Electromagnetic Compatibility in Wearable Devices: A Fuzzy Logic Approach

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Received 08 January 2025; Accepted 01 May 2025

Abstract

Wearable devices, integral to IoT Applications, require stringent performance and reliability constraints. Due to their heterogeneous nature and ideal placement strategies, they may be susceptible to unattended Electromagnetic Interference (EMI). EMI in wearables ideally addresses strategies considering the environment, materials, design, and regulatory compliance. However, most wearables may be used collectively and oriented along paths that may cause disruptions and imprecision in expected behaviours. Our article presents a fuzzy inference system (FIS) that models discrepancies like non-ideal placement positions and movement of devices. The model presents the impact of parameters like frequency, power level, proximity, and size on predicting variation in electromagnetic Interference.

Keywords: Fuzzy Logic, electromagnetic interference, compatibility (EMC), wearables.

Journal of Mobile Multimedia, Vol. 21_3&4, 679–692.
doi: 10.13052/jmm1550-4646.213419

1 Introduction

Wearable devices categorically belong to IoT applications that focus on health tracking and fitness monitoring and require providing quick access to notifications or apps. These electronic gadgets can be worn on the body and are primarily hands-free and portable. Having a significant role in the Internet of Things (IoT) ecosystem, these gadgets enhance connectivity, data collection, and real-time analytics. Examples include smartwatches and fitness bands to track vital health metrics (e.g., heart rate, sleep patterns, physical activity, and chronic disease management like diabetes and heart disease. The objective is to alert users to potential health issues, facilitate proactive management and intervention, and provide users and healthcare providers with valuable health data. In industrial and corporate contexts, wearables monitor employee health and safety by being integrated into clothing and accessories. These devices offer functionalities like activity tracking, temperature regulation, and interactive features while ensuring prevention and alert systems in cases of exposure to harmful conditions. Other wearables applications include location tracking, emergency alerts, and behavioural studies. Monitoring performance and reliability have become critical since such devices are concerned with health and fitness [1–4].

Ideally, wearables can integrate seamlessly with other IoT devices, such as smart home systems, providing users with a connected and automated environment. For example, smartwatches enable communication through notifications, messaging, and calls, enhancing user connectivity without needing a smartphone. However, the increase in the number of devices and the device-per-user ratio shifts the focus on the impact of electromagnetic Interference and coupling caused by such devices. Electromagnetic Interference (EMI) can significantly impact the performance and reliability of wearable devices by causing signal disruptions, sensor accuracy, reduced battery life, data corruption, or loss. Standard methods of mitigating EMI in wearables include shielding, grounding, filtering, and effective, optimized design. The gadgets may be EMI compliant as standalone devices but may falter when used collectively on a body.

As we are aware, the minimum separation distance between wearable devices depends on the communication technology adopted, like Bluetooth, Wi-Fi, etc., as well as the transmission power and frequency bands; the article focuses on studying the impact of variable positioning of such heterogeneous devices on the obtained electromagnetic Interference.

The contribution of the article is to present an inference system that suggests the expected Interference for different positions and orientations of on-body sensors in an indoor environment with multiple other communicating devices.

2 Related Work

In the context of literary works, the effects of EM waves have been investigated on wearable antennae near the human body [6] considering tissue properties, air gap, bending, body movement, and battery radiation [7]. Extensive studies on proximity effects focus on interference and coupling sources, specifically on miniaturized wearables, which are found in related literature [8–10]. Also, interference factors on human body systems (HBC) present an analysis of the effects of frequency, power, modulation, symbol rate, and distance between source and receivers [11]. Further, investigations on wireless On-body propagation characteristics of a smartwatch have depicted S11 parameters, radiation paths, and path loss [12]. Relevant articles, however, focus on something other than the relative positioning of the wearable sensors that may be heterogeneous, with different ideal positions, communication technology, and body movements. Most literary works focus on the experimental evaluation of static sensor positions using simulation software. The complexity and computational cost involved in the full-wave EM simulation motivates us to use an FIS to determine the impacts of EMI. Moreover, FIS is known to perform well under high variability and uncertainty scenarios.

Among the various EMI factors that impact wearable devices, the proposed work focuses on the impact of position, orientation, and how the wearable is worn (e.g., wrist, chest, head). We also analyse user movements and activities to see whether they impact the device's interaction with surrounding electromagnetic fields, affecting performance. Figure 1 presents literary works studied as factors that impact wearable devices due to EMI [11, 13–16].

