On the Influence of Structural Attributes for Assessing Similarity in Population-Based Structural Health Monitoring

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ABSTRACT

The viability of many machine learning methods within Structural Health Monitoring (SHM) is often limited by the lack, or the incompleteness, of the data required for implementing these algorithms. Indeed, learning a data-based SHM predictive model usually requires the dynamic response availability for undamaged and damaged states, and the assumption that both training and test data refer to the same domain. In this framework, the population-based approach to Structural Health Monitoring (PBSHM) aims at improving the performance and the robustness of diagnostic inferences, exploiting the transfer of damage-state knowledge across a population of structures. However, sharing these data produces a meaningful inference only if the structures, and their datasets, are sufficiently similar. Therefore, an initial phase of similarity assessment becomes essential before being able to apply transfer learning algorithms. This phase shows which structures are suitable for knowledge sharing, if any, reducing the possibility of negative transfer. Some distance metrics have been proposed, exploiting abstract representations of structures, such as Irreducible Element (IE) models and Attributed Graphs (AGs). Although these metrics can consider the structure attributes, many performed comparisons mainly concern structural topology. This study aims at broadening the application of similarity assessment, focussing on the geometrical and material differences in the distance metrics. Therefore, a heterogeneous population of laboratory-scale aircraft is analysed. These structures predominantly follow the geometry of a benchmark study conducted by the Structures and Materials Action Group (SM-AG19) of the Group for Aeronautical Research Technology in EURope (GARTEUR). The IE models of these aircraft are produced. Subsequently, Graph Matching Network (GMNs) are used to determine the similarity matrix. The structures in the Garteur population are topologically homogeneous, which enables a more accurate investigation of how attributes can influence distance metrics. This paper constitutes the first step in the Garteur structures population investigation.

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The similarity assessment results will establish which population members are most suitable for applying transfer learning algorithms. It will enable the subsequent development, and experimental validation, of a population-based strategy for damage identification across heterogeneous structures.

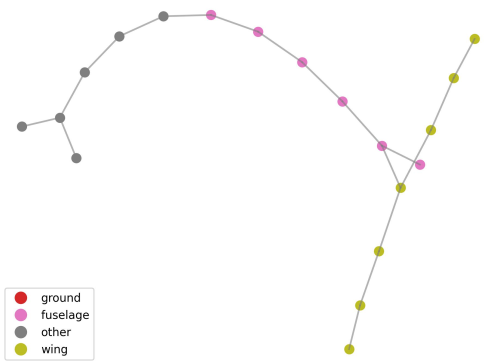
INTRODUCTION

In the context of Structural Health Monitoring (SHM), the limited availability and incomplete nature of experimental measurements, challenge the application of many of the data-based SHM methodologies proposed recently. Thus, the theory of population-based Structural Health Monitoring (PBSHM) has been proposed to address this issue [1–3], by sharing knowledge within a population of structures to improve diagnostic inferences on a target structure for which experimental data may be insufficient. The population can be classified as homogeneous or heterogeneous, based on the similarity between the structures. Homogeneous populations allow for minor differences, such as in construction specifications, whereas heterogeneous populations may comprise many different systems. However, it is crucial to establish structural similarity to determine when information can be shared and prevent "negative transfer", particularly in heterogeneous populations.

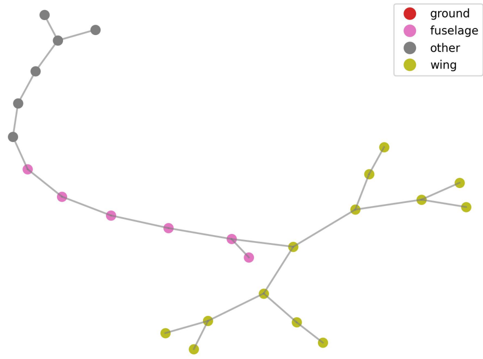
To measure similarity, structures can be represented abstractly in the form of Irreducible Element (IE) models, and Attributed Graphs (AGs) [2]. These models consist of a simple yet representative topological description of the main components of a structure, i.e., elements having a well-established dynamic behaviour, and can be compared via distance metrics. It is possible to associate attributes with each element of the model, which encompass characteristics such as element type, geometry, materials and dimensions. Moreover, elements are connected by relationships, and each of these relationships can have an attribute vector to record their properties.

