

Taguchi-ANOVA optimization of FEM rehabilitation systems

Filippo Laganà¹, Angela Latella² and Carmen Laganà³

Finite element modelling (FEM) has become an important tool for analysing biomechanical behaviour in rehabilitation systems. However, the optimization of model parameters is often performed empirically, resulting in limited reproducibility and increased computational cost. This work proposes a statistical optimization framework for FEM-based rehabilitation systems using the Taguchi method combined with analysis of variance (ANOVA). An L9 orthogonal array was employed to investigate the influence of material, geometric, and loading parameters while reducing the number of simulations required compared with full factorial approaches. The biomechanical response of the system was analysed through three-dimensional FEM simulations implemented in COMSOL Multiphysics. Experimental measurements acquired using a deformation gauge-based electronic acquisition system were used for model validation. ANOVA enabled the identification of the most influential parameters affecting deformation behaviour and mechanical response stability. The optimized configuration showed reduced deformation variability and improved agreement between numerical and experimental results. In particular, the optimization procedure reduced the average modelling error from 12.4% to 4.1%, while improving response consistency under different loading conditions. The proposed methodology provides a computationally efficient and physically interpretable approach for the optimization of rehabilitation-oriented biomechanical systems.

Keywords: FEM, Taguchi method, ANOVA, parametric optimization, biomechanical simulation

1 Introduction

The upper limb motor disability due to neurological conditions, including stroke, spinal cord injury, and neurodegeneration, is an important health problem that impacts the patient's independence and quality of life [1, 2].

Motor recovery from such pathologies is sought through repetitive and task-based rehabilitation training that exploits the principles of neuroplasticity [3-5].

The current rehabilitation strategies are based on subjective measures and fail to include tools for quantitative and objective monitoring, especially outside of the clinics [6, 7]. In recent times, the development of new technologies has been instrumental in shifting the paradigm of rehabilitation. AI, digital medicine, and sensor technology have enabled a higher level of objectivity when assessing motor performances and allowed for adaptive therapy.

Similar sensing, monitoring, and diagnostic architectures have been extensively investigated in biomedical engineering, including portable healthcare devices, non-invasive monitoring systems, and advanced electronic interfaces, demonstrating the importance of reliable signal acquisition and system integration [8-12].

Recent studies have also demonstrated the effectiveness of flexible electronics, wearable dry electrodes, and bioinspired sensing architectures for biomedical monitoring applications, highlighting the importance of reliable signal conditioning and miniaturised acquisition interfaces in healthcare systems [13-15].

Similar embedded acquisition and monitoring architectures have been successfully developed in biomedical systems to ensure signal reliability and in situ diagnostics [16]. Many studies highlighted that machine learning algorithms could efficiently use kinematic and physiological data for classification purposes in rehabilitation [17, 18]. Even if machine learning offers many advantages, it is still subject to high data dependency and lacks physical interpretability, thus making its results fragile [19]. At the same time, FEM simulations represent a well-established method in biomechanical analysis.

The reason lies in the detailed investigation of stress, deformation, and displacement distributions under realistic loading conditions, providing a physically grounded description of tissue behaviour [20]. Similar modelling approaches have been successfully applied to describe complex deformation phenomena in biological systems, particularly in fluid-structure interaction scenarios [21, 22]. Advanced sensing interfaces based on ultra-

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sonic and piezoelectric technologies have also shown promising capabilities for non-invasive biomechanical and bio-medical monitoring applications [23-26]. Hyperelastic models such as the Mooney-Rivlin formulation have been widely adopted to capture the nonlinear mechanical response of soft tissues, achieving a good match with experimental observations [27]. These approaches are typically computationally demanding and require careful parameter selection [28-30]. To overcome the limitations of purely data-driven or purely model-based approaches, hybrid FEM-AI frameworks have recently been proposed.

These approaches combine physics-based simulations with machine learning techniques, allowing the generation of synthetic datasets and improving model interpretability while maintaining predictive capability [31-33]. Although promising, these hybrid systems still suffer from a critical limitation: the absence of a structured methodology for parameter optimization. In most cases, model parameters ranging from material properties and geometric configurations to algorithmic settings are tuned empirically, leading to suboptimal performance and limited reproducibility. Techniques based DoE provide an organised approach to the exploration of parameter spaces involving many dimensions [34, 35]. Design and optimization methodologies based on analytical-numerical approaches have also been applied in environmental and process engineering domains, confirming the versatility of structured optimization frameworks in complex systems [36]. Among such approaches, the Taguchi technique stands out as especially promising because it enables substantial reductions in the number of experiments by employing orthogonal arrays [37-39]. This approach has been successfully applied in several engineering domains to improve robustness and efficiency, including biomedical applications [40]. Similar hybrid optimization strategies combining AI, Taguchi design, and ANOVA have also demonstrated improved robustness and enhanced parameter sensitivity analysis in thermographic monitoring applications [41]. However, its adoption in the optimization of hybrid FEM-AI rehabilitation systems remains limited. Furthermore, in combination with Taguchi design, analysis of variance (ANOVA) allows statistically significant evaluation of the influence of on the resulting performance [42, 43]. This helps identify the most important parameters for optimization, thus allowing making more informed decisions during optimization. While being an effective approach, ANOVA is not widely used in hybrid FEM-AI models where sensitivity of parameters plays a crucial role. A closer examination of the literature reveals a compromise inherent to each of the three approaches discussed above. AI-based systems are flexible and fast but have a low level of interpretability and require training data sets [44, 45]. FEM models are computationally complex and sensitive to parameter settings, although the results obtained by them give a more

realistic picture of the system functioning [46, 47]. In turn, FEM-AI systems represent an attempt to combine benefits of the two first approaches. Unfortunately, there are still no effective methods for system optimization or testing for these models [48, 49].

