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Review / Обзор

Optimizing MEMS-based Navigation Sensors for Aerospace Vehicles

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Abstract. This comprehensive study delves deeply into the intricate domain of optimizing Micro-electromechanical Systems (MEMS)-based navigation sensors for aerospace vehicles. It entails a meticulous examination of MEMS sensors, focusing on their role in guidance, navigation, and control, with particular emphasis on MEMS inertial sensors and crucial performance metrics. The study investigates a spectrum of techniques for sensor optimization, including strategies for enhancing fabrication and production through smart structures and mathematical modeling. Additionally, it explores methodologies and mechanisms for improving navigation sensor fabrication, along with the incorporation of optimizer techniques to manage computational complexities effectively. The key findings underscore the challenges tied to material selection and structural intricacies in optimizing these sensors for aerospace applications. Integration of sensors into integrated circuits, development of advanced mathematical models, and harmonization with artificial intelligence algorithms are vital for boosting sensor performance, while calibration and error mitigation during user deployment are essential. Furthermore, the study underscores the imperative for addressing limitations in sensor accuracy and precision through refined calibration mechanisms and error correction processes. The trajectory for future research involves advancing material selection, mathematical models, and innovative calibration techniques to comprehensively enhance sensor performance and reliability in aerospace applications.

Keywords: performance metrics, calibration, inertial sensors, Artificial Intelligence, mathematical modeling, smart structures

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Оптимизация навигационных сенсоров на основе МЭМС для аэрокосмических транспортных средств

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Нераздельное соавторство.

Аннотация. Проведен анализ исследований, посвященных оптимизации навигационных датчиков, выполненных на основе микроэлектромеханических систем (МЭМС) для аэрокосмических транспортных средств. Рассмотрены МЭМС-датчики, их задачи в управлении, навигации и контроле, особенности инерционных МЭМС-датчиков и важные показатели их производительности. Исследован широкий спектр методов оптимизации датчиков, включая стратегии улучшения производства, изготовления через смарт-структуры и математическое моделирование. Исследованы методология и механизмы улучшения производства навигационных датчиков, а также внедрение методов оптимизации для эффективного управления вычислительными сложностями алгоритмов. Основные результаты подчеркивают вызовы, связанные с выбором материалов и структурными сложностями при оптимизации МЭМС-датчиков для аэрокосмических задач. Интеграция датчиков в интегральные схемы, разработка продвинутых математических моделей и согласование с алгоритмами искусственного интеллекта необходимы для повышения производительности датчиков. Калибровка и устранение ошибок при развертывании датчиков пользователем являются обязательными этапами их внедрения. В работе подчеркивается необходимость нахождения способов для снятия ограничений по точности и прецизионности датчиков путем совершенствования механизмов калибровки и процессов коррекции ошибок. Сделан вывод о том, что направления дальнейших исследований лежат в области разработки новых материалов, построения более точных математических моделей и применения инновационных методов калибровки для всестороннего улучшения производительности и надежности МЭМС-датчиков в аэрокосмических приложениях.

Ключевые слова: показатели производительности, калибровка, инерционные датчики, искусственный интеллект, математическое моделирование, интеллектуальные конструкции

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Introduction

The use of microelectromechanical systems (MEMS) in space applications has shown potential to revolutionize future spacecraft systems, which is why careful attention to material selection is always required. Technology Readiness Levels (TRLs) are a method for estimating the maturity of MEMS-based devices offer miniaturization advantages [1]. MEMS technology offers miniaturization advantages but packaging and testing remain significant challenges that account for a major part of the final cost of MEMS devices [2].

MEMS-based devices offer a promising solution for navigation systems of autonomous aerospace vehicles. However, the performance of sensitive MEMS devices, such as magnetometers, can be significantly affected by the test environment (factors such as electrical activity and ferrous materials), which affects the magnetometer output [3]. Thus, thermal engineers and guidance, navigation, and control (GN&C) engineers have considered both the benefits and challenges when dealing with MEMS technology in space [4]. A potential approach suggested by researchers is topology optimization, which divides MEMS structures into elements and assigns a design variable to each one to determine optimal material distribution [5]. On the other hand [6], emphasized the significance of MEMS features in achieving low mass and high reliability in aerospace systems, as the current industry standard for launching a satellite into low-Earth orbit (LEO) stands at roughly $5,000 per kilogram.

MEMS navigation sensors have gained attention from aerospace engineers and a wide range of users due to their compact size, lightweight, and cost-effectiveness [7]. These sensors have great potential for integration with space instruments and find widespread applications in aviation [8–10]. Their small dimensions and affordable manufacturing make them highly desirable for aerospace-related purposes, leading to a steady increase in global market demand [11].

In recent years, there has been increased interest in MEMS Inertial Measurement Units (IMUs) due to their small size and low cost. IMUs are used to obtain navigation data when GPS signal-unavailable environments or electronic interference are present. However, a major disadvantage of IMUs has been the accumulated error when integrating them with navigation equations alone to find the position [12]. To improve the accuracy of navigation data, various IMU sensors, consisting of accelerometers and gyroscopes, are assembled together into a printed circuit board known as the IMU Cluster that calibration process is needed to optimize the systematic errors [13].

This review will examine topology optimization techniques as potential solutions for the design and material distribution optimization challenges encountered in MEMS navigation sensors. By addressing these advancements and challenges, this review aims to offer valuable insights to researchers, engineers, and industry professionals, fostering progress and innovation in MEMS-based navigation systems across various applications.

1. MEMS in Guidance, Navigation and Control

MEMS technology involves micromachining silicon to create micron-scale structures such as cantilevers, free-standing bridges, membranes, and channels, which are then combined with microelectronics fabrication methodology and technology to produce miniature systems that integrate electronics with sensors, transducers, and actuators. MEMS devices have potential applications in spacecraft GN&C systems for navigational functions. As shown in Table1 [4] the essential functional elements of a spacecraft GN&C system are sensors, processors, and actuators, and MEMS technology can be used to develop miniaturized sensing and control devices, including accelerometers, gyroscopes, star trackers, sun sensors, magnetometers, reaction wheels, and thrusters. MEMS technology for space can be categorized into various areas, such as inertial navigation, RF switches, and variable capacitors. However, reliability is a crucial concern for space hardware due to radiation, thermal cycling, thermal shocks, vibration, and mechanical shock [14; 15].

Table 1

Typical Spacecraft GN&C Attitude Sensing and Control Devices

Attitude Sensing Devices	Navigation Sensing Devices	Attitude Control Actuation Devices
Sun sensors		Thrusters
Earth sensors		Magnetic torquers
Horizon sensors	IMU and IMMU*	Antenna pointing gimbals
Gyroscopes	Gyroscopes	Momentum wheels
Accelerometers	Accelerometers	Reaction wheels
Magnetometers	Magnetometers	Control moment gyros
Fine guidance sensors		Solar array drives

N o t e. When magnetometers are combined to accelerometers and gyroscopes, IMUs are referred to as IMMUs.

