



COMPARISON OF ARTIFICIAL INTELLIGENCE MODELS FOR PREDICTING DISSIPATED ENERGY BASED ON THE BOUC-WEN-FUNG MODEL

Comparação de modelos de inteligência artificial preditiva da energia dissipada a partir do modelo Bouc-Wen-Fung

Guanis de Barros Vilela Junior¹; Raul Marcel Casagrande^{3,4,5}; Ricardo Pablo Passos¹; Túlio Xavier Brandão Rocha²

ISSN: 2178-7514

Vol. 18 | N°. 3 | Ano 2026

<https://www.cpaqv.org>

ABSTRACT

Introduction: The Bouc-Wen-Fung (BWF) hysteretic model can be applied to biomaterials to simulate dissipated energy under various conditions. Its significance in biomechanics is underscored by the ability to test it *in silico* (as a digital twin) prior to *in vivo* application, which can enhance efficiency in training and rehabilitation protocols. **Objective:** To evaluate and compare the predictive performance of machine learning algorithms (Random Forest and Gradient Boosting) in estimating the dissipated energy of the BWF model based on motion amplitude, viscosity, and loading-unloading cycle frequency in biomaterials. **Methods:** An *in silico* dataset comprising 1,000 distinct data points for the model parameters was generated, adhering to their functional constraints. Random Forest (RF) and Gradient Boosting (GB) algorithms were implemented in Python and compared to assess their predictive reliability. **Results:** The RF model achieved an R^2 of 0.980, identifying motion amplitude, viscosity, and loading-unloading cycle frequency as the most significant predictors. For this method, the Mean Absolute Error (MAE) was 0.153 and the Root Mean Square Error (RMSE) was 0.219, which, alongside the performance of the GB technique, corroborates the high predictive accuracy in estimating dissipated energy. A Kendall's tau of 0.92 further demonstrated that both RF and GB are robust strategies for predictive modeling of the dissipative capacity within the BWF framework.

Keywords: Bouc-Wen Fung model; energy dissipation; artificial intelligence.

RESUMO

Introdução: O modelo histerético de Bouc-Wen-Fung (BWF) pode ser utilizado em biomateriais para simular a energia dissipada em diferentes cenários. A importância disto na biomecânica é destacada em função de sua testabilidade *in silico* (gêmeo digital) antes de aplicação *in vivo*, podendo promover um aumento da eficiência no treinamento e na reabilitação. **Objetivo:** avaliar e comparar a capacidade preditiva de algoritmos de inteligência artificial (Random Forest e Gradient Boosting) em estimar a energia dissipada do modelo BWF a partir da amplitude do movimento, da viscosidade e da frequência do ciclo carga-descarga em um biomaterial. **Métodos:** foi consolidado um banco de dados (*in silico*) com mil diferentes dados para as variáveis do modelo, respeitando os limites funcionais do mesmo. Um algoritmo em Python foi utilizado para aplicar os métodos Random Forest (RF) e Gradiente Boosting (GB), comparando-os para testar a confiabilidade do modelo. **Resultados:** o método RF, obteve $R^2 = 0,980$, identificando a amplitude do movimento, a viscosidade e a frequência do ciclo carga-descarga como as variáveis mais relevantes do mesmo. O Erro Médio Absoluto (MAE) foi de 0,153 e a Raiz do Erro Quadrático Médio (RMSE) 0,219, corroborando junto com a técnica GB a alta precisão preditiva do modelo em estimar a energia dissipada; o τ de Kendall foi de 0,92 evidenciando que tanto a RF quanto o GB são estratégias robustas para modelos preditivos da capacidade dissipativa em modelo Bouc-Wen-Fung. Embora os limites de equivalência neste estudo tenham sido regidos por critérios de precisão numérica *in silico*, os resultados estabelecem uma base metodológica para futuras investigações *in vivo*.

Palavras-chave: Modelo Bouc-Wen Fung; dissipação energia; inteligência artificial.

1. International Society of Human Movement Sciences - ISHMS.
2. UNIFIP-Moc / Afya.
3. Instituto Jundiaense de Ortopedia e Traumatologia.
4. Faculdade de Medicina de Jundiaí.
5. Hospital São Vicente de Paulo - Jundiaí.

