Accepted Manuscript

Title: **Circuit Design, Realization, and Test of a Bluetooth Low Energy Wireless Sensor With On-Board Computation for Remote Healthcare Monitoring**

Authors: Petar Šolic´, Riccardo Colella, Giuseppe Grassi, Toni Perkovic´˚ Carlo Giacomo Leo, Ana Cˇulic´, Vladimir Pleština, Saverio Sabina, Luca Catarinucci

Published in: IEEE Journal of Radio Frequency Identification (Volume: 8)
Page(s): 105 - 113
Date of Publication: 06 February 2024
ISSN Information: **Electronic ISSN**: 2469-7281. - **CD**: 2469-729X
DOI: 10.1109/JRFID.2024.3363074
Publisher: IEEE
Funding Agency: 10.13039/501100004488-Croatian Science Foundation through the Project "Internet of Things: Research and Applications" (Grant Number: UIP-2017-05-4206)

Circuit Design, Realization, and Test of a Bluetooth Low Energy Wireless Sensor with On-Board Computation for Remote Healthcare Monitoring

Petar Šolić*, Riccardo Colella‡, Giuseppe Grassi†, Toni Perković*, Carlo Giacomo Leo‡§, Ana Čulić*, Vladimir Pleština*, Saverio Sabina‡§, Luca Catarinucci†
*FESB, University of Split, Split, Croatia
†Department of Innovation Engineering, University of Salento, Lecce, Italy
‡National Research Council, Institute of Clinical Physiology, Research Unit of Lecce, via Monteroni, Lecce, Italy
§MOVE-mentis s.r.l, Cesena, Italy

***Abstract*—The Internet of Things (IoT) framework has transformed sensor data utilization, ushering in a new era of sensors integrated into various aspects of modern environment. A pressing concern in the realm of wearable technology is efficient power management, encompassing low power consumption and reducing battery recharging times. This study introduces an electronic device equipped with a Bluetooth 5.1 Low Energy (BLE) module, capable of detecting, collecting, aggregating and transmitting the Root Sum of Squares Method (RSS) of acceleration readings at consistent time intervals. This multi-frequency wireless controller functions at both sub-1 and 2.4 GHz bandwidths, endorsing the Bluetooth® 5.1 low energy standard and diverse wireless modalities via a Dynamic MultiProtocol Manager (DMM) interface. For demonstration purposes, the BMI160 is has been programmed to internally manage acceleration analyses across three axes, reducing data transmission, and minimizing connection times. This device, integrated with other physiological parameter monitoring systems of an individual/patient, can help correlate any variation in these parameters with the amount of motion. The integration of additional sensors can refine the precision of physiological metric evaluation, broadening the potential applications of such systems in sectors like healthcare and well-being.**

***Index Terms*—Bluetooth Low Energy (BLE), Wireless Sensing, On-Board Computation, Remote Health Monitoring, Root Sum of Squares Method (RSS)**

I. INTRODUCTION

The Internet of Things (IoT) paradigm has revolutionized the utilization of data from the sensing devices paving the way for sensor deployment in virtually every aspect of the modern environment [1]. In addition to integration of the physical objects into the IoT network, there is a growing trend in employing wearable sensors to monitor human-related parameters. Wearable devices have the capability to implement diverse technologies and offer numerous possibilities for continuous monitoring of user-specific information which can be very valuable in the decision making process for some particular domains, i.e. e-health, sport, wellness, smart buildings, entertainment etc [2]. So far, their application has been widely spread in the entertainment domain with growing interest for application in health and well-being segment as a tool for collection of crucial vital parameters of the users. Collected user-related information can then be further employed for diagnosis or provided as input to care providers for for specific actions or interventions [3]. As the IoT framework continues to grow, new opportunities for wearable technologies are emerging. Notably, their innovative application within smart buildings stands out as a device for monitoring human parameters and behavior in order to adjust indoor environmental conditions to meet user comfort requirements. Recent studies are addressing utilization of monitoring technologies for personal thermal comfort. In this context, wearable technologies have been applied to collect users information and apply collected data for decision making process in the building management system for heating, cooling, ventilation and air conditioning systems. Through the utilization of wearable devices, information about different user's parameters can be monitored, such as heart rate, wrist skin temperature, activity-based metabolic rate, electro-dermal activity and wrist skin relative humidity which are found to be useful information for personal thermal comfort modelling. Therefore, personal thermal comfort is investigating the possibilities for linking user's behaviour and / or vital parameters with their subjective evaluation of the indoor thermal conditions and can be approached by monitoring different inputs. Further on, from technical perspective, for data acquisition, diverse technical solutions have been applied in the literature, most frequently for detecting user's skin temperature, metabolic rate, clothing level and heart rate as systematized in [4]. Complementary, the metabolic rate is recognized as influential parameter for thermal comfort by official standard EN ISO 7730 since users thermal sensation is affected by the type of activity and consequently, the metabolic response of a person (MET) expressed as the rate of produced energy per unit surface area of human body (W/m^2). A MET represents the relationship between the energy expenditure rate during an activity and the energy expenditure rate at rest. It is stated that thermal discomfort predictions vary within the metabolic rate and clothing insulation approximation accuracy [5]. Measuring metabolic rate on the site is very

Manuscript received...
This work has been supported by Croatian Science Foundation under the project "Internet of Things: Research and Applications", UIP-2017-05-4206.

difficult and represents quite a challenge to be technically implemented in the smart building infrastructure since it is a very user - specific information and is dynamically changing based on the environmental conditions, user's body properties and the performed activity [6]. To address aforementioned challenge, different technologies have been applied through the thermal comfort studies. In the study [7] kinect camera was used for extraction of the user's behavior and mapping it with heart beats (collected with wearable Fitbit device) to calculate MET value for detected activity. Human activity was also monitored with video camera [8] and MET value for three representative activities was classified with respect to the key points derived from the pose detector. However, approach based on camera application enables uncertainties in the MET calculation since it can not ensure fully individual data collection and it can also be limited by the camera angle and performances. Alternatively, custom heart rate and body temperature sensors were applied in [9] and in paper [10] authors even used a small cellphone for accelerometer data to gain more complete information about user and calculate or predict MET values, depending on the selected approach. Also, commercially available wearable devices such as Apple watch series 4 [11], Microsoft band 2 [12], Empatica E4 [13] have been applied for data acquisition but standardized personal thermal comfort approach is still not developed due to the uncertainty of the selected inputs, applied sensors and the individual differences among the people. In [6] authors have applied Move 3 sensor (Movisens) for activity based MET calculations which could then be used as a real-time metabolic rate input for determining the users thermal comfort satisfaction. However, these sensors are lacking additional information which could more precisely estimate the energy expenditure (and MET), with additional sensors (such as skin temperature, heart rate sensor) instead of just the activity information [14]. Further on, the implementation of additional sensors increases the price and availability of such a device, while also pushing extra load to the batteries.