The main objective of this paper is to suggest an approach to statistical optimization of FEM-AI rehabilitation systems based on Taguchi design and ANOVA evaluation. The main contribution of this work lies in the integration of physics-based modelling, statistical optimization, and data-driven analysis within a unified framework. This methodological approach contrasts with current literature studies that often use an empirical tuning technique to optimize hybrid rehabilitation devices.

The remainder of this paper is organised as follows. In Section 2, the materials and methods section introduce the FEM simulation model, optimization technique using Taguchi design method, and machine learning methodology used in the study. Section 3 discusses the findings, with emphasis on ANOVA analysis and assessment of model performance. Section 4 will summarize the findings and future research directions.

2 Materials and methods

This section outlines the integration of biomechanical finite element modelling, statistical optimization based on the Taguchi method and analysis of variance (ANOVA), as well as the use of machine learning techniques for the evaluation of optimized configurations. The aim is to define a reproducible methodological pipeline capable of reducing computational complexity and improving the reliability of the system.

2.1 FEM modelling and system parameters

Biomechanical modelling was carried out using a three-dimensional finite element model designed to simulate the behaviour of soft tissues under loading conditions representative of rehabilitation exercises. The mechanical behaviour of the material is described using a Mooney-Rivlin hyperelastic model, employed for the non-linear representation of biological tissues [50, 51].

The deformation energy function is given as

$$W = C_{10}(I_1 - 3) + C_{01}(I_2 - 3) \quad (1)$$

where C_{10} and C_{01} represent the material parameters, whilst I_1 and I_2 are the invariants of the deformation tensor. The modelling, implemented in COMSOL® Multiphysics version 5.2, uses the Structural Mechanics Module for the analysis of hyperelastic materials. The domain geometry was defined in a simplified form to represent the volume of soft tissue (Fig. 1).

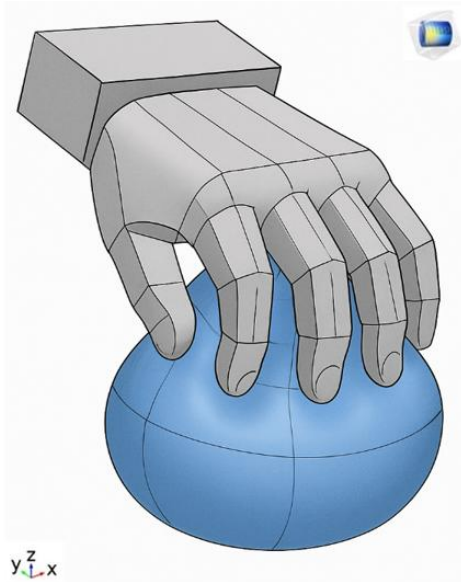


Fig. 1. FEM geometry: glove structure (gray) interacting with deformable latex sphere (blue)

The spatial discretisation was performed using an unstructured tetrahedral mesh. A mesh convergence analysis was conducted by progressively refining the element size until stable values of the output variables (stress, deformation, and displacement) were achieved. The final mesh configuration adopted in the simulations is shown in Fig. 2.

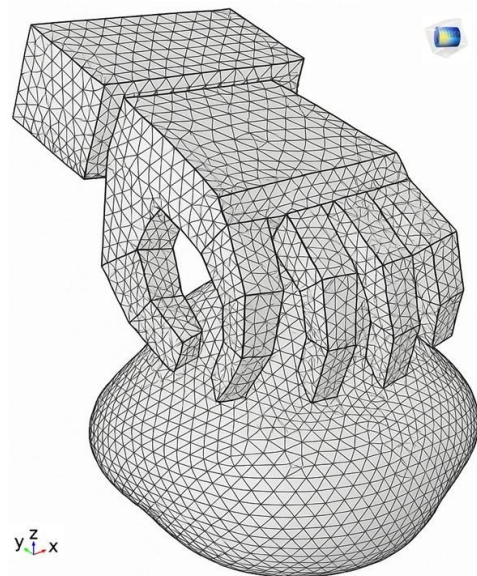


Fig. 2. Unstructured tetrahedral mesh adopted for the FEM model after convergence analysis

The numerical solution was obtained using a stationary nonlinear solver, with convergence criteria defined on both displacement and residual tolerances, ensuring numerical stability under large deformation conditions typical of hyperelastic materials. All model parameters, including material coefficients, geometric variables, and loading conditions, were defined as parametric inputs within the simulation environment. This configuration enables seamless integration with the Taguchi-based experimental design, allowing auto-mated execution of multiple simulation scenarios.

2.2 Electronic signal acquisition and analysis system

To correlate the results of numerical modelling with physically measurable quantities, an electronic acquisition system has been developed specifically for monitoring biomechanical signals during the performance of rehabilitation exercises. The proposed architecture enables the indirect measurement of applied force and deformation using deformation gauge sensors. The deformation gauges were configured in a Wheatstone bridge, a solution commonly used for measuring small changes in resistance associated with mechanical deformation. This configuration improves the system's sensitivity and compensates for any thermal variations, ensuring greater stability of the acquired signal.

The differential output signal from the bridge, typically of very low amplitude, was conditioned using an amplification stage based on an instrumentation amplifier with a high common-mode rejection ratio. Similar low-noise conditioning architectures and charge-sensitive acquisition interfaces have been successfully adopted in biomedical microsystems and lab-on-chip platforms requiring high sensitivity and reduced electromagnetic interference [52].

The amplified signal is subsequently filtered through an analogue low-pass filter to reduce high-frequency noise and improve the signal-to-noise ratio. The acquisition chain is completed by an analogue-to-digital converter, which enables the signal to be digitised and subsequently processed by a dedicated computing unit. Recent advances in biomedical electronic systems have demonstrated the importance of compact and integrated acquisition architectures for improving portability, signal reliability, and real-time monitoring performance [53, 54].