IE models can be compared using graph-matching algorithms which allow for a quantitative evaluation of their similarities. One commonly-used approach, described in [2], involves computing the maximum common subgraph (MCS) between two structures. This subgraph is defined as the largest subset of nodes and edges that are common to both structures, and its size relative to the overall size of the graphs can be used as a measure of their similarity. However, this method could be improved with the implementation of a canonical form of IE models, which has recently been introduced in [4]. Furthermore, the similarity metrics should be capable of taking into account multiple attributes for each node and edge of the graph. The system should be able to manage various types of attributes, including discrete and continuous ones, and must be adaptable to the heterogeneous structures found in the database.

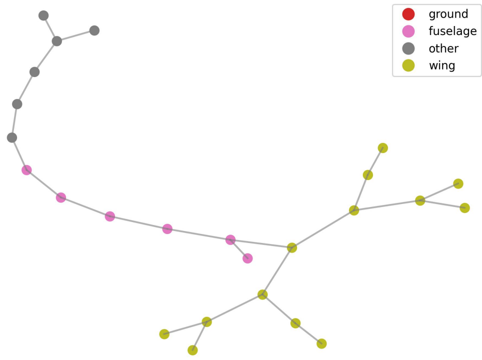
The current study aims to investigate a distance metric based on Graph Matching Networks (GMN) [5], to assess the degree of similarity in a population of laboratory-scale aircraft models. Although these aircraft models have minor topological differences, they are still heterogeneous because of their diverse attributes. This characteristic makes it possible to focus on the influence of the attributes on the GMN-based similarity metrics. The following sections describe the GMN method and introduce the case study of the Garteur aircraft. The results will be presented for different cases, to demonstrate how



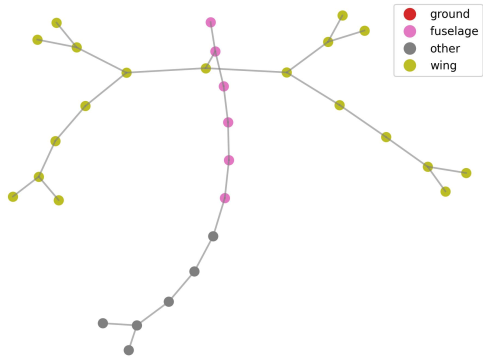
(a) *No-winglets configuration.*



(b) *End-winglets configuration.*



(c) *Middle-winglets/engines configuration.*



(d) *Both-winglets/engines configuration.*

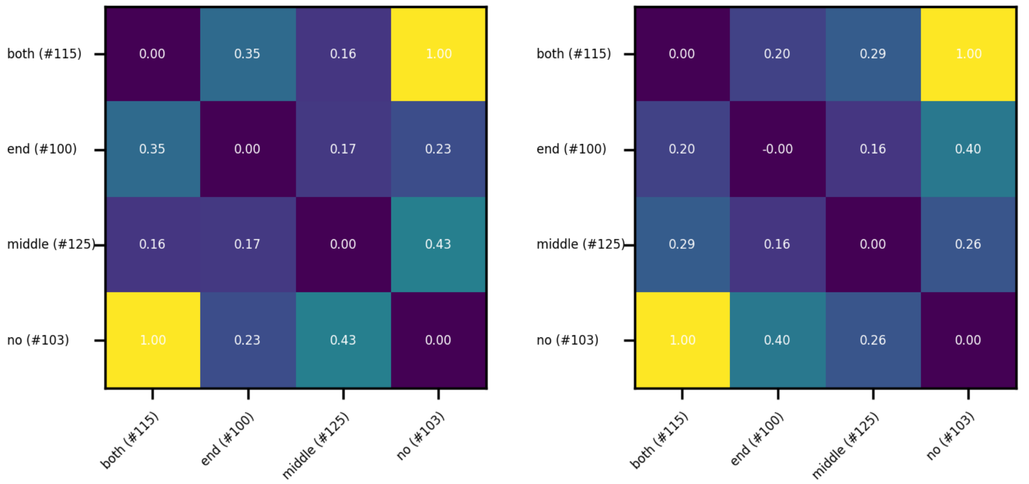
Figure 1. The Garteur IE models in the four topological configurations. No winglets present on the wings, winglets in the middle of the wings to simulate the presence of an engine, winglets at the end of the wings, and winglets in both the middle and end positions.

varying the considered attributes affects the similarity measures between the models.

METHODS

Structural similarity can be assessed using different strategies, according to which structures are being compared, and which parameters are most relevant for the specific case studies. Besides the use of the MCS-based method and the Jaccard index [2], further research focusses on GNNs [4], and Kernel-based methods [6]. This paper expands on the use of Graph Matching Networks.

