Semarak Engineering Journal

Journal homepage:
https://semarakilmu.my/index.php/sej/index
ISSN: 3036-0145

Finite Element Model Updating of a Soft Pneumatic Gripper Using Genetic Algorithm and Abaqus-Based Hyperelastic Calibration

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ARTICLE INFO

Article history:
Received 12 February 2026
Received in revised form 21 March 2026
Accepted 17 April 2026
Available online 12 May 2026

Keywords:
Genetic Algorithm; FEMU; Abaqus; Hyperelastic Calibration; Soft Gripper; Mooney–Rivlin; Optimization; Python Automation

ABSTRACT

This study presents a finite element model updating (FEMU) framework for the calibration of hyperelastic material parameters of a soft pneumatic gripper using a genetic algorithm integrated with Abaqus finite element analysis and Python scripting. The proposed framework was developed to reduce the displacement error between experimental and simulation responses through an automated optimization process. The optimization focuses on the calibration of the Mooney–Rivlin hyperelastic constants C_{10} and C_{01} under pneumatic loading conditions. Experimental displacement values at Node 4401 and Node 5848 were used as target responses during the optimization process. The developed Python workflow automatically updates material parameters, submits Abaqus jobs, extracts displacement responses from the output database, evaluates root mean square (RMS) error, and generates convergence plots and optimization figures. The optimization process reduced the RMS displacement error by approximately 72.4% compared to the initial simulation model. The optimized hyperelastic constants were identified as $C_{10} = 0.214$ and $C_{01} = 0.083$, producing significantly improved agreement between experimental and simulation responses at both monitoring nodes.

1. Introduction

Soft robotic grippers have attracted significant attention in recent years because of their capability to handle fragile and deformable objects safely [1]. Compared to conventional rigid grippers, soft grippers provide higher flexibility, adaptability, and safer interaction with delicate

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https://doi.org/10.37934/sej.14.1.175185

objects during grasping operations [2]. Pneumatic soft grippers are widely used in food handling, biomedical devices, flexible manufacturing systems, and agricultural harvesting because the soft deformable structure allows the gripper surface to conform naturally to irregular object geometries [3]. The increasing demand for flexible automation systems has further accelerated the development of soft robotic technologies for industrial and biomedical applications [4].

The development of soft robotic systems is strongly associated with the advancement of hyperelastic materials and flexible actuator technologies [5]. Silicone-based soft actuators are commonly used because they exhibit large deformation capability, flexibility, and stable elastic response under repeated loading conditions [6]. Several researchers have investigated different actuator configurations to improve deformation efficiency and grasping performance. A pneumatic soft gripper driven by a combination of soft fingers and bellows actuators was developed to improve flexible grasping performance under pneumatic loading conditions [7]. Enhanced object adaptation capability and improved grasping reliability were also reported for soft robotic grippers with deformable finger structures [8].

In agricultural applications, soft robotic systems have demonstrated the capability to reduce damage during harvesting and handling processes [9]. A soft gripper with force feedback and fruit slip detection capability was developed for apple harvesting applications and demonstrated improved adaptability for delicate object handling [10]. Soft grippers have also been applied in food packaging systems where deformation flexibility improves gripping stability and reduces product damage during handling operations [11]. In biomedical applications, soft pneumatic gloves and flexible rehabilitation systems have also been developed to improve human–robot interaction safety and motion flexibility [12].

The mechanical performance of soft robotic actuators strongly depends on nonlinear material deformation behavior [13]. Therefore, accurate characterization and calibration of hyperelastic material properties are important to ensure that finite element simulation results can accurately represent the actual deformation response of the soft actuator [14]. Hyperelastic material models such as Neo-Hookean, Ogden, and Mooney–Rivlin models are commonly used to represent silicone-based material behavior under large deformation conditions [15]. Among these models, the Mooney–Rivlin model is widely applied because it provides stable nonlinear deformation prediction with relatively low computational complexity [16].