1.1. Current Types of MEMS Sensors in Aerospace Navigation

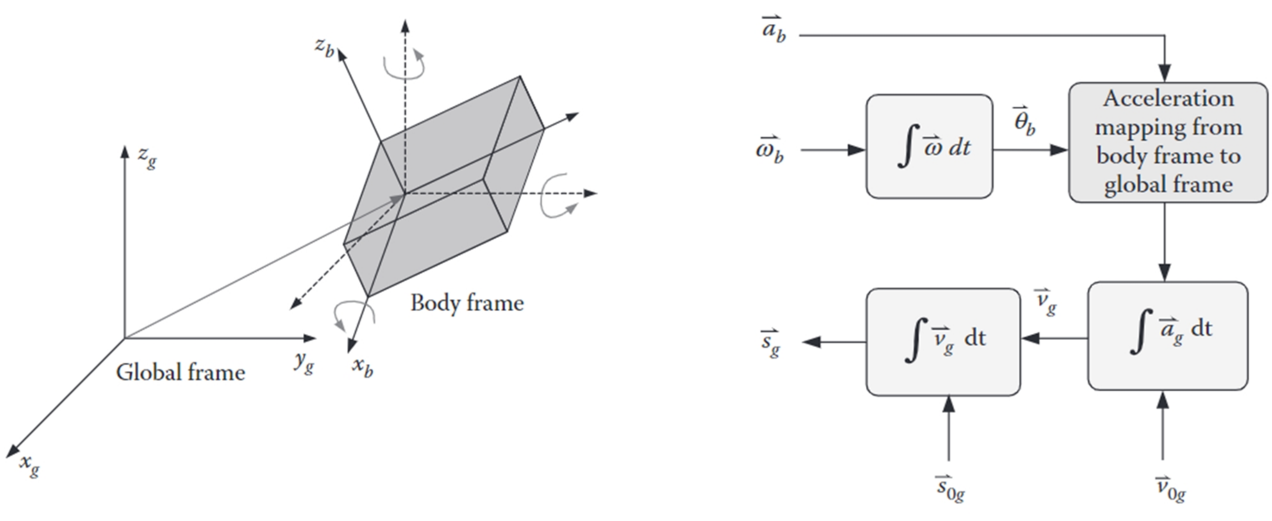
1.1.1. MEMS inertial sensors

The use of Inertial Measurement Units (IMUs) has been integral to navigation and guidance systems in aerospace and military applications. Traditionally, IMUs consisted of three accelerometers and three gyroscopes to sense linear accelerations and angular velocities. However, advancements in Micro-Electro-Mechanical Systems (MEMS) technology have resulted in the development of new low-power wireless transceiver-based applications, leading to smaller, more cost-effective IMUs. These IMUs are implemented as strap-down systems and offer advantages over traditional IMUs, including higher accuracy and lower power consumption. As can be seen in Figure 1 by measuring local angular velocity and linear acceleration, it is possible to determine the moving displacement or absolute position in the global inertial reference frame [16].

MEMS IMMU technology is a critical component in modern aerospace and defense systems, providing precise positioning, velocity, and orientation data crucial for safe and reliable navigation. Furthermore, recent research has shown the potential for MEMS IMUs to improve safety and mobility during space missions through the development of highly accurate gait detection algorithms for various positions of the human body [17–19]. This technology could be integrated into astronaut clothing, providing real-time feedback on movement and position.

1.1.2. Performance Metrics

To ensure cost-effectiveness, reliability, and safety, stable MEMS performance is necessary throughout its life cycle [20]. Achieving high sensitivity and accurate modeling of the sensors is crucial. The harsh environment of aerospace applications requires specialized designs and modeling techniques, such as micro-dampers and protective materials, to withstand conditions like vibrations, shocks, temperature gradients, and fluids. Additionally, compliance with export control regulations and aeronautics development standards and processes is essential, which may involve incorporating anti-proliferation devices and technologies. Table 2 shows the necessary requirements for performance of some prevalent navigation sensors [21].



a *b*

Figure 1. Global Positioning via Local Angular Velocity and Linear Acceleration Measurements. The inertial navigation basic: *a* — strap-down systems; *b* — position calculation
Source: made by the Iniewski et al [16]

Table 2

MEMS for Aerospace Navigations; Standards and Performance

Gyroscope	Accelerometers	IMU
Q factor>100000	Measurement Range, Bandwidth: > 100 g, 500 Hz	Volume: 150 cm^3
Bias stability: 1,30/h drift rate <5°/h	Bias Accuracy of 50μg to 1 mg	Power Consumption: < 3W
Range of Allan Variance of Walk obtained on Rate Gyros: $0.\frac{13^{\circ}}{\ddot{0}}h$	Scale Factor Error of 300 ppm to 1000 ppm	MTBF: 100000 FH

N o t e. The performance metrics of navigation sensors vary for each mission. Therefore, Table 2 specifies the minimum requirements for sensors when performing a simple mission in the aerospace field. To achieve detailed data about Characterization of Inertial Measurement Units under Environmental Stress Screening, refer to the studies of Capriglione et al [22]. For more study, Liu et al [23], and have referred to exact performance metrics of magnetometer

2. Techniques for Optimizing MEMS-Based Navigation Sensors and Solutions

2.1. Fabrication and Production Optimization

Fabrication optimizing methodologies are divided into two main parts:

– selection of *Smart Structure (Materials)*;

– development of *Mathematical Models* for modeling and analysis purposes.

2.1.1. Smart Structure

Smart technology has been extensively employed across science and engineering fields, offering immense potential for highly significant applications. It has successfully addressed challenges in aerospace and electronics through the utilization of innovative materials with electromechanical/magneto mechanical coupling capabilities. These materials have enabled the conversion of energy from one form to another, thereby facilitating the development of sensors and actuators from the same substances. A control mechanism integrated into the system has responded to sensor signals, determining the appropriate actions of the actuators. Researchers worldwide have devised methods to incorporate these components, introducing smartness into systems. Initially, this technology was applied in larger systems, but there has been a growing focus on miniaturization, particularly with the rise of microelectromechanical systems (MEMS), driven by the need for lightweight designs. The engineering of smart systems and MEMS has involved multidisciplinary research and has presented numerous technological challenges. As smart systems technology has expanded into various disciplines, there has been a crucial and timely need to consolidate technological advancements in specific areas, providing valuable insights for practicing researchers in science and engineering who are interested in potential applications of this technology [24; 25].

2.1.2. Mathematical Modeling

In mathematical modeling, the governing differential equation of a system is essential. There are two methods to achieve this. The first method involves isolating a small block from the continuum system, analyzing the 3-D state of stress on the block, and writing the equilibrium equation to obtain the governing equation. Approximations in lower dimensions can be derived from the 3-D equations by converting stresses into stress resultants. This method, known as the Theory of Elasticity, involves dealing with tensors and vectors. An alternative approach is the energy method, where minimizing the energy functional yields the desired governing equations and their associated boundary conditions. This method is widely used in discrete modeling techniques. The Finite Element Method (FEM) is extensively used for analyzing smart structures, but it may become computationally prohibitive for certain scenarios such as high-frequency loads or Structural Health Monitoring (SHM) in composites. In such cases, wave-based techniques are employed [26; 27].

2.2. Review of Navigation Sensors Fabrication Optimizing Methodologies and Mechanisms

In order to enhance the structural optimization of micro-electromechanical devices and select materials that effectively increase optimization parameters such as construction costs, production efficiency, and performance, it is imperative to establish a fundamental framework that serves as a basis for relevant research and provides general principles. Consequently, Varadan et al. [26], have addressed these fundamental principles and their design calculations. However, unlike the compilation of materials by Nithtianov et al. [28], specific optimization solutions have not been discussed. Instead, their work serves as a comprehensive reference for reviewing general principles and the fundamental concept of utilizing smart materials alongside their mathematical modeling.

Ananthasuresh's research provides a comprehensive overview of MEMS design concepts, focusing on system-level synthesis methodology for modifying sensor structure topology. The study emphasizes automating design processes for fixed MEMS transducer topologies, involving identifying design variables, establishing constraints (as shown in Table 3), and formulating a mixed-integer nonlinear optimization problem. The optimization problems are solved through a sequence of linearized sub-problems using sensitivity information. These large-scale problems involve thousands to millions of design variables and relatively few constraints. Clearly in Figure 2, the geometrical parameters and other details of Table 3 are shown. Various methods, such as Optimality Criteria, Sequential Linear Programming, and the Method of Moving Asymptotes (MMA), are employed to solve these optimization problems, with MMA being popular for advanced topology optimization. Quadratic programming methods are not used due to their high computational cost. The solutions to these problems are mesh-dependent and non-unique, but schemes can be implemented to ensure well-posed problems, such as modifying sensitivities within a fixed radius of the element [29]

$$\frac{\partial \widehat{E^H_{pqrs}}}{\partial \rho_k} = \frac{1}{\rho_k \sum_{i=1}^{n} \widehat{H}_i} \sum_{i=1}^{n} \widehat{H}_i \rho_i \frac{\partial E^H_{pqrs}}{\partial \rho_i}. \quad (1)$$

Where the *mesh-independent* convolution operator (weight factor) $\widehat{H}_i$ is written as:

$$\widehat{H}_i = r_{min} - dist(k, i)$$

$$\{i \in N \,|\, dist(k, i) \le r_{min}\}, k = 1, \ldots, N. \quad (2)$$

In this expression, the operator $dist\ (k, i)$ is defined as the distance between the center of the element k and the center of an element i. The convolution operator $\widehat{H}_i$ is zero outside the filter area. The convolution operator for element i is seen to decay linearly with the distance from element k. It is worthwhile noting that the sensitivity converges to the original sensitivity when the filter radius r_{min} approaches zero and that all sensitivities will be equal (resulting in an even distribution of material) when r_{min} approaches infinity [29].

