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A Network-Based Approach to Identifying Key Components in Structural Vibrations

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ABSTRACT

Modeling the dynamics of systems with many interacting components, such as robots, wind turbines, and trusses, remains challenging today. These systems often display complex oscillatory responses to external inputs, and harmful vibrations might be excited along with the desired motion. Understanding the relative importance of individual components or systems aspects to the overall system dynamics could be a vital step towards focused design and maintenance efforts. This work proposes a network-based approach to studying the dynamics of a mechanical system by representing the system as a network of coupled oscillators, where each node corresponds to a machine component and each link denotes a physical connection, such as a weld or bolt. Inspired by studies of dynamics in biological and social networks, we show how network measures can be used to predict the importance of a single oscillator, or component, for shaping the overall dynamics. We further demonstrate under which conditions these conclusions are possible, and where the metrics fail. This study hopes to contribute to the broader field of network-based methods in engineering and yield insights that help focus design and maintenance efforts in the future.

1 | Introduction

The dynamics of large mechanical systems with many interacting components remain difficult to grasp. Aspects such as the large number of degrees of freedom and the complex interaction mechanisms between individual system components contribute to this issue. While elaborate and effective tools exist to study the behavior of a single component or a subset of components in detail, a complete model of a large system, such as a wind turbine or a truss, often remains elusive. The reason for this lies – at least in part – in the complex dynamics introduced by interaction mechanisms arising from joints, bolts and welds, which make it difficult to assess the role individual parts play in shaping the overall system dynamics.

The study of interactions between many agents, or components, is the aim of the relatively novel field of network science [1]. Network science studies systems in the form of nodes connected via edges in an interdisciplinary environment, with applications in the social sciences, biology, or medicine [2]. In the engineering context, network science has, for example, studied the emergent response patterns of power grids subjected to external excitation [3, 4]. Recent work has shown that the same network structure can exhibit very different dynamic behavior, depending on the interaction mechanisms and node internal dynamics [5, 6]. For example, in spreading a disturbance within a system, parts connected to many other components, so-called "hubs" can act as accelerators – like well-connected individuals that can quickly spread rumor on social media – or decelerators – like major crossroads are prone to traffic jams – depending on the system type [5, 6]. The authors in [5] develop an analytical framework to predict the importance of specific nodes, or components, for the overall dynamics based on the interaction and internal dynamic type, and illustrate their method with models from population dynamics, gene regulatory networks, and activation dynamics between brain regions. Other work shows that the stability of states in plant-pollinator networks depends on the strength of interactions and the number of connections of individual agents [7], also highlighting the importance of interaction mechanisms.

In this work, we translate our mechanical model system into a network formulation, where each node corresponds to a mechanical component, and each edge to a physical connection between nodes. This formulation facilitates the study of a mechanical system using methods derived from network science. Since the analytical methodology developed in [5, 6] is limited to a specific form of first-order systems, we aim at developing a similar framework for second-order systems in the context of mechanics. We study the importance of individual components within a system, based on topological and dynamical properties, and show how changes in system structure, interaction mechanisms, and excitation affect the component's importance. We thus hope to contribute a network perspective on mechanical systems that could help untangle the influences of structure, interaction mechanisms, and individual components' dynamics to focus design and maintenance efforts in the future.

The remainder of this work is structured as follows: Section 2 provides information on the model system, the network metrics, and the methods used to perform the analyses. The results are presented in Section 3, followed by a critical discussion in Section 4. The paper is rounded off by a conclusion in Section 5.

2 | Methods

This work studies a model system of many interacting mechanical components as a network with $N = 100$ nodes. Each network node is a linear oscillator representing a machine component, while edges between the nodes represent physical connections between the components, such as bolts or welds, modeled via spring–damper interactions. The equations of motion for the i-th oscillator in a system with linear nearest-neighbor coupling are commonly given as

$$m\ddot{x}_i + d\dot{x}_i - d_c(\dot{x}_{i-1} + \dot{x}_{i+1} - 2\dot{x}_i) + k_l x_i - k_c(x_{i-1} + x_{i+1} - 2x_i) = f_i(t), \quad (1)$$

where oscillator displacement, velocity and acceleration are given by x, $\dot{x}$ and $\ddot{x}$, respectively. The oscillator mass is defined as m, the damping coefficient as d, the linear spring as k_l, and coupling stiffness and damping as k_c and d_c. The forcing $f_i(t) = F_i \cos(\Omega t)$ is defined as harmonic forcing with amplitude F and angular frequency Ω. While the coupling terms are relatively short in a system with only nearest-neighbor coupling, the representation becomes less compact as the number of connections within the system increases. We thus switch to a network representation of the system.

