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COMPARISON OF LEVELS OF PHYSICAL INFORMATIVENESS IN NEURAL NETWORKS FOR CONSTITUTIVE MODELING OF A SOFT ELASTOMER

B. Petrovskyi, I. Dyyak

Ivan Franko National University of Lviv,
1, Universytetska str., 79000, Lviv, Ukraine,
e-mail: Bohdan.Petrovskyi@lnu.edu.ua, ivan.dyyak@lnu.edu.ua

Over the past decade, machine learning (ML) methods have demonstrated significant progress in regression, classification, and modeling of complex dependencies. However, the application of ML in the physical sciences, particularly in solid mechanics, faces a fundamental limitation: classical neural networks do not explicitly incorporate physical laws and may produce predictions that contradict conservation principles, symmetry, or material behavior.

In response, a number of approaches have emerged that integrate physics into the learning process, most notably Physics-Informed Neural Networks (PINNs). Such models have become especially popular in materials science, biomechanics, aerodynamics, and heat transfer. In this study, we propose the following classification of neural-network models according to their level of physical informativeness: purely empirical, feature-level, soft-constrained, and hard-constrained, ranging from models without embedded physics to models with hard-coded physical relations.

In this paper, we consider the problem of approximating the stress-strain relationship for the soft material Ecoflex 00-10 using experimental data obtained according to ISO 37:2017 (uniaxial tension) and ASTM D575-91 (uniaxial compression). The averaged monotonic curve is used as a reference for comparing the approaches. The aim of the study is to compare four levels of physical informativeness in neural networks and to evaluate their impact on accuracy, generalization, and physical consistency in the small-strain regime and during extrapolation. In the present work, physical consistency is understood as correct quasi-linear behavior as $\varepsilon \to 0$, absence of non-physical oscillations in $\sigma(\varepsilon)$, and qualitatively consistent monotonic response under loading.

Key words: constitutive modeling, soft elastomer, Ecoflex 00-10, stress-strain, physics-informed learning, physical informativeness, soft/hard constraints, secant modulus.

1. Introduction

Accurate modeling of constitutive relations is a central problem in solid mechanics and materials science. For soft polymers and elastomers, the stress-strain response is strongly nonlinear and often requires either empirical hyperelastic models or extensive experimental characterization. In practical engineering applications – including biomedical devices and prosthetic components – obtaining reliable constitutive models from limited experimental data remains a significant challenge.

Recent developments in scientific machine learning have introduced neural networks as flexible universal approximators capable of learning complex nonlinear mappings directly from experimental measurements. In solid mechanics, data-driven surrogates have been explored to accelerate numerical modeling and reduce computational cost [7, 8]. However, purely data-driven models frequently exhibit limited extrapolation capability and may violate known mechanical principles, especially when the available dataset is sparse or restricted to a narrow deformation regime. This limitation is particularly critical in constitutive modeling, where physical consistency near the small-strain region and during extrapolation is essential.

To overcome these drawbacks, various strategies have been proposed to incorporate physical knowledge into neural networks. Physics-informed neural networks (PINNs) embed governing equations or constitutive relations into the loss function, thereby improving robustness and generalization [1–3]. Recent reviews further systematize this area, discussing both the methodological spectrum and practical limitations of PINN-type approaches [4]. More broadly, physics-integrated learning approaches have been classified into physics-guided, physics-informed, and physics-encoded paradigms [5], demonstrating multiple mechanisms through which physical knowledge can be introduced into learning architectures. Related developments also include distributed PINN formulations for linear elasticity problems [6].

While these studies provide a systematic comparison of physics-integrated learning frameworks from a general scientific computing perspective [4, 5], substantially less attention has been paid to their targeted application in data-driven constitutive modeling of soft elastomers, especially when tension and compression data are treated jointly. In particular, the relative impact of different levels of physical informativeness on approximating experimentally measured stress-strain relations remains insufficiently explored.

In this work, we investigate this question using Ecoflex 00-10, a soft elastomer widely employed in biomedical and robotic applications, including compliant prosthetic components. The experimental stress-strain data are taken from the open MAGNELIQ initiative and are available via Zenodo [9, 10]. The study focuses on monotonic loading conditions; hysteresis and cyclic effects are not considered.