Autor de correspondência

Guanis de Barros Vilela Junior - guanis@gmail.com

INTRODUCTION

One of the major methodological challenges in the life sciences is understanding the behavior of energy flows across different topological levels, from genetic machinery to the macroscopic scale of complex systems. The control of these energy flows across all scales seems far from yielding robust scientific evidence. Various *in silico* models attempt to simulate the generation, transfer, and dissipation of energy. In this scenario, the complexity and non-linearity of biological systems present a spectacular challenge: biomaterials exhibit systematically altered visco-elasto-plastic behavior in response to endogenous and exogenous stimuli. Models are caricatures of a reality that escapes us every fraction of a second; collected data informs the past of a life that has already changed. Nevertheless, models can infer what might happen, primarily with the digital twin that every human being consolidates as they share their habits and lifestyles in a hyperconnected world—data encompassing physical activity, sedentary time, nutritional quality, stress levels, quality of social relationships, consumed drugs (licit and illicit), as well as inherited genetic and epigenetic traits. With Artificial Intelligence (AI) algorithms and individual big data, the possibilities are both optimistic and pessimistic. The middle path seems the most sensible: using AI ethically to improve the quality of life for all of humanity, rather than as another element of exclusion and conflict.

Far from being a dry formalism, the Bouc-Wen-Fung (BWF) model^(1,2,3,4) proposes that there is no deformation without memory. This statement is easily understood if we observe the relief of any place on the planet; its history is told by the deformations it has undergone over billions of years. By generating data from the BWF model and subjecting it to two distinct learning paradigms—the parallel ensemble of Random Forest and the sequential corrective approach of Gradient Boosting—we seek not only to validate an algorithm but to test whether an equation can teach a machine what it means to have a history. Biomaterials are no different; their elastic, plastic, and viscous properties define what happens to living beings. The BWF model can be useful in understanding hysteretic processes, attesting that the thermodynamic signature must be finely tuned to maintain life.

METHODS

Based on the governing equations of the Bouc-Wen hysteretic model^(1,2,4,5) and Fung's hyperelastic biomaterial model⁽³⁾, a dataset comprising 1,000 distinct data points was consolidated for the model's variables, strictly adhering to their functional limits. A Python-based algorithm applied Random Forest (RF) and Gradient Boosting (GB) methods, comparing them to test the model's reliability. The selection of these algorithms is based on their distinct architectures:

Random Forest (RF): Utilizes ensemble learning where regression is handled via the average of all trees, reducing variance and avoiding overfitting through independence and variability. It efficiently captures global data structures and handles noise.

Gradient Boosting (GB): Focuses on reducing bias through successive iterations. It excels at local refinement, capturing subtle and complex non-linear interactions that RF may not address satisfactorily.

Kendall's tau test (τ) was employed to evaluate the agreement between these paradigms. The evaluated variables included:

Frequency (Hz)
Amplitude (mm)
Viscosity (Pa.s)
Fung's tension (Pa)
Fung's compression (Pa)

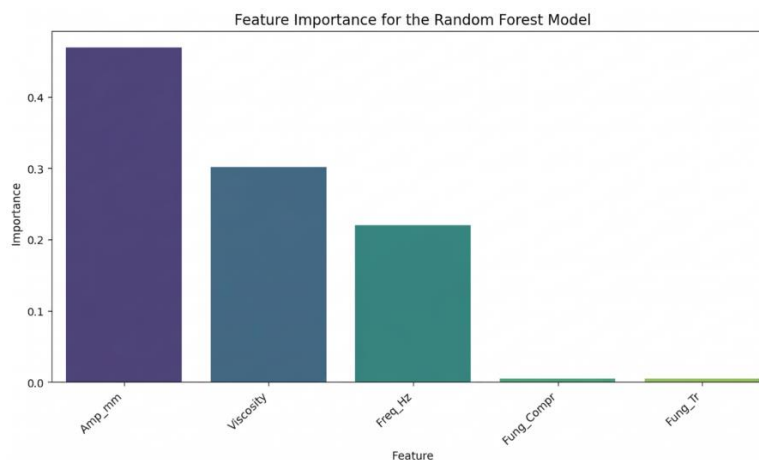
For the assessment of statistical equivalence, the Smallest Effect Size of Interest (SESOI) boundaries were defined in raw units

for the model's output variables. In *in silico* studies, unlike *in vivo* trials, defining equivalence is based on the maximum numerical tolerance acceptable by the solving algorithm rather than clinical relevance. This threshold ensures that any differences below this magnitude are attributed to computational noise, floating-point rounding errors, or solver convergence tolerances (e.g., Newton-Raphson criterion), rather than actual mechanistic divergences in the model^(12,13).