Table 3

Geometric Constraints

Constraint Description	Expression	Min [μm]	Max [μm]
Actuator length	$L_{cy} + 2g + 2w_c$	0	700
Comb-fill	$(2N + 1)w_c + 2Ng - L_{cy}$	700	0
Flexure length	$L_{sy} + 2L_b + 2w_t$	0	700
Total resonator width	$3L_t + w_{sy} + 4L_c - 2x_o + 2w_{cy} + 2w_{cg}$	0	700
Comb clearance during motion	$L_c - (x_o + x_{disp})$	4	200
Minimum comb overlap	$x_o - x_{disp}$	4	200
Shuttle clearance during motion	$L_t - x_{disp} - \frac{w_{sy} + w_b}{2}$	4	200
Shuttle gap in *y*	$\frac{L_{sy} - 2w_{bg} + w_{sg}}{2}$	2	200

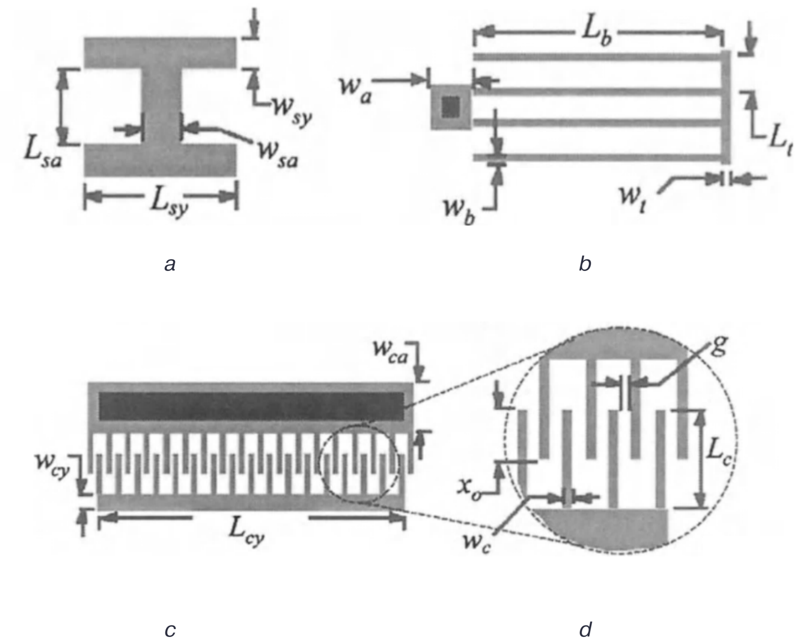


Figure 2. Geometrical parameters and dimensions of the micro resonator elements (sensors):
a — shuttle mass; *b* — folded-flexure; *c* — comb drive with *N* movable 'rotor' fingers;
d — close-up view of comb fingers
S o u r c e : made by the Ananthasuresh [29]

As part of the investigation into the proposed constraints in design and synthesis, Kläui [30] conducted a comprehensive exploration of geometrically confined domain walls, employing a range of magnetometry and imaging techniques. The research encompassed the examination of spin structures, phase diagrams, thermal excitations, stray fields, and magnetic dipolar coupling. However, to enhance the scientific rigor and reliability of the findings, further details regarding the methodological aspects, including experimental setups, sample preparation, and measurement protocols, are required. Additionally, a more comprehensive data analysis would be beneficial.

Compliant mechanisms overcome challenges faced by traditional rigid-body mechanisms, such as backlash, wear, and increased part count. They utilize single-piece flexible structures for force and motion transmission, resulting in dimensions and cost savings in MEMS fabrication. According to the studies conducted by Shuib et al. [31], there are two common approaches for designing compliant mechanisms that include the kinematics-based approach, which represents compliant segments as rigid links with added torsional springs, and the structural optimization-based of approach, which focuses on determining the topology, shape, and size of the compliant mechanism through numerical methods like topology optimization. While compliant mechanisms offer benefits, their design and analysis still pose challenges, including the lack of formal synthesis methods and the complexity of determining force-deflection relationships and optimizing design variables that further research is needed to enhance their effectiveness.

The silicon accelerometer utilizes piezoresistive techniques to convert mechanical motion into an electrical signal. It consists of a silicon base, double cantilever beams, and piezo resistors. Kal and Das [32], explain well this accelerometer achieves a range of ± 13 g with low off-axis acceleration, high resolution, and linearity. this design specifically suggested for aircraft motion sensing in avionics. they stated, the quartz double-ended tuning fork (DETF) accelerometer is qualified for space applications. In completing this research process, Liu et al. [33], focused on a robust optimum design of shape and size for an accelerometer fabricated by silicon micromachining technology is proposed to minimize the effect of variations from micro fabrication without a preliminary assumption on the probabilistic distributions. The sensitivity analysis technology is employed to reduce design space and to find the key parameters that have greatest influence on the accelerometer. Then, the constraint conditions and objective functions for robust optimization and the corresponding mathematical model are presented.

The unit stiffness sensitivity of the spring beams should be equal to the unit mass sensitivity of the detecting mass:

$$\begin{cases} h(x) = \left(\dfrac{\frac{\partial k}{\partial \zeta}}{k} \right) \Big|_{\zeta=0} = \left(\dfrac{\frac{\partial m}{\partial \zeta}}{m} \right) \Big|_{\zeta=0} \le h_0(x) \\ \text{Max}\, k(\boldsymbol{X}), \text{Min}\, S_c(\boldsymbol{X}): \\ \text{Max}\, f(x) = a.\dfrac{1}{S_c} + b.k \end{cases}$$

For this purpose, the unit stiffness sensitivity of the spring beams should be equal to the unit mass sensitivity of the detecting mass. where ζ is a random variable; k is the stiffness of the spring beam; m is the mass the detecting mass; $h_0(x)$ is the initial value of the robust constraints. Max $k(\boldsymbol{X})$, Min $S_c(\boldsymbol{X})$ are Maximum and minimum fabrication errors influence on the performance of the accelerometer and Max $f(x)$, is objective function. This formulation is practically applicable since no statistical information on the uncertainties is required during the process of the robust optimal analysis in advance. Considering that the magnitude of fabrication errors and uncertainties in an accelerometer structure are comparatively large, the present robust optimal design method can be valuable for practical accelerometer design.

The optimization problem is solved by the Multiple-island Genetic Algorithm is employed to solve the optimization problem, and the results are shown in Table 4.

A design methodology for optimizing MEMS impedance matching networks based on the uniformity of the Smith chart coverage is presented by Domingue et al. [34], that approach is validated through a comparison between traditional coplanar waveguide (CPW) designs and improved designs using a slow-wave (SW) structure. The proposed reconfigurable impedance matching network based on distributed MEMS transmission line (DMTL) coupled with the SW structure achieves a 25 % reduction in physical length compared to traditional DMTL. In this regard, a better view of the results of this study are shown in Figure 3.

Table 4

Results of Robust Optimization

Description	Symbols	Initial design	Optimum design
Design variables (mm)	x_1	8	8.774876
	x_2	5	4.485502
	x_3	1.5	1.567798
	x_4	0.8	0.847795
	x_5	0.4	0.379551
	x_6	1.5	1.592313
1st-order natural frequency (Hz)	f_1	25.1349	22.489963
2st-order natural frequency (Hz)	f_2	40.1076	39.126760
Frequency difference (Hz)	f	15	16.636797
Sensitivity of detecting capacitance	k	2.5947e-12	3.16742e-12
Robust constraints	$h(x)$	1.3056e13	1.0914e13

A team of researchers [35], proposed a methodology for determining true chaos in distributed mechanical systems. It focuses on a beam structure with contact interaction, modeling nonlinearity using the Cantor model. The problem is formulated using partial differential equations and solved as an ordinary differential equation system using finite differences and Runge — Kutta methods. The analysis includes nonlinear dynamics methods and the qualitative theory of differential equations. The study confirms the existence of chaotic behavior, synchronization of oscillations, and the convergence of results through signal analysis as shown in Figure 4. Parameter values and methods for reliability and validity are established. The findings emphasize the importance of considering nonlinearities, and a comparison between linear and nonlinear problems with contact interaction reveals reduced chaotization through increased equations and regularization of oscillations.