In the network context, dynamical systems are more commonly represented in a form that distinguishes structure, interaction dynamics, and individual dynamics of the system, instead of the physics-related grouping into inertia, damping, and stiffness

TABLE 1 | Model parameters.

Measure	Symbol	Unit	Value
Mass	m	kg	1
Damping	d	Ns/m	0.01
Linear spring	k_l	N/m	1
Coupling spring	k_c	N/m	0.1
Coupling damping	d_c	Ns/m	[0, 0.01, 0.05]
Forcing amplitude	F	N	10
Forcing frequency	Ω	rad/s	[1.2, 2.0]
Coefficient	α	—	0.1
Graph structure	$\mathbf{A}$		[ER, BA]

Note: Overview of the model parameters used in this study, unless specified otherwise.

terms. Equation (1) can be reformulated into

$$\ddot{x}_i = (1-\alpha)g_0(x_i, \dot{x}_i) + \alpha \sum_j^N A_{ij} g_1(x_i, x_j, \dot{x}_i, \dot{x}_j) + f_i(t), \quad (2)$$

for one oscillator, or in this context, node, i. The node's internal dynamics are given by $g_0(x_i, \dot{x}_i) = -1/m(d\dot{x}_i + k_l x_i)$. The adjacency matrix $\mathbf{A}$ represents the system structure, A_{ij} is the entry in the i-th row and j-th column of the matrix. In an unweighted network, the matrix is binary, such that $A_{ij} = 1$ if two nodes are connected, and $A_{ij} = 0$ if two nodes are not connected. In the undirected case, each link from i to j also connects j to i, such that the matrix is symmetric. We consider an undirected, unweighted network here. Undirectedness is a reasonable assumption since each physical connection will affect both components that it connects, unless phenomena such as backlash are involved. Unweightedness represents the assumption of homogeneity throughout the system. Note that the adjacency matrix only contains information on which nodes, or components, are connected to whom, but gives no information on the interaction mechanism. The interaction mechanism $g_1(x_i, x_j, \dot{x}_i, \dot{x}_j) = k_c/m(x_i - x_j) + d_c/m(\dot{x}_i - \dot{x}_j)$ describes the type of dynamical interaction between two connected components i and j. The remaining formulations are the same as in Equation (1). A coefficient α can be used to steer the relative importance of a node's internal dynamics against the interaction. Table 1 provides an overview of the parameter values used throughout the work.

Figure 1 shows exemplary dynamics of an oscillator network with $N = 100$ nodes, coupling damping $d_c = 0$, forcing frequency $\Omega = 1.2$, and Erdős-Rényi structure. The remaining parameters are set according to the values in Table 1. The bottom image shows each node's dynamics for a period of $t = 100$ s with color coded amplitudes. The top panels depict the networks structure with node sizes representing the oscillation amplitudes, illustrating how the excitation of a single node spreads over the network. The top left corner shows one node in the system.

2.1 | Network Topology

The previous section introduces the model system and a possible network perspective on the mechanical dynamics. This section is

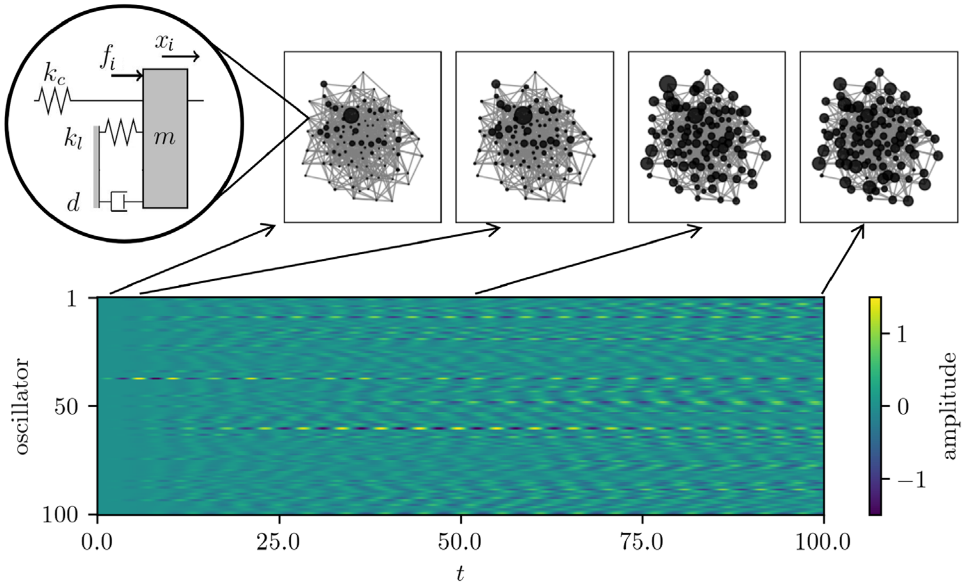

FIGURE 1 | Model system and exemplary dynamics. Dynamics of an Erdős–Rényi network with $N = 100$ nodes, depicted over a time span of $t = 100$s. A single node is excited with the frequency $\Omega = 1.2$ within the system's resonant regime. In this example, the coupling between nodes exhibits only spring-type dynamics with coupling damping $d_c = 0$.