3 Methodology

EMI/EMC depends on factors such as design, which includes circuit layout and design, shielding, and signal integrity. The electrical factors that impact

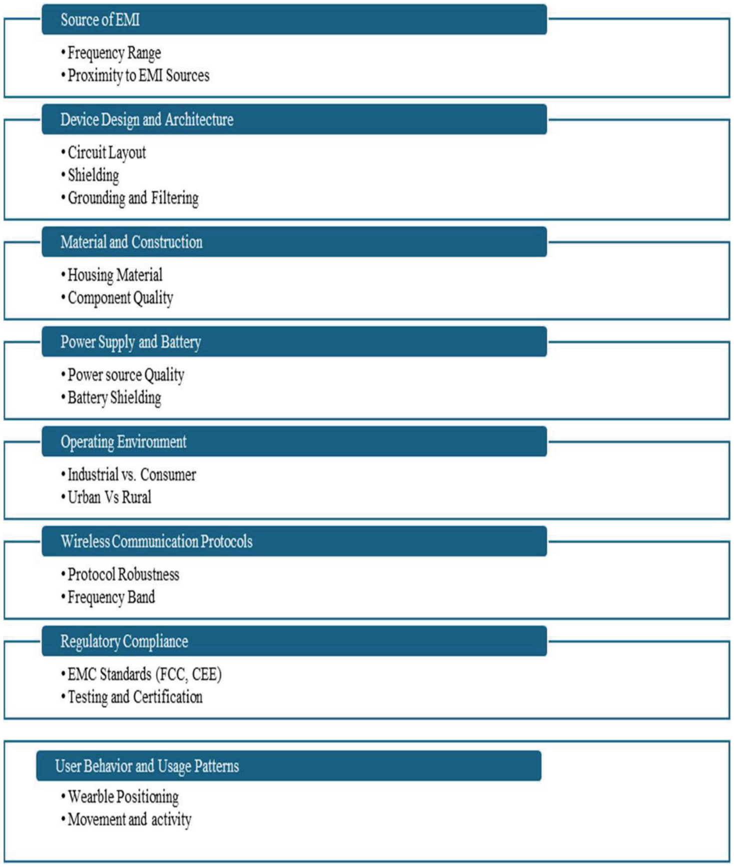


Figure 1 Existing research on EMI for wearable devices.

this are signal frequency and power levels. Usually, higher frequency and power levels result in higher levels of EMI. Impedance matching grounding and bonding are also used to reduce the potential for emission and improve EMC. Other factors, such as the ambient electromagnetic environment, affect both emission and susceptibility. In context to wearable devices, these factors can be modelled as fuzzy rules to their underlying imprecision caused due to movement, proximity, type and functionality of the applications. The frequency range becomes uncertain due to factors like modulation techniques, harmonics, and frequency drift. Similarly, the power levels may vary due to operating conditions, aging of the components, power management systems like temperature changes, and power supply voltage. Therefore, the need arises to account for these imperfections by incorporating margin into the design and using components with higher tolerance to EMI. Placement among multiple devices can significantly affect EMI/EMC performance. The reason primarily is due to various communication protocols with close transceivers, the shielding effect of the human body at the sides, and vulnerable areas with less natural shielding. Clothing layers and materials may also attenuate EM waves.

3.1 Fuzzy Inference System

We consider a fuzzy inference system to predict the causes of varying electromagnetic Interference observed in contrast to the set rules and attribute it to the Interference caused by location placement and orientation of wearable devices that are not fixed. Typical wireless body area networks encounter multiple sensors that collaborate to monitor the human body. Restricting only SaO2, Pulse, and Thoracic sensors, the article aims to observe variations in received data due to interference among them under the movement of body parts housing the sensors. Further, owing to the large number of parameters affecting EMI, we restrict our analysis by considering the following assumptions:

- Shielding and grounding are adequate for individual devices.
- Devices are placed on the body without direct body contact.
- The environment considered is indoor (controlled environment with predictable conditions).

