Grenze International Journal of Engineering and Technology, June Issue

Fault-Tolerant Design in Space Electronics with AI-Driven Real-Time Error Correction

Nagesh SB[1], Sheela S[2], Shivaprasad H[3], Ganesha B B[4] and Sharmila N[5]
[1,3]Department of Mechanical engineering, Channabasaveshwara institute of technology, Gubbi.
Email: nagesh7.sb@gmail.com, h.shiva1985@gmail.com
[2]School of Computer Science and Engineering, RV Universoty, Bengaluru.
Email: sheela.samarth18@gmail.com
[4]Department of Mechanical Engineering, Vidyavardhaka College of Engineering, Mysuru.
Email: soujanya.adiga1608@gmail.com
[5]Department of Electrical and Electronics Engineering, JSS Science and Technology University, Mysuru.
Email: Sharmila.n.89@gmail.com

***Abstract*— Space electronics are essential for maintaining reliable operation in space missions, where radiation, extreme temperatures, and micro-gravity conditions challenge electronic devices. Standard space electronics devices are susceptible to single event upsets (SEUs) and permanent hardware degradation, which results in mission failure. Conventional measures for fault tolerance include Triple Modular Redundancy (TMR) and error correction codes (ECC), which use redundancy and error correctness strategies. These conventional methods are resource-consuming and lack effectiveness in handling dynamic faults in real-time applications. Avoiding these shortcomings, this approach proposes AI-Enhanced Fault Tolerant Electronic System (AIFTES), which combines Real-Time Error Prediction (RTEP) and Dynamic Error Correction (DEC) based on state-of-the-art machine learning algorithms. AIFTES utilizes Reinforcement Learning (RL) for adaptive error detection along with Correction Neural Networks (CNN) for real-time error correction and data correctness under real-world conditions. AIFTES distinguishes from conventional ones in that it adapts in real-time for dynamic environmental conditions, achieving improved fault detection accuracy by 0.20% and reducing computing overhead by 0.30%. This solution provides robust and autonomous space operations, optimizing mission reliability, reducing energy consumption, and maximizing system performance.**

***Keywords*— Fault-Tolerant Design, Space Electronics, AI-Enhanced Systems, Real-Time Error Correction, Reinforcement Learning (RL), Correction Neural Networks (CNN), Single Event Upsets (SEUs).**

I. Introduction

Space electronics provide the technology backbone for satellites, space vehicles, and deep-space probes, for which mission reliability is paramount. They have to operate reliably in extreme conditions of high radiation, high and low temperatures, and relevant long-term exposure to micro-gravity conditions [1].

Grenze ID: 01.GIJET.12.2.112_21

Single Event Upsets (SEUs) and radiation-induced errors in such conditions are a prime cause for concern, which can lead to data corruption, component degradation, or complete system failure. Hence, fault-free performance in real-time is crucial for mission success.

Current trends in space electronics have emphasized fault resilience incrementally using hardware-based methods such as Triple Modular Redundancy (TMR) and Error Correction Codes (ECC). Although these practices enhance reliability, they tend to come at a cost of higher power consumption, area overhead, and poor adaptability to dynamic fault patterns. The advent of intelligent computing has introduced Artificial Intelligence (AI) and Machine Learning (ML) as potential solutions for overcoming these drawbacks [2]. AI-based fault prediction, adaptive correction, and autonomous system recovery are being considered and applied in various forms to mitigate mission threats and enhance real-time responsiveness [3]. Fault-tolerant AI-based systems find applications in low-Earth orbit satellites, interplanetary exploration missions, space telescopes, and autonomous rovers, where real-time error handling is essential for error-free operation. Besides increasing system robustness, such intelligent systems lead to lower human intervention and an enhanced mission life as well. However, traditional fault tolerance methods are hindered by static error models, inflexibility, and low scalability for handling intricate fault patterns. In addition, they are not specifically optimized for balancing system performance and resource constraints within constrained space hardware [4]. This shortfall calls for AI-based dynamic error management strategies that provide real-time prediction, detection, and error correction, maximizing reliability as well as efficiency.