The objective is to compare four levels of physical informativeness - purely empirical, feature-level, soft-constrained, and hard-constrained models - for approximating the constitutive response of Ecoflex. The comparison is performed in terms of prediction accuracy, generalization behavior, computational cost, and physical consistency near the quasi-linear regime. Unlike existing reviews that analyze learning paradigms in a broad multiphysics context [5], the present study concentrates specifically on material-property approximation and the practical implications of embedding different forms of physical knowledge into neural networks.

2. Problem Statement

2.1. Motivation

Predicting stress in materials from strain is a key problem in solid mechanics and engineering. In the classical approach, this relationship is defined through experimental curves $\sigma(\varepsilon)$. However, for complex materials such as soft elastomers, deriving an analytical model is nontrivial due to pronounced nonlinearity.

To address this, the present work considers a neural-network approximation of the relationship between strain ε and stress σ using an experimental dataset. In addition, the influence of the level of physical informativeness on model accuracy and physical consistency is investigated.

2.2. Problem Description

We consider the approximation of the stress-strain dependence (σ-ε) for a soft elastomer material Ecoflex 00-10, widely used in biomechanical and robotic applications, including medical and prosthetic devices requiring high compliance and safe human interaction.

Physically, the considered dependence represents the material response under monotonic uniaxial loading in both tension and compression:

$$\sigma = f(\varepsilon), \tag{1}$$

where $\varepsilon \in \mathbb{R}$ is the engineering strain and $\sigma \in \mathbb{R}$ is the engineering stress. Here, $\varepsilon > 0$ corresponds to tension and $\varepsilon < 0$ corresponds to compression.

The engineering strain is defined as

$$\varepsilon = \frac{l - l_0}{l_0}, \tag{2}$$

where l_0 is the initial specimen length before loading and l is the current length under load.

The engineering stress is defined as

$$\sigma = \frac{F}{A_0}, \tag{3}$$

where F is the measured axial force (positive in tension and negative in compression) and A_0 is the initial cross-sectional area of the specimen, used for computing nominal (engineering) stress.

The dataset includes experiments performed under both uniaxial tension (ISO 37:2017) and uniaxial compression (ASTM D575-91). In the present study, the combined monotonic stress-strain data were used without explicitly separating the loading modes. The study focuses on monotonic loading conditions. Due to the nonlinear behavior of the material, the dependence $\sigma(\varepsilon)$ is approximated using neural networks.

2.3. Mathematical Formulation

Let $N_\theta(\varepsilon)$ be a neural network with parameters θ that approximates the stress σ for given strain values ε:

$$\hat{\sigma} = N_\theta(\varepsilon), \tag{4}$$

where $\hat{\sigma} \in \mathbb{R}$ is the predicted stress.

Notation.

- $\varepsilon \in \mathbb{R}$ – engineering strain;
- $\sigma \in \mathbb{R}$ – engineering stress;
- $\hat{\sigma} \in \mathbb{R}$ – stress predicted by the network;
- $\boldsymbol{\varepsilon} = (\varepsilon_1, \dots, \varepsilon_N)^\top \in \mathbb{R}^N$ – vector of experimental strain values;
- $\boldsymbol{\sigma} = (\sigma_1, \dots, \sigma_N)^\top \in \mathbb{R}^N$ – vector of experimental stress values;
- $\theta \in \mathbb{R}^P$ – vector of neural network parameters;
- $L \in \mathbb{R}$ – loss function;
- $E_{\text{eff}} \in \mathbb{R}_+$ – effective secant modulus estimated in a quasi-linear strain region.

The training problem is formulated as minimizing the mean squared error:

$$L_{\text{MSE}}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \Big(N_\theta(\varepsilon_i) - \sigma_i \Big)^2, \tag{5}$$

where N is the number of experimental points and $(\varepsilon_i, \sigma_i)$ are strain–stress pairs.

