across them. This model provides guidance on differential potentials for progress, which suggests that some products, given their underlying technologies, may require more resources in order to make progress than another set of products employing alternative technologies. We do not make the recommendation that products that have less progress potential should receive no resourcing. Some products may have important social benefits, such as job creation or environmental protection, which our model ignores. The main contribution of our research is in explaining the differential progress potential inherent in real products so that differential investment can be made.

Our model is limited by several important assumptions. First, the model considers endogenous characteristics only. That is, we do not take into account any exogenous factors such as market size, industry structure, or a company's capability to deliver the technological improvements. Second, this model does not take into account whether the knowledge dependency exists within the company or outside of the company (or industry). In related research on innovation networks, which model relationships between companies, those companies and innovation networks that have strong and dense connections tend to perform better in terms of achieved innovation outcomes [49,50]. Our research could contribute to the research in innovation networks by revealing the necessary degree of interdependence due to the node degree, clustering, and degree of modularization of knowledge for the product they are designing. From the standpoint of managerial practice in innovation networks, our prescription for increasing or decreasing the modularity of the innovation network would be based on the degree of modularity of the knowledge, rather than the degree of modularity of the product architecture.

Finally, our model does not consider the underlying physics of the specific energy harvesting devices and the currently known physical ceilings. Piezoelectric energy harvesters are currently limited in application to small-scale devices that have modest power requirements rather than large-scale power generation, which is where wind, solar, and wave technologies are currently being deployed. In other words, they occupy different market niches for energy harvesting. However, the piezoelectric energy harvesters may prove to be the disruptive technology [51] since they are currently being used to address "non-consumption" in new consumer products for which battery technology is not practical, and, as the Innowattech product demonstrates, appear to have an upward pathway to utility-scale energy generation by harvesting vibrations from large-scale infrastructure such as roads and railways.

While this work has taken initial steps toward establishing the link between knowledge complexity and forecasting product progress potential, there is much more potential along this line of reasoning. First, the knowledge structure utilized in this paper is based upon a fairly limited standard ontology applicable to the description of electromechanical devices. We used a standard vocabulary to enable the description of a class of products in a uniform way. Other ontologies having a larger vocabulary may be applied without loss of generality of the approach. Additionally, other ontologies would be more appropriate for other technologies and domains such as microelectronics or biological systems. In order to obtain more technological forecast insight from this approach, it would be valuable to obtain historical data on successive generations of products to calculate the edit distance, that is, the amount of graph transformation between the knowledge structures of successive generations [52] as a way to relate the rate of progress to knowledge complexity.

Further, the three hypotheses we present can be looked upon as initial points of departure for reasoning more deeply about progress potential and innovation capacity using topological properties of networks. Our hypotheses are currently monotonic; for example, the first hypothesis says that progress potential increases as node degree and clustering coefficient decrease, and we have empirically verified this finding for the current sets of data. However, a deeper theoretical question for future enquiry is, "How low can you push the node degree or clustering coefficient so that you get the "fastest" or "most optimal" progress potential?" The boundary conditions are a (lowest) node degree and clustering coefficient of 0. However, this is physically meaningless in terms of products as well as knowledge structures. There can be no knowledge structure if there are no edges in the network. There has to be a physically meaningful answer to the question, "How low can we push the node degree or clustering coefficient?" Therefore, one interesting line of reasoning in future research would be to combine the hypotheses presented here with research on small-world networks. It is known, for example, that even in very sparse networks, the small-world properties of low average path distance in the network allow for efficient global information transfer [53]. Hypothesis 1 can be extended and tested further as follows: Progress potential *increases* as node degree and clustering coefficient decrease. However, progress potential *decreases* at the point when the knowledge structure ceases to be a small-world network. In other words, since the addition of each extra edge not only provides more flexibility in knowledge exchange but also has associated costs of structure formation and maintenance, the revised hypothesis claims that progress potential is optimal when there are 'just enough' edges in the knowledge structure to ensure efficient knowledge exchange. Therefore, the condition on small-world networks can provide a lower bound on the theoretical question of how low we should push the node degree and clustering coefficient yet still ensure progress potential. This is an example of how the hypotheses presented in this paper can provide the preliminary basis to question more deeply about the topological properties of knowledge structures of products and their influence on rates of progress.

We hope that the present analysis helps to provide new ways of thinking about how to forecast progress potential so as to invest an appropriate level of resources into ensuring that emerging technologies progress.

6. Conclusions

This paper presented a new approach to forecast the progress potential of a product and new hypotheses on the role of product knowledge structure complexity in progress potential. Whereas prior studies have sought to relate progress potential to product architecture complexity, this paper takes the approach that it is the structure and complexity of knowledge underlying the product that is relevant. Such a perspective is consonant with the intuition that the progress potential for products is difficult because there is a cost associated with advancing knowledge. While product architectures can be changed, thus reducing the degree of architectural complexity, knowledge structures may be less mutable. Knowing the structure of knowledge may give an indication as to the level of investment necessary to make advances.

The method we have outlined follows a five-step procedure: 1) select a set of products achieving a similar primary function; 2) produce a functional model for each product; 3) combine the functional models into a tensor, decompose the tensor with HOSVD, and identify the modular organization of the tensor; 4) calculate the node degree, clustering coefficient, community size, and membership number for each product at the various levels of hierarchical modular organization of the tensor; and 5) assess the progress potential based on these topological properties.

The paper provides key building blocks for characterizing progress potential based on concepts from complex network theory. The analysis of the knowledge structures at various levels of modular organization applies the characteristic of redundancy in complex networks to study the complexity of the knowledge structures. The extensibility of the approach to multi-dimensional representations of product knowledge makes it possible to explore the properties of knowledge for a product in a manner that takes into account the complementarity and dependency of knowledge.

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