One of the critical challenges today for wearable electronics is power management and low energy consumption, including battery recharging. Daily usage patterns, including data sampling and telemetry frequency, often require continual monitoring of crucial parameters, which can quickly deplete the battery. Although instant feedback is desirable, it can be resource intensive. Furthermore, wearable devices that monitor vital metrics may encounter limitations in data transmission to cloud platforms, as they often rely on smartphones connected to the internet through Wi-Fi or 4G mobile networks [15], [16], [17]. Such real-time transmission usually faces two major drawbacks: they result in a large amount of data to be collected and analyzed on the receiver's end (such as 3-axis accelerometer data), and it leads to high energy consumption due to continuous transmission [15].

This paper is an extension of a paper published previously in the SpliTech conference [18]. In this paper, we introduce a modular device that utilizes Bluetooth® 5.1 Low Energy (BLE) for wireless sensing, coupled with integrated computational capabilities. This device employs a computational measure, notably the Root Sum of Squares Method (RSS), within a specified time frame (for instance, 1 minute). This approach ensures efficient use of the node's RF component, facilitating the immediate interpretation of the transmitted data by the receiver. Empirical studies have demonstrated the efficacy of the RSS measure in capturing the comprehensive intensity of an individual's physical activity, positioning it as a prime metric for monitoring such activities. Furthermore, incorporation of energy-efficient computational functionalities within the sensor node not only optimizes power consumption but also curtails the volume of data requiring transmission. This design choice aligns with the potential deployment of wireless communication protocols with reduced data rates, like BLE, which are inherently designed for energy-conservative applications [19], [15], [20], [21], [22], [23], [24], [25]. It is pertinent to emphasize that the system can be augmented with auxiliary sensors, such as cardiac rate monitoring devices or electrodermal activity detectors, to bolster the accuracy of physiological metric assessments. Integrating data from a gamut of sensors provides a holistic perspective on an individual's physiological condition. The architecture of the proposed solution remains modular, allowing seamless integration with diverse sensor types as required.

II. BLE Platform for RMS IMU data acquisition, elaboration, and transmission

An electronic device with a Bluetooth® 5.1 Low Energy (BLE) radio has been developed that is capable of detecting, collecting, aggregating, and transmitting the RSS of the acceleration data at regular intervals to any standard BLE device. The system is designed around specific components identified during technological scouting, including the CC1352R1 from Texas Instruments. This wireless multiprotocol and multiband microcontroller operates on sub-1 GHz and 2.4 GHz frequencies, supporting Bluetooth® 5.1 Low Energy (BLE) protocol and other wireless communication protocols through a Dynamic Multiprotocol Manager (DMM) driver. Its low-power wireless communication design is ideal for sensing devices and phisiological parameters. The device can achieve a maximum transmission power of +5 dBm at 2.4 GHz with a current consumption of 9.6 mA. Battery life can be maximized by setting policies for switching between transmission bursts and standby states, which consumes only 0.85 µA of current while maintaining complete data in RAM. The CC1352R also boasts a low standby current of only 5 µA at +85 °C.

The Bosch BMI160 IMU unit is a 6-DOF inertial measurement unit that integrates a 3-axis accelerometer and a high-performing 3-axis gyroscope with 16-bit resolution. This system enables the acquisition of acceleration or angular velocity data while consuming low power. The FIFO buffer function is partly responsible for this low power consumption, as it allows for the accumulation of samples in memory (collected at frequencies up to 1600 Hz) even when the master microcontroller is in standby. The BMI160 is provided with standard I2C/SPI communication interface, a 16-bit builtin AD converter, a 16-bit data gyroscope with ranges ±125, ±250, ±500, ±1000, and ±2000 °/s, and an accelerometer with ranges ±2, ±4, ±8, and ±16g. To create a compact hardware

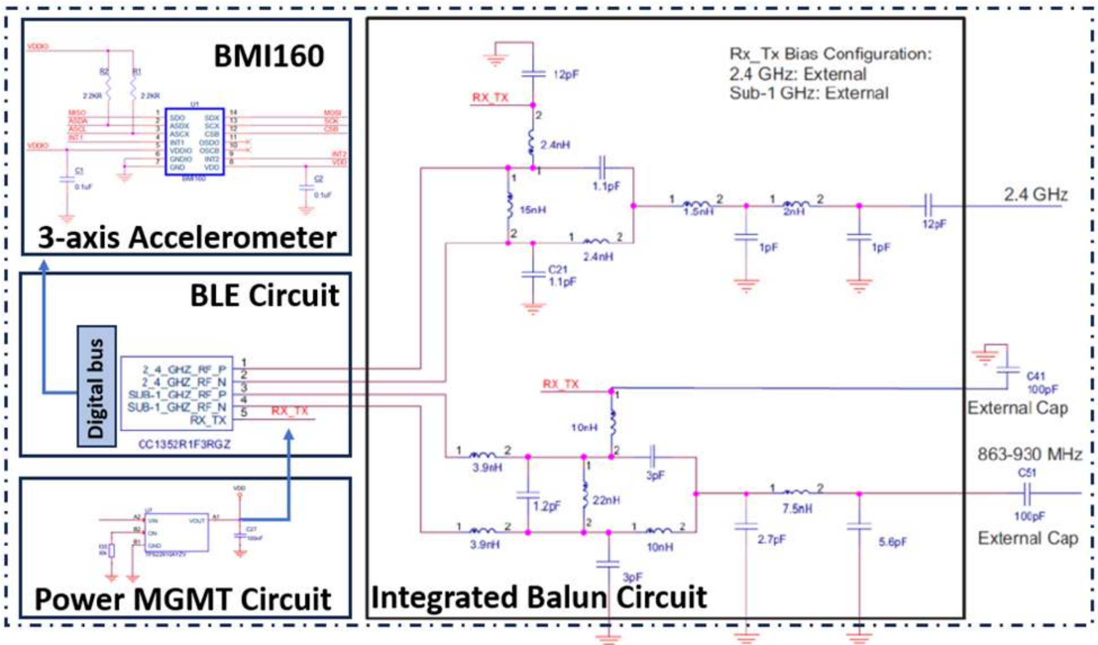


Fig. 1: Architecture of the developed BLE circuit.

solution that meets the project requirements, it was necessary to develop a device to produce compatible firmware for the proposed solution.