Finite element analysis (FEA) has become an important numerical tool in soft robotics research because it can simulate nonlinear deformation, hyperelastic material behavior, and large strain response under pneumatic loading conditions [17]. Abaqus finite element software is commonly used for soft robotic simulations because of its capability to perform nonlinear structural analysis involving contact interaction and hyperelastic materials [18]. Dynamic finite element modeling techniques have also been introduced to improve the prediction accuracy of soft robotic actuator deformation behavior [19].

Several studies have demonstrated that finite element analysis can successfully predict deformation response and bending behavior of soft robotic structures [20]. Simulation-driven optimization frameworks have also been introduced to improve soft gripper design efficiency and structural performance [21]. Geometry optimization and material optimization methods have been applied to improve the grasping capability and flexibility of soft pneumatic grippers [22]. However, most hyperelastic parameter calibration procedures are still performed manually using repeated trial-and-error simulation approaches [23-27]. Such procedures require significant computational time and repeated simulation iterations before suitable material parameters can be identified [24]. Conventional hyperelastic calibration procedures commonly rely on repeated manual adjustment of material constants followed by iterative finite element simulation until acceptable agreement between experimental and numerical responses is achieved. Such approaches are highly dependent on user experience and typically require substantial computational time due to repeated manual intervention. In contrast, the proposed GA-FEMU framework automates the entire calibration procedure including material updating, Abaqus job execution, displacement extraction, and optimization evaluation. The automated workflow significantly reduces repetitive manual processes while improving optimization repeatability and convergence consistency. Furthermore, the global search capability of the genetic algorithm reduces the possibility of convergence toward local optimum solutions compared to conventional gradient-based or manual trial-and-error approaches.

Optimization algorithms have been widely used to improve engineering parameter identification and structural optimization processes. Among various optimization techniques, genetic algorithms are widely applied because of their strong global search capability and robustness in solving nonlinear optimization problems. Genetic algorithms are particularly suitable for nonlinear material calibration because the optimization process does not require gradient information and can avoid local optimum solutions during the search process. Structural optimization using genetic algorithms has demonstrated stable convergence behavior and effective parameter identification capability in nonlinear optimization studies.

The integration of finite element model updating (FEMU) techniques with optimization algorithms has further improved numerical calibration capability in engineering simulations [29]. FEMU approaches are commonly used to minimize the difference between experimental responses and numerical simulation predictions through parameter updating procedures [29-30]. In soft robotics applications, FEMU methods can improve the prediction accuracy of hyperelastic deformation behavior and reduce the dependency on manual parameter tuning.

A soft pneumatic gripper with bellows actuator configuration was previously developed and evaluated experimentally and numerically using Abaqus finite element simulation. The study demonstrated that finite element simulation can successfully predict the bending deformation behavior of the soft actuator under pneumatic loading conditions. However, the hyperelastic parameter calibration process still required manual tuning and repeated simulation trials before acceptable agreement between experiment and simulation could be achieved.

Therefore, this study proposes a Python-based genetic algorithm finite element model updating (GA-FEMU) framework for hyperelastic material calibration of a soft pneumatic gripper. The proposed methodology integrates Abaqus finite element analysis, automated Python scripting, and genetic algorithm optimization to minimize the displacement error between experimental and simulation responses. The developed framework automates the entire calibration process including material updating, Abaqus simulation execution, displacement extraction, RMS error evaluation, convergence monitoring, and optimization visualization. The proposed methodology is expected to improve calibration efficiency while reducing manual computational effort for nonlinear hyperelastic material identification.

The novelty of the proposed framework lies in the integration of automated Abaqus finite element model updating (FEMU), Python-based data extraction, and genetic algorithm optimization into a single computational workflow specifically developed for soft pneumatic actuator calibration. Unlike conventional manual trial-and-error calibration methods, the proposed framework automatically updates hyperelastic material constants, executes Abaqus simulations, extracts displacement responses from selected monitoring nodes, evaluates RMS error, and generates optimization convergence data without manual intervention.

2. Methodology

2.1 Experimental Setup and Deformation Testing

The soft actuator was fabricated using silicone-based hyperelastic material to produce bending deformation under pneumatic pressure loading conditions. The experimental testing was conducted to obtain the deformation response of the soft gripper which was later used as target data during the finite element model updating process.