dedicated to the possibilities for analysis this transformation yields. The definition of network metrics is taken from [2], unless specified otherwise. The topology of a network with N nodes and E edges is defined by its adjacency matrix $\mathbf{A} \in \mathbb{R}^{N\times N}$. As described in the previous section, the matrix is binary and symmetric for an unweighted, undirected network such as the one studied here. There are different ways of generating network structures, each specialized to produce a network with specific structural properties. These properties are described by a number of network metrics. This work focuses on node-centric measures. One important aspect of the network structure is its mean degree $z = 2E/N$, which describes how many connections each node has on average, and degree distribution p_δ, which measures the distribution of individual node degrees across the network. Two centrality measures, degree δ_i and betweenness c_i, can be interpreted as a measure of the structural importance of an individual node, or, correspondingly, of the respective mechanical component. The degree, or degree centrality δ_i, of an individual node i is given as

$$\delta_i = 1/(N-1)\sum_{i\neq j}^{N} A_{ij}, \tag{3}$$

counting all the edges connected to node i and normalizing by the maximum possible number of edges a node could have. In our setup, each node corresponds to a mechanical component, and each link models a physical connection between components. Therefore, a node i with high degree centrality c_i represents a mechanical component that has many direct connections to other parts, in other words, a component that is "central" to the structure. In contrast, a node with low degree centrality symbolizes an element with only a few direct physical connections to other parts, for example, a part at the edge of a structure. The betweenness centrality c_i counts the fraction of all pairs of shortest paths that pass through a node. A shortest path is the connection between two nodes that minimizes the number of other nodes traveled through. The betweenness centrality of node i is computed as

$$c_i = \sum_{j,k} \frac{\sigma(j,k,|i)}{\sigma(j,k)}, \tag{4}$$

where $\sigma(j,k)$ is the number of shortest paths (j,k) between nodes j and k and $\sigma(j,k,|i)$ is the number of those paths passing through node i [8]. Translated to the mechanical system, a shortest path from node j to node k corresponds to the route from component j to component k that passes through the smallest number of intermediate parts in between. An element with a high degree of centrality lies on many shortest paths. In other words, this part occupies a place that lies between many other components, though it is not necessarily directly connected to a large number of nodes. In the model used throughout this work, forcing is applied to a single node. The distance l_i of a node from the forced node k is computed as the shortest path length from node i to node k. In our setting, the forced node represents a forced or perturbed mechanical component. The distance from the forced node describes how removed a given component is from the perturbation.

We consider two types of networks: An Erdős-Rényi (ER) graph [9], which is a random graph characterized by a Poisson degree distribution

$$p_{\delta,\mathrm{ER}} = \frac{z^\delta e^{-z}}{\delta!}, \tag{5}$$

where z is the networks mean degree and δ the individual node degree, as before. Erdős–Rényi graphs are generated by successively adding nodes to a network and adding each of the possible new edges with probability $p = 0.1$. A Barabási–Albert (BA) graph [10] is another form of random graph grown by preferential attachment, specifically, a new node is more likely to connect to a node that already has a high degree. Each additional node has $q = 5$ edges. The BA graph exhibits power-law degree distribution in the form of

$$p_{\delta,\mathrm{BA}} \sim \delta^{-3}, \tag{6}$$

resulting in a so-called scale-free model.

The metrics and characteristics presented in this subsection are useful for the topological analysis of a network. Centrality measures can define the "structural" importance of nodes within the structure. It has to be noted that this description neglects the physical layout of a network in space. The next subsection describes the procedure when dynamics are added to the network structure.

2.2 | Dynamics on Networks

Following the static analysis with topological network metrics in Section 2.1, this section expands the view to the dynamics on networks. This approach considers the full model system of Equation (2) beyond the network structure encoded in the adjacency matrix $\mathbf{A}$. Generally, the link structure of the network is assumed to be fixed, or changes in the structure occur on a time scale much slower than the relevant dynamics [11]. In contrast, adaptive network models or dynamics of network models describe systems where both structural changes and dynamics occur at similar time scales, such as in infection networks, where links break as healthy individuals avoid contact with infected individuals. In other words, the model assumes a fixed mechanical structure, where connections between the physical components do not vary at a time scale close to the one of the dynamics.