Fig. 1 shows the architecture of the circuit implemented in this work. The BLE circuit is powered by a dedicated power management circuit. The digital interface of the BLE circuit is connected with the BMI160 accelerometer through the I2C digital bus. The radio front-end matching network of the BLE circuit is based on the 0900PC15A0036 passive chip designed by Johanson Technology[1]. The circuit block integrates all the components required for impedance matching, balun transformation, and harmonic filtering on both radio interfaces on the CC1352R. Moreover, it properly "merges" together the TX-RX chains to use a unique antenna.

At the firmware level, the system is optimized for motion analysis, capturing acceleration data along all three spatial axes. It can accurately calculate Root Mean Square (RMS) acceleration values over customizable time intervals, ranging from 6 seconds to 6 minutes (Fig. 2). This architecture empowers the system to capture and analyze motion data with precision, making it suitable for a wide range of applications, including health monitoring. The firmware is programmed to alternate between the sleep and active phases, ensuring that the BMI160 accelerometer operates in specific intervals to capture data when needed. A sampling rate of 25 frames per second has been considered to calculate the RMS value. An important feature of the system is the remote reconfiguration. A specific BLE characteristic enables external devices to modify sensor parameters and data acquisition settings. This aspect enhances the system versatility and adaptability to different monitoring scenarios, enabling real-time adjustments as needed. More

[1]https://www.johansontechnology.com/datasheets/0900PC15A0036/0900PC15A0036.pdf

```
static void PeriodicTask(void)
{
   i2cTransaction.writeBuf = txBuffer2;
   i2cTransaction.writeCount = 1;
   i2cTransaction.readBuf = rxBuffer;
   i2cTransaction.readCount = 1;
        txBuffer2[0] = 0x01;
     // txBuffer2[1] = 0x01; //shootdown mode
       i2cTransaction.slaveAddress = (0xA0>>1);

    rslt += bmi160_read_accel_xyz(&myaccelxyz);
    Display_printf(dispHandle, 22, 0, "accelo: x = %d, y = %d,z = %d\n",myaccelxyz.x
           , myaccelxyz.y, myaccelxyz.z);

   if(timer == IMUINTERVAL) {
       //primo ciclo
      myaccelxyzRMS.x = myaccelxyz.x;
      myaccelxyzRMS.y = myaccelxyz.y;
      myaccelxyzRMS.z = myaccelxyz.z;
   }
   else{
   myaccelxyzRMS.x= sqrt(((myaccelxyzRMS.x* myaccelxyzRMS.x) + (myaccelxyz.x*
          myaccelxyz.x))/2);
   myaccelxyzRMS.y= sqrt(((myaccelxyzRMS.y* myaccelxyzRMS.y) + (myaccelxyz.y*
          myaccelxyz.y))/2);
   myaccelxyzRMS.z= sqrt(((myaccelxyzRMS.z* myaccelxyzRMS.z) + (myaccelxyz.z*
          myaccelxyz.z))/2);
   }
  charValue5[0] = ((pktnum)>>8) & 0xff; // seq number
  charValue5[1] = ((pktnum)>>0) & 0xff; // seq number
  charValue5[2] = ((myaccelxyzRMS.x)>>8) & 0xff;
  charValue5[3] = ((myaccelxyzRMS.x)>>0) & 0xff;
  charValue5[4] = ((myaccelxyzRMS.y)>>8) & 0xff;
  charValue5[5] = ((myaccelxyzRMS.y)>>0) & 0xff;
  charValue5[6] = ((myaccelxyzRMS.z)>>8) & 0xff;
  charValue5[7] = ((myaccelxyzRMS.z)>>0) & 0xff;
  charValue5[8] = txBuffer2[0];
  charValue5[9] = txBuffer2[1];

    SetParameter(CHAR5, CHAR5_LEN, charValue5);
 }

 timer--;
}
```

Fig. 2: Sketch of the code implementing the routine to get, elaborate, and transmit acceleration values.

in general, the firmware has been optimized to manage the power usage. Moreover, the radio power configuration is set to -3 dBm during communication, which is ideal for reliable connections with nearby smartphones. However, the system architecture is designed for adaptability, allowing the dynamic adjustment of the radio output power to 5 dBm when an increased transmission strength is required. This flexibility

Fig. 3: The designed low-power BLE device equipped with BMI160 accelerometer device.

ensures that the system can adapt to different operating environments and distances.

III. Results

In this section, the designed BLE device shown in Fig. 3 has been tested to verify its applicability in clinical studies. Specifically, the device has been designed and specifically programmed to perform acceleration processing on the three measured axes on-board, thereby reducing the amount of data to be transmitted as well as the communication time. Indeed, the data communication phase is known to be power hungry.

To achieve this, for every minute of observation (although this time can be adjusted as desired), the device evaluates the root mean square value (RMS) of the acceleration along the x-axis, the y-axis and the z-axis, and then communicates it to the collecting BLE node, which can be a smartphone or any data collection node.

This device, integrated with other physiological parameter monitoring systems of an individual/patient, can help correlate any variation in these parameters with the amount of motion. In fact, an increase in heart rate during long and strenuous physical activity is certainly less significant than the same increase during rest.