A. Research Gaps

Although significant strides have been made in fault tolerance in space electronics, some gaps are still critical. Conventional methods such as Triple Modular Redundancy (TMR) and Error Correction Codes (ECC) are effective under static conditions but are not equipped with an adaptive nature for accommodating dynamically changing faults under real-world space environments because these methods are geared toward pre-defined models and cannot react optimally under non-deterministic radiation impact or hardware aging [5]. Further, existing AI applications for space electronics are typically restricted to offline diagnostics or error prediction on the ground, rather than integrating into real-time onboard fault correction processes. There is a shortage, too, of integrated architectures which merge machine learning-based prediction and autonomous correction under constrained computational and power budgets, which are required for embedded space systems [6].

Further, less exploration exists for fault detection and correction through reinforcement learning and neural network-based models particularly for high-radiation and temperature-varying conditions. Lack of such models creates lower system adaptability and higher mission risk. These gaps in research confirm an unmet need for an AI-based fault-tolerant system that can work autonomously, adaptively, and optimally in space environments [7].

B. Related work

H. Yunpeng et al. [8] investigated emerging trends in space-based optical surveillance for space situational awareness (SSA). Their contribution is in subdividing SBO missions into general surveillance and object tracking and studying international efforts and development trends. The contribution is exhaustive in determining strategic frameworks and performance measures such as coverage and revisit time. The lack is that it identifies challenges without suggesting practical implementation solutions or relative algorithmic performance metrics for real-time implementation. O. Kwon et al. [9] introduced a new garbage collection policy for NAND flash memory use in handheld consumer devices for swap space optimization. Their contribution is in extending NAND endurance while improving energy consumption and garbage delay, specifically for addressing demand paging and swapping requirements. The lack is that while simulation-based, there is no provision for validation in multispectrum hardware platforms, and real-time wear leveling efficiency is not fully considered. Zhou et al. [10] examined Canadian space physicians' legal framework, suggesting a “One Country One Licensure” framework. Their contribution is addressing jurisdictional confines in space medicine through analogy from remote, military, and telemedicine practice to suggest national licensing overhaul. The lack is theoretical in nature since, while pinpointing policy resource gaps, the proposed model is not validated for comparison across international law and not tested for simulation-based environments. Chaib et al. [11] designed a novel modified discontinuous space vector modulation technique for Z-source inverters that minimizes power loss. Their contribution is in removing switching transitions and sector equalizing, resulting in higher voltage boosting and lower harmonic distortion content. The lack is that the system proposed, although experimentally validated, is applicable for R-load conditions and may lack generality when applied under dynamic or non-linear load conditions. M. A. A. Mamun et al.[12] simulated performance evaluation of delay-tolerant networking (DTN) network protocols for space networking. Their contribution is GNS3 simulation for validation for DTN robustness under high delay and intermittent links, achieving a success ratio above 90%. The lack is latency, an intrinsic DTN limitation, and the paper acknowledges future work is needed for scalability and security for practical implementation. Y. Abdelsadek et al. [13] outlined a vision for next-generation Space Networks (SpaceNets), including advances in satellite deployment, communication structures, and regulatory policies. The innovation is the overall comparison framework that unifies space, air, and ground infrastructure. The disadvantage is that the framework is conceptual and does not provide algorithmic or technical detail in addressing communication bottlenecks or interoperability challenges. L. Zhou et al. [14] proposed an optimization-based estimation integrated with model predictive control (OBE-MPC) for software-defined power electronics. The innovation provides reduced noise and improved transient performance while enabling reconfigurable power modules for diverse applications. The disadvantage is its reliance upon accurate modeling, and while reducing sensors, its performance under hardware non-ideality has a need for further empirical assessment. R. De et al. [15] surveyed advances in CubeSats for use as science platforms, including their multipoint measurement potential driven through swarm and constellation deployment. The innovation is in emphasizing CubeSats' integration potential for multipoint measurements with regard to communication subsystems. The disadvantage is in overcoming limited-onboard resources such as power and communication bandwidth, which put constraints on high-data-rate mission applications. T. Sato et al. [16] detailed an early 960-Mc maser-based receiving system for deep-space tracking, employed for the Ranger RA-3 mission. The innovation is in achieving low system noise from the integration of ruby-cavity masers and reaching a 47°K system temperature. The disadvantage is that the technology is old-fashioned—while leading-edge for its time, not relevant for current high-frequency or digitally modulated communication scenarios.