Prior work on the interplay of interaction mechanisms, internal dynamics, and network topology has developed an approach to analytically predicting the role of hubs in specific first-order systems [5]. By iteratively freezing nodes to determine their contribution to the overall dynamics, the authors track to flow of a disturbance through a network and show that there are different classes of dynamical networks. Further work in [6] expands the framework to propagation times.

Here, we compute the importance of an individual node for the dynamics by measuring the impact its removal has on the overall system dynamics. The procedure is illustrated in Figure 2: First, the dynamic response of the entire network to the excitation of a single node is obtained numerically. Then, an individual node i is removed from the network, and the dynamics are re-computed through numerical simulation. Initial conditions, forcing, and all other factors are kept constant. The dynamics before and after the removal of the i-th node are compared. The difference between the time series is computed as the surface similarity parameter (SSP) [12, 13], defined as

$$SSP(\mathbf{x}_j, \hat{\mathbf{x}}_j) = \frac{\sqrt{\int |F_{\mathbf{x}_j}(k) - F_{\hat{\mathbf{x}}_j}(k)|^2 dk}}{\sqrt{\int |F_{\mathbf{x}_j}(k)|^2 dk} + \sqrt{\int |F_{\hat{\mathbf{x}}_j}(k)|^2 dk}}, \tag{7}$$

where the Fourier transform $F_{\mathbf{x}_j}$ of the time series $\mathbf{x}_j$ is used along with the wave number k to measure the similarity of two signals in Fourier space [13]. This error metric has been proposed as an L^2 norm-based error metric that uniformly penalizes errors in amplitude, frequency, and phase within a single metric [13]. The code is available at [14]. The SSP for the dynamics of all remaining nodes is reduced to a mean and standard deviation, capturing the overall change in the entire system dynamics introduced by the node removal. The error is plotted against the node's centrality properties, namely degree centrality c_i and betweenness centrality δ_i, to reveal the connection between a node's structural importance and the impact of its removal on the dynamics. The procedure is repeated for each node to yield a picture of the effect of each node removal. In a mechanical system, this process corresponds to removing a mechanical component along with all its connections to its neighboring parts and measuring the effect of the elimination on the overall structural dynamics. The error introduced by the removal of a component is then related to its structural properties. The intuition might be that removing a more central part, for example, a part that shares physical connections with many other components, induces a higher error into the system. As studies from other fields illustrate that this assumption is not always correct (see Section 1), the idea behind this work is to analyze whether and under which conditions this intuition is correct. The following section presents the results for different setups.

3 | Results

Following the procedure described in Figure 2, this work aims to relate structural properties of nodes or mechanical components to their importance for the overall system dynamics. A network of oscillators is perturbed by exciting a single node, equivalent to forcing a single mechanical component. By iteratively removing the remaining nodes individually from the structure, the importance of that part in shaping the overall dynamics can be quantified. This section first introduces the impact of node removal for a baseline system with random structure, specific forcing frequency, and a purely spring-type interaction mechanism between the components. For this baseline system, the relation between structural properties and impact of node elimination is shown in Figure 3. A more detailed illustration of the interrelations between the different structural properties of a node and the error its removal induces to the overall dynamics is given in Figure 4. After these initial studies, we examine how the relationship between a component's structural properties and its significance for the system dynamics changes as we vary the forcing frequency, network structure, and interaction mechanisms of the model. Figure 5 depicts these results.

Figure 3 shows the results for the baseline system with ER topology, forcing frequency $\Omega = 2.0$, and no damping in the interaction mechanism. The left panel shows the network structure, with node sizes representing the oscillation amplitudes for exemplary dynamics and colors corresponding to the error metrics in the remaining panels. The mean and standard deviation of the SSP error introduced to the dynamics of all nodes by the removal of an individual node are plotted against several topological metrics, namely degree centrality δ_i, betweenness centrality c_i, and proximity to the forced node l_i. For both centrality measures,

