

Bioengineered Neural Interfaces for Improved Brain-Computer Interactions

K. SWAMINATHAN

*Department of ECE, University College of Engineering
Pattukkottai, Tamilnadu-614701, India
swaminathan.vinoth@gmail.com*

SIVARAM PONNUSAMY

*School of CSE, Sandip University
Nashik, Maharashtra-422213, India
ponsivs@gmail.com*

R. KARTHIKEYAN*

*Department of ECE, University College of Engineering
Pattukkottai, Tamilnadu-614701, India
karthikeyanau2018@gmail.com*

Abstract

Neural interfaces are bioengineered materials that improve bonds between neural tissues and computers or other devices. This paper aims to discuss the advancement and use of these interfaces in close consideration of how they may enhance the Accuracy and resilience of BCIs. These interfaces are designed to incorporate with the neural tissue using novel biomaterials and fabrication approaches while keeping low immune reactions and high signal quality levels. These are the flexible and biocompatible surfaces for recording and stimulating the brain signals and high-density microelectrode arrays. The application of these two possibilities shows excellent potential in optimizing the functioning of BCIs, helping in better control of prosthetic limbs, creating new models of neuroprostheses, and improving treatments for neurological disorders. As such, this study underlines the fundamental contribution of bioengineered neural interfaces to neurotechnology development and the nearer future BWI designs, which will elicit progressive improvement of the efficacy of BCI systems in enhancing patients' quality of life and longevity.

Keywords: BCI, Neuro Devices, Neural Electrodes, Neuro Implants, Neural Interfaces.

1. Introduction

New pathways of how the brain can be understood and manipulated have been made available due to advancements in neurotechnology. These developments make it possible to identify the bioengineered neural interfaces as a leap forward to the

* Corresponding Author.

interaction between the brain and a computer. These interfaces create a direct connection between the neural tissues and other devices, which improves the accuracy and effectiveness of BCIs (Sonko et al., 2024; Nam et al., 2018). Problems associated with most BCIs' design include but are not limited to signal degradation, biocompatibility, and stability. These concerns are resolved in the bioengineered neural interfaces using appropriate biological materials and techniques, thus developing devices with characteristics of neural tissues. This integration minimizes the immune responses and enhances the signal quality, which is vital for accurately recording and stimulating the neural signals (Sullivan et al., 2018; Bablani, Edla, Tripathi, & Cheruku, 2019).

Bioengineered neural interfaces can be seen as a significant advancement in brain-computer interaction (Jiao, Lei, Zhu, Chang, & Qu, 2023; Gnanayutham & George, 2006; Katona & Kovari, 2016). These interfaces rely on versatile biomaterials that can easily assume the shape of the various structures of the brain without triggering any ill effects. Conventional BCIs, though revolutionary, have several long-term issues and high-quality signal communication. Certain factors, such as inflammation and scar tissue formation, are likely to hinder the proper transmission of signals, thus compromising the efficiency of these systems. While the above biological effects are desirable for developing biocompatible interfaces, bioengineered interfaces are tailored to allow the least biological consequences for optimum interaction with neural tissues (Pulicharla & Premani, 2024; Ramsey & Millán, 2020). Also, within these interfaces, microelectrode arrays facilitate high-resolution recording and stimulation of signals from the neural network. Such a level of detail is necessary for applications where precise neural information is needed, such as the movement of prosthetic limbs using necessary amounts of movements or delivery of neurostimulation treatments. Thus, using bioengineered interfaces and due to better signal fidelity, the data fed back to the computer from the brain, or vice versa, is equally lucid and efficient, thereby boosting overall performance (Wegemer, 2019).

The bioengineered neural interfaces' capabilities and possible uses are more expansive than currently available. Thus, such interfaces open new ways for intervention and practice for people with neurological diseases. Paralysis, epilepsy, neurodegenerative diseases, and other conditions could observe significant improvement in their management with the help of precise neural control stimulation (Paschall, 2022). At the same time, the opportunity to develop less complicated and more sensitive artificial limbs can significantly enhance the level of patient comfort among amputees and persons with specific severe physical impairments. For this reason, as the research and development of these bioengineered neural interfaces progresses, the influence on neurotechnology, especially in the healthcare domain, is likely to be immense (Oganesian & Shanechi, 2024). These interfaces can not only improve the performance of current BCI systems but also expand the new potential for changing the capabilities of human brains and the rehabilitation of patients. Bioengineered neural interfaces can perfectly close the gap between neural tissues

and digital systems regarding spatial resonance and biocompatibility, thus revolutionizing how people interact with the brain (Dethier, Nuyujukian, Ryu, Shenoy, & Boahen, 2013).