For physics-regularized models, an additional penalty term is introduced to control deviation from the quasi-linear constitutive behavior observed in the small-strain regime:

$$L_{\text{phys}}(\theta) = \Big(N_\theta(\varepsilon) - E_{\text{eff}}\varepsilon\Big)^2, \tag{6}$$

where E_{eff} is the effective secant modulus estimated in the quasi-linear deformation region.

The combined loss function is defined as

$$L(\theta) = L_{\text{MSE}}(\theta) + \lambda_{\text{phys}} L_{\text{phys}}(\theta), \tag{7}$$

where $\lambda_{\text{phys}} > 0$ controls the strength of the physical regularization. In this study, the parameter λ_{phys} was selected empirically. A value of $\lambda_{\text{phys}} = 0.1$ was found to provide a reasonable balance between approximation accuracy and physically consistent behavior in the small-strain regime.

2.4. Experimental Data

The experimental data were taken from the open MAGNELIQ dataset (Horizon 2020, GA No. 899285), publicly available via Zenodo [9, 10], which contains stress-strain curves for elastomers with different Shore hardness values.

The tests were performed using an Instron 5965 machine with a 1 kN load cell. The specimen preparation and testing protocols follow ISO 37:2017 [11] and ASTM D575-91 [12] as referenced in the dataset documentation.

In this study, the averaged curve for Ecoflex 00-10 was used as the reference for comparing the four levels of physical informativeness in neural networks. The final processed dataset used for training consists of 687 stress-strain pairs obtained from the averaged monotonic tension and compression curves.

2.5. Baseline Physical Relation and Effective Modulus

Since the material exhibits nonlinear hyperelastic behavior, the classical Young's modulus at infinitesimal strain is not directly applicable over the full deformation range. Therefore, an effective secant modulus was estimated within the quasi-linear strain region and used to introduce a physically meaningful linear stiffness term $E_{\text{eff}}\varepsilon$ into the neural network input space.

For Ecoflex 00-10, the estimated effective secant modulus is $E_{\text{eff}} \approx 1.7463 \times 10^4$ Pa. It was computed as the mean value of the ratio σ/ε within the quasi-linear strain interval $0.5 < \varepsilon < 2.0$, which was identified based on visual inspection of the experimental stress–strain curve, i.e.,

$$E_{\text{eff}} = \left\langle \frac{\sigma}{\varepsilon} \right\rangle_{0.5<\varepsilon<2.0}. \tag{8}$$

3. Levels of Physical Informativeness in Neural Networks

This section describes four approaches to constructing neural networks for approximating the stress-strain relationship, which differ in the degree of integration of physical knowledge.

3.1. Pure ML Model (Fully Empirical Model)

The simplest approach is a fully empirical neural network trained exclusively on experimental data without incorporating physical relations:

$$\sigma = N_\theta(\varepsilon), \qquad \sigma \in \mathbb{R},\ \varepsilon \in \mathbb{R}. \tag{9}$$

The loss function is defined as

$$L_{\text{pure}}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\Big(N_\theta(\varepsilon_i) - \sigma_i\Big)^2, \qquad L_{\text{pure}}(\theta) \in \mathbb{R}. \tag{10}$$

3.2. Feature-Level Model (Model with Physical Features)

In the feature-level approach, physically motivated features are incorporated at the input level. In this work, the input feature vector is constructed as:

$$\mathbf{x} = \begin{bmatrix} \varepsilon \\ \varepsilon^2 \\ E_{\text{eff}}\varepsilon \end{bmatrix} \in \mathbb{R}^3. \tag{11}$$

The neural network is defined as $\sigma = N_\theta(\mathbf{x})$, and the loss function as

$$L_{\text{feat}}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\Big(N_\theta(\mathbf{x}_i) - \sigma_i\Big)^2, \qquad L_{\text{feat}}(\theta) \in \mathbb{R}. \tag{12}$$

3.3. Soft-Constrained Model

In the soft-constrained approach, the physical relation is introduced as an additional penalty term in the loss function:

$$L_{\text{soft}}(\theta) = L_{\text{MSE}}(\theta) + \lambda_{\text{phys}}\, L_{\text{phys}}(\theta), \qquad L_{\text{soft}}(\theta) \in \mathbb{R}. \tag{13}$$

The parameter $\lambda_{\text{phys}} > 0$ determines the balance between data-fitting accuracy and satisfaction of the physical law. Larger values of λ_{phys} enforce stronger adherence to the quasi-linear baseline, while smaller values prioritize approximation of the observed data.