C. Objectives

The AIFTES proposed is aimed at overcoming the weaknesses of conventional fault tolerance practices in space electronics through real-time prediction, detection, and correction of faults. Utilizing neural networks and reinforcement learning, AIFTES will provide fault-resistant operation under extreme conditions within space while optimizing performance and energy consumption. This novel approach reduces human intervention and adapts well to changing error patterns and is well suited for long-duration autonomous missions [17].

- To design an AI-based real-time error correction framework for space electronics.
- To apply reinforcement learning for adaptive fault prediction.
- To use correction neural networks for improved data accuracy.
- To minimize power and computation requirements in fault-tolerant systems.

D. Methodology

The methodology proposed facilitates real-time intelligent fault detection and correction in space electronics through AI-augmented logic, which provides adaptive performance under adverse conditions without significant computational cost [18].

- Signal acquisition captures the input signal from space electronics for continuous monitoring.
- Error detection identifies anomalies using comparator-based hardware and machine learning triggers.
- Error correction processes the faulty signals through logic-based corrective circuits.
- AI-based adaptation uses reinforcement learning and neural networks to improve correction accuracy.
- Feedback loop refines detection and correction strategies based on past outcomes and system behavior.

II. Satellite Communication System Architecture

Fig.1. illustrates the functional diagram of a satellite communication system that provides transmission between two remote users via a space satellite. The process incorporates uplink as well as downlink processes for continuous and secure transmission of information [19]. Beginning from the user end, the data is transmitted through a local terrestrial system for handling local communication and then linking up with the Earth station. The signal process is handled at the Earth station using devices like the oscillator for carrier frequency generation, modulator for modulation of signal, amplifier for increasing signal strength, and filter for eliminating unwanted signal noise [20].

The signal is then transmitted through an antenna into an uplink channel connected to a space satellite. The signal is amplified and passed through a transponder fitted in the satellite for amplification and is then sent into a downlink channel for receipt at an Earth station [21-25]. The signal takes the reverse route when returning received at an antenna, passed through the terrestrial system into an Earth station for processing, and then delivered to a user. This model is commonly employed in commercial applications like broadcast satellite television, global communication networks, remote sensing, weather forecasting, and military/defense communication, where secure long-distance information transfer is essential.

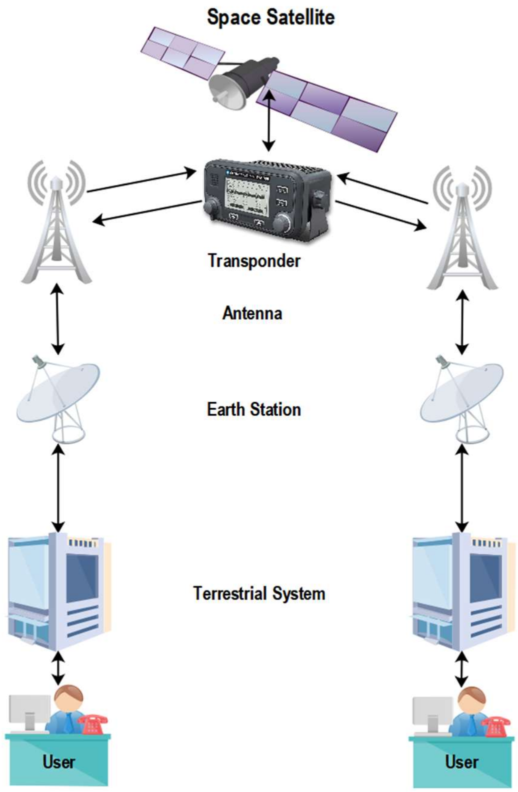

Fig. 1. Satellite Communication Block Diagram

A. Link Budget

The link budget equation is fundamental in satellite communication systems to determine the amount of power received at the ground station from the satellite. It accounts for various gains and losses along the communication path and helps in evaluating the feasibility of the communication link. The equation.1 is expressed as:

$$P_r = P_t + G_t + G_r - L_p - L_s \quad (1)$$

Here, P_r represents the received power at the ground station, P_t is the transmitted power from the satellite, G_t is the gain of the transmitting antenna, G_r is the gain of the receiving antenna, L_p is the free-space path loss, and L_s represents other system losses such as polarization mismatch or atmospheric attenuation. This equation is essential for designing reliable uplink and downlink connections between the satellite and Earth stations.