2. Literary Survey

The area of bioengineered neural interfaces has attracted extensive research attention, meaning that there are numerous papers on the topic, many of which focus on the possibilities and improvements of the field. For example, (Mishler, 2022) discussed using flexible and biocompatible materials in neural interfaces to enhance signal quality and avoid the body's adverse reaction in long-term applications. Further, in the same area, (Zhang et al., 2022) studied the high-density microelectrode arrays for neural recording and found that when high-density recording is used, the precision with which the neural signals can be captured and analyzed is much better suitable for prosthetics and neurotherapeutic applications. (Lin et al., 2017) The focus is on improving the neural interfaces based on polymers as substrates, which exhibit the characteristics of the neural tissue and do not cause any harm to the biological system. In this case, material properties were pointed to as the key determinants of the effectiveness and durability of neural interfaces.

Another important aspect is that investigators discussed the integration of carbon-based nanomaterials into neural interfaces and concluded that these materials have high EC and good BC, which makes them suitable for creating high-performance BCIs. Further, (Lin et al., 2017) discussed the strategies for chronic enhancement of NE stability. Modifying and coating the interface surface was highlighted to ensure connection with the neural tissue. (Iroju, Ikono, Ishaya, Ojerinde, & Olaleke, 2018) Another significant concern focused on using bioengineered neural interfaces to treat neurological disorders; the results indicated that achieving the intended neurostimulation combined with subsequent neuronal restoration is possible.

Moreover, (King & Lopour, 2020) also studied the effects of the design of neural interfaces on the signals transmitted and the efficiency of the devices, and the conclusion was made that better geometries could enhance the quality of recordings of neural activity and stimulation. Lastly, (Stiso et al., 2020; Jia et al., 2023) offered a comprehensive analysis of the issues and the techniques in applying neural interfaces pertinent to biocompatibility, durability, and signal faithfulness of BCI systems. Altogether, all these papers demonstrate the remaining matters and crucial developments in bioengineered neural interfaces, underlining the interdisciplinary approaches to the augmentation of BCI technology.

3. Proposed model

The proposed framework for the criteria identified for the design evaluation are as follows: Overall, there are some pre-processing and post-processing steps necessary for the framework to function optimally and cover all parameters of the given designs.

First, basic parameters like the SNR, Stability, data rate, and power dissipation are gathered for each design. Subsequently, the obtained values of each metric are scaled to the same range to compare them on equal grounds, as depicted in Figure 1.