The circuit diagram of the data acquisition system is shown in Fig. 3, which highlights the deformation gauge bridge, the analogue signal conditioning stage and the digital acquisition interface.

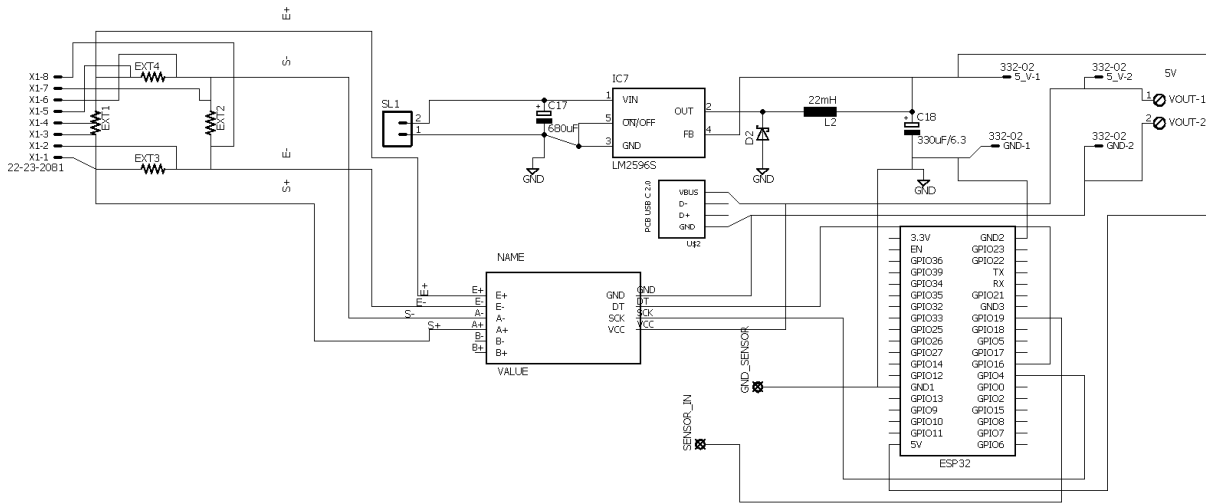


Fig. 3. Schematic diagram of the acquisition circuit

This architecture enables reliable measurement of the deformation of the elastic system, allowing the applied force to be derived indirectly and the equivalent stiffness of the limb to be estimated. In particular, the relationship between the biomechanical quantities under consideration can be expressed as a function of time, assuming a simplified model in which deformation is proportional to the ratio of applied force to system stiffness. During the performance of the rehabilitation exercise, the applied force tends to increase progressively as muscle capacity improves, whilst the limb's stiffness increases in response to biomechanical adaptation. Consequently, the measured deformation initially shows a high trend, due to the reduced ability to generate force and lower stiffness, before stabilising over time as the subject's performance improves.

This representation allows the experimentally acquired data to be directly correlated with the results of the FEM simulations, providing a coherent basis for the integrated analysis of the system and for the subsequent phase of parametric optimization. The data acquisition system has been implemented and validated at the prototype stage, enabling experimental verification of the correct signal conditioning and the consistency of the acquired measurements with the modelled biomechanical behaviour.

2.3 Parametric optimization using Taguchi and ANOVA

Parameter optimization was carried out using the Taguchi method, which allows for the efficient exploration of multidimensional parameter spaces using orthogonal arrays. An L9 orthogonal array was therefore adopted, enabling the analysis of multiple factors at three levels with a reduced number of experiments compared to a full factorial approach. Five main factors were con-

sidered, including the material parameters (C_{10} , C_{01}), the geometric parameters (thickness t , radius r) and the applied force (F).

Each parameter was discretised into three levels, selected to represent a meaningful range of biomechanical and operational conditions. In order to efficiently explore the parameter space and reduce the number of simulations required, the Taguchi method based on orthogonal arrays, shown in Tab. 1, was adopted.

Table 1. Orthogonal matrix

Experiment	C_{10}	C_{01}	t	r	F
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	2	1	2	3	1
5	2	2	3	1	2
6	2	3	1	2	3
7	3	1	3	2	1
8	3	2	1	3	2
9	3	3	2	1	3

Although the standard L9 orthogonal array is designed for four factors at three levels, it was extended in this work to include a fifth parameter, assuming that higher-order interaction effects are negligible. This assumption is commonly adopted in preliminary optimization studies and allows maintaining computational efficiency without significantly affecting the reliability of the results.

This approach allows the effect of multiple factors at different levels to be analysed using a limited number of experiments, whilst maintaining the statistical significance of the results. To quantitatively assess the influence of each factor on system performance, an analysis of variance (ANOVA) was conducted. This statistical method enables the decomposition of the total variability of the response into contributions associated with each parameter.

In particular, the contribution ratio of the i -th factor was computed as (2)

$$P_i = \frac{SS_i}{SS_{tot}} \cdot 100 \quad (2)$$

where SS_i represents the sum of squares associated with the factor under investigation, and SS_{tot} is the total sum of squares. The integration of the Taguchi method with ANOVA allows not only the identification of the optimal parameter combination, but also a quantitative evaluation of the relative importance of each factor. This combined approach provides a robust outline for parameter optimization, reducing computational cost while maintaining statistical reliability.

The results of the ANOVA analysis, together with the identification of the optimal configuration, are presented and discussed in Section 3.

3 Results and discussion

This section presents and discusses the results obtained from the integration of finite element modelling, a data acquisition system based on deformation gauges, and a parametric optimization methodology based on Taguchi's design of experiments and analysis of variance (ANOVA). The aim is to quantitatively assess the consistency between the numerical model and the experimental data, as well as to demonstrate the effectiveness of the proposed optimization approach in identifying the optimal system configuration.