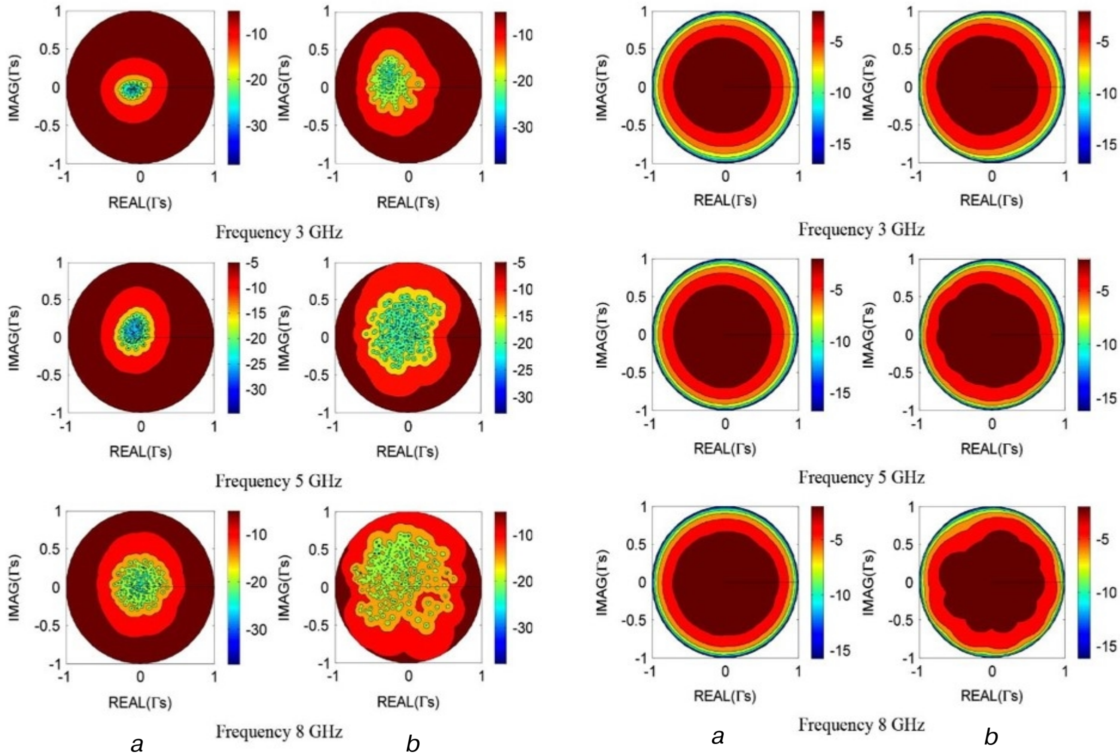


Figure 3. Measured return loss performance and Measured power transfer performance:
From left-side: Measured return loss performance over the gamma plane
for the fabricated designs (in decibels): *a* — CPW design; *b* — SW design.
From right-side: Measured power transfer performance over the gamma plane
for the fabricated designs (in decibels): *a* — CPW design; *b* — SW design
S o u r c e : made by the Domingue et al. [34]

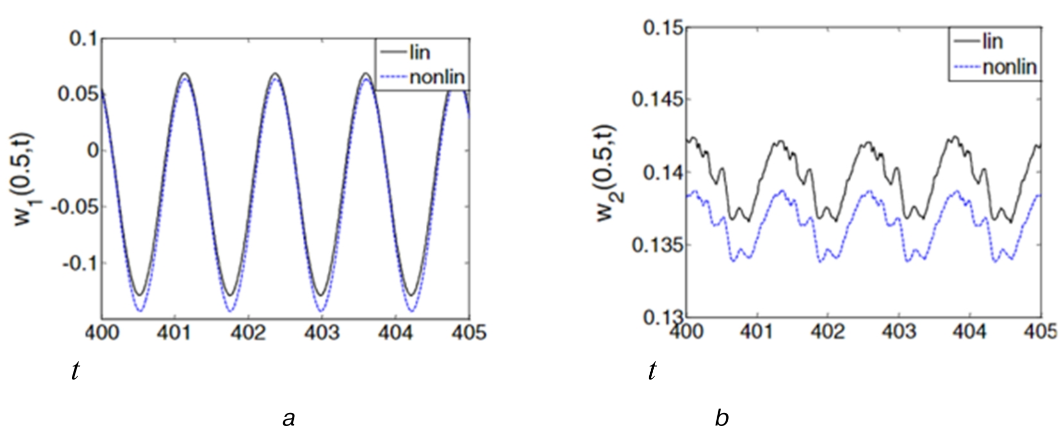


Figure 4. Comparison of beam signals. Beam signals, with and without geometric nonlinearity:
a — Beam 1; *b* — Beam 2
S o u r c e : made by the Krysko et al. [35]

The recent research of Nguyen, Saltykova and Krysko [36], focused on analyzing the nonlinear dynamics of MEMS cantilever beams using mathematical models and the finite element method with the ANSYS software package. The researchers investigated the dependence of vibration characteristics on geometric parameters and considered spatial vibrations in a 3D space. The study presented results such as time signals, phase portraits, wavelet spectra, and Fourier spectra. The advantage of using the finite element method is its ability to capture complex geometries and nonlinear behavior accurately. However, the explicit integration method, specifically the Euler method, employed for solving the problem has limitations in terms of stability and accuracy, especially for long-term simulations. The research highlights the importance of considering spatial vibrations and provides insights into the effects of beam geometry on vibration amplitudes and frequencies. Overall, the research contributes to the understanding of MEMS cantilever beam dynamics but could benefit from more advanced numerical integration techniques to improve accuracy and stability in long-duration simulations.

The main purpose of the investigated methodologies for fabrication on the surface of the smart material or the desired semiconductor is to check the possibility of reducing the dimensions of the desired sensor IC, and the proposed calculations and modeling are more focused on the manufacturing accuracy. Scientists [28], mentioned this issue in the review of the presented equations and modeling that mechanical sensitivity in the event of unmatched modes is significantly decreased since the quality factor of the sense mode is no longer fully exploited. In particular, for the range $\frac{f_s}{2Q_s} < \Delta f < f_s$ the mechanical sensitivity for the unmatched frequency condition can be expressed as:

$$\frac{\Delta C_D}{\Delta \Omega} \Big|_{\text{unmached}} = 2\frac{C_{0,S}}{y_0} = F_c(t)\frac{Q_s}{K_s} =$$

$$= 4\frac{C_{0,s}}{y_0}\frac{2}{360}\frac{F_{D,\max}}{b_D 2 \quad f_s}\frac{\text{c}\quad \text{s}(2 \quad f_D t)}{Bw_{\text{unmached}}}.$$

As a rule of thumb, the higher the required bandwidth, the lower the mechanical sensitivity that can be obtained from a MEMS gyroscope. On the other hand other studies explain the electromechanical systems of accelerometers and provide insights into their operation and interface circuitry. Shaeffer et al. [37], discussed the challenges of achieving DC accuracy, minimizing drift, and addressing thermal variations for accelerometers. Finally, they mentioned upon vibratory rate gyroscopes, which measure angular rate of rotation based on detecting Coriolis acceleration. Table 5 has referred more typical methodologies to optimizing MEMS fabrication.