The experimental setup consisted of an air compressor, pressure regulator, pneumatic tubing system, and displacement observation setup. Controlled pneumatic pressure was supplied gradually into the internal chamber of the soft actuator to generate bending deformation. The deformation response was observed and recorded throughout the loading process.

The process begins with mold preparation followed by silicone mixing and casting. After the curing process, the actuator was removed from the mold and assembled with pneumatic tubing for deformation testing. The bellows geometry was designed to improve flexibility and bending capability during pneumatic loading. The soft actuator was fabricated using silicone elastomer material through a mold casting process. Pneumatic pressure was supplied using an air compressor connected to a pressure regulator with gradual pressure increment capability. The displacement response of the soft actuator was recorded during deformation testing using visual measurement and reference markers placed near the actuator surface.

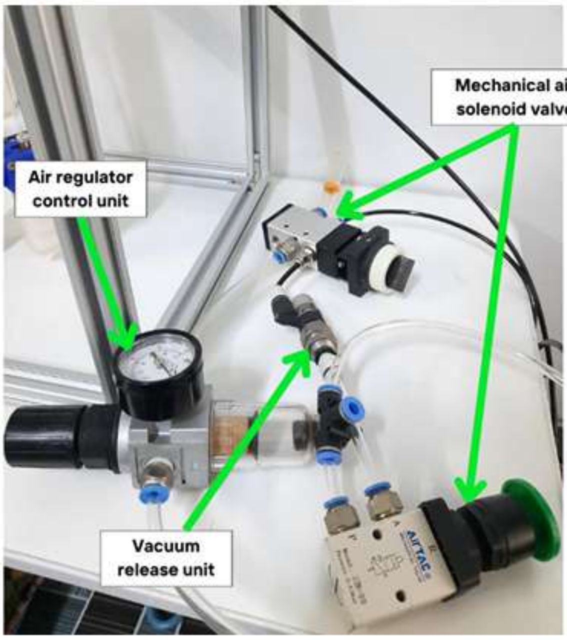
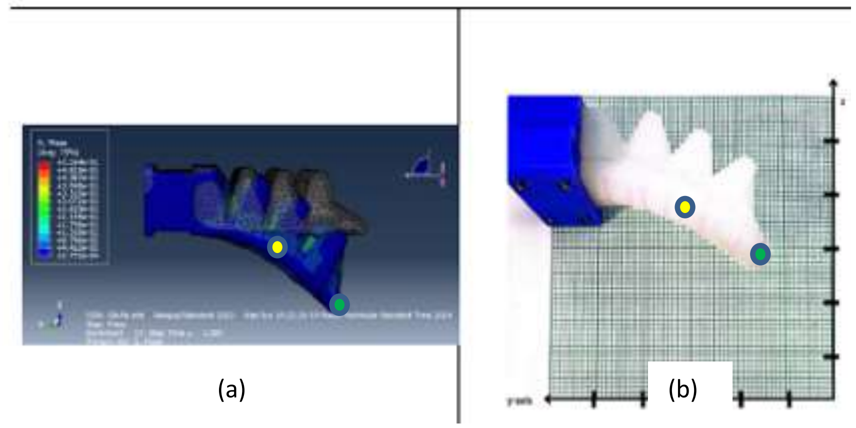


Fig. 1. Experimental setup of the soft pneumatic gripper under pneumatic pressure loading condition

The experimental deformation testing procedure is summarized in Figure 1 and Figure 2. The pressure loading was applied gradually to evaluate the deformation response of the soft finger structure. The displacement responses were measured at selected locations of the actuator and later used as target responses during the optimization process.



(a) (b)

Fig. 2. (a) Simulation displacement at referred points (b) experiment

The experimental procedure begins with the preparation of the pneumatic loading system followed by pressure regulation adjustment. After the soft actuator was connected to the pneumatic system, controlled air pressure was supplied into the actuator chamber. The deformation response generated during pneumatic loading was recorded for displacement evaluation.

The experimental target displacement values used during the calibration process are summarized in Table 1.