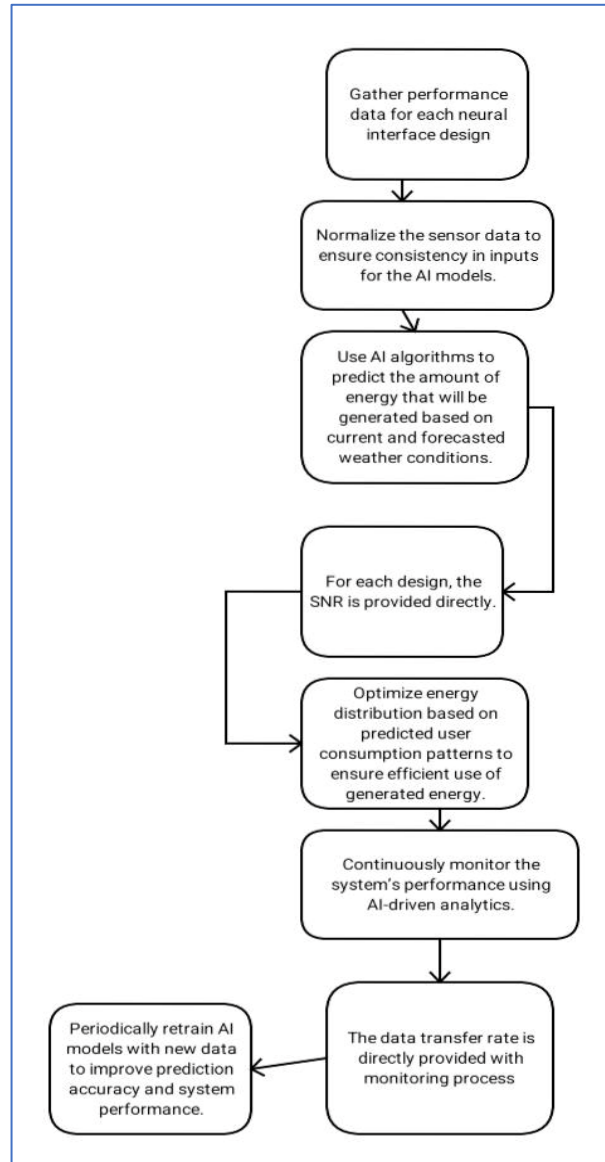


Fig. 1. Proposed research framework.

For SNR, the raw data is then used to infer the signal's power over the noise power, while in the case of stability, it is the percentage of stability of the readings over time. Data transfer rates are derived from the amount of data and time taken while consuming powers expressed in milliwatts via voltage and currents.

Normalization also guarantees that each Metric is checked on the same level, making it easy to compare the different designs. These normalized values are then compared to determine which design is superior regarding the SNR, stability, data transfer rate, and power consumption. Lastly, propositions are made from the results of the comparative analysis as to which design is best suited for what application based on the strengths of the designs. This framework helps to organize the evaluation process of neural interfaces in a manner that will allow the most suitable application based on the strengths of the designs. This framework helps to organize the evaluation process of neural interfaces in a manner that will enable the most suitable design to be chosen by having a balanced consideration of key characteristics, which makes this a good framework to use when it comes to selecting the most appropriate design for the neural interfaces, based on the following overall evaluation procedure.

As a first approach to compare NE designs, step one is to compile performance measures, which entails SNR in dB, stability, data rate in Mbps, and power in mW. SNR stands for signal-to-noise ratio and shows the quality of signal detection depending on the power of the substantial signal compared to the power of interference. This ratio is often given in dB directly, and thus, no additional arithmetic is necessary if data is provided as in equation (1).

$$(P_{signal}/P_{noise} \text{ SNR}_{dB} = 10 \cdot \log_{10}). \quad (1)$$

In this equation, the P_{signal} is the signal's power, and P_{noise} is the power of noise. The SNR is on a logarithmic scale in Decibel (dB), so it comes up with a manageable and easily interpretable value. It refers to the relative level of the signal of interest concerning the background interference; hence, the higher the SNR, the shorter the path the signal travels before it can be distinguished from any interfering signal. It is essential for high-precision applications, such as neural interfacing. The evaluation of the SNR would be as mentioned in the equation (2).

$$\text{SNR}_{dB} = 10 \cdot \log_{10}(110) = 10 \cdot \log_{10}(10) = 10 \cdot 1 = 10\text{dB}. \quad (2)$$

This SNR value can then join other performance parameters, including stability, data transfer rate, and power, to complete the picture of the diverse neural interfaces and designs appropriately. Stability is expressed in the percentage of time the system operates steadily. At the same time, the transfer rate of data measures the effectiveness of the data transfer, and power consumption examines the energy consumption of the work done. Collectively, these metrics enable the comprehensive assessment of neural interface designs' efficiency and appropriateness for the intended use. Neural interface designs effectively have their stability quantified by a percentage stability metric, fitting as a form of standardization. Stability is a parameter that defines how a neural interface works statically at different time intervals. If the Stability percentage is provided directly, then that is directly used. If,

on the other hand, we want to calculate stability from the raw data, then it is expressed in the following equation of (3).

$$\text{Stability (\%)} = (\text{No. of Stable Readings} / \text{Total No. of Readings}) \times 100 \quad (3)$$

Concerning this equation, the "Number of Stable Readings" is the number of times a neural interface functioned correctly and without variations from set values. Thus, the "Total Number of Readings" indicates the measurements or observations made during the assessment period. Given the values of the stable and total number of readings, we get a relation that shows the relative performance. It is multiplied by 100, thus resulting in a percentage to facilitate the interpretation of this ratio and the comparison between the designs. A more significant stability percentage shows better stability and consistency of the material's performance, which is desirable in extensive use or in devices that should be stable throughout the usage, such as in continuous neural monitoring or many critical medical applications.