GMNs have been proposed as an extension to GNNs, for similarity assessment [5]. By leveraging a cross-graph attention mechanism to match nodes across different graphs and identify their differences, GMNs allow computing a similarity score with increased accuracy as a result of node and edge attribute embedding. Graph Matching Networks



(a) *Topology-only assessment.*

(b) *Introduction of element and relationship types, and contextual attributes.*

Figure 2. Distance matrix of the aircraft population based on the four topology classes.

(GMNs) have been introduced to measure the similarity of IE models of bridges in the PBSHM database [4]. While the primary focus is on graph topology, GMNs enable including numerical and categorical attributes as vectors for each node and edge. Therefore, after assessing the ability of GMNs for topological comparisons, element and relationship types have been integrated into a bridge case study in [7].

In this study, the use of GMNs is extended to a population of laboratory-scale aircraft, which are represented by IE models. These models are developed from the benchmark study conducted by the Structures and Materials Action Group (SM-AG19) of the Group for Aeronautical Research Technology in EURope (GARTEUR) [8]. Hence, variations in geometries, materials and dimensions are introduced to create a comprehensive experimental dataset, including the structures analysed in [9]. These variations result in a heterogeneous population, although with limited topological differences, from the presence of winglets, or engines, in four possible configurations (examples of the corresponding IE models are shown in Fig 1).

The construction of the Garteur IE model is described in [10], where its topology is compared with a broad population, including bridges and aircraft. However, to train the network for the similarity assessment task, it is necessary to provide a large dataset, consisting of pairs of graphs (G_1, G_2) with an associated label $t \in \{-1, 1\}$, where $t = 1$ when G_1 and G_2 are similar and $t = -1$ when G_1 and G_2 are dissimilar.

A synthetic dataset of Garteur aircraft has therefore been generated, comprising 5000 IE models. These are distinguished into twenty similarity classes, depending on four topological configurations and five scaling groups. In addition, the attributes of materials, geometry, and element dimensions are randomly defined for each class. Initially, the GMN is applied using just the four different winglet topologies for classifying similar and dissimilar models. Afterwards, this is expanded to include the scaling groups as features to be examined for determining the degree of similarity.