Once the device was developed and tested in the laboratory, several experiments were conducted asking a volunteer to place the prototype device in the pocket and connect it to a smartphone via BLE. The volunteer performed various activities: i) running from one wall to another and back with sensor on pelvis, ii) running on the spot with sensor on pelvis, iii) doing intense activity with sensor on pelvis, iv) doing intense activity with sensor on the wrist, v) doing soft homework with sensor on pelvis and vi) running up and down on two ramps of stairs while sensor on pelvis. Data is related to different activities after the elaboration. In each case there are approximately 3 minutes of data. Data are taken averaging each 6 seconds.

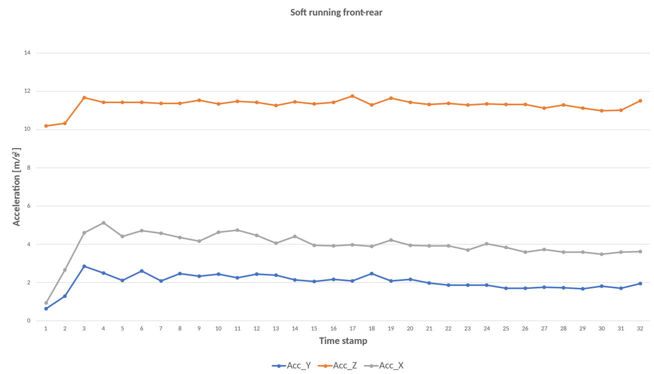


Fig. 4: Soft running front rear

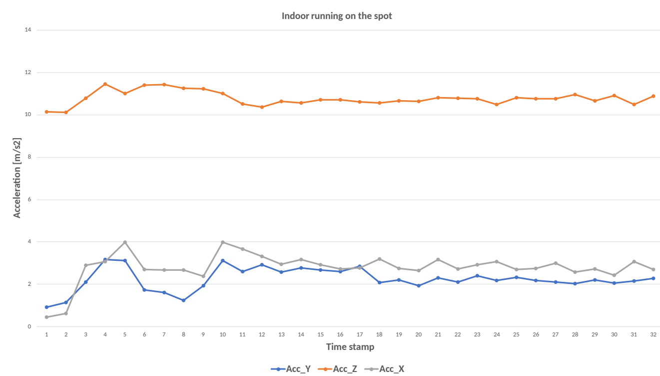


Fig. 5: Indoor running on the spot

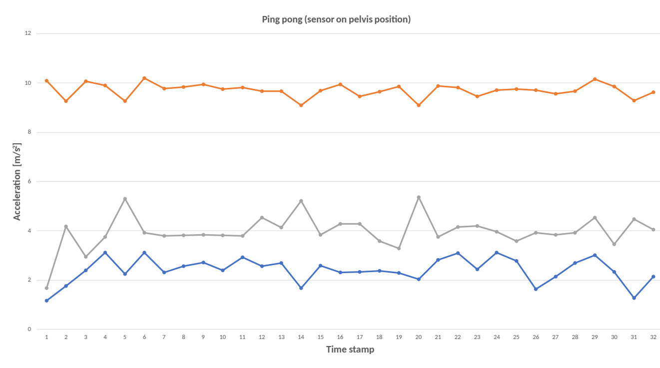


Fig. 6: Doing intense activity (sensor on pelvis position)

In Fig. 4 it can be seen that the person started running at time 0 from nearly static conditions, since the orange curve is along Z (up and down) and under static conditions should be 9.81. Moreover, the gray curve is along X (in front of the person) under static conditions, is 0, while the blue curve is along Y (to the right and left of the person), where under static conditions, it is 0.

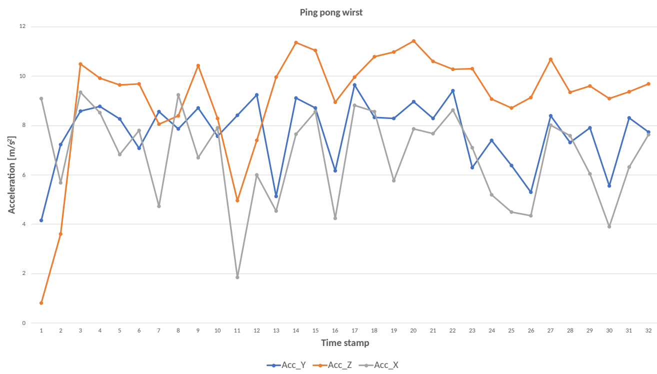


Fig. 7: Intense activity (sensor on wrist).

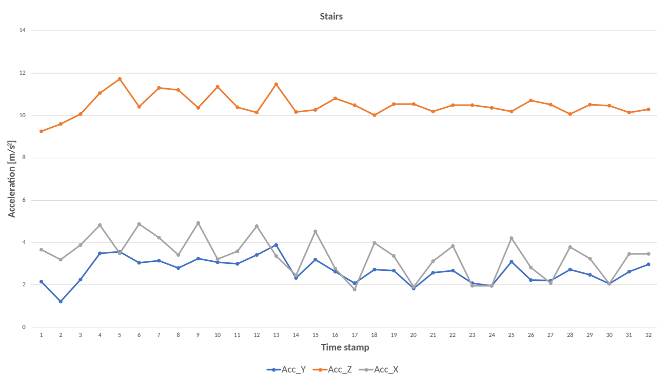


Fig. 8: Walking on the stairs.

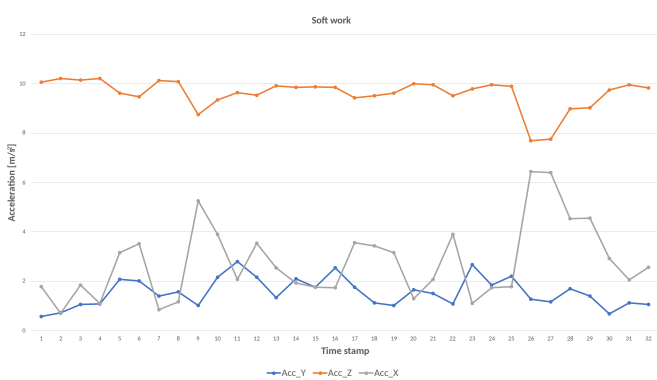


Fig. 9: Soft work.