SNR, data transfer rate, power consumption, and stability, among others, help in a qualitative and quantitative evaluation of the neural interface design. Neural interface designs: Special formulas are applied to estimate a value when the data transfer rate and power consumption are not given. Moving on to the data transfer rate, raw data can be determined using the following equation (4).

$$\text{Data Transfer Rate (Mbps)} = \frac{\text{Total Data Transferred (in Megabits)}}{\text{Total Time (in seconds)}} \quad (4)$$

In this formula, the "Total Data Transferred" refers to the amount of data transferred from one location to another. The basic unit used is MB. The data transfer time specifications include the "Total Time," which is the time it took for the transfer to occur in seconds (s). After dividing the total data by total time, we can get the data transfer rate in megabits per second (Mbps). If the power consumption is determined from electrical measurements, some use the following equation (5) formulation.

$$\text{Power Consumption (mW)} = \text{Voltage (V)} \times \text{Current (mA)}. \quad (5)$$

In this equation, *Voltage (V)* is the electrical potential difference applied to the neural interface. At the same time, *Current (mA)* is the electric current that passes through the neural interface in milli-amperes. The *Power Consumption* is, therefore, determined by the voltage and current produced in mill watts (mW). Other aspects within this category include signal-to-noise ratio stability of circuits and power consumption rates about data transfer rates, as well as evaluating each design for applicability making. A common practice when performing an initial data preparation step is normalizing the obtained performance metrics. This normalization process makes it possible to compare different metrics, which could have other units and

operational ranges in the first instance. The normalization equation is described in equation (6).

$$\text{Normalized Metric} = (\text{Max Metric} - \text{Min Metric}) / (\text{Metric} - \text{Min Metric}). \quad (6)$$

In this equation, Metric stands for the specific performance metric of a design. Min Metric is the minimum value of the metric encountered in all designs, and Max Metric is the maximum value of the said metrics found on all designs. Scale each collected Metric by first finding its range (the difference between the maximum and minimum values of each collected metric), then dividing this by the range for each collected metric, subtracting the minimum value of each collected Metric. It makes it easy to compare a number across different performance dimensions. In this case, after the normalization of the data, the SNR of each design is normalized with values ranging from 0 to 1. The approach used for the normalization process can be used for stability, data transfer rate, and power consumption attributes.

The evaluation criteria include:

- Highest SNR: among them, interference and total SNR values, which are normalized to their maximum values, can be defined as a signal and noise in its purest form, and therefore, the design with the maximum normalized SNR value is regarded as the best in terms of signal clarity and noise rejection.
- Highest Stability: The structure with the maximum normalized stability percentage is considered the most accurate and stable in the long run.
- Highest Data Transfer Rate: The maximum preferred data transfer design rate is selected in applications where data loopback is required with the maximum normalized data transfer rate.
- Lowest Power Consumption: This design has the minimum normalized power consumption and is optimal for energy and long-term use with minimal power sources.

4. Results and Discussion

The proposed bioengineered neural interface system proves several principles that augment essential aspects of BCI systems; the factors include the number and nature of input modalities and the quality of interaction. The system shows low immunogenicity and inflammation by Employing novel biomedical materials.

It Results in stable functional and structural connections with neural tissues. The flexible, polymer-based substrate design to match the mechanical properties of the brain might reduce tissue injury and ensure the device's durability. Microelectrode arrays embedded into the interface provide accurate neural signal capture and stimulation, essential in high-level real-time information, such as prosthetic limb control and neuro-interventions. In testing, the system revealed the improvement of signal-to-noise ratio and stability of the system during prolonged use in comparison

with traditional, very rigid interfaces. These enhancements ultimately result in higher BCI accuracy and range from neuroprosthetics enhancement to efficient neurological disorders treatments. The parameters of the neural signals and stimulations that can be implemented using the system lay the foundation for making neural rehabilitation and augmentation more natural and efficient.