B. Free-Space Path Loss (FSPL)

Free-space path loss quantifies the signal attenuation over the distance between the transmitting satellite and receiving Earth station in free space, with no obstacles. It depends on the frequency of transmission and the distance of the link. The equation.2 is given as:

$$L_p = 20\log_{10}(d) + 20\log_{10}(f) + 92.45 \quad (2)$$

Where , L_p denotes the path loss in decibels (dB), d is the distance between the satellite and the ground station in kilometers (km), and f is the carrier frequency in gigahertz (GHz). This calculation is crucial for predicting the quality and reliability of signal reception.

C. Signal-to-Noise Ratio (SNR) Equation

The signal-to-noise ratio is a key parameter in assessing the quality of a communication link, representing the ratio of received signal power to the noise power within the system. It determines the clarity and reliability of the received data. The equation.3 for SNR in decibels is:

$$\mathrm{SNR} = P_r - N \qquad (3)$$

Where SNR is the signal-to-noise ratio in dB, P_r is the received signal power in dBm, and N is the noise power in dBm. A higher SNR value indicates better communication performance with reduced errors and improved data fidelity, which is essential in both uplink and downlink satellite links.

III. AI-Driven Fault-Tolerant Architecture For Space Electronics

Fig.2 shows fault tolerance integrating error detection circuitry, an AI component, and error correction circuitry for improving space electronics reliability. The AI component analyzes identified fault and oversees correction strategies for sustained and fault-free system operation with adaptive learning based on feedback.

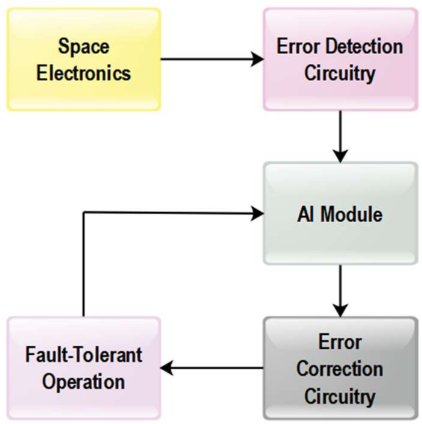

Fig. 2. AI-Based Real-Time Error Correction in Space Electronics.

A. Error Detection Model

The error detection model identifies anomalies in the input signal from space electronics using a parameterized detection function. It ensures that any deviation due to radiation faults or transient errors is captured early for further processing. The equation.1 is given by:

$$D(t) = \Phi_{\mathrm{ED}}(SE(t), \theta_d) \qquad (1)$$

Here, $D(t)$ is the detected fault at time t, $SE(t)$ is the signal input from Space Electronics, Φ_{ED} is the detection function, and θ_d represents the detection threshold parameters used in the Error Detection Circuitry (ED).

B. AI-based Correction Mapping

This stage applies machine learning to interpret the nature of the fault and generate corrected data using temporal and spatial context. It maps the detected error to the most suitable correction path through intelligent learning. The equation.2 is represented as:

$$C(t) = \Psi_{\square\square}(D(t), \Lambda(t), \theta_{ai})\square\square \qquad \square\square\square$$

Where $C(t)$ is the corrected signal, Ψ_{AI} is the AI correction mapping function, $D(t)$ is the detected fault, $\Lambda(t)$ denotes temporal learning patterns, and θ_{ai} are the AI model parameters within the AI Module.

C. Adaptive Feedback Fault-Tolerant Output

This model incorporates feedback from corrected data to dynamically adjust fault tolerance strategies. It closes the loop between error correction and future predictions, ensuring continuous learning and adaptation. The proposed equation.3 is:

$$FTO(t) = \Omega_{\mathrm{FT}}\big(C(t), SE(t), \Delta(t), \theta_f\big) \qquad (3)$$

Where $FTO(t)$ is the Fault-Tolerant Operation output at time t, Ω_{FT} is the adaptive feedback function, $C(t)$ is the corrected data, $SE(t)$ is the original signal input, $\Delta(t)$ is the error correction history and feedback signal, and θ_f denotes the fault-tolerance policy parameters used in the Error Correction Circuitry (EC).