For soft indoor running on the spot in Fig. 5 it can be seen that the curve along Z is greater than 9.81 because while running on the spot, there are accelerations along Z up and down. However, there are no significant accelerations along X and Y, which indeed remain low and comparable to each other.

On the other hand, considering the graph in which the person is running (soft) forward and backward in Fig. 4, it can be seen that the gray curve (Y) increases because there is a displacement in that direction, while the blue curve remains almost unchanged because there are no significant variations in acceleration along X.

Now let us observe the graph related to an intense activity in Fig. 6. In this case, we expect variations along Z to be less pronounced compared to running. This is clearly visible in the graph, where we can observe on Acc_Z value closer to 9.81 compared to the previous cases, and accelerations comparable to those during running along the other two directions. When moving the sensor to the player's wrist in Fig. 7, the situation changes dramatically, with significant accelerations possible in all directions, as can be seen from the graph. The graph related to stairs is also interesting in Fig. 8. The tester starts strong, and we observe accelerations along Z much higher than those during a soft run. However, after a while, fatigue sets in, and the accelerations stabilize at values slightly above 10 m/s². In this case as well, accelerations along X are higher than those along Y, as naturally expected. Devices like these are also useful for monitoring the daily activities of patients or the elderly. For this purpose, we analyzed a daily life situation. The volunteer was asked to perform light household chores: turning on the stove, taking food from the fridge, moving small furniture, etc. The graph in Fig. 9 shows that there is, in fact, no significant acceleration along Z, but there are irregular accelerations compared to the other directions. As a final point, it is important to emphasize once again that all tests have been conducted in an environment almost empty where only a single BLE sensor was present, and the receiving BLE device at not more than 10 m of distance. While the findings provide valuable insights, it is essential to acknowledge that certain limitations may arise. However, these limitations are inherently related to the BLE technology itself. Specifically, it is expected that increasing the number of sensors, scalability considerations are reasonable. Specifically, the system is designed to support the number of active connections permitted by the BLE technology, which consists in a maximum of 37 active connections in a limited space comparable with a room, considering the number of available channels and the collision avoidance protocol employed. Moreover, the maximum expected communication distance of 10 meters has been verified using a personal smartphone as the data collector. While the presence of obstacles or non-line-of-sight (nLOS) conditions can potentially reduce this range, it is not a significant concern in our specific case due to the proximity of the devices. Moreover, variations in signal strength due to environmental factors such as interference, obstacles, and non-line-of-sight conditions may impact the practical range of the system. Nevertheless, these observations align with common considerations in BLE-based applications, and the proposed work serves as a step towards the exploration of this technology for physiological parameter monitoring.

Power consumption

To show the low-power nature of the proposed system, current consumption has been measured using EnergyTrace Technology[2]. Figure 10 shows the current absorption of the proposed set-up. As can be seen, BLE advertisement messages are sent approximately every 40 ms, with peak absorption reaches 7.2 mA, while the duration of packet transmission is around 7 ms. The duration of BLE connection and data

[2] https://www.ti.com/tool/ENERGYTRACE

TABLE I: Monitoring technologies employed in personal thermal comfort studies

Ref	Environmental sensors	Sensors for occupant-related information
[7]		Kinect camera, Fitbit
[6]	Data logger TROTEC BZ 30 for indoor environment (temperature, relative humidity and CO_2 level)	Move 3 wearable device
[11]	Hot-wire anemometer sensor, SHT75 digital sensor	Apple watch series 4
[13]	Digital psychrometer thermo-hygrometer	Empatica E4 wristband
[26]	Siemens thermostat, sper scientific data logger	Hesvit S3 wristband
[10]	iButton for air temperature near subject	iButton device (skin temperature), Polar H7 strap (heart rate), small-size cell-phone for accelerometer data (activity levels)
[27]	Air temperature, ambient light level sensors	BLE proximity beacon (Estimote proximity beacons), motion sensor

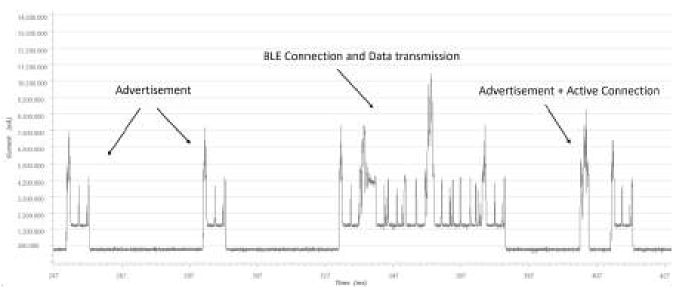


Fig. 10: Current absorption of the overall setup.

transmission is around 50 ms, with a peak reaching 10 mA. Once the connection has been established, in addition to the advertising message, an active connection is sent. This clearly indicates that low current consumption of the device, as well as sub-mA consumption of the Bosch BMI160 IMU unit with low BLE consumption, makes the device an ideal choice for activity monitoring applications during a longer time period.

IV. Discussion - Limitations and the Future Work

The proposed technical solution has a perspective for application as a standalone device or combined with other user-related sensors, i.e. heart rate, skin temperature. This approach can be applied to develop user monitoring platforms in various domains such as health [28], biomedicine [29], ambient assisted living [30], sport [31], smart building [4]. In the study presented herein, a focus was placed on the application of an accelerometer for personal thermal comfort. Through the literature, accelerometry data was frequently used in thermal comfort studies, as presented in Table I. In existing studies, the accelerometer was applied most often as a part of a smart wearable device to obtain additional user-specific information. In studies [13] and [6], specialized platforms were applied for monitoring with corresponding wearable devices designed for research purposes, Empatica E4 [13] and Move 3 [6]. Furthermore, in research [11], [7], [26], commercially available branded smart bracelets / watches were applied for user-related data acquisition, more specifically Apple watch 4 [11], Fitbit [7] and Hesvit S3 [26]. However, commercially available products are within the higher price range, which limits their wider application. Therefore, the authors in studies [10] and [27] have proposed a more affordable approach with custom sensors. In [10], authors used a small-size cell-phone in a wrist pocket to measure accelerometer data for activity level representation and in [27] authors also used a custom onboard motion sensor.