3.4. Hard-Constrained Model

A quasi-linear baseline is embedded directly into the architecture:

$$\sigma(\varepsilon) = E_{\text{eff}}\varepsilon + N_\theta(\varepsilon), \tag{14}$$

where the network approximates only the nonlinear deviation from the baseline.

The loss function is defined as

$$L_{\text{hard}}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\Big(E_{\text{eff}}\varepsilon_i + N_\theta(\varepsilon_i) - \sigma_i\Big)^2, \qquad L_{\text{hard}}(\theta) \in \mathbb{R}. \tag{15}$$

3.5. Comparison of the Approaches

The main characteristics of the four levels of physical informativeness are summarized in Tabl. 1.

Table 1

Comparison of levels of physical informativeness in neural networks

Approach	Physics in inputs	Physics in loss	Level of physical consistency
Pure ML model	no	no	absent
Feature-level model	yes	no	limited
Soft-constrained model	no	yes	partial
Hard-constrained model	no	yes	guaranteed

4. Neural Network Architecture and Training Process

4.1. Overall Network Architecture

For all four levels of physical informativeness, the same baseline architecture of a fully connected multi-layer perceptron (MLP) was used.

- input layer: 1 neuron (Pure ML, Soft, Hard) or 3 neurons (Feature-level);
- hidden layers: 4 layers with 256 neurons each;
- output layer: 1 neuron (stress $\sigma \in \mathbb{R}$).

The selected architecture represents a compromise between expressive capacity and training stability. Preliminary tests with smaller and larger neural networks indicated that the 4×256 configuration is sufficiently flexible to capture the nonlinear stress–strain relation, while still remaining stable during training. Since the main objective of this study is comparative assessment of different levels of physical informativeness rather than architecture optimization, the same baseline architecture was retained for all models to ensure a fair comparison.

4.2. Activation Function

The Swish activation function was used in the hidden layers:

$$\mathrm{Swish}(x) = x\,\mathrm{sigm}(x), \tag{16}$$

where

$$\mathrm{sigm}(x) = \frac{1}{1+e^{-x}}, \tag{17}$$

is the sigmoid function and $x \in \mathbb{R}$ is the neuron input.

4.3. Data Normalization

Input and output data were normalized:

$$\varepsilon^* = \frac{\varepsilon - \varepsilon_{\min}}{\varepsilon_{\max} - \varepsilon_{\min}}, \quad \sigma^* = \frac{\sigma - \sigma_{\min}}{\sigma_{\max} - \sigma_{\min}}. \tag{18}$$

4.4. Training Procedure

All neural networks were implemented and trained using the TensorFlow framework [13]. The experiments were executed in Google Colab [14]. Training was performed by minimizing the corresponding loss function using the Adam optimizer.

Training hyperparameters:

- learning rate: 10^{-3};
- number of epochs: 300;
- batch size: 32.

4.5. Data Split

The data were split into training and test sets with an 80/20 ratio. The test set was used to evaluate generalization performance.

5. Results and Comparative Analysis

This section presents numerical results for the four levels of physical informativeness. The evaluation is performed using quantitative accuracy metrics and from the perspective of physical consistency of the obtained stress–strain relations.

5.1. Visual Comparison of Stress–Strain Curves

Observations from Fig. 1. The Pure ML and Feature-level models achieved small approximation error within the range covered by the data; however, deviations from the quasi-linear baseline $\sigma \approx E_{\text{eff}}\varepsilon$ were observed in the small-strain region. The Soft-constrained model reduced these deviations due to the physical penalty term, whereas the Hard-constrained model reproduced the baseline as $\varepsilon \to 0$ due to embedding $E_{\text{eff}}\varepsilon$ in the architecture.