3.1 Results of FEM simulations

The finite element simulations were carried out using the L9 orthogonal matrix described in Section 2, enabling the influence of the model parameters to be analysed across a limited number of experimental configurations. For each experiment, the main mechanical parameters were extracted, including maximum deformation, equivalent stress and displacement. The simulations revealed a marked dependence of the mechanical response on both material properties and loading conditions. Higher values of the hyperelastic coefficients produced an increase in equivalent stiffness, resulting in a non-linear variation of deformation. Likewise, increasing the applied load generated higher stress

and displacement values, consistently with the expected behaviour of hyperelastic materials. The corresponding FEM simulation results for the different experimental configurations are shown in Fig. 4.

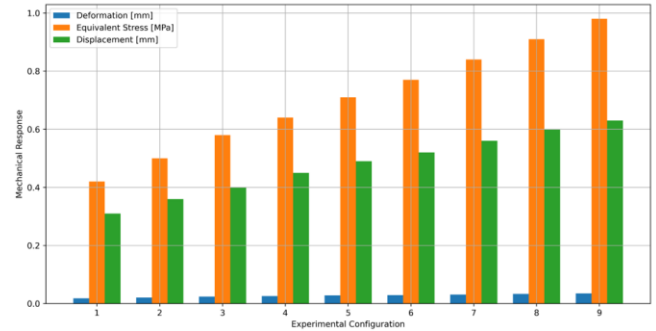


Fig. 4. Results of FEM simulations

The maximum equivalent stress obtained from the simulations was 0.98 MPa, while the maximum displacement reached 0.63 mm under the highest loading condition. The average deformation across the orthogonal matrix experiments was 0.028 mm, with a standard deviation of 0.004 mm. Comparison of deformation, stress and displacement for the different experimental configurations. The column chart illustrates the variation of deformation, stress and displacement across the experimental configurations. Higher parameter levels are associated with increased mechanical response, while the observed dispersion confirms the sensitivity of the model to the selected input parameters.

3.2 Results from the data acquisition system

The deformation gauge-based data acquisition system enabled real-time monitoring of changes in biomechanical parameters during the performance of the rehabilitation exercise. The acquired signals were processed to obtain the relevant parameters, including applied force, equivalent limb stiffness and deformation of the elastic system.

The temporal evolution of the acquired signals was consistent with the expected biomechanical response of the system. Limb stiffness follows a similar comparison across configurations indicating biomechanical adaptation in response to the applied stimulus. The deformation of the elastic system, on the other hand, is initially high and tends to stabilise over time, suggesting an improvement in the mechanical efficiency of the system. The measured force ranged from 0.5 N to 5 N, while the equivalent stiffness increased from approximately 1.0 N/mm to 4.0 N/mm during the rehabilitation sequence. The deformation values remained within the expected biomechanical range, confirming the stability

of the acquisition chain. The simultaneous analysis of force, stiffness and deformation provides useful information regarding the biomechanical adaptation of the system during the rehabilitation task. In particular, the progressive increase in the applied force is associated with a corresponding increase in equivalent stiffness, whilst the deformation tends to stabilise after the initial loading phase.

This behaviour is consistent with the expected response of a mechanically adaptive rehabilitation system and confirms the reliability of the acquired measurements. The temporal evolution of the acquired biomechanical parameters is reported in Fig. 5.

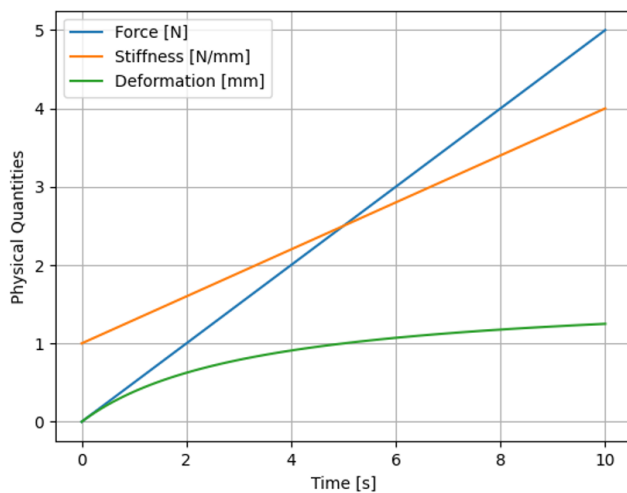


Fig. 5. Temporal evolution of biomechanical parameters

The graph clearly highlights the relationship between the three variables: the simultaneous increase in force and stiffness leads to a relative reduction in deformation, in accordance with the theoretical model adopted. This behaviour represents a direct indicator of rehabilitation progress and provides an experimental basis for the validation of the numerical model.

3.3 Results of the Taguchi-ANOVA optimization

The results obtained from the simulations were analyzed using ANOVA in order to quantify the influence of individual parameters on the system's response. Maximum deformation was selected as the reference variable for the analysis.

The combined application of the Taguchi method and ANOVA analysis made it possible to identify the optimal system configuration, characterized by a reduction in response variability and an improvement in mechanical stability. To provide a concise and integrated representation of the results, a combined graph was produced that relates the percentage contribution of the parameters

obtained via ANOVA analysis to the system's performance in the baseline and optimized configurations.