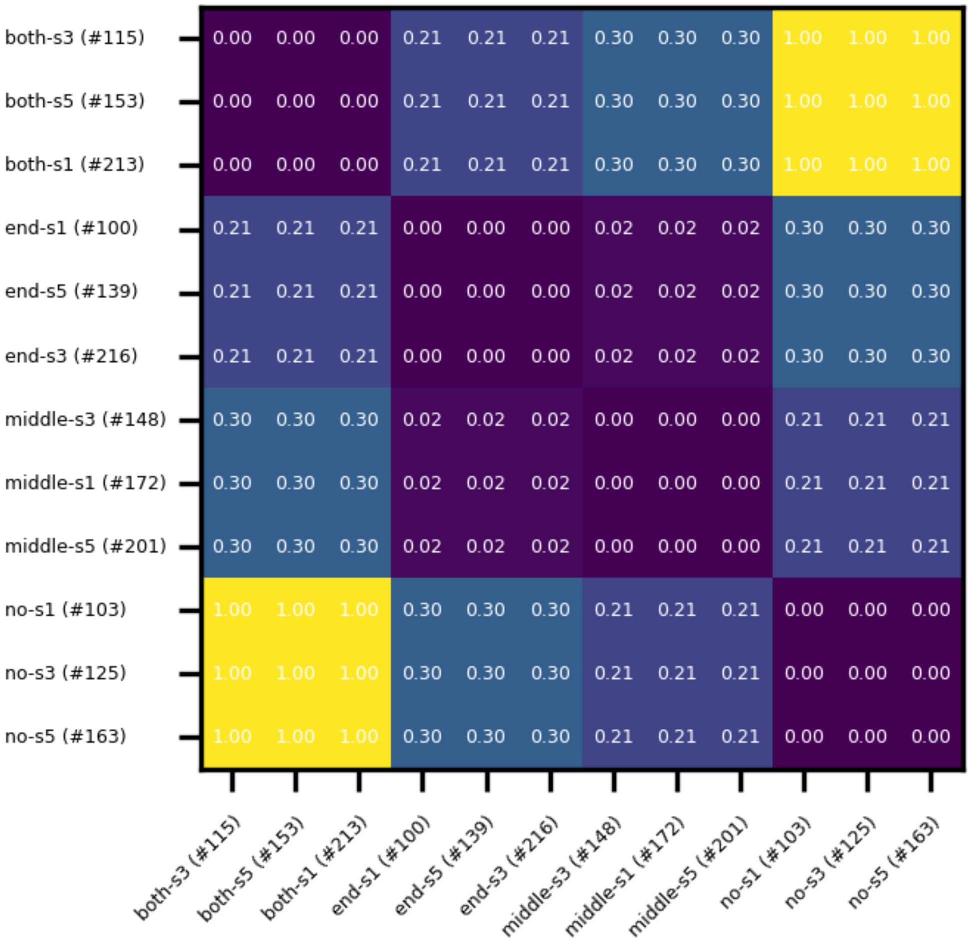


Figure 3. Distance matrix of the aircraft population based on the four topology classes, embedding element and relationship types, element contextual, material and geometry attributes. This is a subset of the results and the full result can be seen in Appendix (a).

RESULTS

The GMN is trained using pairs of Garteur IE models from the dataset, which is split into training, validation and test sets. For analysing the effects of attributes, multiple hypotheses on the classification rule and different combinations of attributes are included in the network. The first similarity assessment rule only concerns topology-based classes (no winglets, end winglets, middle winglets or engines and both winglets and engines). Aircraft of the same class are labelled as similar, otherwise they are labelled as dissimilar. Fig 2a shows the results of the comparison if no attributes are embedded in the network. The results are expressed in terms of graph distance, normalised between 0 and 1. It

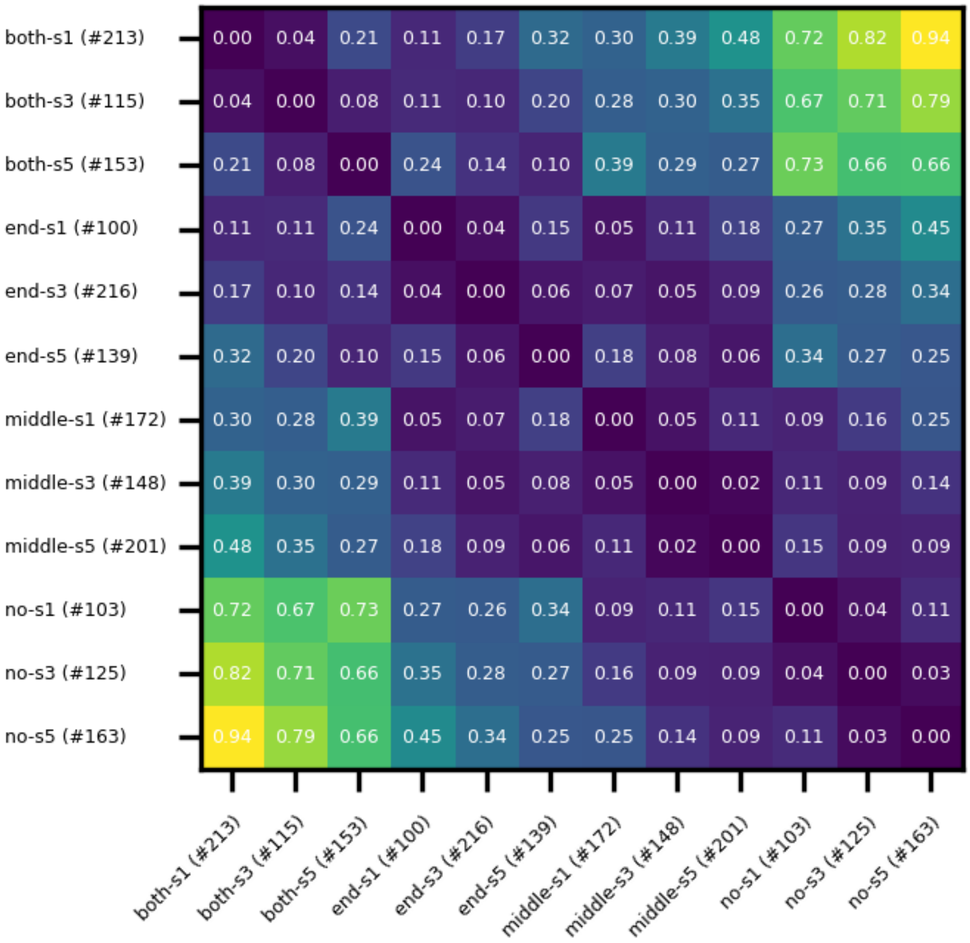


Figure 4. Distance matrix of the aircraft population based on the twenty classes (topology and scaling group), embedding element and relationship types, element contextual, material and geometry attributes. This is a subset of the results and the full result can be seen in Appendix (b).

can be noted how the GMN is able to distinguish the various classes, giving maximum distance values between no-winglets graphs and graphs with both winglets and engines. However, for improved performance, it is necessary to introduce some attributes. Fig 2b shows how, by embedding the attributes of element and relationship types, and especially the contextual attributes, the middle-winglets/engines class can be better distinguished from the others.