5.2. Quantitative Accuracy Metrics

The models were compared using the mean squared error (MSE) and the coefficient of determination R^2. The R^2 coefficient is defined as

$$R^2 = 1 - \frac{\sum_{i=1}^{N_{\text{test}}} (\sigma_i - \hat{\sigma}_i)^2}{\sum_{i=1}^{N_{\text{test}}} (\sigma_i - \bar{\sigma})^2}, \tag{19}$$

where $\hat{\sigma}_i$ is the model prediction, $\bar{\sigma}$ is the mean stress over the test set, and N_{test} is the number of test points.

To assess the stability of the obtained results, additional experiments were performed using different random train-test splits of the dataset. Across these runs, the hard-constrained model consistently retained extremely high predictive accuracy, with R^2 values remaining close to unity ($R^2 \approx 0.998$–0.9999), confirming the stability and robustness of the obtained result (see Tabl. 2).

It should be noted that the coefficient of determination R^2 is not the only quality criterion in this work. For physics-informed approaches, a decrease in R^2 relative to purely empirical models is an expected consequence of introducing physical constraints, which reduce approximation flexibility but improve physically consistent behavior in the small-strain regime and during extrapolation.

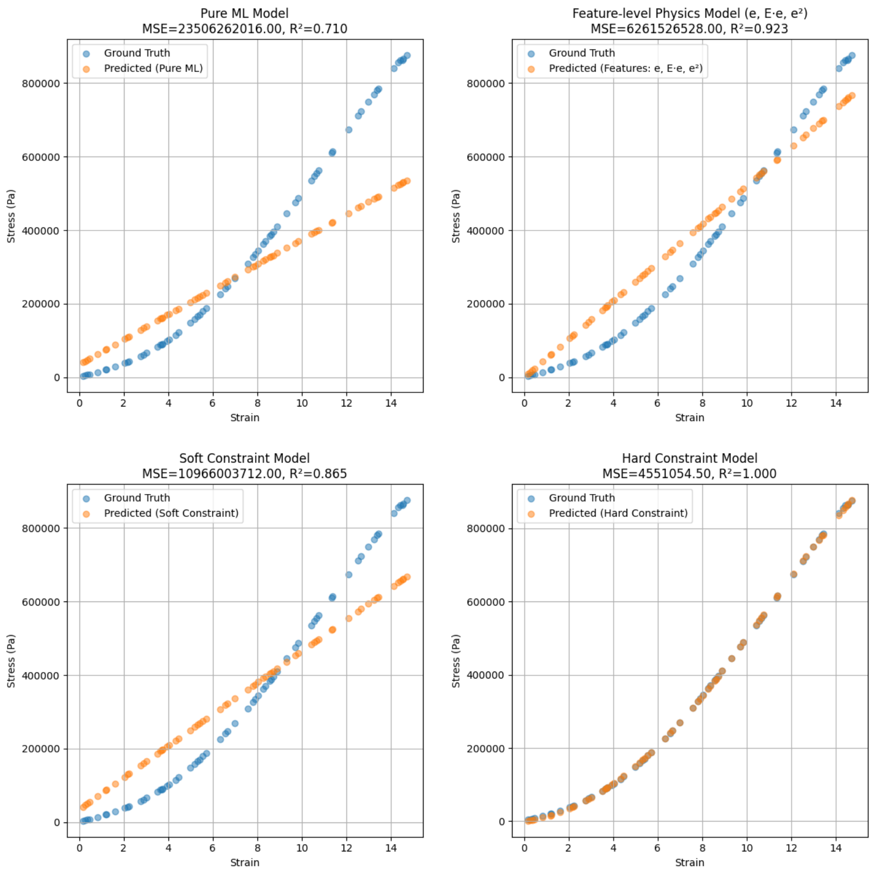

Fig. 1. Comparison of the experimental stress-strain curve with predictions from models of different levels of physical informativeness.

Table 2

Accuracy and training time comparison of models with different levels of physical informativeness

Model	MSE	R^2	Training time, s
Pure ML	2.3506×10^{10}	0.7101	155
Feature-level	6.2615×10^{9}	0.9228	154
Soft-constrained	1.0966×10^{10}	0.8648	99
Hard-constrained	4.5511×10^{6}	0.9999	140

5.3. Physical Consistency Analysis

Physical consistency was assessed by examining model behavior in the small-strain regime and during extrapolation. More specifically, the comparison considered: (i) agreement with the quasi-linear baseline as $\varepsilon \to 0$, (ii) absence of non-physical oscillations in the predicted curve, and (iii) preservation of qualitatively monotonic response under monotonic loading. The Pure ML and Feature-level models may violate the quasi-linear baseline at small strains, whereas the soft approach controls physical behavior through a penalty term, and the hard approach enforces the baseline by construction.