Table 5

Optimization Methodologies Based on Challenges and Typical Techniques Selecting

Challenge	Main Solution or techniques	Advantages/Disadvantages	Ref
CMOS compatible integrated MEMS process for fabricating a differential capacitance-based sensor on a SOI (Silicon-On-Insulator) wafer	Deep Reactive Ion Etching (DRIE) process	Overall, the challenge lies in developing a process that enables the integration of MEMS and CMOS technologies, while ensuring proper electrical isolation, maintaining mechanical	[38]
To find an effective method for depositing thick layers of SU-8 photoresist, particularly for applications such as microfluidics and polymeric membranes fabrication using lithography	1) Spin Coating 2) Self-Planarization 3) Sandwiching	The sandwiching technique has several advantages over spin coating and self-planarization. It ensures thickness uniformity, eliminates surface irregularities, and allows for efficient production of thick and uniform coatings. The technique is simple, fast, and achieves the desired thickness in a single step, overcoming some limitations of other coating methods	[38]
To optimize the sensitivity of micro-cantilever sensors by incorporating stress — concentration — regions (SCR) and modeling their effects	Integration of stress concentration regions (SCR) on a micro-cantilever sensor to improve its performance	Advantage of the technique used is that it enhances the performance of the micro-cantilever sensor by increasing — the differential surface stress through the incorporation of SCR holes. However, the disadvantage is that designs with multiple SCR holes may not provide significant improvements in performance while adding complexity and cost.	[38]

Ending of the Table 5

Challenge	Main Solution or techniques	Advantages/Disadvantages	Ref
Characterization of residual stresses in microelectromechanical systems (MEMS)	Measuring deformation or deflection and applying mathematical models to extract stress values and material properties	Relies on the Stoney formula, which is based on simplified assumptions and may lead to modeling errors in certain cases	[39]
Integrating gyroscope and accelerometer sensors into a compact package while maintaining mechanical stability and electrical compatibility with existing systems	1) Heavily doped silicon sensor mechanisms and a MEMS foundry at Honeywell 2) Use of a vibration isolator in the IMU design, leveraging the design of the vibration isolator	Vibration isolator helps attenuate external vibrations at critical sensor resonant frequencies, allowing the IMU to maintain full performance even under harsh tactical conditions with high vibration levels	[40]
To develop and optimize a IMU for use in the Lobster-Eye X-ray Satellite to achieve high precision and stability in measuring angular rates while considering the specific requirements and constraints of satellite applications	1) Frequency Stabilization and Frequency Split Mitigation. 2) Anti-Interference Design of External Environment. 3) Self-Calibratio	Overall, the technique and solution offer significant advantages in terms of performance, size, and versatility, making the MEMS IMU a valuable choice for high-precision navigation applications. However, certain trade-offs and limitations (such as: Limitations in Absolute Accuracy & Sacrifice in Range and Bandwidth) should be considered based on the specific requirements of the application	[41]
Improving performance parameters, and optimizing design features to enhance the precision and robustness of MEMS vibrating gyroscopes for applications in harsh environments	In summary, the techniques and solutions in this research involve understanding the fundamentals of vibrating gyroscopes, addressing mode-matching challenges, exploring different gyroscopic designs like gimbal and multi-axis gyroscopes, and finding ways to minimize mode mismatch during microfabrication processes	1) Mode Mismatch Challenges. 2) Limited Bandwidth. 3) Sensitivity to External Factors. 4) Complex Design and Calibration	[42]

N o t e . These are classical methods for optimizing Micro-Electro-Mechanical sensors and navigation micro devices. Additional sources provide ample opportunities to explore and extract further examples for analysis [43].

3. Modern Fabrication Methodologies

In contemporary design practices, there is a prominent inclination among scientists to leverage various levels of artificial intelligence (AI) with the aim of diminishing calculation errors and curtailing production costs associated with micro-electromechanical devices [44]. This trend has consequently facilitated the amalgamation of conventional optimization techniques with cutting-edge technologies such as machine learning, neural networks, and related methodologies [45; 46].

3.1. Unveiling Modern Methodologies for MEMS Navigation Sensor Fabrication

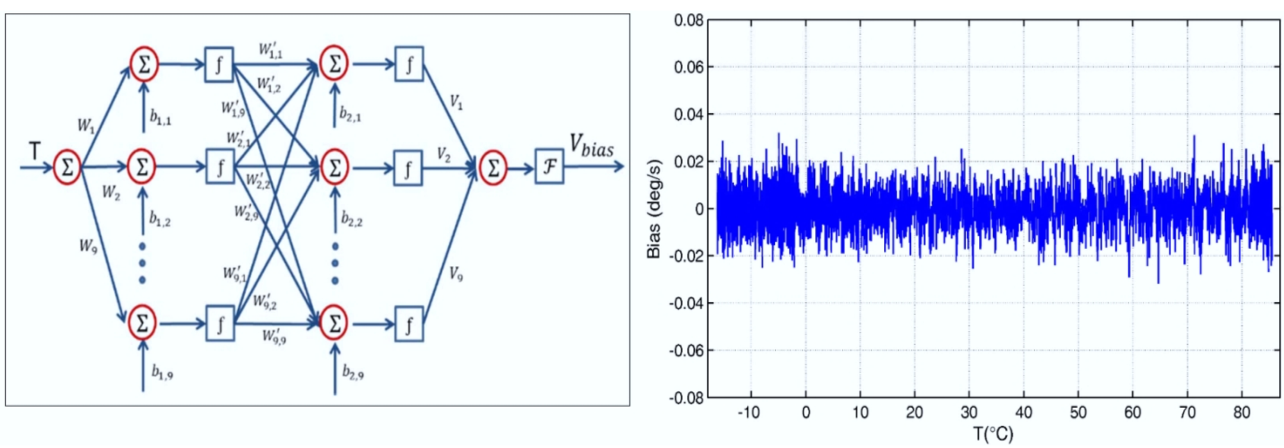
Fontanella et al [47], conducted research to optimize the calibration of an IMU by addressing bias drift error caused by temperature variations in MEMS gyroscopes. They proposed using *Back-Propagation (BP) Neural Networks* as a solution to improve calibration accuracy and reduce residual errors compared to the polynomial fitting method. The study included an analytical model for bias, a description of the standard calibration procedure, and a comparison of flight attitude angles calculated using both methods. In this context, the *Least Mean Squares* (LMS) curve fitting method is employed for constructing a temperature model of the sensor's zero-bias. By using a polynomial of order m to approximate the relationship between experimental data, the following expression is derived:

$$v_i = B_i - \sum_{j}^{m}{}_{0}\, a_j T_i^j.$$

Here, T_i represents temperature, B_i represents the corresponding gyro output, and v_i represents the error between the gyro output and the value calculated using the regression equation (where *'i'* ranges from 1 to n, the number of samples of static IMU data). Employing LMS theory, the aim is to minimize the square of v_i to determine the optimal coefficients a_j: $\varphi(a_0, a_1, \ldots, a_m) = \sum_{i=1}^{n} v_i^2 \longrightarrow \min$.

After thorough evaluation, the efficacy of the neural network calibration technique was conclusively demonstrated. Finally, the useful effect of neural network on beam signals is shown in Figure 5.

Modeling the random drift of MEMS gyroscopes is an important research area because it directly contributes to improving the accuracy of MEMS gyroscopes. For this purpose, in line with Fontanella et al's research [47], the key contribution of Xing et al.'s research [48], is in reconstructing MEMS gyroscope random drift data using PSR method and subsequent analysis using both BP-ANN and CPSO-LSSVM methods. It is important. In this study investigated the non-linear and non-constant random drift characteristics of MEMS gyroscopes. The proposed approach in this paper consists of using a wavelet filter to reduce the noise in the original data of MEMS gyroscopes, followed by reconstruction of the random drift data using phase space reconstruction (PSR). The reconstructed data are then used to build a model using a least squares support vector machine (LSSVM), with the model parameters optimized through chaotic particle swarm optimization (CPSO). The CPSO-LSSVM method effectively reduces the standard deviation of random drift through compensation, as shown in Table 6, and shows superior prediction accuracy compared to BP-ANN, as shown by statistical indices such as MAE, RMSE and ARE are shown for the test data set.



a *b*

Figure 5. Comparison of beam signals:
a — Structure of the BP Neural Network adopted for modelling;
b — Compensated bias, obtained using the BP Neural Network calibration method (z-axis gyroscope of Axitude AX1)
S o u r c e: made by the Fontanella et al. [47]

Table 6

The statistical analysis of BP-ANN and CPSO-LSSVM. MAE

Model	Group Ⅰ	Group Ⅱ	Group Ⅲ
	MAE,°/S	**RMSE, °/S**	**ARE**
BP-ANN	0.0421	0.0554	11.10%
CPSO-LSSVM	0.0099	0.0263	8.86%
Before compensation,°/S	0.00354	0.00412	0.00328
After compensation, °/S	0.00065	0.00072	0.00053

Note. MAE — mean absolute error; RMSE — root mean square error; ARE — average relative error.

Upon examining Table 5, a notable reduction in the standard deviation of the random drift was evident following compensation. These findings provide additional evidence to support the effectiveness and credibility of the CPSO-LSSVM method. Consequently, this approach proves to be a viable and gratifying means of constructing the model for MEMS gyroscope random drift.