RESULTS

The coefficient of determination ($R^2 = 0.980$) indicates that the Random Forest model explains 98% of the variance in the dependent variable (dissipated energy) using the provided independent variables, suggesting high predictive power. In the context of human locomotor system biomaterials, a high R^2 is crucial for biomaterial design and *in silico* simulations.

Figure 1 illustrates the relative impact of each variable on energy dissipation:



Amplitude (Displacement) - 46.9%: The dominant factor in energy dissipation. In the locomotor system, this relates to the amount of movement or deformation a tissue or implant experiences. Greater range of motion leads to higher energy dissipation by cartilaginous material or synovial fluid.

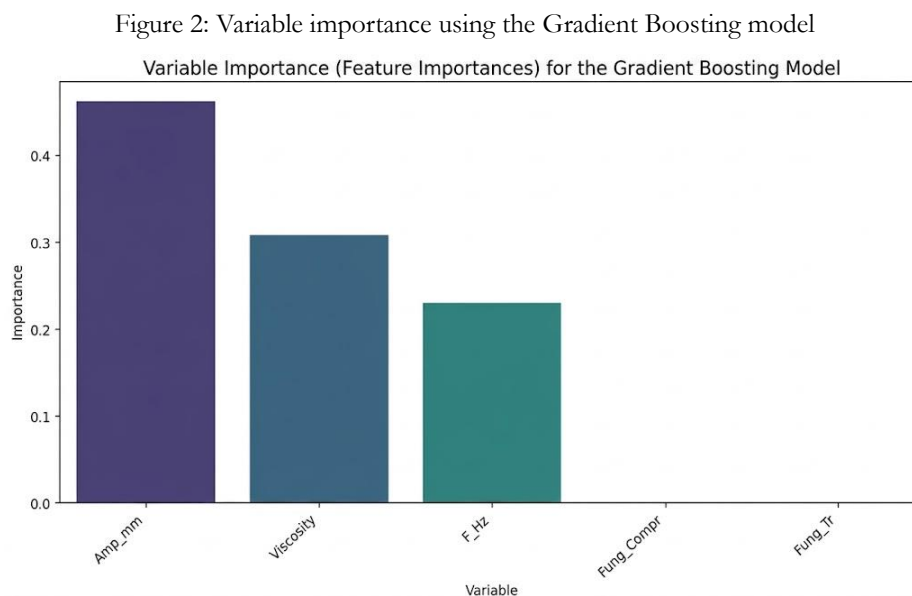
Viscosity - 30.1%: Indicates resistance to flow or gradual deformation under stress. Viscoelastic biological tissues (cartilage, synovial fluid, bone) convert mechanical energy into heat during cyclic deformation, which is vital for shock absorption and protecting adjacent structures.

Frequency of Force Application - 22.0%: Reflects the constant cyclic loading

tissues undergo (e.g., stepping frequency). Effective energy dissipation at physiological frequencies is highly desirable to prevent stress accumulation and fatigue.

Fung's Tension and Compression - 0.5% each: Suggests that intrinsic material compressibility has minimal impact on energy dissipation in this dataset. Shear or other forms of visco-elastic deformation are likely more relevant than pure compression.

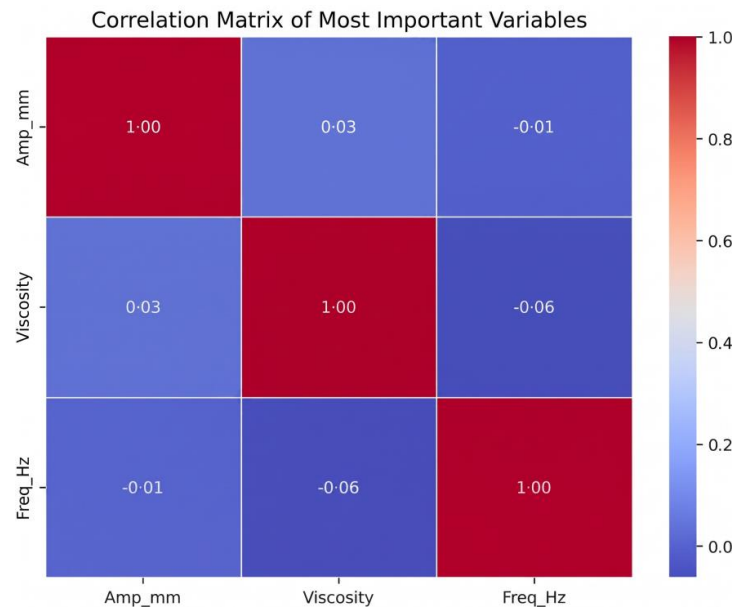
The Gradient Boosting (GB) results corroborated the RF findings, showing highly similar variable importance.