3.2 Experimental Set Up

An equivalent IoT scenario was configured in Netsim, which comprised 11 sensors [17]. However, applications from only three sensors were considered, as most wearable devices integrate multiple functions on a single wearable. The applications periodically generated packets and forwarded them to the server via a 6LowPAN gateway. The application packet inter-arrival time was set to 4 msecs. Figure 2 depicts the data collected from multiple sensors deployed on the human body. For analysis, we consider SaO2, Pulse and Thoracic sensors which are placed at different positions and the impact of varying signal frequency, power levels and distance are measured. Multiple experiments were carried out by placing the sensors in close proximity. With the help of Net Sim simulator, we collected data related to SNR, packet losses, increased latency and observed for discrepancies in the collected data.

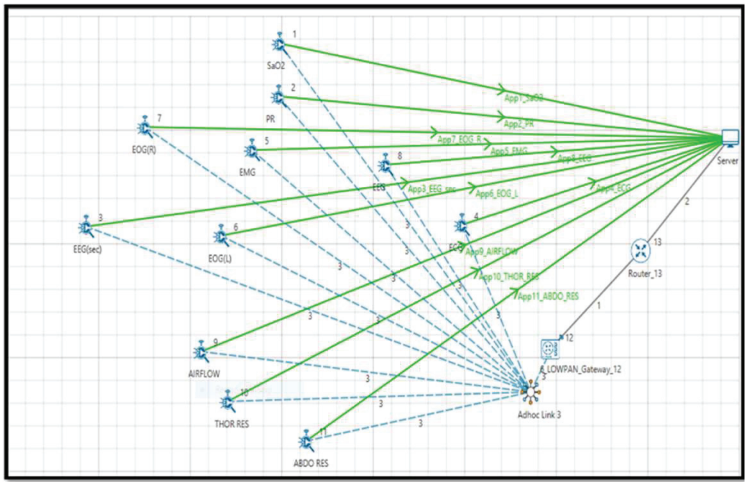


Figure 2 Simulation of Multiple sensors on the human body on the basis of real-world dataset.

Table 1 FIS parameters

Parameter	Membership	Value
Signal Frequency	Low	0–1 GHz
	Medium	1–5 GHz
	High	5 Ghz and above
Power level	Low	0–10 dBm
	Medium	10–20 dBm
	High	20 dBm and more
Proximity and coupling	Close	less than 10cm
	Near	10–50 cm
	Far	more than 50 cm
Size and Compactness	Compact	A normalized scale of 0–1.
	moderate spread	
	large spread	

On the basis of data patterns observed, we propose a fuzzy inference model to predict EMI.

4 Results and Analysis

Designing wearables to minimize the impact of electromagnetic Interference (EMI) involves careful consideration of their positioning on the body, the

(a)

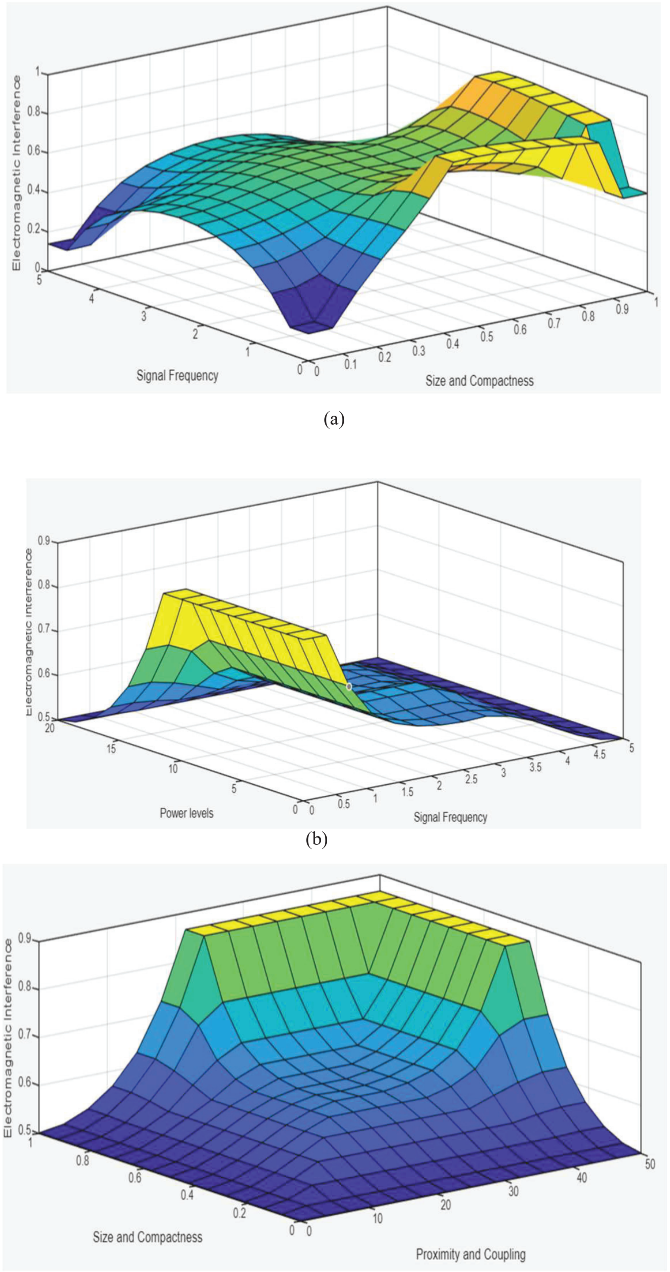
(b)