The set of these researches, despite all the advantages, did not provide an answer for the performance of the proposed solution at higher resonant frequencies and expanding its frequency range. Therefore, Pertin et al [49] have focused on optimizing the design of a conical piezoelectric MEMS vibration energy harvester using artificial intelligence techniques, in order to increase the harvester's performance at higher resonant frequencies and expand its frequency range.

FEM simulations generated datasets used to train an artificial neural network (ANN) for optimization algorithms. Two training methods of Levenberg — Marquardt (LM) [50; 51] and Scaled Conjugate Gradient (SCG) [52; 53] and two optimization methods of GAM (Goal Attainment Method) [54] and Genetic Algorithm (GA) [55–59] were compared. The results showed that the genetic algorithm with ANN trained by SCG provided the best solution. The optimized structure achieved over five times more power below 200 Hz and a wider frequency range. The proposed harvester is suitable for low-frequency energy harvesting and can be applied to similar structures. The approach allows for further improvements and investigations using different algorithms for ANN training or optimization (In order to learn more about the structure of the methods mentioned in this paragraph, refer to the given references).

Different training methods and approaches yield distinct artificial neural network (ANN) fitting functions, which are evaluated using two key metrics: mean squared error (MSE) and regression coefficient (R). The MSE measures the dissimilarity between the desired target *'t'* and the ANN's generated output 'a', with lower values indicating better performance. The regression coefficient R, also known as the coefficient of correlation, gauges the correlation between the target and the ANN's output, aiming for a value closer to one for superior performance where N is the number of examples in a dataset, and $\bar{t}_i$ is the arithmetic mean of the target values.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - a_i)^2}{\sum_{i=1}^{N}(\bar{t} - \ _i)^2}.$$

Regression coefficients above 95.152 % were obtained using the Levenberg-Marquardt (LM) training algorithm, considered satisfactory. The correlation between targets and ANN outputs is not automatically computed for the two outputs, but separate assessments are conducted to ascertain the ANN's capability to achieve favorable results for new data. The LM training method outperformed the SCG training algorithm in terms of MSE, particularly in predicting the frequency and power of the first resonant mode. The LM training method yielded an MSE an order of magnitude lower than the SCG training method's MSE for predicting the normalized frequency of the resonant mode (3.8398×10−4).

The ANN fitting functions obtained using the LM training algorithm exhibited regression coefficients above 95.152 %, indicating good performance as shown in Figure 6. However, since the ANN generates output as a two-column vector, the correlation between the targets and the ANN outputs is not automatically calculated. Separate analysis was conducted to assess the ANN's capability to achieve satisfactory results for new data. On the other hand, applying the SCG training algorithm yielded even better regression coefficients, surpassing 95.468 %. The LM training method outperformed other methods in terms of mean squared error (MSE), particularly in predicting the frequency and power of the first resonant mode. The MSE for the LM method was 3.8398×10−4, significantly lower than that of the SCG method. Although a perfect fit to the training data does not guarantee a reliable predictive model, the ANN was further tested using unseen data.

3.2. Integrating Optimizer Techniques for Managing Computational Complexity

The challenge of researchers is finding optimal, suboptimal solutions and reducing computing costs for MEMS design and developing a bionic CAD system [60]. On the other hand meeting modern MEMS element design requirements requires complex multi-physics analysis, accurately describing the project structure. Furthermore, new knowledge accumulation and synthesis of sub-optimal solutions are also crucial. Koryagin et al's proposed approach [61], offers a promising direction for bionic CAD development, balancing computational complexity and competitive device solutions. Cognitive adaptation and the use of cognitive knowledge banks are proposed to handle the complexity of MEMS design that goal is to find optimal and suboptimal solutions by utilizing cognitive knowledge banks and adaptive methods. Thus, there is a complex mathematical model of the designed system shown below:

$$k = \left\{\frac{f}{u}, \{J_c c/C\}: \{J_a a/A\}, \{J_e e/E\} \to \{J_b b/B\}\right\},$$

where: k is a mathematical model, A & B is a set of input, output variables of the model, C is a semantic network (Figure 7), J is a semantic network synthesis operator, $\frac{\boldsymbol{f}}{\boldsymbol{u}}$ is a computing mechanisms complex, E is a structured system pattern.

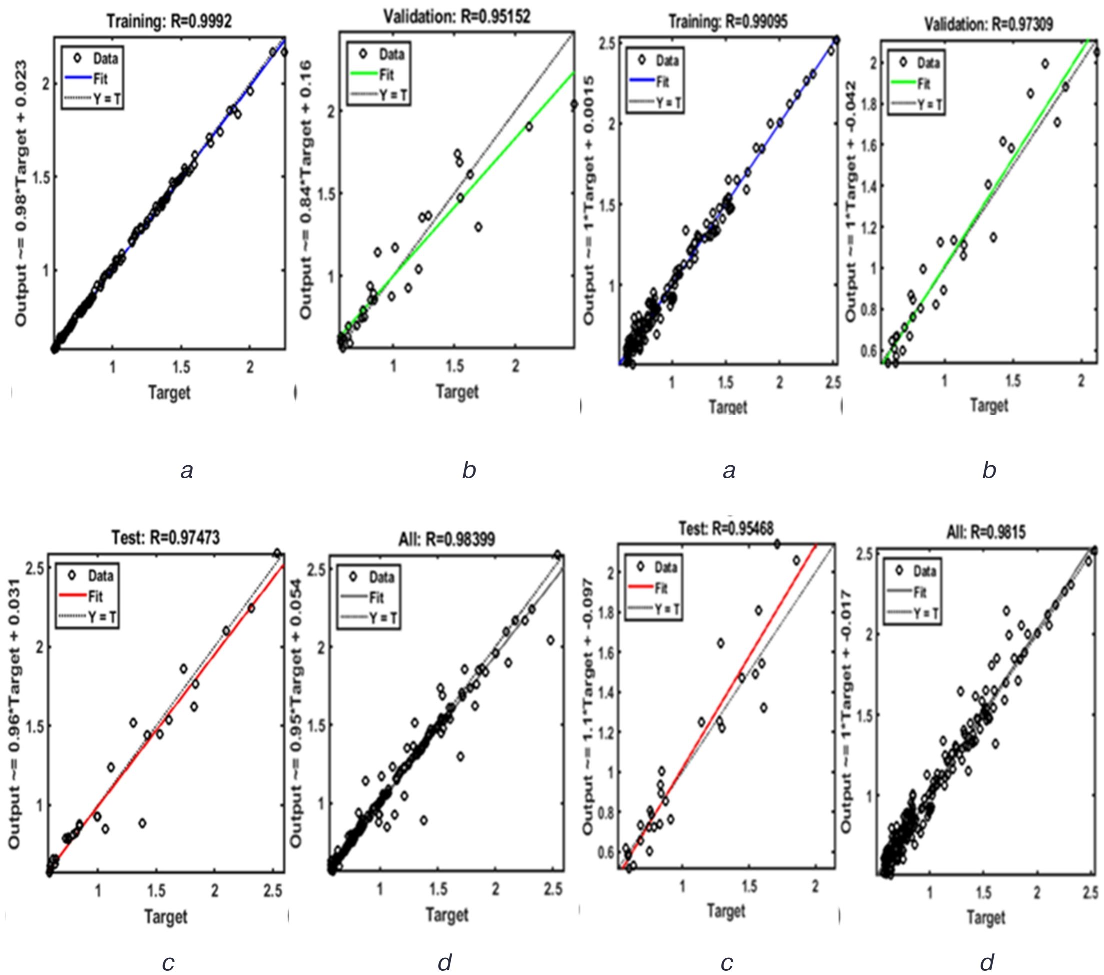


Figure 6. Regression diagrams for the ANN trained
by applying Levenberg — Marquardt algorithm & Scaled Conjugate gradient Algorithm:
a — training dataset; *b* — validation dataset; *c* — dataset used for testing;
d — dataset with all three aforementioned groups of data
S o u r c e: made by the Pertin et al. [49]

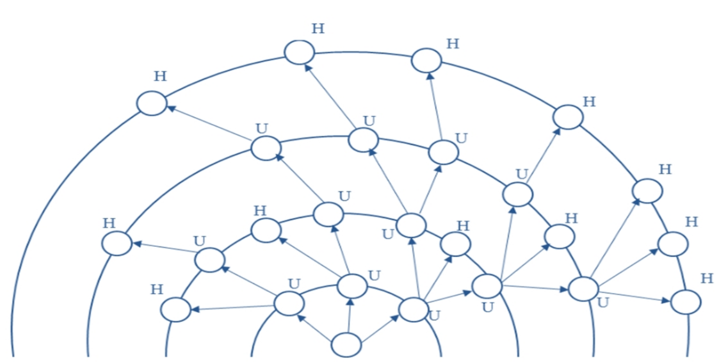


Figure 7. Example of the semantic wave:
B — home domain, Б — home domain, E — terminal nodes, U — intermediate vertex
S o u r c e : made by the Koryagin et al. [61]

Partial differential equations (PDEs) describe MEMS element dynamics. Simulating them is complex due to multiple physical processes. SAM technology enables optimization in MEMS design cycles. The bionic CAD system's core architecture includes models, preprocessor, bionic search, and postprocessor blocks. It has allowed parallelization, search management, and solution generation.