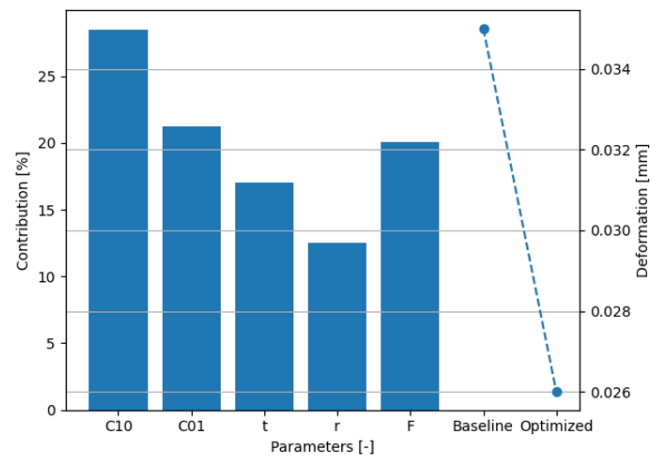


Fig. 6. Percentage contribution of the parameters obtained via ANOVA analysis and comparison between the baseline configuration and the optimized configuration in terms of deformation (mm)

Figure 6 highlights the predominance of material parameters over other factors. This result is consistent with the hyperelastic nature of the model and confirms the importance of correctly identifying constitutive parameters in biomechanical modelling. The ANOVA results indicated that the parameter C_{10} provided the highest contribution to deformation variability (28.5%), followed by C_{01} (21.2%) and the applied force F (20.1%). The optimization procedure reduced the average percentage error between FEM and experimental data from 12.4% to 4.1%. All reported values are expressed as mean values derived from the Taguchi experimental design, with variability assessed through statistical dispersion metrics.

Material parameters, especially C_{10} , play a critical role in influencing the performance of the model. This is attributed to the fact that the differences recorded in the deformations rely heavily on the material parameters. However, when contrasting the baseline and the optimized models, one notices that there is a measurable reduction in the number of deformations. These results confirm that the optimization process is strongly influenced by the relative contribution of the material and loading parameters identified through ANOVA analysis.

3.4 Integrated comparison and discussion

The integration of results obtained through FEM simulation, experimental data acquisition and statistical optimization enables a comprehensive assessment of the behaviour of the proposed system and the effectiveness

of the methodology developed. Finite element modelling provided a physically consistent description of the system's biomechanical response, whilst the data acquisition circuit based on deformation gauges allowed the numerically obtained parameters to be experimentally validated. Finally, the combined application of the Taguchi method and ANOVA analysis made it possible to identify the most influential parameters and reduce the discrepancy between simulation and actual behaviour.

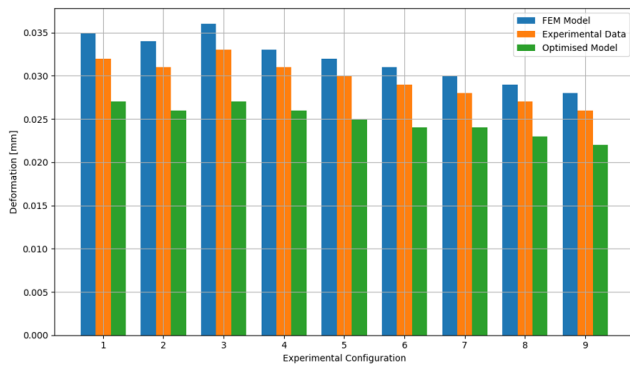


Fig. 7. Comparison between FEM, experimental measurements and the optimized model

The comparative plot is depicted in Fig. 7. It illustrates the comparison of the outcomes of the simulation using the FEM method, experimental results, and optimal results. It is evident that the model's outcomes have been verified by comparing the simulated data and experimental data. Both agree well, demonstrating the suitability of the hyperelastic model chosen and the data collection system used. The optimized configuration exhibits lower deformation values compared to the baseline model, as highlighted by the reduced column magnitudes.

This representation enables a direct comparison between FEM results, experimental measurements and optimized outputs without suggesting a continuous column-based representation between data points.

From a biomechanical perspective, this result suggests that the optimization procedure acts primarily on the parameters influencing the equivalent stiffness of the system, reducing oscillations in the mechanical response and improving the repeatability of the simulations. Furthermore, the closeness between numerical and experimental data demonstrates that the proposed framework is capable of realistically representing the behaviour of the rehabilitation system.

Comparison of the percentage error of the FEM model and the error of the optimized model relative to

experimental measurements. Figure 8 presents a column-based comparison of the percentage error associated with each experimental configuration. The FEM model exhibits limited error variability across configurations, as indicated by the relatively uniform column heights. The use of discrete columns avoids the misinterpretation of the data as a continuous dependency and emphasises the statistical comparison between individual experiments.

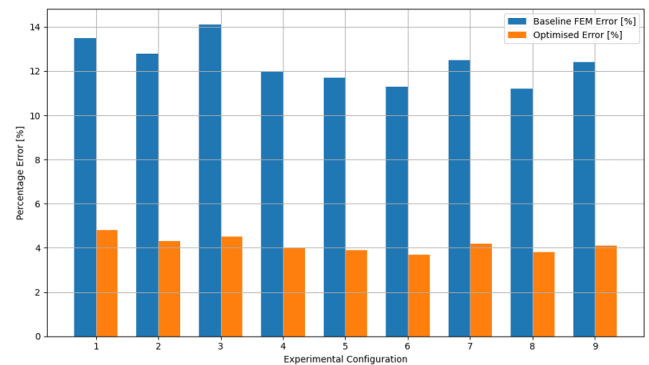


Fig. 8. Error reduction following Taguchi-ANOVA optimization

However, the application of parametric optimization allows for a measurable reduction in error in most of the experiments considered. It is observed that configurations characterised by higher values of the hyperelastic coefficients initially exhibit greater errors, attributable to the model's sensitivity to the material's constitutive parameters. Following optimization, the error dispersion is reduced and the system's behaviour appears more stable. An approximate 67% reduction in modelling error was achieved after optimization, demonstrating the effectiveness of the Taguchi-ANOVA framework in improving the agreement between numerical and experimental results. This confirms that the combination of Taguchi and ANOVA represents an effective tool for selecting optimal parameters in complex biomechanical systems. A joint analysis of Figs. 7 and 8 highlights how the proposed methodology not only improves the performance of the numerical model but also enhances the consistency between simulation and actual experimental behaviour. This aspect represents one of the most innovative elements of this work, since in recent literature FEM, experimental data acquisition and statistical optimization techniques are frequently treated as independent approaches.