	Rule
1	If (Signal Frequency is Low) and (Power levels is low) and (Proximity and Coupling is Close) and (Size and Compactness is Large) then (Electromagnetic Interference is Medium) (1)
2	If (Signal Frequency is Medium) and (Power levels is low) and (Proximity and Coupling is Near) and (Size and Compactness is Moderate) then (Electromagnetic Interference is Medium) (1)
3	If (Signal Frequency is High) and (Power levels is low) and (Proximity and Coupling is Close) and (Size and Compactness is Less) then (Electromagnetic Interference is High) (1)
4	If (Signal Frequency is High) and (Power levels is High) and (Proximity and Coupling is Near) and (Size and Compactness is Less) then (Electromagnetic Interference is High) (1)
5	If (Signal Frequency is Medium) and (Power levels is Medium) and (Proximity and Coupling is Near) and (Size and Compactness is Moderate) then (Electromagnetic Interference is Medium) (1)
6	If (Signal Frequency is High) and (Power levels is low) and (Proximity and Coupling is Far) and (Size and Compactness is Large) then (Electromagnetic Interference is Low) (1)
7	If (Signal Frequency is Medium) and (Power levels is High) and (Proximity and Coupling is Far) and (Size and Compactness is Moderate) then (Electromagnetic Interference is Low) (1)
8	If (Signal Frequency is Medium) and (Power levels is High) and (Proximity and Coupling is Close) and (Size and Compactness is Less) then (Electromagnetic Interference is High) (1)
9	If (Signal Frequency is High) or (Power levels is High) or (Proximity and Coupling is Close) or (Size and Compactness is Less) then (Electromagnetic Interference is High) (1)
10	If (Signal Frequency is Medium) or (Power levels is low) or (Proximity and Coupling is Far) or (Size and Compactness is Moderate) then (Electromagnetic Interference is Low) (1)

(c)

Figure 3 FIS (a) Representation (b) Rule Map (c) Sample rules.

frequency of operation, and the power levels they use. Even though most devices are tested and certified individually, they are not tested in a combined environment. Therefore, the FIS model considered four antecedents: signal frequency, power level, size and compactness, proximity and coupling for indoor environments. We restrict our discussion to only indoor environments. The model predicts expected variation in data values when simulated caused by Interference. The details of the membership functions are presented in Table 1. We adopt the Mamdani model for our analysis.

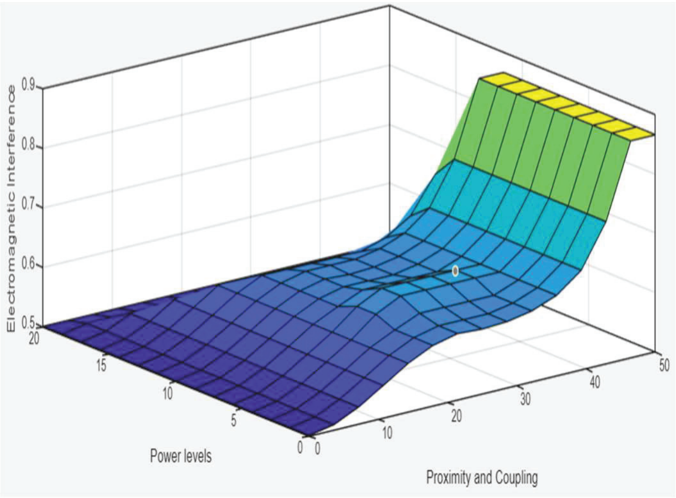


(a)