The experimental approach in [7] and [11] did not emphasize the accelerometry data but rather the heart rate data for the MET calculation and in [26] also the skin temperature and relative humidity. The activity information from the accelerometer was complementary information in later studies.

On the other hand, in the studies [6], [13], [10] accelerometry data was processed to infer the activity level of the user to calculate the metabolic rate, an important parameter for thermal comfort. In [6], authors pointed out the importance of measured dynamic MET (with accelerometry sensor) over static MET (constant, tabular values), since it reflects the state of occupant sensation more accurately. Activity - based metabolic rate can further be used for the calculation of the predicted mean vote index (PMV) and determine occupant satisfaction with the thermal comfort criteria [6], or development of novel predictive thermal comfort models [13], [10]. So far, the authors have applied various machine learning prediction algorithms for different approaches, with accelerometry data being one of the inputs. In [6] artificial neural network (ANN) was applied for predicting MET response with validation being above 90%. In [10] personal comfort models were most effectively developed using algorithms falling under the "Ensembles of Trees" category with accuracy of 76% and Cohen's kappa 35%. Authors are pointing out that existing smart wristbands equipped with time, heart rate, and acceleration data exhibit a maximum predictive power of 71% and Cohen's kappa 18%. However, according to [10], prediction power could be enhanced to 77% accuracy and 43% Cohen's kappa if skin temperature and weather data streaming are added to the device. In [13] the influence of activity-based metabolic for predicting personal thermal comfort rate was studied employing a wearable monitoring device together with environmental sensors. Authors have recorded superior predictive performances up to 8.5% when leveraging metabolic rate as a predictor. Although personal thermal comfort is well covered topic lately, it is still developing and lacking of standardization in the methodology and results evaluation. As a part of the future work this issue should be addressed through systematization of potential parameters to be used and extraction of optimal machine learning algorithms and performance validation indicators to facilitate the comparability among proposed solutions.

When talking about the proposed low cost BLE accelerometry device in thermal comfort context, it could bring valuable contribution in the low power perspective. Also, it could be combined with other compatible user-oriented or environmental sensors to gain additional information. However, this approach is not without limitations. When applied in massive buildings, Bluetooth signal strength decreases with increasing distance between receiver and transmitter which makes it the most critical point for application in the real environments [28]. Therefore, as a part of the future work, testing BLE accelerometer with other sensors in the real environment would be valuable.

In conclusion, we highlight the potential of using accelerometer-based devices for monitoring personal thermal comfort, emphasizing the need for future research to address challenges in signal strength and integration with other sensors, to enhance the applicability and accuracy of these low-cost, user-friendly devices in diverse real-world settings.

V. CONCLUSION

The study has successfully highlighted the potential of wearable technology in monitoring and enhancing personal thermal comfort in smart building infrastructures. Some circuits have been designed, which include a BLE device (equipped with the BMI160 accelerometer) along with a power management circuit and a balun circuit. The approach, which exploits synthetic IMU measures such as RSS, has shown promise in clinical studies, emphasizing its capability to process acceleration on multiple axes, thereby optimizing data transmission and communication time. The integration of such devices with other physiological monitoring systems can provide valuable insights into individual variations in response to different activities. Moreover, the challenges posed by real-time data transmission to cloud platforms were addressed by proposing a modular Bluetooth low energy device for wireless sensing. This approach not only conserves energy but also offers interpretable data for various applications. As wearable technology continues to evolve, it holds the potential to revolutionize the way we understand and respond to individual thermal comfort needs in smart environments. For future work, a broader set of activities could be performed to increase the system capabilities by training a machine learning algorithm in order to classify thermal comfort for other activities of patients/elderly/sportspeople based on both the actions performed and the energy used to perform them.

REFERENCES

[1] J. Culic Gambiroza, T. Mastelic, I. Nizetic Kosovic, and M. Cagalj, "Dynamic monitoring frequency for energy-efficient data collection in internet of things," *Journal of Computational Science*, vol. 64, p. 101842, 10 2022.

[2] S. Jameer and H. Syed, "A dcnn-lstm based human activity recognition by mobile and wearable sensor networks," *Alexandria Engineering Journal*, vol. 80, p. 542 – 552, 2023, cited by: 0; All Open Access, Gold Open Access. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85170422601&doi=10.1016%2fj.aej.2023.09.013&partnerID=40&md5=e6401817d114523834a435851de8a5f8

[3] A. Pantelopoulos and N. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 1, pp. 1–12, 2010.

[4] A. Čulić, S. Nižetić, P. Šolić, T. Perković, and V. Čongradac, "Smart monitoring technologies for personal thermal comfort: A review," *Journal of Cleaner Production*, vol. 312, p. 127685, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095965262101903X

[5] B. Olesen and K. Parsons, "Introduction to thermal comfort standards and to the proposed new version of en iso 7730," *Energy and Buildings*, vol. 34, no. 6, pp. 537–548, 2002, special Issue on Thermal Comfort Standards. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S037877880200004X

[6] S. Nižetić, N. Pivac, V. Zanki, Agis, and M. Papadopoulos, "Application of smart wearable sensors in office buildings for modelling of occupants' metabolic responses," *Energy and Buildings*, vol. 226, p. 110399, 08 2020.

[7] H. Na, J.-H. Choi, H. Kim, and T. Kim, "Development of a human metabolic rate prediction model based on the use of kinect-camera generated visual data-driven approaches," *Building and Environment*, vol. 160, p. 106216, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360132319304263

[8] S. Zhang, Y. Cheng, M. Olaide Oladokun, Y. Wu, and Z. Lin, "Improving predicted mean vote with inversely determined metabolic rate," *Sustainable Cities and Society*, vol. 53, p. 101870, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210670719321869

[9] A. Youssef, N. Caballero, and J.-M. Aerts, "Model-based monitoring of occupant's thermal state for adaptive hvac predictive controlling," *Processes*, vol. 7, no. 10, 2019. [Online]. Available: https://www.mdpi.com/2227-9717/7/10/720

[10] S. Liu, S. Schiavon, H. P. Das, M. Jin, and C. J. Spanos, "Personal thermal comfort models with wearable sensors," *Building and Environment*, vol. 162, p. 106281, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360132319304913

[11] Y. Fang, Y. Lim, S. E. Ooi, C. Zhou, and Y. Tan, "Study of human thermal comfort for cyber–physical human centric system in smart homes," *Sensors*, vol. 20, no. 2, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/2/372

[12] F. Alsaleem, M. K. Tesfay, M. Rafaie, K. Sinkar, D. Besarla, and P. Arunasalam, "An iot framework for modeling and controlling thermal comfort in buildings," *Frontiers in Built Environment*, vol. 6, 2020. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fbuil.2020.00087

[13] J. Lee and Y. Ham, "Physiological sensing-driven personal thermal comfort modelling in consideration of human activity variations," *Building Research & Information*, vol. 49, no. 5, pp. 512–524, 2021.