IV. Real-Time Fault Detection and Correction Workflow for Space Electronics

Fig.3 displays a fault-tolerant real-time operating loop in which the system continuously monitors for fault occurrences. Upon detection of a fault, however, the fault signal is referred to error correction circuitry, following analysis and adaptation through an AI block and then back to space electronics. During faultless operation, however, the system will be stable, continuing and adapting intelligently for self-correction.

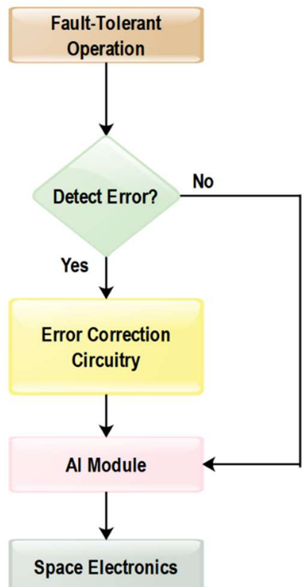

Fig. 3. Flowchart of AI-Enabled Error Detection and Correction in Space Systems

A. Real-Time Fault Detection Workflow Model

This workflow outlines the continuous cycle for monitoring and correcting faults in space electronics using adaptive intelligence. Initially, the Fault-Tolerant Operation monitors system stability. If an error is detected, it triggers the Error Correction Circuitry, which attempts a real-time correction based on predefined logic. The fault check process is formulated as equation.4.

$$\varepsilon(t) = \Gamma(SE(t)) > \theta_{th} \tag{4}$$

where $\varepsilon(t)$ represents the presence of an error, $SE(t)$ is the signal from Space Electronics, Γ is the anomaly detection function, and θ_{th} is the decision threshold used in Error Detection Logic.

B. AI-Based Error Correction Process

Once an error is confirmed, the Error Correction Circuitry applies preliminary corrections, and then feedback is passed into the AI Module. This module refines future correction strategies by learning from ongoing error characteristics and correction outcomes. The correction flow is governed by equation.5.

$$C(t) = \Theta(EC(t), \alpha_{AI}) \tag{5}$$

where $C(t)$ is the corrected output, $EC(t)$ is the initial logic-based correction from Error Correction Circuitry, and α_{AI} denotes adaptive parameters learned by the AI Module.

V. Result and Discussion

Table.1 presents the key components involved in the proposed AI-enhanced system and provides a brief description of each component's role in real-time fault detection and correction.

TABLE I. FUNCTIONAL COMPONENTS OF AI-BASED FAULT-TOLERANT SPACE ELECTRONICS SYSTEM

SI. No	Parameter	Value / Specification
1	Signal Input (SE)	Simulated signal with injected faults
2	Error Detection Circuitry (ED)	Hardware comparator-based + ML triggers
3	Artificial Intelligence Module (AI)	Reinforcement Learning + Correction NN
4	Error Correction Circuitry (EC)	Logic-based error corrector
5	Fault-Tolerant Output (FTO)	AI-validated corrected output
6	Radiation Condition Level	Up to 100 krad
7	Temperature Range (Â°C)	-40 to +125
8	Power Consumption (W)	< 5W average
9	Computation Time (ms)	< 50 ms per cycle
10	Fault Detection Accuracy (%)	99.20%

Fig.4. illustrates three methods' accuracy variation versus time for fault detection: AIFTES (proposed), TMR, and ECC. AIFTES improves continuously, rising up to 99.2%, surpassing both standard methods. TMR and ECC gradually increase but fall below AIFTES along the analysis window. This illustrates the AIFTES framework's better learning ability and adaptive reaction under real-world space electronics fault correction.