The GB results (Figure 2) are supported by an $R^2 = 0.99$. This consistency between the two algorithms increases confidence regarding the most influential variables. Both models exhibited very low Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), suggesting high precision in predicting dissipated energy. RF

demonstrated high robustness against outliers, whereas GB's tendency to fit outliers at all costs can sometimes degrade the model^(7,8). These three primary variables should be prioritized in future in vivo research, particularly concerning biomaterial development aimed at improving human health.

Figure 3: Correlation matrix among the most relevant variables in the BWF model



The low correlations (both positive and negative) confirm that amplitude, frequency, and viscosity are highly independent within this framework, operating with extremely low redundancy and attesting to the model's topological efficiency.

Figure 4: Dispersion between Amplitude and the log of energy

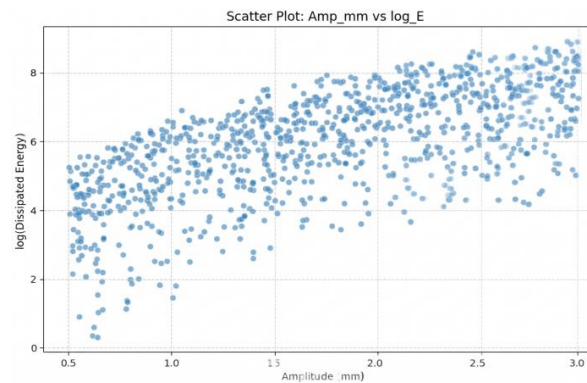


Figure 4 illustrates the dispersion between amplitude (mm) and the log of dissipated energy, showing a clear upward trend in dissipated energy as amplitudes increases. Notably, for a constant amplitude of 1.0 mm, the log of dissipated energy fluctuates between ~ 1.5 kPa and 6.5 kPa—a variability factor of $\sim 100,000$. This highlights the non-deterministic nature of dissipated energy, given its dependence on multiple interacting variables.

Figure 5: Comparison between Random Forest and Gradient Boosting techniques

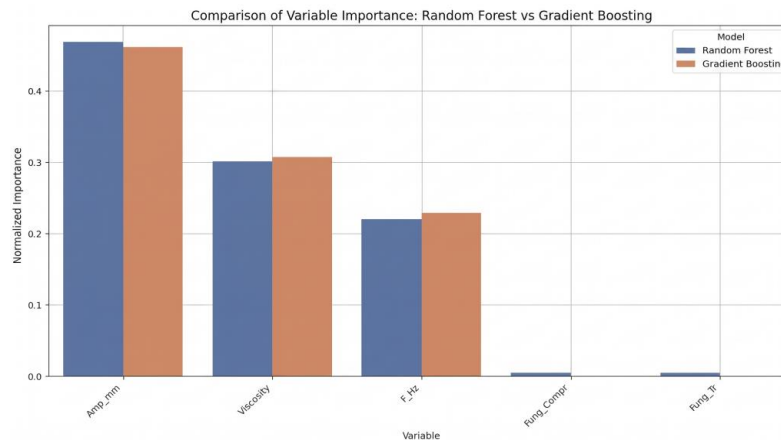


Figure 5 compares the two predictive models for dissipated energy based on the in silico BWF model, showing no significant differences between them. However, in the GB model, the Fung Tension variable does not contribute to energy dissipation, while Fung Compression plays a vastly reduced role compared to the three main variables.

FINAL CONSIDERATIONS

The comparison between two predictive techniques (RF and GB) for dissipated energy in hysteretic systems demonstrated the mathematical rigor of the BWF model. Although the equivalence bounds in this study were governed by in silico numerical precision criteria, the results establish a methodological foundation for future in vivo investigations.

In subsequent studies, equivalence limits (SESOI) will be derived from the constitutive parameters of biological tissues, as described in Fung's theory of viscoelasticity (FUNG, 1993). This will allow the model's numerical tolerance

to be translated into thresholds of biomechanical relevance and cellular mechanotransduction.

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Notes:

1) The authors declare that there are no conflicts of interest of any nature.

2) The authors declare, where applicable, their adherence to policies regarding the ethical use of Artificial Intelligence, disclosing this in the acknowledgments or methods section of the article, in accordance with WAME (World Association of Medical Editors) guidelines.



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