Adaptive Control Strategies through Knowledge-Infused Deep Learning

MSc project

Develop a new strategy based on reinforcement learning (actor-critic framework) to control adaptive structures under general loading. Given the structural state under loading (state p), and a target state which could be defined by a target shape and limits on the internal forces (state a), the model is responsible to output appropriate actuator commands to control the structure from state p to a. Linear actuators are assumed to be fitted on some of the structural elements. The change of length (or stiffness) of the actuators modifies the structure geometry as well as the internal forces.

During damage, one of more actuators might not work at full capacity and one or more structural elements might have collapsed. This scenario will be considered to train the control model to mitigate the effect of damage by redirecting the stress away from critically stressed elements. Deep Deterministic Policy Gradient will be adopted to learn simultaneously the “policy” function as well as the “value” function. To incorporate previous knowledge, the structure-control system might be represented through graph neural networks with an appropriate embedding and propagation operator in combination with reinforcement learning.

Thesis supervision, writing, and examination will be carried out in English.

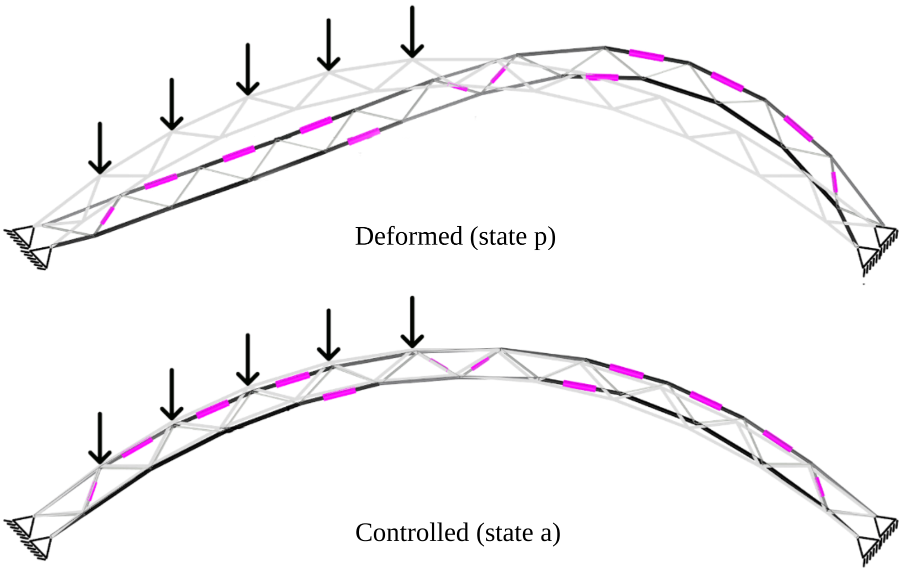

Figure 1 Deformed and controlled states

Supervision

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Key requirements

Bachelor’s degree in civil engineering, architecture and/or computer science.
Knowledge of structural mechanics including dynamic analysis.
Knowledge of (or strong interest to learn) machine learning.
Knowledge of (or strong interest to learn) mathematical and structural optimization.
Knowledge of (or strong interest to learn) MATLAB programming language.
Advanced spoken and written English.

Background

Adaptive structures can modify their shape and internal forces through sensing and actuation in order to counteract the effect of external loading (e.g., stress, deformation) [1], [2]. This way, significant material mass, embodied carbon and whole-life energy can be saved since the structure does not rely only on passive resistance to take the load but can alter its response to satisfy required limits in material strength and stiffness [3]. Most design and control methods have been developed for adaptive structures in the form of trusses and frames with linear actuators strategically placed on some of the structural elements[4]. The structural layout and actuator placement have been optimized simultaneously together with the derivation of control commands[5], [6]. Adaptive structures are typically designed with the objective to minimize material mass as well as whole-life energy encompassing the energy embodied in the material as well as an operational share for adaptation under loading during service[7]. The ability to control deflections within tight limits, is particularly beneficial for stiffness-governed configurations such as high-rise and slender buildings (height-to-depth ratio > 5:1) as well as long-span bridges [8]. Several methods for static and dynamic compensation have been successfully developed and tested [9]–[11]. However, little attention has been given to methods that enable "learning" from experience to improve the control model over time as well as to deal with geometric and material nonlinearity that might occur after damage.