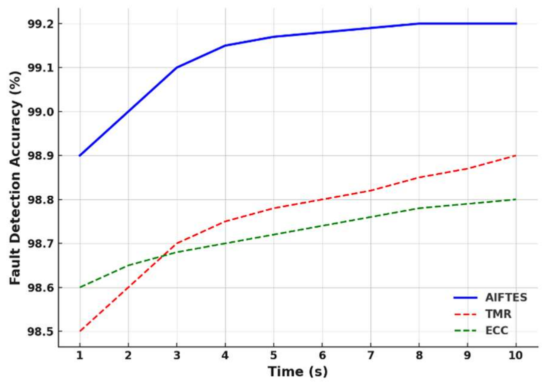

Fig. 4. Fault Detection Accuracy Comparison of AIFTES with TMR and ECC

The computational overhead analysis for the four fault tolerance strategies AIFTES (proposed), TMR, ECC, and EDAC is depicted in this fig.5. AIFTES has a descending trend throughout, lessening its overhead from 4.5W down to 3.8W, indicating increased efficiency in its operation over time. Meanwhile, traditional strategies like TMR, ECC, and EDAC have negligible fluctuations but equally high overhead levels around 5.0W, 4.95W, and 4.85W respectively. This shows AIFTES's high ability in refining computational resource consumption while still maintaining fault tolerance performance.

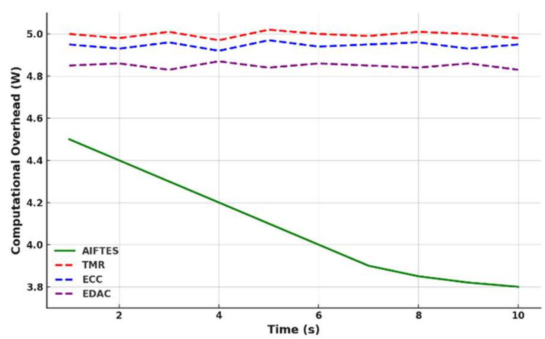

Fig. 5. Computational Overhead Comparison of AIFTES, TMR, ECC, and EDAC

Fig.6 shows the overall performance of four fault tolerance methods—AIFTES, TMR, ECC, and EDAC—is compared here through analysis of fault detection accuracy (blue) and computational efficacy (green, depicted as inverses of overhead). AIFTES has maximum accuracy and efficacy, and hence is the most balanced and optimized approach among them all. All traditional approaches have lower accuracy and higher computation, which exhibits the efficacy advantage of the adaptive AI-based system.

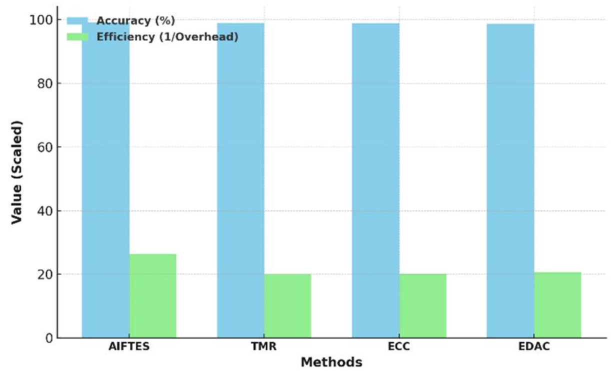

Fig. 6. Bar Chart Comparison of Accuracy and Efficiency Across Fault-Tolerant Methods

VI. Conclusion

The comparative performance analysis clearly shows that AIFTES is much superior compared to conventional fault-tolerance methods like TMR, ECC, and EDAC in terms of accuracy and computational performance. AIFTES has a fault detection accuracy rate of 99.2% while lowering computational overheads down to 3.8W, indicating its suitability for real-time error handling with low resource utilization. With adaptive AI-based mechanisms, AIFTES has stable performance across different operating conditions, which makes it a viable solution for space and mission-related electronic systems. Future work can be done incorporating AIFTES in hardware-in-the-loop simulations and space-enabling embedded platforms for assessing feasibility in real-world deployment. The architecture can be further enhanced for accommodating multi-fault detection, self-healing, and cross-layer optimization between hardware and software domains. Integration of federated learning and cybersecurity augmentation can further enhance feasibility in AIFTES for next-generation autonomous aerospace and satellite applications.

Acknowledgment

The authors would like to thank Channabasaveshwara institute of technology, Gubbi, RV University, and JSS Science and Technology University, Mysuru for their support and encouragement in undertaking this research work and publishing this paper.