Validation involves comparing calculation results with published data and experiments. The adaptive MEMS design system based on SAM tech reduces computational costs and simulation errors. Computational intelligence is widely used in MEMS design, but bionic systems with AI and cognitive technologies are more promising compared to traditional methods.

4. Discussion

To overcome the challenges associated with optimizing MEMS-based navigation solutions, a comprehensive approach must be adopted. This includes meticulous material selection, sophisticated mathematical modeling techniques, and rigorous calibration procedures. The integration of AI methods can certainly enhance the optimization process, but it should be acknowledged that the foundation for effective optimization lies in addressing fundamental issues.

The optimization of functional errors in MEMS sensors within electronic circuits has long been a challenge for users. Leveraging the Kalman filter and artificial intelligence has significantly enhanced the accuracy and precision of navigation mission outputs. However, researchers are actively seeking more optimal and integrated solutions to further optimize these sensors at the user level. These endeavors serve as a promising basis for future research in the field [62; 63].

Conclusion

In the conclusion of this paper several key results and insights can be summarized. These conclusions reflect the findings and contributions:

1. Optimizing MEMS navigation sensors for aerospace vehicles poses challenges in material selection and structural complexities.

2. Integration of sensors into an IC and efficient mathematical modeling are crucial for performance. While AI can optimize sensor data, ensuring seamless integration and compatibility between AI algorithms and the sensor hardware can be challenging.

3. Calibration during startup and mitigating functional errors by users are essential.

4. MEMS-based sensors may have limitations in terms of accuracy and precision, especially in demanding navigation applications. Addressing these issues could involve improving the sensor's calibration and error correction mechanisms.

5. Future research should refine material selection, advance mathematical models, and explore novel calibration techniques. Enhancing sensor performance and reliability in aerospace requires a multidimensional approach and focus on fundamental challenges.

References

1. Zukersteinova A. *Skill Needs in Emerging Technologies: Nanotechnology*. Cedefop; 2007.

2. Salomon P. MEMS — *Recent Developments, Future Directions.*

3. Litman K. *Static and dynamic assessment of the accuracy and precision of FOUR SHIMMER 2r microelectronic measuring systems (MEMS)*. 2015.

4. Osiander R, Champion J, Darrin MAG. *MEMS and Microstructures in Aerospace Applications*. Taylor & Francis; 2006.

5. Gaura E, Newman R, Kraft M, Flewitt A. *Smart MEMS and sensor systems*. Imperial College Press (ICP); 2006.

6. Janson SW. Aerospace applications of MEMS. In: *MEMS/MOEMS Components and Their Applications II*. Vol. 5717. SPIE; 2005:1. https://doi.org/10.1117/12.601836

7. Ko WH. Trends and frontiers of MEMS. *Sens Actuators A Phys*. 2007;136(1):62–67. https://doi.org/10.1016/j.sna.2007.02.001

8. Liddle JD, Holt AP, Jason SJ, O'Donnell KA, Stevens EJ. Space science with CubeSats and nanosatellites. *Nat Astron*. 2020;4(11):1026–1030. https://doi.org/10.1038/S41550-020-01247-2

9. Winkler S, Buschmann M, Kruger L, Schulz HW, Vorsmann P. *Multiple Sensor Fusion for Autonomous Mini and Micro Aerial Vehicle Navigation*. 2007.

10. Wilson WC, Atkinson GM, Barclay RO. *NASA NDE Applications for Mobile MEMS Devices and Sensors*.

11. Barhoum A, Altintas Z. Advanced Sensor Technology_ Biomedical, Environmental, and Construction Applications-Elsevier (2022). Published online 2022.

12. PHM Society, American Industrial Arts Association, Institute of Electrical and Electronics Engineers. *2014 IEEE Aerospace Conference: Yellowstone Conference Center, Big Sky, Montana, March 1-8, 2014.* 2014.

13. Bittner DE. *Advances in MEMS IMU Cluster Technology for Small Satellite Advances in MEMS IMU Cluster Technology for Small Satellite Applications Applications*. 2015. https://researchrepository.wvu.edu/etd

14. Setter N. *Electroceramic-Based MEMS: Fabrication-Technology and Applications (Electronic Materials: Science & Technology)*. 2005.

15. IEEE Electron Devices Society. *The 15th International Conference on Solid-State Sensors, Actuators & Microsystems : Transducers 2009 : Denver, Colorado, U.S.A., June 21-25, 2009, Sheraton Denver Hotel.* IEEE Electron Devices Society; 2009.

16. Iniewski K, Ricketts D, Ham D, Morris J, Iannone E. *Fundamental Technology and Applications*. 2013.

17. Shi LF, Liu H, Liu GX, Zheng F. Body Topology Recognition and Gait Detection Algorithms with Nine-Axial IMMU. *IEEE Trans Instrum Meas*. 2020; 69(3):721–728. doi:10.1109/TIM.2019.2906969

18. Shi LF, Zhao Y Le, Liu GX, Chen S, Wang Y, Shi YF. A Robust Pedestrian Dead Reckoning System Using Low-Cost Magnetic and Inertial Sensors. *IEEE Trans Instrum Meas*. 2019;68(8):2996–3003. https://doi.org/10.1109/TIM.2018.2869262

19. Cao Z, Hu L, Yi G, Wang Z. Arm Motion Capture and Recognition Algorithm Based on MEMS Sensor Networks and KPA. In: *2021 International Conference on Electronic Information Engineering and Computer Science, EIECS 2021*. Institute of Electrical and Electronics Engineers Inc.; 2021:133–139. https://doi.org/10.1109/EIECS53707.2021.9588046

20. Institute of Electrical and Electronics Engineers, et al. *The 2nd IEEE International Symposium on Inertial Sensors and Systems IEEE ISISS 2015: March 23–26, Hawaii, USA*; 2015.

21. Leclerc J. MEMs for Aerospace Navigation. *IEEE Aerospace and Electronic Systems Magazine*. 2007;22(10): 31–36. https://doi.org/10.1109/MAES.2007.4385708

22. Capriglione D, Carratù M, Pietrosanto A, Sommella P, Catelani M, Signorini L. Characterization of Inertial Measurement Units under Environmental Stress Screening. *IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Dubrovnik, Croatia,* 2020;1–6. https://doi.org/10.1109/I2MTC43012.2020.9129263

23. Liu S, Liang H, Xiong B. An out-of-plane electromagnetic induction based resonant MEMS magnetometer. *Sens Actuators A Phys*. 2019;285:248–257. https://doi.org/10.1016/j.sna.2018.11.003

24. Flatau AB, Chong KP. Dynamic Smart Material and Structural Systems. *Engineering Structures*. 2002;24(3): 261–270. https://doi.org/10.1016/S0141-0296(01)00093-1

25. Fitzgerald AM, Fitzgerald AM. *45 MEMS Inertial Sensors*.; 2021.

26. Varadan VK, Vinoy KJ, Gopalakrishnan S. *Smart Material Systems and MEMS: Design and Development Methodologies*. Wiley; 2006.

27. Barba PDi, Wiak S. *MEMS: Field Models and Optimal Design*. Lecture Notes in Electrical Engineering 573; 2020.

28. Kraft M, White N (Neil M). *MEMS for Automotive and Aerospace Applications*. Vol. 556. (Nihtianov S, Luque A, eds.). Woodhead Publishing Limited; 2014.