Table 1
Experimental displacement responses used during optimization process

Parameter	**Value**
Pressure Loading	0.03 MPa
Target Node 1	Node 4401 🟢
U3 Displacement at Node 4401	-58 mm
Target Node 2	Node 5848 🟡
U3 Displacement at Node 5848	-19 mm

The experimental displacement values shown in Table 1 were later compared directly with the finite element simulation results during the optimization process.

2.2 Finite Element Modeling and Simulation Procedure

The finite element model of the soft pneumatic gripper was developed using Abaqus CAE based on the actual geometry dimensions of the fabricated actuator. The simulation procedure was designed to reproduce the experimental loading condition and deformation response as accurately as possible. The overall finite element simulation workflow developed in Abaqus CAE is shown in Figure 3 below. The modelling procedure begins with geometry development followed by hyperelastic material definition, mesh generation, application of boundary conditions, pressure loading, and displacement extraction.

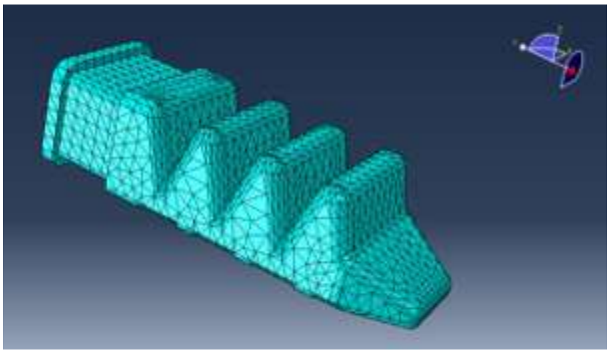


Fig. 3. Finite element model and mesh configuration of the soft pneumatic gripper developed in Abaqus CAE

The geometry of the soft actuator was modeled directly in Abaqus CAE using the actual dimensions of the fabricated soft finger. The internal chamber and bellows geometry were included in the model to reproduce the pneumatic deformation behavior observed experimentally. The hyperelastic material behavior of the silicone actuator was defined using the Mooney–Rivlin material model because the model is widely used for nonlinear rubber-like materials involving large deformation conditions [23]. The material constants used during the optimization process were: C_{10} and C_{01}. The finite element model developed in Abaqus CAE is shown in Figure 3. The model includes the soft actuator geometry, internal pneumatic chamber, and mesh configuration used during the nonlinear simulation process.

Hybrid tetrahedral elements were used because they are suitable for nonlinear hyperelastic analysis involving nearly incompressible materials. The use of hybrid elements improves numerical stability during large deformation simulation of silicone materials. The simulation type used in this study was static general nonlinear analysis. The static analysis approach was selected because the deformation behavior of the soft actuator occurred gradually under controlled pneumatic pressure loading conditions. The nonlinear geometry option (NLGEOM = ON) was activated to account for large deformation effects during bending deformation. The boundary condition configuration used during the simulation process. One end of the soft actuator was fixed to prevent rigid body motion while pneumatic pressure loading was applied to the internal chamber surface.

Hybrid tetrahedral elements were used because they are suitable for nonlinear hyperelastic analysis involving nearly incompressible. The displacement responses were extracted at Node 4401 and Node 5848 because these locations represented important deformation regions of the soft actuator during bending motion. Node 4401 was selected near the tip deformation region while Node 5848 was selected near the middle deformation region to capture both global and local deformation responses. Node 4401 and Node 5848 were selected because these locations represent two critical deformation regions of the soft actuator, namely the tip deformation region and the middle bending region. The selected nodes were chosen to capture both global bending deformation and local deformation behavior simultaneously. The pressure loading applied during the simulation process was: 0.01 MPa. The displacement responses extracted from the Abaqus output database (.odb) were compared directly with the experimental displacement results during the optimization process. The root mean square (RMS) error used during the optimization process is expressed as:

$$RMS_{error} = \left(\frac{1}{n}\sum_{i=1}^{n}\left(U_{exp,i} - U_{sim,i}\right)^{2}\right)^{\frac{1}{2}} \quad (1)$$

where: $U_{exp,i}$ represents the experimental displacement response, $U_{sim,i}$ represents the simulated displacement response, and n represents the total number of displacement data points used during the calibration process. The search boundaries used for the hyperelastic material constants are summarized in Table 2 below.