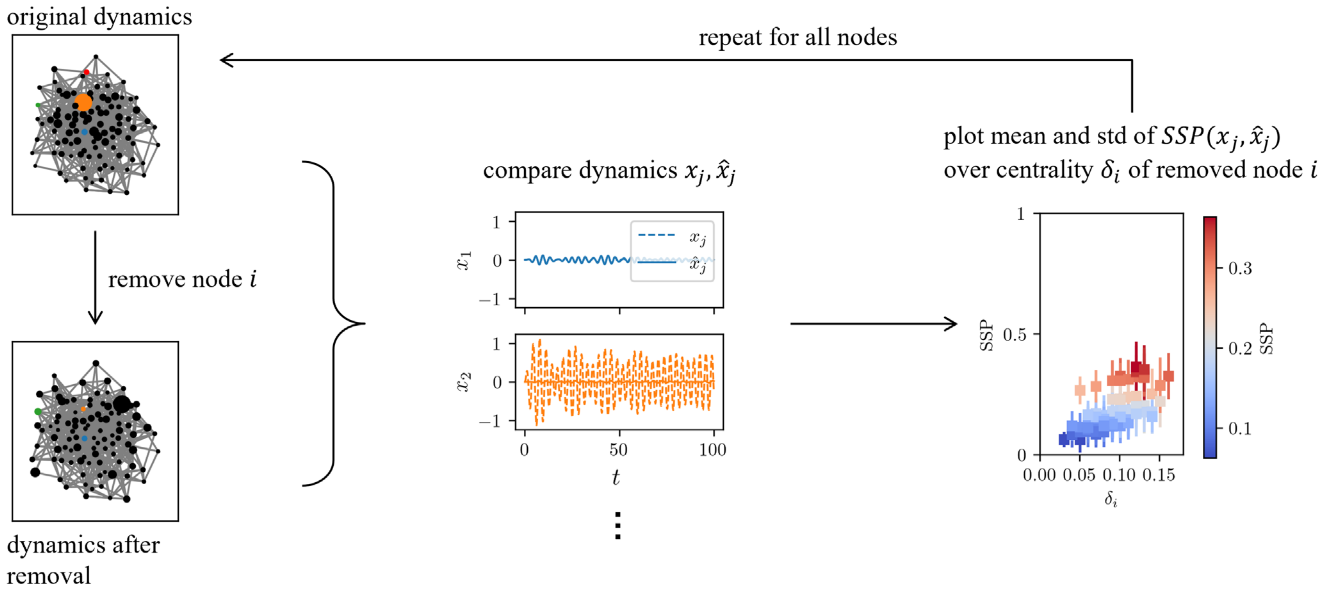

FIGURE 2 | Method and graphical abstract. The dynamics of all remaining nodes before (x_j) and after ($\hat{x}_j$) the removal of node i (in red) are compared using the SSP metric. Every node j is affected differently: In the example, the dynamics x_1 of node 1 (in blue) barely differs before and after removal, but a large effect can be seen in the dynamics x_2 of node 2 (in orange). The mean and standard deviation of the SSP across all remaining nodes are plotted over the centrality measure of the removed node i, here the degree centrality δ_i. The procedure is repeated for all nodes except the excited one. In the right sub-figure, each box corresponds to the change in system dynamics induced by the removal of a single node. The colors in this sub-figure correspond to the value of the SSP as indicated by the color bar.