In order to quantitatively summarize the improvements obtained after optimization, the main performance indicators of the baseline and optimized configurations are reported in Tab. 2.

Table 2. Performance comparison before and after optimization

Parameter	Baseline model	Optimized model
Average deformation (mm)	0.035	0.026
Average error (%)	12.4	4.1
Standard deviation (mm)	0.006	0.003
Maximum displacement (mm)	0.63	0.51
Response stability	Moderate	High

Quantitative comparison confirms that the optimization procedure improved both the mechanical stability and the agreement between numerical and experimental results, supporting the effectiveness of the proposed Taguchi-ANOVA approach. In this study, however, these three methodologies are integrated within a single methodological framework, enabling the combination of physical interpretability, experimental validation and parametric optimization. This approach overcomes the limitations typically associated with purely numerical or exclusively data-driven models, providing a more robust platform for the analysis of advanced rehabilitation systems. The integration of numerical modelling, sensing electronics, and optimization strategies is increasingly recognised as a key aspect in the development of next-generation intelligent biomedical devices and adaptive rehabilitation systems [55-58].

From an applied perspective, the results obtained demonstrate that optimizing material parameters and loading conditions leads to a more stable mechanical response, reduced system variability and greater simulation reliability. The optimized configuration demonstrated improved mechanical stability and reduced variability, supporting the applicability of the proposed approach in advanced biomechanical rehabilitation scenarios.

4 Conclusions

A statistical optimization framework for FEM-AI rehabilitation systems based on the integration of finite element modelling, experimental signal acquisition and Taguchi-ANOVA analysis has been presented. The proposed methodology was developed to address one of the main limitations of current hybrid rehabilitation systems, namely the absence of a structured and quantitatively validated optimization strategy for the selection of model parameters and operating conditions. The finite element simulations enabled the analysis of the biomechanical response of the system under different

loading and material configurations, providing a physically interpretable representation of tissue behaviour. The implementation of the real acquisition system incorporating deformation gauge sensors provided an opportunity for validating the numerical model and observing the biomechanical quantities during physical rehabilitation exercises. The analysis showed that there is good correlation between the data obtained from simulations and experiments, proving the validity of the chosen modelling technique. The application of the Taguchi design of experiment method made it possible to considerably reduce the computational cost of exploring the multidimensional parametric space, without decreasing the statistical accuracy of the findings. Besides, the ANOVA analysis helped determine which factors have the greatest impact on the system's response, revealing that hyperelastic material properties play a pivotal role in defining its mechanical properties and stability. The joint analysis proved that the optimization technique helps reduce the difference between FEM calculations and actual values, increasing the stability and accuracy of biomechanical responses. Specifically, the optimal model shows less deformation dispersion and lower percentage error compared to the initial one. Another major strength of this research is the holistic incorporation of numerical simulation, experimental validation and statistical optimization into a single framework. In contrast with many other similar studies, in which finite element methods, sensor systems and optimization algorithms were used separately, the developed framework merges these approaches to achieve a more robust and physically consistent model for rehabilitation purposes. The future research will include the extension of this approach to more complicated anatomical structures as well as the exploration of new optimization algorithms based on machine learning and artificial intelligence. Another important aspect that future studies will take into account is the analysis of larger datasets of experimental results and patients' specific conditions.

References

- [1] A. Calderone, Andrea, et al. "Towards transforming neuro-rehabilitation: the impact of artificial intelligence on diagnosis and treatment of neurological disorders." *Biomedicines*, vol. 12, no. 10 pp. 2415, 2024.
- [2] J.S.W. Ho, et al. "The effectiveness of robotic-assisted upper limb rehabilitation to improve upper limb function in patients with cervical spinal cord injuries: a systematic literature review." *Frontiers in Neurology*, vol.14, pp. 1126755, 2023.
- [3] M.L. Huckabee, R. Flynn, and M. Mills. "Expanding Rehabilitation Options for Dysphagia: Skill-Based Swallowing Training: M.-L. Huckabee et al.: Skill-Based Swallowing Rehabilitation." *Dysphagia*, vol. 38, no.3, pp. 756-767, 2023.
- [4] F. Laganà, et al. "FEM-based modelling and AI-enhanced monitoring system for upper limb rehabilitation." *Electronics*, vol. 14, no.11, pp. 2268, 2025.
<https://doi.org/10.3390/electronics14112268>.