Table 2
Hyperelastic material search boundaries used during optimization process

Parameter	**Minimum**	**Maximum**
C_{10}	0.01	0.5
C_{01}	0	0.5

2.3 Genetic Algorithm Optimization Procedure

The optimization framework was developed using Abaqus Python scripting integrated with a genetic algorithm optimization process. The objective of the optimization process was to minimize the displacement error between experimental and simulation responses by updating the hyperelastic material constants automatically. The overall genetic algorithm optimization workflow developed in this study is shown in Figure 4 below.

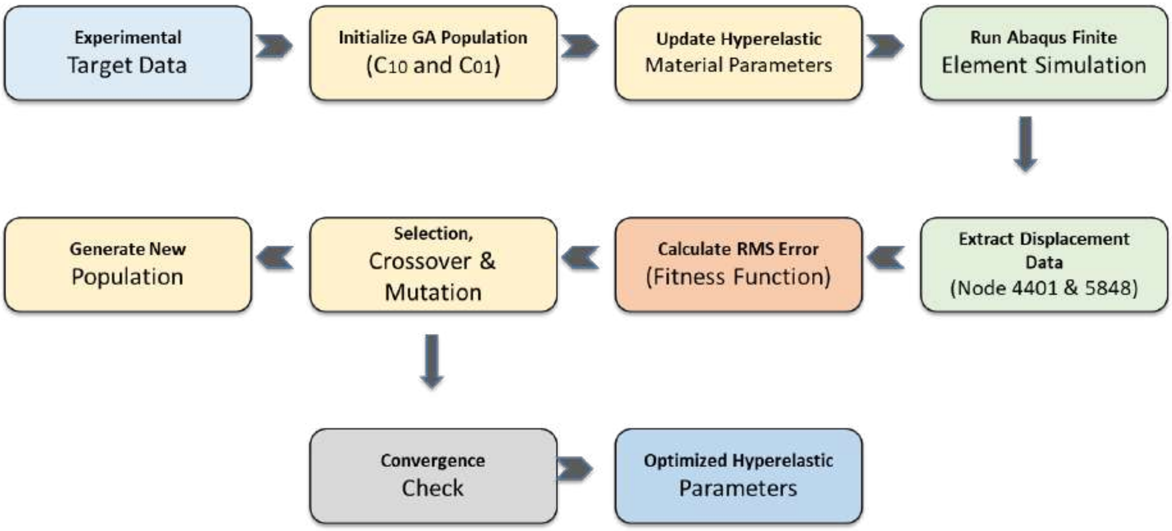


Fig. 4. Flow chart of the genetic algorithm optimization framework integrated with Abaqus simulation

The optimization process begins with random population initialization where each candidate solution consists of a combination of hyperelastic constants C_{10} and C_{01}. The generated candidate solutions were automatically assigned to the Abaqus finite element model using Python scripting. The Abaqus simulation was subsequently executed automatically for each candidate solution. After the simulation process was completed, the displacement responses at Node 4401 and Node 5848 were extracted automatically from the Abaqus output database. The extracted displacement values were compared directly with the experimental displacement responses. The RMS error used as the fitness function during the optimization process is expressed as:

$$\text{RMS Error} = \sqrt{\frac{1}{2}\left[\left(U3_{4401}^{\text{sim}} - U3_{4401}^{\text{exp}}\right)^2 + \left(U3\,\frac{\text{sim}}{5848} - U3_{5848}^{\text{exp}}\right)^2\right]} \tag{2}$$

where: $U3^{\text{sim}}$ represents the simulated displacement response, and $U3^{\text{exp}}$ represents the experimental displacement response. Candidate solutions with lower RMS error values were considered as fitter individuals during the optimization process. Tournament selection was implemented to select suitable parent candidates for reproduction. Arithmetic crossover was subsequently used to generate new offspring solutions by combining the hyperelastic constants of two parent solutions. Mutation was introduced to improve global search capability and avoid premature convergence during the optimization process. The optimization process was repeated continuously until the maximum generation number or convergence condition was achieved. The genetic algorithm parameters used in this study are summarized in Table 3 below.