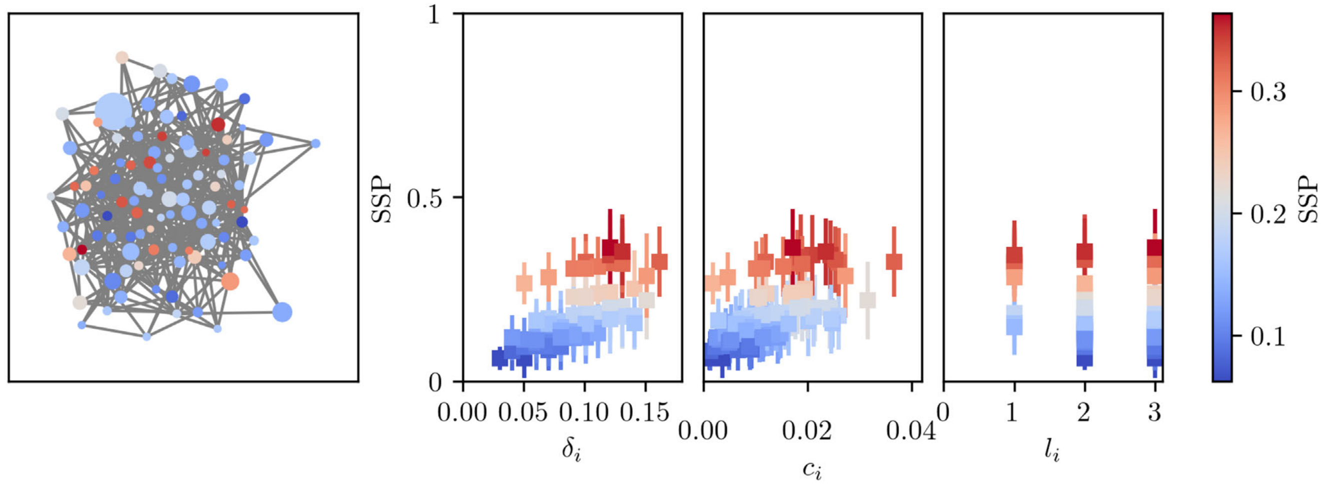

FIGURE 3 | Importance of a single component for the overall system dynamics, measured by the error its removal introduces into the system. Left panel: The network structure of an ER network for comparison. Node sizes represent oscillation amplitudes in one exemplary setting where node 7 has been removed, colors correspond to the SSP error induced by a nodes removal, given by the color bar on the right-hand side. Remaining panels: Error metric SSP over node degree δ_i, betweenness centrality c_i, and distance from the forced node l_i. Each data point stands for the removal of one node, the box, and the whiskers, indicating the mean and standard deviation of the error introduced to the dynamics of all remaining nodes. Color corresponds to the SSP values, allowing for connection to the network on the left. The model system is the baseline system with ER topology, coupling damping d_c=0, and forcing frequency $\Omega = 2.0$.

there is a trend of the error growing as the centrality of the removed node increases, indicating that more central nodes are more important in shaping the system dynamics. The subplot on the right presents the SSP for different distances from the forced node, providing a less clear picture. In relation to a mechanical structure, these results can be interpreted to indicate that, for the given structure, forcing and purely spring-type interaction mechanism, the centrality of a component is related to its role in shaping the system dynamics. In other words, a part that is either connected to many other parts or lies on the shortest connection between many elements, contributes more significantly to the system dynamics than a part with fewer connections. The proximity of a component to the forced part does not seem to play an important role.

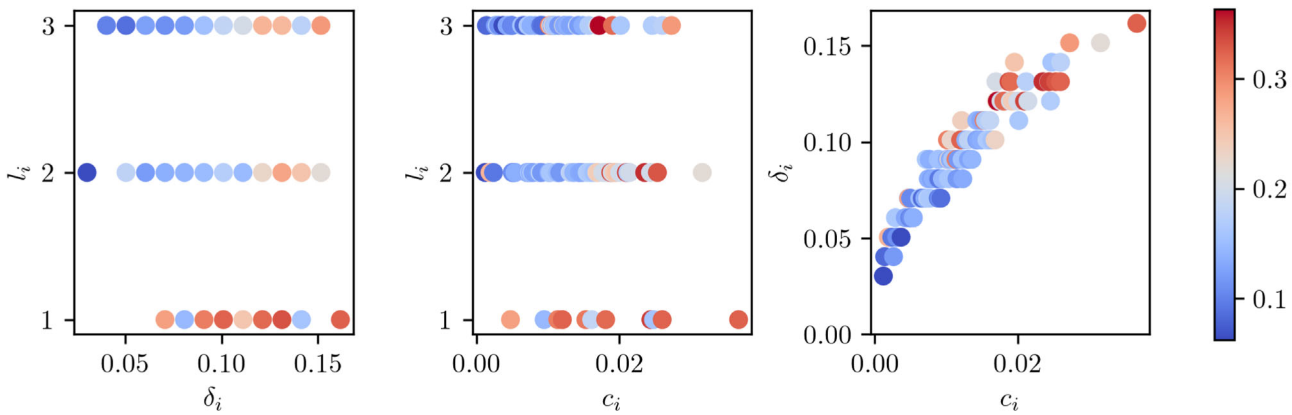

FIGURE 4 | Interrelation between node metrics and node importance. The panels show the same results as Figure 3, but error metrics are shown over a combination of two metrics. Left panel: distance from forcing l_i vs. degree δ_i, middle panel: distance from forcing l_i vs. betweenness centrality c_i, and right panel: degree δ_i vs. betweenness c_i. In many cases, several data points exist for a given combination of metrics; hence, average mean values are shown. Colors correspond to those in Figure 3.