Recent studies have shown good potential in applying reinforcement learning (RL) combined with graph neural networks (GNNs) to various structural design and optimization tasks. Generally, the use of *knowledge graphs* (KG) has shown that it is possible to overcome interpretation problems typical of *data-driven* methods [12]. For example, neural networks (NNs) are excellent function approximators that can infer the underlying model from observations but are typically difficult to interpret and lack mechanisms for incorporating existing knowledge. Graphs can represent complex systems because they can encode information about the system entities and their inter-relationships. The use of graph neural networks (GNNs) [13] has shown great potential in diverse learning tasks that involve complex physics. For example in [14] the dynamic behavior of several physical systems was successfully learned by representing the state of the system with particles expressed as nodes in a graph. The dynamic behavior has been computed through the learned "message-passing", i.e., in this case, the exchange of energy and momentum among a particle and its neighbors.

A GNN involves a graph embedding whereby the information contained in the graph is aggregated and transformed into a latent vector space representation that can be more easily employed for learning. Embeddings must be able to transform a graph structure into a vector space albeit still capturing the graph topology, vertex and edge features. Assuming each node and edge has several attributes, embeddings enable working on a reduced representation of the graph using simple and fast vector operations. Depending on the embedding, tasks such as node classification, clustering, or regression as well as edge classification and link predictions (i.e., existence or absence of an edge between two nodes) can be performed. It is also possible to abstract at the graph level producing a feature map for the whole graph which can be employed for classification or regression.

The use of graphs has enabled the extension of deep neural models to non-Euclidean domains (i.e., geometric deep learning). Figure *2* shows the schematic representation of a GNN model. GNNs typically comprise several stacked layers in which different operators are employed to propagate information. In [15] it is shown that a graph structure can be encoded directly using a neural network model. Using graph spectral theory, a convolution operator has been defined based on the eigendecomposition of the graph Laplacian. The convolution operator has been used as a propagation operator to aggregate information from the graph structure and convert it into a latent vector.

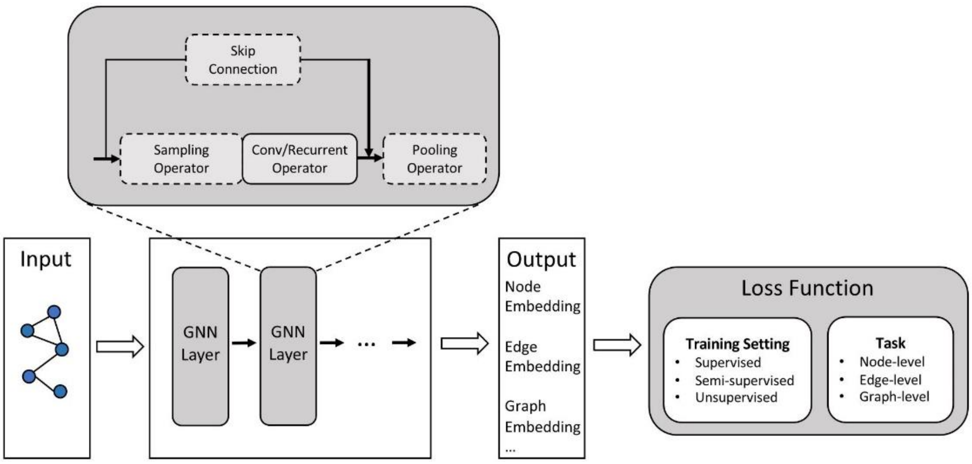

Figure 2 Schematic representation of a GNN model [13]

Graph-convolutional networks have enabled the implementation of agents (e.g., actor-critic networks) that use a more direct representation of the physical system and have been successfully employed for learning tasks that involve diverse objectives including structural optimization [16], [17] and control of the structural dynamics [18]. A reinforcement learning framework based on Deep Determinist Policy Gradient (DDPG) [18] and graph convolutional neural networks (GCNN) [15] has been developed for optimization of the bracing directions in grid shells [19]. The structure is represented as a graph, node and element properties including internal forces are functions defined on the graph vertices. A convolution operator defined in the graph spectral domain is employed as a propagation operator and for node embedding by aggregating and converting information from adjacent nodes and members into a latent vector. The DDPG and actor-critic network framework is key to enable continuous state-action spaces. The agent can obtain solutions that compare in quality to those obtained by a genetic algorithm and it can be applied to similar configurations without re-training thus showing good potential to save significant computation time. Similar studies on the use of graph neural networks combined with reinforcement learning for structural design and optimization have been carried out in [16].

References

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