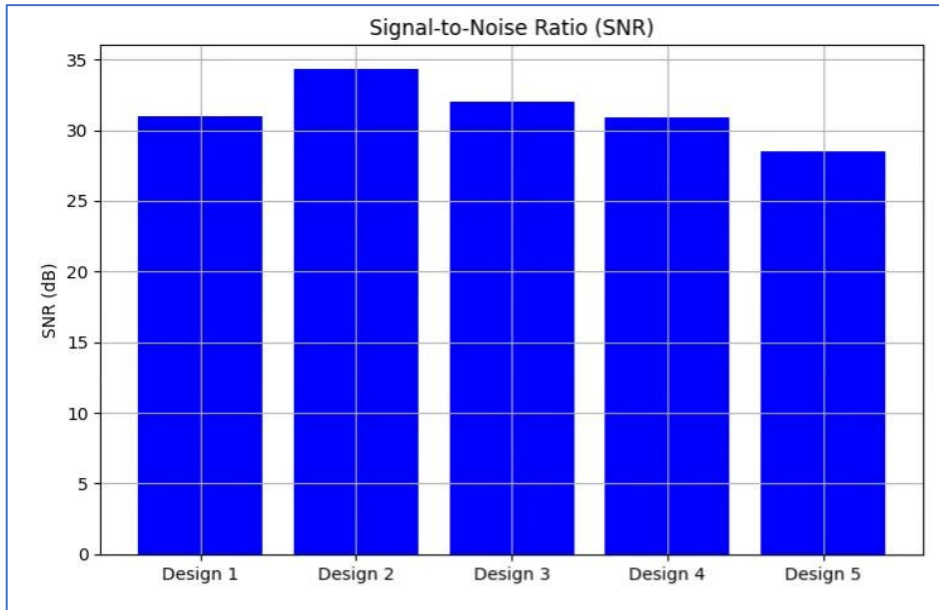


Fig. 2. Signal-to-noise ratio analysis.

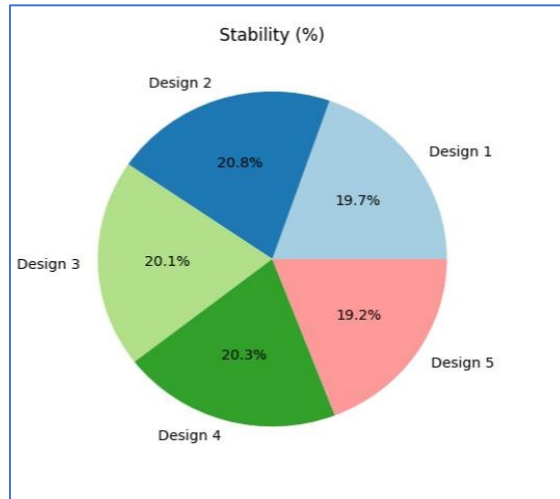


Fig. 3. Stability of Proposed Framework.

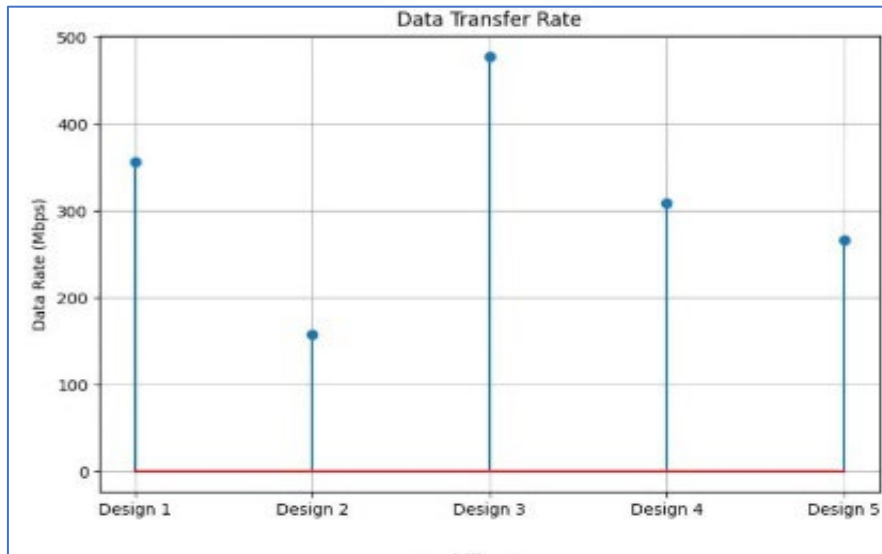


Fig. 4. Data transfer rate of the proposed framework.