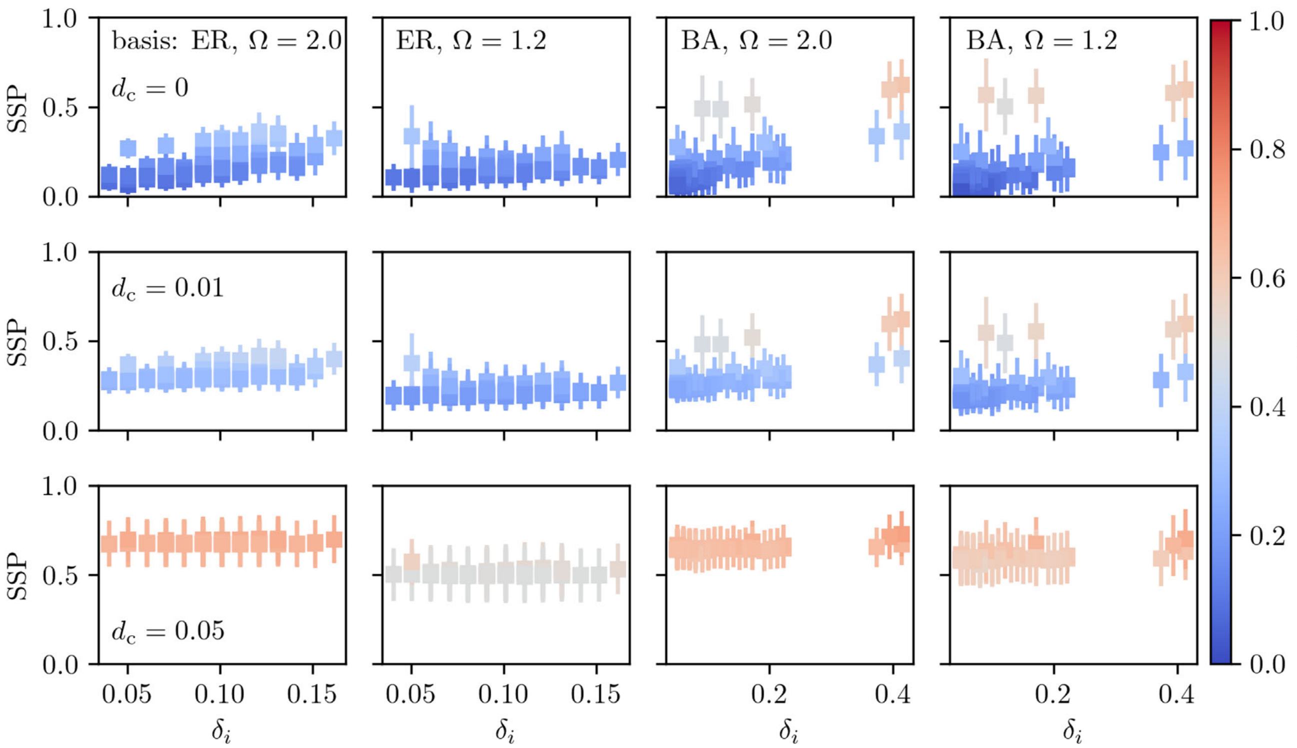

FIGURE 5 | Variation in node importance as system parameters change, represented as SSP over node degree δ_i. Upper left corner: The basis system with Er topology, excitation frequency $\Omega = 2$, and no damping in the interaction mechanism. The second row from the left changes the excitation frequency to the resonant regime around $\Omega = 1.2$ while keeping the ER topology. The two right-hand side columns show the same results for BA topology. The node degree δ_i shows a broader range compared to the ER network, with only a small number of nodes with high degrees. The rows contain the results for different levels of damping in the interaction mechanism: The top row has no damping $d_c = 0$, in the middle row, small damping $d_c = 0.01$ is introduced and increased to $d_c = 0.05$ in the bottom row. Colors correspond to the SSP metrics in [0,1], see the color bar on the right.

The results in Figure 3 present error measures for an individual network metric, aiming to infer node importance as a function of a single metric. However, it is also conceivable that a combination of metrics could provide a clearer image. Figure 4 thus displays the SSP error measure over the combinations of two metrics, distance from forcing l_i versus degree δ_i on the left, distance from forcing l_i versus betweenness centrality c_i in the middle, and degree δ_i versus betweenness c_i on the right. The data is the same as in Figure 3. As data points overlap for some metrics (e.g., there are several nodes with distance from forcing $l_i = 2$ and degree centrality $c_i = 0.1$, average mean SSPs are shown in these cases. The color code corresponds to the values of Figure 3 and the color bar. Results indicate that nodes closer to the forced node and with higher centrality, as well as nodes with high scores on both centrality measures, are more important for shaping the system dynamics.