[14] F. Richert. (2017) Activity monitoring and existing algorithms regarding energy expenditure estimation: A short review. Accessed: 2023-09-10. [Online]. Available: https://www.movisens.com/

[15] B. H. Brinkmann, P. J. Karoly, E. S. Nurse, S. B. Dumanis, M. Nasseri, P. F. Viana, A. Schulze-Bonhage, D. R. Freestone, G. Worrell, M. P. Richardson, and M. J. Cook, "Seizure diaries and forecasting with wearables: Epilepsy monitoring outside the clinic," *Frontiers in Neurology*, vol. 12, p. 690404, July 2021.

[16] A. M. Lonzetta, P. Cope, J. Campbell, B. J. Mohd, and T. Hayajneh, "Security vulnerabilities in bluetooth technology as used in iot," *Journal of Sensor and Actuator Networks*, vol. 7, no. 3, 2018.

[17] L. Guo, J. Kou, and M. Wu, "Ability of wearable accelerometers-based measures to assess the stability of working postures," *International Journal of Environmental Research and Public Health*, vol. 19, no. 8, APR 2022.

[18] P. Šolić, R. Colella, T. Perković, C. G. Leo, S. Sabina, and L. Catarinucci, "Exploring the potential of bluetooth low energy for wireless sensing and on-board computation in remote health monitoring," in *2023 8th International Conference on Smart and Sustainable Technologies (SpliTech)*, 2023, pp. 1–3.

[19] A. Pantelopoulos and N. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 1, pp. 1–12, 2010.

[20] V. S. Sree, R. Royea, K. J. Buckman, M. Benardis, J. Holmes, R. L. Fletcher, N. EYK, U. Acharya, and J. D. I. Ellenhorn, "An introduction to the cyrcadia breast monitor: A wearable breast health monitoring device," *Computer Methods and Programs in Biomedicine*, vol. 197, p. 105758, 2020.

[21] A. Kimura, Y. Mitsukura, A. Oya, M. Matsumoto, M. Nakamura, A. Kanaji, and T. Miyamoton, "Objective characterization of hip pain levels during walking by combining quantitative electroencephalography with machine learning," *Sci Rep*, vol. 11, 2021.

[22] S. Liaqat, K. Dashtipour, K. Arshad, and N. Ramzan, "Non invasive skin hydration level detection using machine learning," *Electronics*, vol. 9, no. 7, 2020.

[23] S. Veenab and D. J. Aravindhar, "Remote monitoring system for the detection of prenatal risk in a pregnant woman," *Wireless Personal Communications*, vol. 119, February 2021.

[24] R. E. Stirling, D. B. Grayden, W. D'Souza, M. J. Cook, E. Nurse, D. R. Freestone, D. E. Payne, B. H. Brinkmann, T. Pal Attia, P. F. Viana, M. P. Richardson, and P. J. Karoly, "Forecasting seizure likelihood with wearable technology," *Frontiers in Neurology*, vol. 12, 2021.

[25] R. Brard, L. Bellanger, L. Chevreuil, F. Doistau, P. Drouin, and A. Stamm, "A novel walking activity recognition model for rotation time series collected by a wearable sensor in a free-living environment," *Sensors*, vol. 22, no. 9, May 2022.

[26] Z. Deng and Q. Chen, "Development and validation of a smart hvac control system for multi-occupant offices by using occupants' physiological signals from wristband," *Energy and Buildings*, vol. 214, p. 109872, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378778819336060

[27] K. Konis, S. Blessenohl, N. Kedia, and V. Rahane, "Trojansense, a participatory sensing framework for occupant-aware management of thermal comfort in campus buildings," *Building and Environment*, vol. 169, p. 106588, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360132319308005

[28] K. Zovko, D. Begušić, P. Šolić, and T. Perković, "Low-cost ble bracelet as patients monitoring platform: range restrictions," in *2022 IEEE International Conference on E-health Networking, Application Services (HealthCom)*, 2022, pp. 119–123.

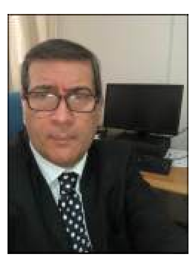
[29] A. Kuzmin, A. Ivashchenko, and E. Ryabova, "Biomedical applications of accelerometers: general directions and publication trends," *Biomedical Engineering*, 2023, cited by: 0. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85176752625&doi=10.1007%2fs10527-023-10320-9&partnerID=40&md5=1cb6d0a1fb7b0178d22c7e1025858980

[30] P. Martínez, N. Gordillo-Castillo, and D. Cortés Sáenz, "Towards fluid intake quantification in older adults: An algorithm for movement detection using accelerometry and gyroscope sensors," vol. 96, 2024, Conference paper, p. 222 – 231, cited by: 0. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85177197509&doi=10.1007%2f978-3-031-46933-6_24&partnerID=40&md5=10ce9c9e318051a2df67d2d05e649fef

[31] A. Biró, S. M. Szilágyi, L. Szilágyi, J. Martín-Martín, and A. I. Cuesta-Vargas, "Machine learning on prediction of relative physical activity intensity using medical radar sensor and 3d accelerometer," *Sensors*, vol. 23, no. 7, 2023, cited by: 1; All Open Access, Gold Open Access, Green Open Access. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85152333644&doi=10.3390%2fs23073595&partnerID=40&md5=69c6d921110a1e5b643b116b8476cdf4

Petar Šolić received his MS degree in 2008, and PhD in 2014 at the University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, Split; Croatia. Currently, he is university assistant professor, vice-dean for finances at University of Split, FESB and Waveform CEO, where so far combination of education (high school economics, graduated from computer science and PhD in improving performances of low-power electronics) provide insights on the balanced innovative approach. He is/was PI for several national/EU research/technology transfer projects worth of 400k EUR. He is winner of several important awards, such as two national prizes for science in field of technical sciences awarded from Croatian parliament (both as a young researcher (2015.), and in senior category (2020.)), and the award from Croatian academy of technical sciences for people under 35 (2020.). He authored 100 publication in scientific conferences and journals.