The implementation used in this study is available in a public Colab notebook [15].

6. Conclusions

A comparative analysis of four levels of physical informativeness in neural networks was performed for approximating the stress–strain relationship of Ecoflex 00-10. The results indicate that purely empirical models can fit the data but do not guarantee physically meaningful behavior near the quasi-linear region or during extrapolation. Introducing physically motivated features improves stability but does not enforce consistency. Soft constraints provide a trade-off between accuracy and consistency, whereas hard constraints embed the baseline relation directly into the model and ensure physically consistent behavior in the small-strain limit.

The obtained results also suggest practical recommendations regarding the choice of model type. Purely empirical models are suitable mainly for interpolation within the range of available data, when physical consistency outside the training region is not critical. Feature-level models are attractive when simple physically motivated descriptors are available and a low implementation overhead is desired. Soft-constrained models are preferable when approximate physical knowledge is available and one seeks a balance between predictive flexibility and physically consistent behavior. Hard-constrained models are the most appropriate when a reliable baseline constitutive relation is known in advance, since they provide the best physical consistency and the most stable extrapolation behavior.

Therefore, for constitutive modeling tasks in which the small-strain regime and extrapolation are important, incorporation of physical knowledge directly into the learning procedure or architecture should be considered preferable to purely empirical fitting.

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ПОРІВНЯННЯ РІВНІВ ФІЗИЧНОЇ ІНФОРМАТИВНОСТІ НЕЙРОННИХ МЕРЕЖ ДЛЯ КОНСТИТУТИВНОГО МОДЕЛЮВАННЯ М'ЯКОГО ЕЛАСТОМЕРУ

Б. Петровський, І. Дияк

Львівський національний університет імені Івана Франка,
вул. Університетська 1, Львів, 79000, Україна,
e-mail: Bohdan.Petrovskyi@lnu.edu.ua, ivan.dyyak@lnu.edu.ua

За останнє десятиліття методи машинного навчання продемонстрували значний прогрес у задачах регресії, класифікації та моделювання складних залежностей. Водночас застосування нейронних мереж у фізичних науках, зокрема в механіці твердого тіла, має принципове обмеження: класичні моделі не враховують фізичні закони явно і можуть давати прогнози, що суперечать законам збереження, симетрії або матеріальній поведінці.

У відповідь сформувався спектр підходів, що інтегрують фізику в процес навчання, зокрема Physics-Informed Neural Networks (PINNs). Такі моделі широко застосовують у матеріалознавстві, біомеханіці та суміжних галузях. У цій роботі запропоновано таку класифікацію моделей нейронних мереж за рівнем фізичної інформативності: суто емпіричні, feature-level, soft-constrained та hard-constrained.

У цій роботі розглянуто задачу апроксимації залежності "напруження-деформація" для м'якого матеріалу Ecoflex 00-10 за експериментальними даними розтягу (ISO 37:2017) та стиску (ASTM D575-91). Усереднену монотонну криву використано як еталон для порівняння підходів. Метою дослідження є порівняння чотирьох рівнів фізичної інформативності нейронних мереж та оцінювання їхнього впливу на точність, узагальнюваність і фізичну узгодженість у малодеформаційному режимі та під час екстраполяції. У цій роботі під фізичною узгодженістю розуміється коректна квазілінійна поведінка при $\varepsilon \to 0$, відсутність нефізичних осциляцій у залежності $\sigma(\varepsilon)$ та якісно узгоджена монотонна реакція матеріалу при монотонному навантаженні.

Ключові слова: конститутивне моделювання, еластомер, Ecoflex 00-10, напруження-деформація, фізично-інформоване навчання, фізична інформативність, soft/hard constraints, секантний модуль.