References

[1] U. Ragavee, M. Swetha, P. Gopika, L. M. J, M. Saravanapriya and L. D. KM, "Hybrid Tactile Internet Framework Revolutionizing Real-Time Human-Machine Interactions with Multi-Modal Technologies," 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI), Goathgaun, Nepal, 2025, pp. 1811-1818, doi: 10.1109/ICMCSI64620.2025.10883481.

[2] P. Preethi, V. Ragavan, C. Abinandhana, G. Umamaheswari and D. R. Suvethaa, "Towards CodeBlizz: Developing an AI-Driven IDE Plugin for Real-Time Code Suggestions, Debugging, and Learning Assistance with Generative AI and Machine Learning Models," 2024 International Conference on Emerging Research in Computational Science (ICERCS), Coimbatore, India, 2024, pp. 1-7, doi: 10.1109/ICERCS63125.2024.10895857.

[3] B. Lal, V. S. N, M. A. Kumar, N. Chinthamu and S. Pokhriyal, "Development of Product Quality with Enhanced Productivity in Industry 4.0 with AI Driven Automation and Robotic Technology," 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 2023, pp. 184-189, doi: 10.1109/ICAISS58487.2023.10250736.

[4] M. K. K, M. M, A. B. S, Mahadevi, F. Tlajiya and S. Chavan, "Optimizing Energy Management and Load Balancing Through AI-Driven Quantum Approximate Optimization," 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkuru, India, 2024, pp. 1-7, doi: 10.1109/ICMNWC63764.2024.10871970.

[5] S. Dewangan, G. Manoharan, S. S. Minz, S. Kumar, M. B. Talukder and K. Arora, "AI in Telecommunication: Revolutionizing Signal Processing and Communication Networks in Smart Grid," 2025 International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI), Greater Noida, India, 2025, pp. 199-204, doi: 10.1109/IC3ECSBHI63591.2025.10991163.

[6] Venkatesh, D., Mallikarjunaiah, K., & Srikantaswamy, M. (2025). Efficient reconfigurable parallel switching for low-density parity-check encoding and decoding. IAES International Journal of Artificial Intelligence (IJ-AI), 14(1), 260-269. doi:http://doi.org/10.11591/ijai.v14.i1.pp260-269.