29. Ananthasuresh GK. *Optimal Synthesis Methods for MEMS*. Vol. 13. Springer US; 2003. https://doi.org/10.1007/978-1-4615-0487-0

30. Azzerboni B, Asti G, Pareti L. *Magnetic Nanostructures in Modern Technology*. (Ghidini M, ed.). Springer-NATO Science for Peace and Security Series; 2006. http://www.nato.int/science

31. Shuib S, Ridzwan MIZ, Kadarman AH. Methodology of compliant mechanisms and its current developments in applications: A review. *Am J Appl Sci*. 2007; 4(3):160–167. https://doi.org/10.3844/ajassp.2007.160.167

32. Kal S., Das S. (2006). Development of silicon and quartz-based MEMS high precision accelerometers. *Indian Journal of Pure & Applied Physics*, *45*, 299–303.

33. Guo D, Wang J, Jia Z, Kang R, Gao H, Wang X. *Advances in Materials Manufacturing Science and Technology XIII Volume II*.; 2009.

34. Domingue F, Fouladi S, Kouki AB, Mansour RR. Design methodology and optimization of distributed MEMS matching networks for low-microwave-frequency applications. *IEEE Trans Microw Theory Tech*. 2009; 57(12):3030–3041. https://doi.org/10.1109/TMTT.2009.2034218

35. Krysko VA, Krysko AV, Saltykova OA, Papkova IV. *Nonlinear Dynamics of Contact Interaction of MEMS Beam Elements Accounting the Euler-Bernoulli Hypothesis in A Temperature Field*. 2017.

36. Nguyen VK, Saltykova OA, Krysko AV. Investigation of nonlinear spatial oscillations of a MEMS beam. *Computer science and information technology. Materials of the International Scientific Conference*. Saratov: IC Nauka Publ.; 2016:286–288. (In Russ.) EDN: WFWNQV

37. Shaeffer DK. MEMS Inertial Sensors: A Tutorial Overview. *IEEE Communications Magazine*. 2013;51(4): 100–109. https://doi.org/10.1109/MCOM.2013.6495768

38. Khine L, Tsai JM. *NEMS/MEMS Technology and Devices*. Selected, peer reviewed papers from the International Conference on Materials for Advanced Technologies (ICMAT 2011), Symposium G: NEMS/MEMS and microTAS, 26 June to 1 July 2011, Suntec, Singapore. 2011. https://doi.org/10.4028/b-3EnkIB

39. Chen KS, Ou KS. MEMS residual stress characterization: Methodology and perspective. In: *Handbook of Silicon Based MEMS Materials and Technologies*. Elsevier; 2020:787–801. https://doi.org/10.1016/B978-0-12-817786-0.00039-6

40. Johnson B, Albrecht C, Braman T, et al. Development of a Navigation-Grade MEMS IMU. In: *INERTIAL 2021 — 8th IEEE International Symposium on Inertial Sensors and Systems, Proceedings*. Institute of Electrical

and Electronics Engineers Inc.; 2021. https://doi.org/10.1109/INERTIAL51137.2021.9430466

41. Zhao W, Cheng Y, Zhao S, et al. Navigation grade mems imu for a satellite. *Micromachines (Basel)*. 2021;12(2):1–12. https://doi.org/10.3390/mi12020151

42. Gill WA, Howard I, Mazhar I, McKee K. A Review of MEMS Vibrating Gyroscopes and Their Reliability Issues in Harsh Environments. *Sensors*. 2022; 22(19). https://doi.org/10.3390/s22197405

43. Hajare R, Reddy V, Srikanth R. MEMS based sensors — A comprehensive review of commonly used fabrication techniques. In: *Materials Today: Proceedings*. Vol 49. Elsevier Ltd; 2021:720–730. https://doi.org/10.1016/j.matpr.2021.05.223

44. Goebel R, Tanaka Y, Wahlster W. Autonomous and Intelligent Systems. *Third International Conference, AIS 2012, Aviero, Portugal, June 25-27, 2012, Proceedings.* Springer Berlin Heidelberg; 2012;283. https://doi.org/10.1007/978-3-642-31368-4

45. Kumar A, Pradeep B, Mallick K, Liu CM, Balas Editors VE. *Studies in Computational Intelligence 903 Bio-Inspired Neurocomputing*. http://www.springer.com/series/7092

46. Carbonell JG, Siekmann J. *Lecture Notes in Artificial Intelligence 3397 Subseries of Lecture Notes in Computer Science*; 2004.

47. Fontanella R, Accardo D, Caricati E, Cimmino S, Simone DDe. (2016). An Extensive Analysis for the Use of Back Propagation Neural Networks to Perform the Calibration of MEMS Gyro Bias Thermal Drift. *IEEE*, 1–9.

48. Xing H, Hou B, Lin Z, Guo M. Modeling and compensation of random drift of MEMS gyroscopes based on least squares support vector machine optimized by chaotic particle swarm optimization. *Sensors (Switzerland)*. 2017;17(10). https://doi.org/10.3390/s17102335

49. Pertin O, Guha K, Jakšić O. Artificial intelligence-based optimization of a bimorph-segmented tapered piezoelectric mems energy harvester for multimode operation. *Computation*. 2021;9(8). https://doi.org/10.3390/computation9080084

50. Calandra H, Gratton S, Riccietti E, Vasseur X. On a multilevel Levenberg–Marquardt method for the training of artificial neural networks and its application to the solution of partial differential equations. *Optim Methods Softw*. 2022;37(1):361–386. https://doi.org/10.1080/10556788.2020.1775828

51. Yu H, Wilamowski BM. *2–2 Intelligent Systems*; 2011.

52. Abraham A. Meta learning evolutionary artificial neural networks. *Neurocomputing*. 2004;56(1-4):1–38. https://doi.org/10.1016/S0925-2312(03)00369-2

53. Mohamad N, Zaini F, Johari A, Yassin IM, Zabidi A. Comparison between Levenberg-Marquardt and Scaled Conjugate Gradient Training Algorithms for Breast Cancer Diagnosis using MLP. *6th International Colloquium on Signal Processing & its Applications.* Malacca, Malaysia, 2010:162–169. https://doi.org/10.1109/CSPA.2010.5545325

54. Rahmani S, Amjady N. Enhanced goal attainment method for solving multi-objective security-constrained optimal power flow considering dynamic thermal rating of lines. *Applied Soft Computing Journal*. 2019;77:41–49. https://doi.org/10.1016/j.asoc.2019.01.014

55. Sivanandam SN, Deepa SN. *Introduction to Genetic Algorithms*. Springer-Verlag Berlin, Heidelberg; 2008. https://doi.org/10.1007/978-3-540-73190-0

56. Sastry K, Goldberg D, Kendall G. Genetic Algorithms: The Design of Innovation. In: *Genetic Algorithms: The Design of Innovation.* 2nd ed. Springer; 2010:97–125.

57. Haupt RL, Haupt SE. *Practical genetic algorithms second edition*. 2nd ed. Wiley; 2004.

58. Katoch S, Chauhan SS, Kumar V. A review on genetic algorithm: past, present, and future. *Multimed Tools Appl*. 2021;80(5):8091–8126. https://doi.org/10.1007/s11042-020-10139-6

59. Alam T, Qamar S, Benaida M. Genetic Algorithm: Reviews, Implementations, and Applications. *International Journal of Engineering Pedagogy*. 2020. https://doi.org/10.36227/techrxiv.12657173

60. Regassa Hunde B, Debebe Woldeyohannes A. Future prospects of computer-aided design (CAD) — A review from the perspective of artificial intelligence (AI), extended reality, and 3D printing. *Results in Engineering*. 2022;14. https://doi.org/10.1016/j.rineng.2022.100478

61. Koryagin S, Klachek P, Vasileva V. Development of bionic approaches in the microelectromechanical systems design based on cognitive knowledge bank. *2017 14th International Conference the Experience of Designing and Application of CAD Systems in Microelectronics (CADSM),* Lviv, Ukraine, 2017:285–288. https://doi.org/10.1109/CADSM.2017.7916136

62. Institute of Electrical and Electronics Engineers. *NAECON 2018 — IEEE National Aerospace and Electronics Conference,* Dayton, OH, USA, 2018.

63. Cong L, Yue S, Qin H, Li B, Yao J. Implementation of a MEMS-Based GNSS/INS Integrated Scheme Using Supported Vector Machine for Land Vehicle Navigation. *IEEE Sens J.* 2020;20(23):14423–14435. https://doi.org/10.1109/JSEN.2020.3007892

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