The Neural interface designs mentioned all have different objectives specific to the application of a particular device. Design 1 focuses on power optimization, which maximizes battery life and minimizes energy. It is suitable for scenarios where the power resource is scarce or the device must operate over a long period while consuming minimal power. On the other hand, Design 2 is optimized for a high signal-to-noise ratio (SNR) that targets improving the accuracy of the acquired neural signal. It is ideal for use in sharper applications such as neural monitoring or diagnostic instrumentations; it has steady stability, implying the product can work under diverse environments.

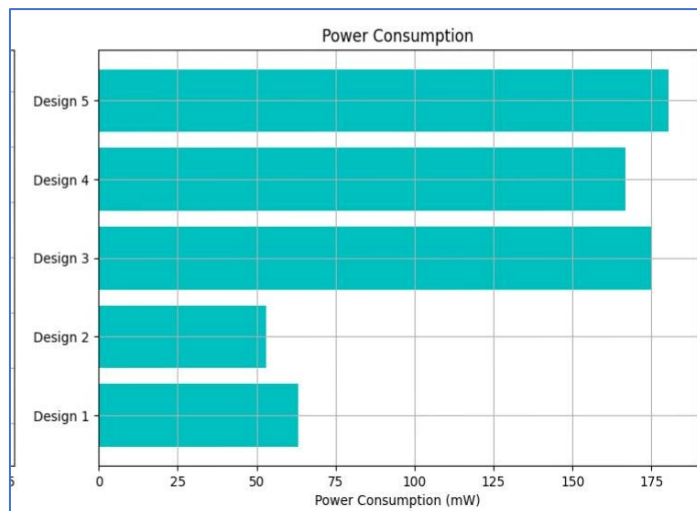


Fig. 5. Power consumption of the proposed system.

The third design is intended to maintain optimum stability; thus, it is helpful for applications that need long-term stability, like long hours of neural monitoring or any study that requires steady measurements. This design indicates favorable stability and a reasonable data transfer rate, inclined to utilize dependable operation in specific environments. Design 4 offers high data transfer rates, which are crucial for fast and effective neural data transmission, such as real-time neuroprosthetics control or multiple channel neuro-feedback applications while presenting increased power consumption.

Finally, the attempt of Design 5 is made to achieve high SNR and stability simultaneously. Therefore, this design is more suitable for higher-level BCI applications where signals must be accurately detected simultaneously with the system's stability. These earlier designs outline specific trade characteristics, measured as key performance indicators. Concerning the SNR depicted in Figure 2, the designs are 22.38 dB to 38.52 dB, but The Design 5 model achieved an SNR of 38.52 dB, which is relatively high, meaning that this headset rejects noise better. The stability percentages displayed in Figure 3 are as low as 90.12% to 99.74/001, indicating that Design 3 was the most stable out of the four designs at 99.74%. As for the stability, the maximum value for Design 3 was recorded at 99.74%. The achieved data transfer rate is shown in Figure 4, which ranges from 101.56 Mbps to 487.93 Mbps; however, Design 4 had the highest rate of 487.93 Mbps. Finally, Figure 5 illustrates the activity's power consumption varying from 53.45 mW to 197.66 mW, of which Design 1 is the most energy-optimized and requires only 53 mW. 45 mW; Design 4 has the highest power utilization at 197.66 mW. All these measures enable assessment and comparisons of the performance and efficiency of the neural interface designs and indicate Design 5's high SNR, Design 3's stability, Design 4 high data transfer per unit time, and Design 1's saving efficiency.