Table 3
Genetic algorithm parameters used during optimization process

Parameter	**Value**
Population Size	30
Number of Generations	20
Elitism	2
Crossover Probability	0.8
Mutation Probability	0.2
Number of CPUs	4
Number of Domains	4
Memory Allocation	60%

3. Results and Discussion

The optimization results demonstrate that the proposed GA-FEMU framework successfully improves the agreement between experimental and finite element simulation responses. Figure 5(a) presents the convergence behavior of the genetic algorithm optimization process. The RMS error decreases progressively throughout the generations, indicating that the optimization process successfully improves the displacement agreement between experiment and simulation. Figure 5(b) illustrates the evolution of the optimized hyperelastic constants C_{10} and C_{01}. Large parameter variation is observed during the early generations because the initial population is generated randomly within the predefined search boundaries. As the optimization progresses, both hyperelastic constants gradually stabilize. Figure 5(c) presents the C_{10}–C_{01} error landscape generated from all evaluated candidate solutions. The low-error region represents combinations of hyperelastic constants that produce better agreement between experimental and simulation responses. Figure 6(a) and Figure 6(b) show the displacement response at Node 4401 and Node 5848 respectively. The optimized simulation model produces displacement behavior closer to the experimental response compared to the initial simulation model. Figure 6(c) compares the final displacement values between experiment, initial simulation, and updated simulation. The optimized model demonstrates lower displacement deviation from the experimental data. Figure 6(d) presents the absolute displacement error before and after calibration. The optimized simulation model significantly reduces the displacement error at both monitoring nodes.

The improved calibration accuracy achieved through the proposed framework is important for soft robotic design applications because accurate hyperelastic material representation directly affects deformation prediction, actuator bending behavior, and grasping performance evaluation. Improved finite element prediction capability may reduce physical prototyping requirements during soft actuator development and improve the reliability of simulation-driven design optimization processes. The framework may also support future soft robotic applications involving adaptive gripping systems, biomedical devices, rehabilitation systems, and agricultural harvesting systems where accurate deformation prediction is essential.

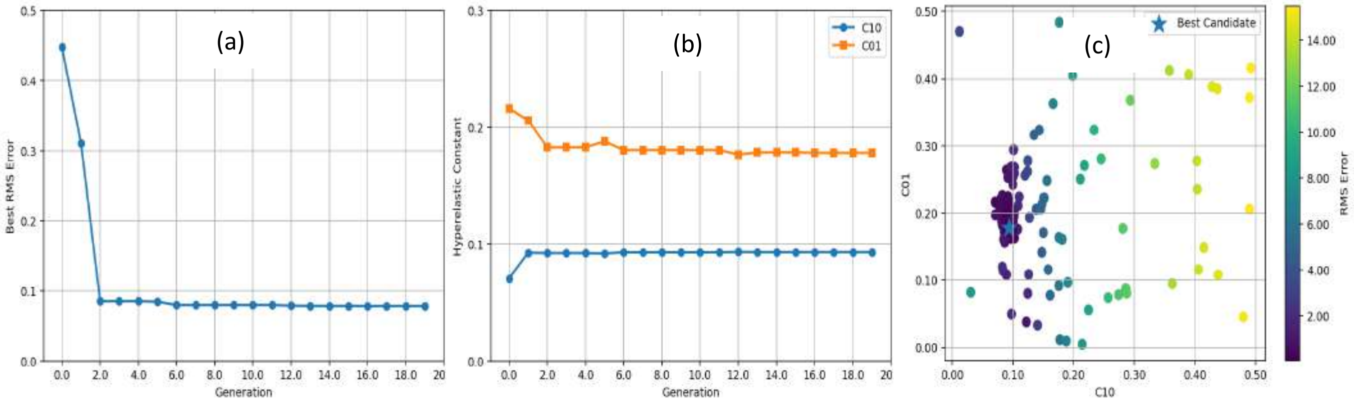


Fig. 5 (a). Best RMS error convergence throughout generations, (b). Evolution of optimized C_{10} and C_{01} ,(c). C_{10}–C_{01} error landscape