Results so far indicate that in the given baseline system, structurally important nodes, in other words, nodes with high centrality, also have a higher importance in the dynamical system. Prior work on biological and social networks has shown that there are three classes of dynamical networks, where central nodes, so-called "hubs" play different roles [5, 6]. In some cases, these "hubs" may act as accelerators, decelerators, or be of no special importance, depending of the interaction mechanism and internal dynamics. It appears that the system considered in Figure 3 could be placed in a category where hubs, or nodes with high centrality, tend to be more important. In the following, we will study whether similar phenomena can be observed in the mechanical dynamics context. To that end, different aspects – namely the topology, excitation, and interaction mechanisms – of the baseline model are modified. Following the same iterative procedure as before, the SSP is computed for the removal of each individual node and plotted against the degree centrality δ_i. Figure 5 shows the SSP over degree centrality δ_i baseline system with ER structure, excitation frequency $\Omega = 2.0$, and an undamped interaction in the top left panel. The top row presents the results for the undamped interaction with different excitation frequency $\Omega = 1.2$ in the second column, and different structure BA in the two right columns. The change in structure is also visible in the degree centrality δ_i on the x-axis, where the BA network has a much broader range with only a few high-degree nodes. The BA degree distribution would correspond to only a few mechanical components sharing many physical connections with the other parts, while most parts have only a few connections. The change in topology does not seem to affect the overall trend of more central nodes being more important: As in the ER structure, where the components share a more similar connectivity, parts with many connections play a larger role in the overall system dynamics. However, the BA network seems to come with two different layers of nodes, a bottom layer with lower SSP and a top layer with higher SSP, but both layers seem to follow the overall trend. For both ER and BA topology, the change in excitation frequency does not appear to change the results much. The middle row introduces a small amount of damping $d_c = 0.01$, to the interaction mechanism, which is increased to $d_c = 0.05$ in the bottom row. This addition corresponds to damping phenomena which often play a signification role in joints. The change in the interaction mechanism has a significant effect on the observed error. First, the overall error level increases for all system variations, and second, the relative difference in node importance disappears. In the systems with the more strongly damped interactions, the removal of each node seems to introduce a very similar error, indicating that all nodes share the same relative importance. Translated to the mechanical context, this observation implies that a small amount of damping the connections between the components significantly changes the way individual nodes contribute to the overall dynamics. While central components with many connections are more important in the case of undamped interactions, the importance of nodes with different levels of connectivity equalizes as damping becomes more significant in the joints.

These results indicate that not only the topological properties of a node or component, such as its centrality, determine the importance of a node for forming the dynamics of a system, but the interaction dynamics play a crucial role in shaping the relative importance. It seems like this observation holds for different harmonic excitations as well as different network topologies.

4 | Discussion

Though the methods have been adapted from the ones used in [5, 6] to fit the mechanical context, some parallels of the results presented in Section 3 to those presented in [5, 6] can be observed. First, it is clear that the same network topology can exhibit qualitatively different dynamics depending on the interaction mechanism. Second, it seems that the linear oscillator dynamics with spring-only coupling can be classified into a family of systems where hubs are more important than less connected nodes, independent of the exact network structure. Third, as a sufficient amount of damping is introduced into the interaction mechanism, all nodes appear to be equally important, indicating that a second family with homogeneous importance exists. In this study, we did not observe a phenomenon related to the third group described in [5, 6], where hubs are less important than other nodes.

So far, these findings are limited to homogeneous systems and numerical studies. Developing a fully analytical framework for the interplay of topology and dynamics in general second-order systems and expanding the analysis to heterogeneous systems could be an interesting path for further research. We would also like to expand our model with more complex interaction mechanisms that resemble real-world physical connections, such as bolts, welds, or screws, more closely.

5 | Conclusion

In this work, we have modeled a mechanical structure as a network of coupled oscillators and used network-based methods to study the significance of individual components for the overall system dynamics. Results show that the dynamics arise from an intricate interplay of structure, interaction mechanisms, and internal dynamics, and that the topology or structural properties alone do not yield sufficient information to assess the role of a component. From these results, we infer that the interaction mechanism represents a very important factor in guiding the nodal importance, influencing the relative importance of nodes of nodes depending on their centrality significantly. Without damping in the interaction, more central nodes, that is, more strongly connected machine parts, appear more important; thus, design efforts could be focused on those specific components. As damping is added to the interaction mechanism, the importance becomes more homogeneous, guiding focus away from the central parts. In the future, it might be possible to leverage these findings for practical application, for example, in guiding design efforts. If a system is found to be of the first type, but central components cannot be changed for other functional reasons, it might be possible to add a more damped interaction, which will decrease the importance of that central component, such that changes to other, less constrained components, become effective. On the other hand, if only specific central part of a system of the second type can be changed, adding stiffer connections could help increase the importance of that specific part. With this study, we hope to illustrate a possible application of network-based methods for the analysis of large, multi-component systems, aiming to integrate these methodologies into the design and maintenance of mechanical structures

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