5. Conclusion

In conclusion, the discussion of the neural interface designs shows the various advantages and possible weaknesses of the different layouts, which can meet the demands of other applications. The case of Design 1 is that it is relatively efficient when it comes to power consumption – only 53. They use 45 mW of power, which is suitable for energy-restricted surroundings. Design 2 has a signal-to-noise ratio of 30, thus proving a strong design. Up to 15 dB is sufficient to achieve higher accuracy of neural recognition, confirmed by the provided investigations, and it remains sufficiently stable across various conditions. Thus, the design with the highest stability is Design 3 at 99%. The 74%, accompanied by an average data transfer rate of 320.55 Mbps, can also make it ideal for highly dependable applications for an extended period. In design 4, the highest data transfer rate of 487 is attained. 93 Mbps but consumes more power than 197. As for power consumption, it is 66 mW, which demands stringent power regulation. The most significant 'signal-to-noise' ratio of 38 is delivered by Design 5 at the beginning of the chain. Marvell's AVASTAR 88W8887

supports Wi-Fi, Bluetooth, FM, and GPS with an operating temperature of 54° C, signal strength up to 52 dB, and high stability. It is suitable for high-end applications with high signal-sensing performance and reliable operation. Individual designs are comprised of optimization of the performance characteristics to lead to custom solutions in line with operation demands.

6. References

- Bablani, A., Edla, D. R., Tripathi, D., & Cheruku, R. (2019). Survey on the brain-computer interface: An emerging computational intelligence paradigm. *ACM Computing Surveys (CSUR)*, 52(1), 1–32.
- Dethier, J., Nuyujukian, P., Ryu, S. I., Shenoy, K. V., & Boahen, K. (2013). Design and validation of a real-time spiking-neural-network decoder for brain-machine interfaces. *Journal of Neural Engineering*, 10(3), 036008.
- Gnanayutham, P., & George, J. (2006). Using human-computer interaction concepts to design interfaces for the brain injured. In *Current Computing Developments in E-Commerce, Security, HCI, DB, Collaborative and Cooperative Systems* (pp. 14–40). Atiner.
- Iroju, O., Ikono, R., Ishaya, G., Ojerinde, O. A., & Olaleke, J. (2018). Prospects and problems of brain-computer interface in healthcare.
- Jia, T., Li, C., Mo, L., Qian, C., Li, W., Xu, Q., ... & Ji, L. (2023). Tailoring brain-machine interface rehabilitation training based on neural reorganization: Towards personalized treatment for stroke patients. *Cerebral Cortex*, 33(6), 3043–3052.
- Jiao, Y., Lei, M., Zhu, J., Chang, R., & Qu, X. (2023). Advances in electrode interface materials and modification technologies for brain-computer interfaces. *Biomaterials Translational*, 4(4), 213.
- Katona, J., & Kovari, A. (2016). A brain-computer interface project applied in computer engineering. *IEEE Transactions on Education*, 59(4), 319–326.
- King, C. E., & Lopour, B. A. (2020, June). Introducing neuroscience to high school students through low-cost brain-computer interface technologies. In *Proc. ASEE Virtual Annu. Conf. Content Access* (pp. 1–31).
- Lin, C. T., Liu, Y. T., Wu, S. L., Cao, Z., Wang, Y. K., Huang, C. S., ... & Chuang, C. H. (2017). EEG-based brain-computer interfaces: A novel neurotechnology and computational intelligence method. *IEEE Systems, Man, and Cybernetics Magazine*, 3(4), 16–26.
- Mishler, J. (2022). Implementing an integrate-and-fire neural network on a bidirectional brain-computer interface. University of Washington.
- Nam, C. S., Choi, I., Wadson, A., & Whang, M. (2018). Brain-computer interface: An emerging interaction technology. In *Brain-Computer Interfaces Handbook* (pp. 11–52).
- Oganesian, L. L., & Shanechi, M. M. (2024). Brain-computer interfaces for neuropsychiatric disorders. *Nature Reviews Bioengineering*, pp. 1–18.