In addition, the study focusses on the effect of the dimensions of the test structures. Along with materials and geometry, the dimensions play a significant role in vibration-based features that can be extracted experimentally and used in knowledge transfer. Thus, it is intended to study how to embed these attributes in the graphs and how to integrate them into the similarity rule used in the GMN training. In the third case analysed, material types, geometry types and contextual labels are introduced as categorical attributes for each graph node, according to the possibilities established by the PBSHM schema. Regarding dimensions, the normalised element length is introduced into the attribute array for each node. The effects of these attributes in the topology-based similarity evaluation are shown in Fig 3. It is noticeable that the attributes result in an increased distance between the two middle configurations and the end-winglets and both-winglets configurations. Furthermore, attributes cause a slight variation in the distance values within each cluster. However, to observe the dimensions influence, it is necessary to introduce them in the classification rule used to label the graph pairs. The dataset is divided into five clusters according to the scaling factor of the IE model compared to the original one. Therefore, by classifying the graphs as similar if they exhibit the same topology and scaling group, the distances shown in Fig 4 are obtained. The clustering of topological classes is less distinct because of the simultaneous effect of the scaling ratios. Hence, distance values are closer between the various topological classes. However, the matrix shows increasing distance values with the change in topology from the both-winglets configuration to the no-winglets one. Furthermore, for each combination of topology classes, an increasing distance is observed as the scaling factor between the IE models increases.

CONCLUSIONS

In conclusion, this study investigates the use of Graph Matching Networks (GMN) for examining the impact of graph attributes on similarity assessment. Specifically, the analysis is conducted on the population of Garteur aircraft, where the main differences concern element attributes. The findings demonstrate that incorporating attributes, such as element and relationship types, and contextual labels, significantly improves the GMN ability to distinguish between various topological classes. Moreover, the study explores the effect of dimensions on the similarity metric's performance. To assess this effect, further partitioning of the dataset based on the scale factor is necessary. These results suggest that incorporating attributes in the GMN and considering them in the classification rule could enhance similarity evaluation accuracy and facilitate knowledge transfer in the PBSHM system. Further research is required on how to incorporate additional structural attributes such as material mechanical properties, and how to define their role in the definition of similarity within the GMN, according to the case study of interest.