- [5] M. Bonanno, et al. "Assistive technologies for individuals with a disability from a neurological condition: A narrative review on the multimodal integration." *Healthcare*, vol. 13, no. 13, pp. 1580, 2025.
- [6] R. Lloréns, et al. "Tracking systems for virtual rehabilitation: Objective performance vs. subjective experience. A practical scenario." *Sensors*, vol. 15, no.3, pp. 6586-6606, 2015.
- [7] Y. Zhou, et al. "Machine learning-based computer vision for depth camera-based physiotherapy movement assessment: A systematic review." *Sensors*, vol. 25, no. 5, pp. 1586, 2025.
- [8] M. Menniti, et al. "Portable Non-Invasive Ventilator for Homecare and Patients Monitoring System," *IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Jeju, Korea, pp. 1-5, 2023. <https://doi.org/10.1109/MeMeA57477.2023.10171872>.
- [9] S. A. Pullano, et al. "Design of an electronic interface for single-photon avalanche diodes." *Sensors*, vol. 24, no.17, pp. 5568, 2024. <https://doi.org/10.3390/s24175568>.
- [10] F. Laganà, et al. "Air-Coupled Ultrasound Systems for Biomedical Applications: Advances in Sensors, Electronic Interfaces and Signal Processing Strategies." *Sensors*, vol. 26, no .5, pp. 1692, 2026. <https://doi.org/10.3390/s26051692>.
- [11] C. Wang, et al. "Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform." *Bioelectronic Medicine*, vol. 9, no. 1, vol. 17, 2023.
- [12] Z. Fang, et al. "A Review of Emerging Electromagnetic-Acoustic Sensing Techniques for Healthcare Monitoring," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 16, no. 6, pp. 1075-1094, Dec. 2022,
- [13] S.A. Pullano, C.D. Critello, A.S. Fiorillo. "Triboelectric-induced Pseudo-ICG for cardiovascular risk assessment on flexible electronics". *Nano Energy*, vol. 67, pp. 104278, 2020.
- [14] S.A. Pullano, V.D. Kota, K. Kakaraparty, A.S. Fiorillo, I. Mahbub. "Optically Unobtrusive Zeolite-Based Dry Electrodes for Wearable ECG Monitoring". *IEEE Sensors Journal*, 22, no. 11, pp. 10630–10639, 2022.
- [15] M.L. Coluccio, S.A. Pullano, M.F.M Vismara, N. Coppedè, G. Perozziello, P. Candeloro, F. Gentile, N. Malara. "Emerging designs of electronic devices in biomedicine". *Micromachines*, vol. 11, no 2, 2020.
- [16] F. Laganà. "Design and Simulation-Based Validation of an Embedded Acquisition Architecture for In Situ PCB Integrity Monitoring in Biomedical Devices." *Electronics*, vol. 15, no .4, pp. 833, 2026. <https://doi.org/10.3390/electronics15040833>.
- [17] S. Wei, and Z. Wu. "The application of wearable sensors and machine learning algorithms in rehabilitation training: a systematic review." *Sensors*, vol. 23, no. 18, pp. 7667, 2023.
- [18] L. Manin, et al. "Application of FTIR and PCA-LR metabolites recognition for bergamot essential oil authentication." *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 352, no. 5, pp. 127561, 2026. <https://doi.org/10.1016/j.saa.2026.127561>
- [19] E. Barbierato, and A. Gatti. "The challenges of machine learning: A critical review." *Electronics*, vol. 13, no.2, pp. 416, 2024.
- [20] D. Qiu, and D. Weiss. "Local mechanical characterization of cardiovascular tissues: methods, challenges, and pathways to clinical use." *Frontiers in Mechanical Engineering*, vol. 11, pp. 1703081, 2025.
- [21] F. Laganà, et al. "Computational model of cell deformation under fluid flow based rolling." *2019 E-Health and Bioengineering Conference (EHB)*. Iasi, Romania, 2019, pp. 1-4. <https://doi.org/10.1109/EHB47216.2019.8970065>.
- [22] S. Schoenborn, S. Pirola, M. A. Woodruff and M. C. Allenby, "Fluid-Structure Interaction Within Models of Patient-Specific Arteries: Computational Simulations and Experimental Validations," in *IEEE Reviews in Biomedical Engineering*, vol. 17, pp. 280-296, 2024
- [23] S.A. Pullano, C.D. Critello, M.G. Bianco, M. Menniti, A.S. Fiorillo. "PVDF Ultrasonic Sensors for In-Air Applications: A Review". *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 68, no. 7, pp. 2324–2335, 2021
- [24] A.S. Fiorillo, S.A. Pullano, M.G. Bianco, C.D. Critello. "Bioinspired US sensor for broadband applications". *Sensors and Actuators A: Physical*, vol. 294, pp. 148–153, 2019.
- [25] A.S. Fiorillo, S.A. Pullano, C.D. Critello. "Spiral-Shaped Biologically-Inspired Ultrasonic Sensor". *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 67, no. 3, pp. 635 – 642, 2020.
- [26] A.S. Fiorillo, S.A. Pullano, M.G. Bianco, C.D. Critello. "Ultrasonic transducers shaped in archimedean and fibonacci spiral: A comparison". *Sensors*, vol. 20, no. 10, 2020.
- [27] H.B. Khaniki, et al. "A review on the nonlinear dynamics of hyperelastic structures." *Nonlinear Dynamics*, vol. 110, no. 2, pp. 963-994, 2022.
- [28] J.M. Northrup, et al. "Conceptual and methodological advances in habitat-selection modeling: guidelines for ecology and evolution." *Ecological Applications*, vol. 32, no.1, pp. e02470, 2022.
- [29] F. Laganà, et al. "System-Level Optimization of Electrode Excitation Strategies in 3D Electrical Impedance Tomography." *Electronics*, vol. 15, no. 6, pp. 1159, 2026. <https://doi.org/10.3390/electronics15061159>.
- [30] M. Bursch, et al. "Best-practice DFT protocols for basic molecular computational chemistry." *Angewandte Chemie*, vol. 134, no. 42, pp. e202205735, 2022.
- [31] R. Phellan, et al. "Real-time biomechanics using the finite element method and machine learning: Review and perspective." *Medical Physics*, vol. 48, no.1, pp. 7-18, 2021.
- [32] J. Yu, et al. "A review of the use of finite element simulation and machine learning techniques in the morphological analysis of breast tissue." *Computer Methods in Biomechanics and Biomedical Engineering*, pp. 1-20, 2026.
- [33] D. Nath, et al. "Application of Machine Learning and Deep Learning in Finite Element Analysis: A Comprehensive Review: D. Nath et al." *Archives of computational methods in engineering*, vol. 31, no.5 pp. 2945-2984, 2024.
- [34] A. Serani, and M. Diez. "A survey on design-space dimensionality reduction methods for shape optimization." *Archives of Computational Methods in Engineering*, vol. 33, pp. 1671–1698, 2025.
- [35] R. Priyadarshi, and R. R. Kumar. "Evolution of swarm intelligence: a systematic review of particle swarm and ant colony optimization approaches in modern research." *Archives of Computational Methods in Engineering*, vol. 32, no. 6, pp.3609-3650, 2025.
- [36] F. Laganà, et al. "Optimized analytical-numerical procedure for ultrasonic sludge treatment for agricultural use." *Algorithms*, vol. 17, no.12, pp. 592, 2024. <https://doi.org/10.3390/a17120592>
- [37] V. Roquemen-Echeverri, and C. Mosquera-Lopez. "Recent advancements and applications of physics-informed machine learning in biomedical research." *Current Opinion in Biomedical Engineering*, vol. 35, pp. 100612, 2025.
- [38] C. Meng, et al. "When physics meets machine learning: A survey of physics-informed machine learning." *Machine Learning for Computational Science and Engineering*, vol. 1, no .1, pp. 20, 2025.
- [39] A. Rahdar, et al. "Hybrid physics-informed machine learning and nanobiosensing strategies for precision liver cancer diagnostics." *Computational Biology and Chemistry*, pp. 109025, 2026.
- [40] I. N. Weeraratna, et al. "Engineering with biomedical sciences changing the horizon of healthcare-a review." *Bioengineered*, vol. 15, no. 1, pp. 2401269, 2024.
- [41] F. Laganà, et al. "Hybrid AI-Taguchi-ANOVA Approach for Thermographic Monitoring of Electronic Devices." *Eng*, vol. 7, no .1, pp. 28, 2026. <https://doi.org/10.3390/eng7010028>.