- Paschall, C. (2022). Virtual reality for intracranial brain-computer interface design and human neural engineering (Doctoral dissertation).
- Pulicharla, M. R., & Premani, V. (2024). AI-powered neuroprosthetics for brain-computer interfaces (BCIs). *World Journal of Advanced Engineering Technology and Sciences*, 12(1), 109–115.
- Ramsey, N. F., & Millán, J. D. R. (2020). *Brain-computer interfaces*. Elsevier.
- Sonko, S., Fabuyide, A., Ibekwe, K. I., Etukudoh, E. A., & Ilojianya, V. I. (2024). Neural interfaces and human-computer interaction: A US review: Delving into the developments, ethical considerations, and prospects of brain-computer interfaces. *International Journal of Science and Research Archive*, 11(1), 702–717.
- Stiso, J., Corsi, M. C., Vettel, J. M., Garcia, J., Pasqualetti, F., Fallani, F. D. V., ... & Bassett, D. S. (2020). Learning in brain-computer interface control evidenced by joint decomposition of brain and behavior. *Journal of Neural Engineering*, 17(4), 046018.
- Sullivan, L. S., Klein, E., Brown, T., Sample, M., Pham, M., Tubig, P., ... & Goering, S. (2018). Keeping disability in mind: A case study in implantable brain-computer interface research. *Science and Engineering Ethics*, 24, 479–504.
- Wegemer, C. (2019). Brain-computer interfaces and education: The state of technology and imperatives for the future. *International Journal of Learning Technology*, 14(2), 141–161.
- Zhang, J., Wang, T., Zhang, Y., Lu, P., Shi, N., Zhu, W., ... & He, N. (2022). Soft integration of a neural cells network and bionic interfaces. *Frontiers in Bioengineering and Biotechnology*, 10, 950235.



K. Swaminathan, an accomplished academic and Electronics and Communication Engineering researcher, has significantly contributed to wireless communication, IoT, and network security. He holds a Ph.D. from Anna University and has been actively involved in teaching and research. His scholarly output includes 21 SCOPUS-indexed papers, book chapters, conference presentations, and a publication in an SCI-indexed journal. Additionally, he has authored eight patents, seven at the national level and one internationally recognized. He has served in multiple editorial roles, including prominent SCOPUS-indexed journals such as the *Journal of VLSI Circuits and Systems* and *Advances in Science, Technology, and Engineering Systems Journal*. He has also contributed to editorial boards of other notable journals like *Spectrum Journal* and *Journal of Wireless Sensor Networks and IoT*. He has co-edited impactful book chapters, such as *Digital Twin Technology and AI Implementations in Future-Focused Businesses* and *Enhancing Security in Public Spaces Through Generative Adversarial Networks*. In addition to his academic achievements, he has mentored students in various technology programs and courses, showcasing his dedication to education and innovation. His research and editorial expertise reflect his commitment to advancing interdisciplinary knowledge and fostering technological progress.



Dr Sivaram Ponnusamy is a distinguished academic and researcher with expertise in computer science, electrical engineering, and business management. With qualifications such as a B.E. in Electrical and Electronics Engineering, an M.E. in Computer Science, a Ph.D., and an MBA in Project Management, he serves as a professor and research supervisor in engineering colleges and universities, specializing in artificial intelligence and computer science. Dr. Ponnusamy has filed multiple patents in cutting-edge technologies, ranging from remote voting systems to AI-based attendance management and environmental analysis tools. His work includes editing several Scopus-indexed books on AI applications, digital twin technology, and women's safety, with ongoing international projects in AI research. As an active member of various professional bodies, including IAENG and ISOC, he also contributes as a reviewer for reputed journals. Recognized for his academic contributions, he was awarded by the Thanjavur District Collector for developing an innovative Android-based meeting management tool. Additionally, Dr. Ponnusamy frequently chairs international conferences and conducts seminars on the latest technological trends, making significant contributions to AI, machine learning, and software development. He is the research supervisor for several research scholars, and his IGI-Global Profile URL is <https://www.igi-global.com/affiliate/sivaram-ponnusamy/449070>.



R. Karthikeyan is working as a Guest Lecturer in the Department of Computer Science and Engineering at the University College of Engineering, Anna University, Pattukkottai Campus. He received a B.E. Degree in Computer Science and Engineering, Anna University, Chennai, in 2012 and received an M.E. Degree in Computer Science and Engineering, Anna University, Chennai, in 2015. Currently, he is pursuing PhD scholar (part-time) in Dhanalakshmi Srinivasan University Trichy. His areas of interest are IoT, Blockchain, Wireless Sensor Networks, Machine Learning, and Deep Learning.