# Machine learning tools for predicting mechanical properties of elastomers

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**Abstract.** Fatigue life characterization of elastomeric materials and structures under cyclic mechanical loads requires many experiments [1,2,3]. These experiments are both costly and time-consuming. This is all the more true when fatigue life reinforcement is observed for non-relaxing loading conditions [4,5,6]. Therefore, predicting the fatigue life with a limited amount of data is of great interest. In the present study, this issue is investigated by applying machine learning tools. For several years now, machine learning methods are applied to material science [7]. Many works introduce machine learning tools for chemistry [8,9,10], physics [10,11,12] and mechanics [13,14,15]. Nevertheless, they have not yet been applied in the field of fatigue of materials and this is the aim of the present study.

Many different methods are part of “machine learning” [16]. This research work focuses on supervised learning to carry out the regression [17]. Even though neural networks show good results when working with a large dataset, it requires generally having a large amount of data available [18,19,20]. For this reason, our work is based on experimental datasets collected in several studies on fatigue of elastomers in the literature, coupled with a purely numerical-based enriching data method. This method enables us to train a neural network that predicts different lifetime scenarios, which are discussed and interpreted according to the physical meaning of the prediction.

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