ACKNOWLEDGMENT

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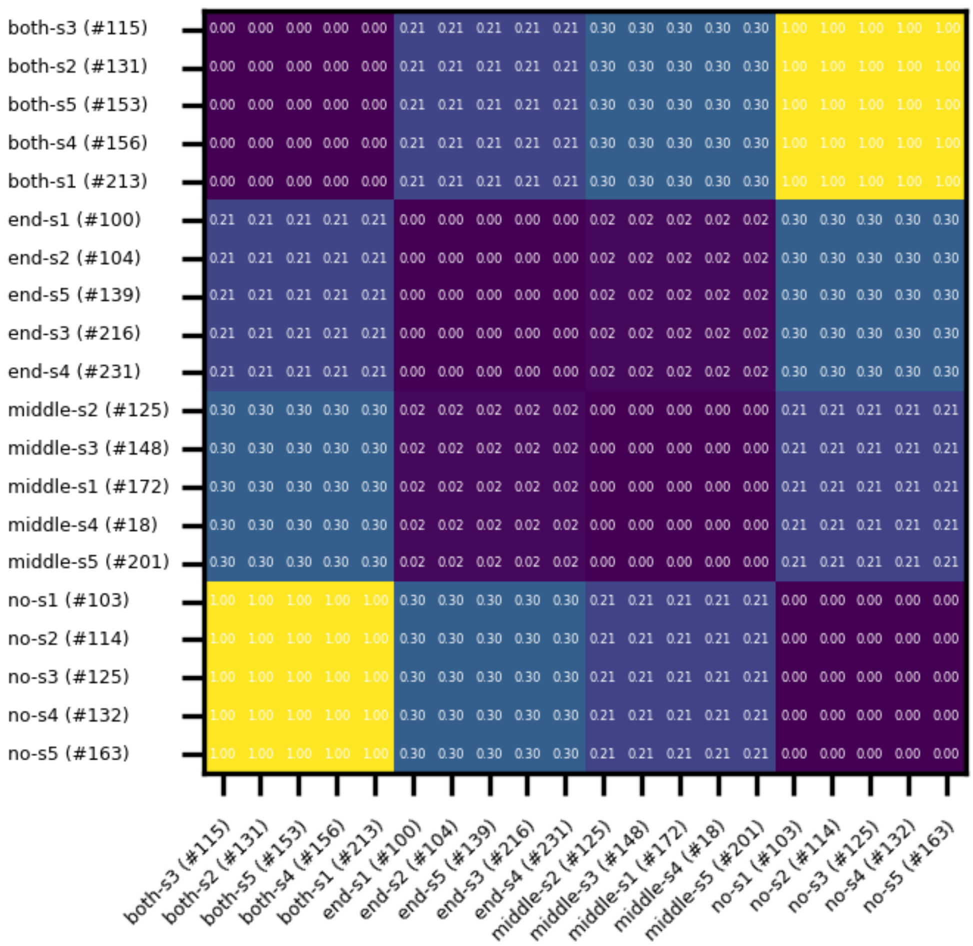
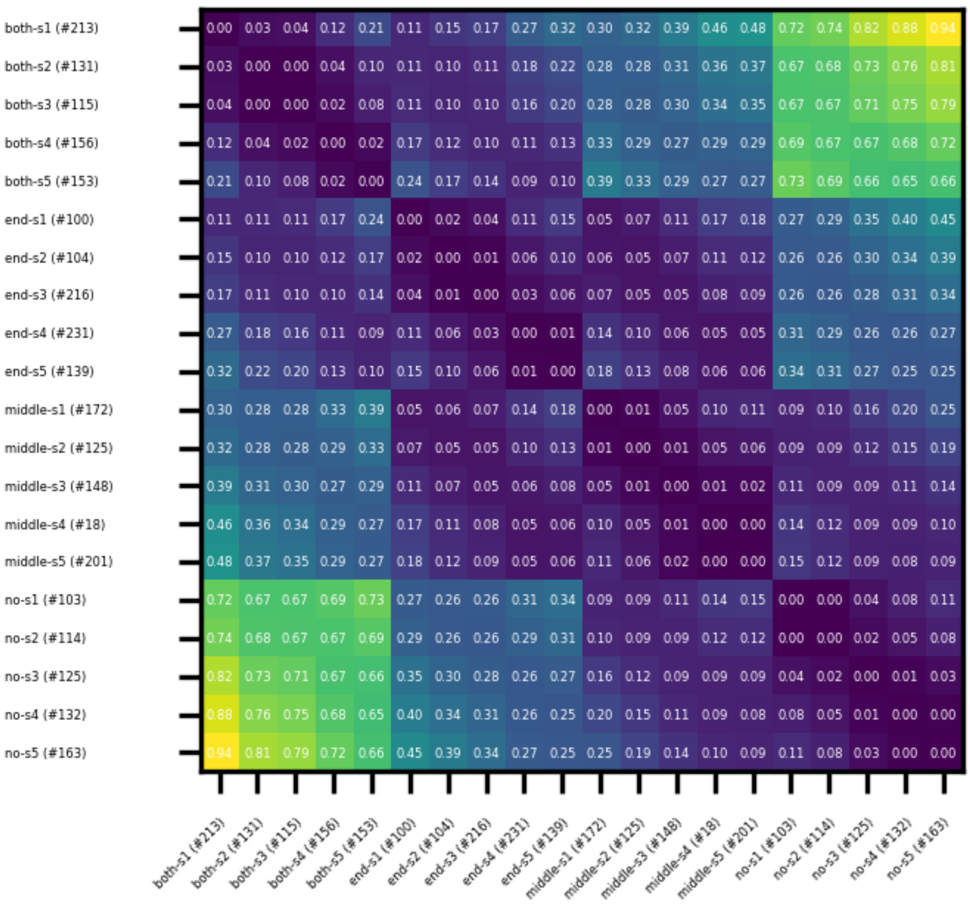
APPENDICES



(a) Distance matrix of the aircraft population based on the four topology classes, embedding element and relationship types, element contextual, material and geometry attributes.



(b) Distance matrix of the aircraft population based on the twenty classes (topology and scaling group), embedding element and relationship types, element contextual, material and geometry attributes.