- [42] W.H. Chen, et al. "A comprehensive review of thermoelectric generation optimization by statistical approach: Taguchi method, analysis of variance (ANOVA), and response surface methodology (RSM)." *Renewable and Sustainable Energy Reviews*, vol. 169, pp. 112917, 2022.
- [43] M. W. Hisam, et al. "The versatility of the Taguchi method: Optimizing experiments across diverse disciplines." *Journal of Statistical Theory and Applications*, vol. 23, no. 4, pp. 365-389, 2024.
- [44] Q. Xu, et al. "Interpretability of clinical decision support systems based on artificial intelligence from technological and medical perspective: a systematic review." *Journal of healthcare engineering*, vol. 2023.1, pp. 9919269, 2023.
- [45] M. Ennab, and H. Mcheick. "Enhancing interpretability and accuracy of AI models in healthcare: a comprehensive review on challenges and future directions." *Frontiers in Robotics and AI*, vol. 11, pp. 1444763, 2024.
- [46] C. Shen, et al. "Differentiable modelling to unify machine learning and physical models for geosciences." *Nature Reviews Earth & Environment*, vol. 4, no.8, pp. 552-567, 2023.
- [47] K. Xu, et al. "Data-Driven materials research and development for functional coatings." *Advanced Science*, vol. 11, no. 42, pp. 2405262, 2024.
- [48] X. Yang, et al. "Segmentation and Classification of Lung Cancer Images Using Deep Learning." *Applied Sciences*, vol. 16, no. 2, pp. 628, 2026.
- [49] O.I. Owolabi, et al. "FEM and ANN approaches to wind turbine gearbox monitoring and diagnosis: a mini review." *Journal of Reliable Intelligent Environments*, vol. 9, no.4, pp. 399-419, 2023.
- [50] M. Agarwal, et al. "Multiscale computational and artificial intelligence models of linear and nonlinear composites: a review." *Small Science*, vol.4, no.5, pp. 2300185, 2024.
- [51] S.N.S.H. Chittajallu, et al. "A review on damage and rupture modelling for soft tissues." *Bioengineering*, vol. 9, no.1, pp. 26, 2026.
- [52] H. Wang, C. Britton, F. Quaiyum, S.A. Pullano, L. Taylor, A.S. Fiorillo, S.K. Islam. "A Charge Sensitive Pre-Amplifier for Smart Point-of-Care Devices Employing Polymer-Based Lab-on-a-Chip". *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 65, no. 8, pp. 984 – 988, 2018.
- [53] U. Mohammad, et al. "A Comprehensive Analytical Approach to Introspect Efficient Miniaturized Circuit-Level Designs for Biomedical Signal Acquisition: A Tutorial Brief." *IEEE Sensors Journal*, vol. 26, no. 5, pp. 6567-6578, 2026.
- [54] D. De Carlo, et al. "Development of an Integrated System for Remote Monitoring of Circuit Integrity in Biomedical Devices," *In E-Health and Bioengineering Conference (EHB)*, IASI, Romania, 2024, pp. 1-6, <https://doi.org/10.1109/EHB64556.2024.10805740>
- [55] C. Wang, et al. "Artificial intelligence enhanced sensors-enabling technologies to next-generation healthcare and biomedical platform." *Bioelectronic Medicine*, vol. 9, no.1, pp. 17, 2023.
- [56] M. R. Marinescu, et al. "Next-Gen Healthcare Devices: Evolution of MEMS and BioMEMS in the Era of the Internet of Bodies for Personalized Medicine." *Micromachines*, vol. 16, no.10, pp. 1182, 2025.
- [57] H. Ponnambalath Mohanadas, et al. "Artificial intelligence applications in medical devices for personalized health care solutions: systematic review." *Journal of Medical Internet Research*, vol. 28, pp. e72410, 2026.
- [58] X. Guo, et al. "Advances in Intelligent Nano-Micro-Scale Sensors and Actuators: Moving Toward Self-Sustained Edge AI Microsystems." *Advanced Materials*, vol. 37, no.50, pp. e10417, 2025.

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