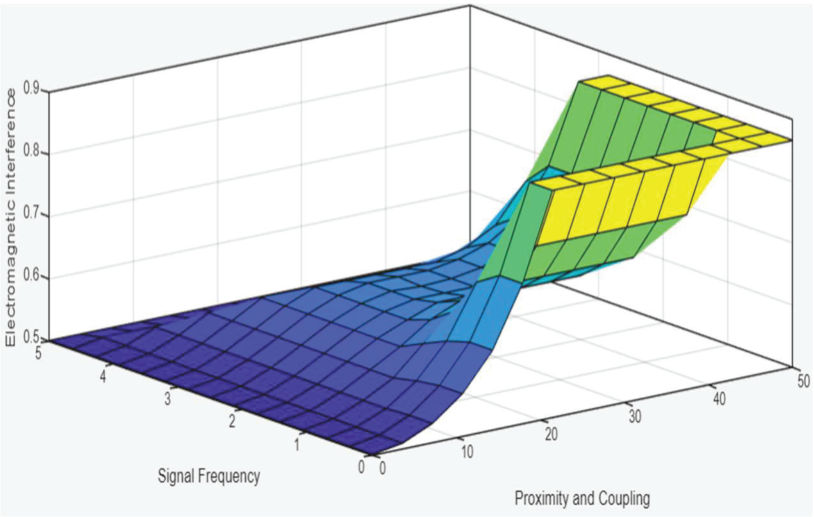
(b)

(c)

Figure 4 Continued



(d)



(e)

Figure 4 Electromagnetic Interference observations under (a) Size and signal frequency variations, (b) Power levels and frequency, (c) Size and proximity and coupling of devices, (d) Power levels and proximity, (e) Signal frequency and proximity.

Based on relevant literature and the corresponding simulations, the FIS developed and the corresponding rule map with sample rules are depicted in Figures 3(a), (b), and (c), respectively. The key factor considered was signal frequency, which was the operational frequency of the wearable device. The power levels refer to the device's transmission power levels. Proximity and interference coupling were the distance of the device from the source of Interference. The physical size and design compactness were also considered. Table I refers to FIS parameters considered for the categorization of these parameters as low, medium or high; close near and far etc. The FIS used a set of rules to model the relationship between the placement strategy of the devices and the EMI impact.

Figures 4(a), (b), and (c) present the impact of varying levels of parameters on electromagnetic Interference. We observe that the highest value of EMI is obtained for higher values of proximity rather than the signal frequency or power level of devices. We can observe from Figure 3(b) that for a fixed distance and orientation, a change in signal frequency generates low to moderate EMI. However, for fixed values of frequency at 2.4 GHz, the EMI increases to high when the sensor distance is reduced or the proximity is altered. Thus, we validate our model to show the impact of positioning and orientation of placed sensors on the human body. For analysing the impact of proximity of devices with varying levels of signal frequency and power levels, Figures 4(d) and 4(e) depict higher EMI for higher proximity among the devices.

5 Conclusion

With our established FIS model, we confirmed that wearables' placement on the body is a major factor in determining how exposed they are to electromagnetic fields (EMI) and how that exposure affects their performance. To guarantee maximum performance and user experience across all contexts and usage circumstances, manufacturers must consider these positioning aspects during the design and testing phases. We also suggest that appropriate placement can lessen the negative impacts of electromagnetic Interference (EMI) on wearable devices when paired with design techniques like shielding and filtering. The limitations, however, of the FIS is that its performance depends on the quality of fuzzy rules and membership function accuracy, which are derived from expert knowledge. Any incompleteness or inaccuracy would result in unreliable predictions. Therefore, as a countermeasure, we employed a simulation-based experimental scenario to derive and confirm the rules designed. Further analysis of parameters like user body interaction, sensitivity analysis, and validation on real-world scenarios will be presented in future work.

Acknowledgement

The authors gratefully acknowledge the financial support received from DST, under SERB Power grant no. SPG/2021/002212 for carrying out this research.

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Biographies

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