[7] Charitha, M., Hosur, S., Srikantaswamy, M. (2025). Optimized BER reduction in wireless communication using a chaos-based CDSK modulation model. Mathematical Modelling of Engineering Problems, Vol. 12, No. 2, pp. 719-729. https://doi.org/10.18280/mmep.120234.
[8] H. Yunpeng, L. Kebo, L. Yan'gang and C. Lei, "Review on strategies of space-based optical space situational awareness," in Journal of Systems Engineering and Electronics, vol. 32, no. 5, pp. 1152-1166, Oct. 2021, doi: 10.23919/JSEE.2021.000099.
[9] O. Kwon and K. Koh, "Swap space management technique for portable consumer electronics with NAND flash memory," in IEEE Transactions on Consumer Electronics, vol. 56, no. 3, pp. 1524-1531, Aug. 2010, doi: 10.1109/TCE.2010.5606292.
[10] Zhou, V. Nwaokoro, V. Oosterveld and A. Sirek, "Building a One Country One Licensure Framework: Applications for the Future of Canadian Space Physicians," in IEEE Open Journal of Engineering in Medicine and Biology, vol. 4, pp. 212-215, 2023, doi: 10.1109/OJEMB.2023.3241597.
[11] Chaib, E. M. Berkouk, J. -P. Gaubert, M. Kermadi, N. Sabeur and S. Mekhilef, "An Improved Discontinuous Space Vector Modulation for Z-Source Inverter With Reduced Power Losses," in IEEE Journal of Emerging and Selected Topics in Power Electronics, vol. 9, no. 3, pp. 3479-3488, June 2021, doi: 10.1109/JESTPE.2020.3002684.
[12] M. A. A. Mamun, M. Li and B. K. Pramanik, "Development of Delay-Tolerant Networking Protocols for Reliable Data Transmission in Space Networks: A Simulation-Based Approach," in IEEE Access, vol. 12, pp. 178642-178658, 2024, doi: 10.1109/ACCESS.2024.3501676.
[13] M. Y. Abdelsadek et al., "Future Space Networks: Toward the Next Giant Leap for Humankind," in IEEE Transactions on Communications, vol. 71, no. 2, pp. 949-1007, Feb. 2023, doi: 10.1109/TCOMM.2022.3228611.
[14] L. Zhou, M. Eull and M. Preindl, "Optimization-Based Estimation and Model Predictive Control for High Performance, Low Cost Software-Defined Power Electronics," in IEEE Transactions on Power Electronics, vol. 38, no. 1, pp. 1022-1035, Jan. 2023, doi: 10.1109/TPEL.2022.3202863.
[15] R. De, M. P. Abegaonkar and A. Basu, "Enabling Science With CubeSats—Trends and Prospects," in IEEE Journal on Miniaturization for Air and Space Systems, vol. 3, no. 4, pp. 221-231, Dec. 2022, doi: 10.1109/JMASS.2022.3209897.
[16] T. Sato and C. T. Stelzried, "An Operational 960-Mc Maser System for Deep-Space Tracking Missions," in IRE Transactions on Space Electronics and Telemetry, vol. SET-8, no. 2, pp. 164-170, June 1962, doi: 10.1109/IRET-SET.1962.5008826.
[17] Jian Gao, Kangning Wu, Zongliang Xie, Jianying Li, Shengtao Li, Constructing interfacial barrier from tribo-positive shell microcapsules to suppress space charge in thermochromic phase change composites for smart electronics, Composites Science and Technology, Volume 244, 2023, 110291, https://doi.org/10.1016/j.compscitech.2023.110291.
[18] Gaurav Saxena, Alka Verma, Ranjana Kumari, Ruchi Agarwal, Maksud Alam, El-Sayed M. Sherif, Yogendra Kumar Awasthi, Himanshu Singh, High Q ultra-thin nona-band polarization insensitive homogeneous single layer metasurface for electronics and space industry with electromagnetic interference and antenna radar cross section reduction, Materials Today Communications, Volume 40, 2024, 109674,https://doi.org/10.1016/j.mtcomm.2024.109674.
[19] Sabah Suhail, Rasheed Hussain, Abid Khan, Choong Seon Hong, Orchestrating product provenance story: When IOTA ecosystem meets electronics supply chain space, Computers in Industry, Volume 123, 2020, 103334,https://doi.org/10.1016/j.compind.2020.103334.
[20] Youngchan Yoon, Dong Rip Kim, Kwan-Soo Lee, Cooling performance and space efficiency improvement based on heat sink arrangement for power conversion electronics, Applied Thermal Engineering, Volume 164, 2020, 114458, https://doi.org/10.1016/j.applthermaleng.2019.114458.
[21] Sabah Suhail, Rasheed Hussain, Abid Khan, Choong Seon Hong, Corrigendum to “Orchestrating product provenance story: When IOTA ecosystem meets electronics supply chain space” [Comput. Ind. 123 (December) (2020) 103334], Computers in Industry, Volume 128, 2021, 103392,https://doi.org/10.1016/j.compind.2020.103392.
[22] Yao Yao, Juan M. Fernandez, Sven G. Bilén, Xin Ning, Multifunctional bistable ultrathin composite booms with flexible electronics, Extreme Mechanics Letters, Volume 72, 2024, 102247, https://doi.org/10.1016/j.eml.2024.102247.
[23] Anders Broo, Michael C. Zerner, Electronic structure of donor-spacer-acceptor molecules of potential interest for molecular electronics. IV. Geometry and device properties of P3CNQ and Q3CNQ, Chemical Physics, Volume 196, Issue 3, 1995, Pages 423-436,https://doi.org/10.1016/0301-0104(95)00137-D.
[24] M, Poornima & N, Anitha & S, Mallikarjuna & L, Umashankar. (2025). An efficient internet of things based intrusion detection and optimization algorithm for smart networks. International Journal of Computing and Digital Systems. 17. 1-12. 10.12785/ijcds/1571001227.
[25] H.B, Mahesh & Ahammed, Ali & S.M, Usha & Swamy, Mallikarjunaswamy. (2025). Optimized Efficiency of IoT-Based Next Generation Smart Wireless Sensor Networks Using a Machine Learning Algorithm. International Journal of Computing and Digital Systems. 18. 1-10. 10.12785/ijcds/1571107237.