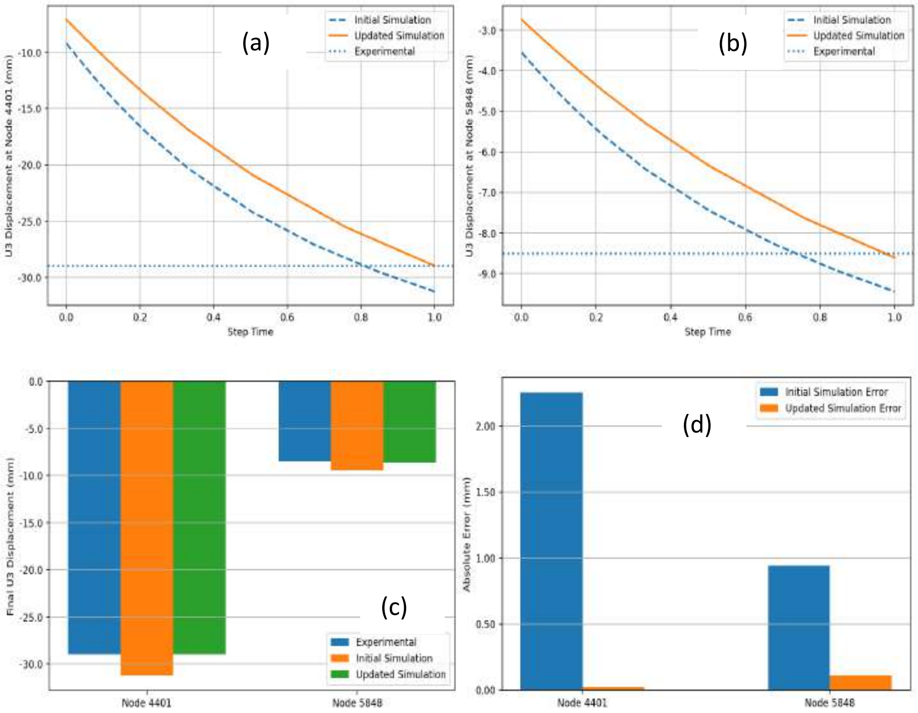


Fig. 6 (a). U3 displacement response at Node 4401, (b). U3 displacement response at Node 5848, (c). Final displacement comparison, (d). Absolute displacement error comparison

Several limitations of the present study should be acknowledged. First, the optimization process required repeated nonlinear finite element simulations, resulting in relatively high computational cost during large population evaluations. Second, the optimization performance may be influenced by the selected genetic algorithm parameters such as population size, mutation probability, and crossover probability. Furthermore, the present framework considered only static pressure loading conditions and did not include dynamic deformation effects, viscoelastic material behavior, or contact interaction during gripping applications. These limitations will be addressed in future studies through multi-point deformation tracking, multi-pressure calibration, and surrogate-assisted optimization methods.

Future work will focus on extending the framework toward multi-pressure and multi-objective optimization to improve parameter robustness under varying loading conditions. Additional deformation monitoring nodes and image-based deformation tracking methods may also be incorporated to improve full-field calibration accuracy. Furthermore, surrogate-assisted optimization and machine learning-based response prediction may be investigated to reduce computational cost associated with repeated nonlinear finite element simulations.

4. Conclusions

This study presented a Python-based GA-FEMU framework for hyperelastic material calibration of a soft pneumatic gripper using Abaqus finite element analysis and genetic algorithm optimization. The proposed methodology successfully integrated experimental validation, finite element simulation, automated Python scripting, and genetic algorithm optimization.

The optimization results demonstrated that the proposed framework successfully improved the agreement between experimental and simulation responses. The convergence behavior indicated that the genetic algorithm successfully identified suitable hyperelastic material constants for the soft pneumatic gripper model. Future work may include multi-pressure optimization, multi-objective optimization, DOE integration, and optimization of other soft robotic actuator systems.

Acknowledgement

This research was funded by a grant from Universiti Teknologi Malaysia (UTM) under the Potential Academic Staff (PAS) Grant (Vote No. / Reference No.: PY/2024/02312).

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