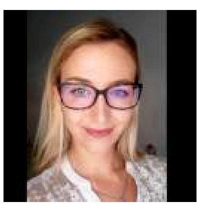
Riccardo Colella received the M.Sc. degree (with honors) in Telecommunication Engineering from the University of Salento (Italy) in 2010, and the Ph.D. degree from the same University in 2015. He is a Researcher at the National Research Council of Italy (CNR). His research interests are mainly focused on Analog/RF circuit modeling, RF-powered IoT sensing systems, radio systems, and printable/3D-printable electronics. He authored about 150 papers that appeared in international journals and conferences, two book chapters with international diffusion, and a patent.



Giuseppe Grassi received the laurea degree in Electronic Engineering (with honors) from the Universita di Bari, Bari, Italy, and the Ph.D. degree in Electrical Engineering from the Politecnico di Bari, Bari, Italy, in 1994. In 1994 he joined the Dipartimento di Ingegneria dell'Innovazione, Università del Salento, Lecce, Italy, where he is currently a Professor of Electrical Engineering. His research interests include complex systems, synchronization properties and chaos-based cryptography, dynamics of nonlinear systems, artificial intelligence, neural networks applied to wind and photovoltaic systems. He has published 150 papers in international journals (source: Web of Science) and about 100 papers in proceedings of international/national conferences. From 2008 to 2011 he served as an Associate Editor for the IEEE Transaction on CAS-II. From 2010 to 2013 he served as an Associate Editor of the IEEE CAS Magazine. He is a Senior Member of IEEE and a member of the IEEE Technical Committee on Nonlinear Circuits and Systems. From January 2012 to January 2016 he served as the Director of the Centro Cultura Innovativa d'Impresa, a interdepartmental center of the Università del Salento with an annual budget of over 10 millions euros in research on emerging technologies. From January 2016 to January 2019 he served as the Head of the Department of Engineering for Innovation at the Universita del Salento. Since November 2019 he has served as a Pro-Vice Chancellor for Administration and Finance.

Toni Perković is currently employed as Associate Professor at Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture (FESB) at University of Split (Croatia). His research interests include the design and analysis of security protocols for wireless networks, the design of energy-efficient communication protocols for wireless networks, location privacy in IoT networks, as well as the application of artificial intelligence and deep learning techniques to develop energy-efficient and cost-efficient IoT devices. He participates in the organization of international scientific conferences and professional events and is engaged as an editor of special editions of scientific journals. He is a member of the professional associations IEEE and ACM.

Carlo Giacomo Leo is an Economist with a background in health economics (HE) and health technology assessment (HTA). From 09/2013 to 31/12/2018 he was Lecturer at the School of Medicine, Tufts University, Boston. From 06/2012 to 07/2013 he was Research Fellow at the Division of Clinical Decision Making, Tufts Medical Center, Boston. Since 2005, he has been a researcher at the National Research Council, Institute of Clinical Physiology (CNR-IFC); since 2012, he has been the Chief of the branch of Lecce of the CNR-IFC. His research interests lie in the fields of Public Health, HE, and HTA . These areas encompass: a) the economic evaluation of health care programs; b) the analysis, modeling, representation, and implementation of healthcare pathways; c) evidence-based medicine through the conduct of systematic reviews and meta-analysis.



Ana Čulić is currently employed as junior researcher and PhD student at Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, University of Split, Croatia. She received her Master's degree in Industrial Engineering from the University of Split, Croatia in 2018, defending her diploma thesis 'Techno-economic feasibility analysis of photovoltaic power stations in the Republic of Croatia' under the supervision of Prof. D. Dr. Sandro Nizetic. Her interests include energy efficiency, renewable energy sources, smart technologies as she is currently studying smart technologies for investigation of personal thermal comfort. She was a part of the team involved in the project "Internet of Things: Research and Applications" under the leadership of assoc. prof. Petar Šolić. She is involved in the organization of the international conferences on smart and sustainable technologies and is engaged as an editorial assistant for the Energy Sources, Part A: Recovery, Utilization, and Environmental Effects Journal.

Vladimir Pleština is currently employed as Associate Professor of Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture (FESB) at University of Split, Croatia. His main research interests are education in IT and engineering, computer vision, analysis and image processing, artificial intelligence, IoT and robotics, uncertainty in measurement and expert systems. Vladimir Pleština is one of the editors in Journal of Technology education and author of several papers from field of IT, engineering and constructive education approach. He is a member of Robotic Society Split and Secretary General of Polytechnic association and lifelong education.

Saverio Sabina received the M.Sc. degree in Information Science from the University of Pisa. He is a Researcher at the National Research Council, Institute of Clinical Physiology. He has a background in Health Informatics, Bioinformatics and Health Technology Assessment. His research activity is focused on the analysis of healthcare pathways and processes, and on the modelling, representation and implementation of the workflows that can act as rational organization of them. His interests also cover methods and tools for the analysis of posture and movement. He authored several scientific works among international journals, international proceedings and chapters of books.

Luca Catarinucci is Associate Professor in Electromagnetic Fields at the Department of Innovation Engineering, University of Salento, Italy, and holds the chairs of "Microwaves" and "Electromagnetic Solutions for Hi-Tech". He leads a dynamic Research Group with a keen focus on RFID and cutting-edge electromagnetic technologies in the realm of IoT. His research also encompass the deployment of advanced electromagnetic simulation tools, the electromagnetic characterization of diverse materials, and the application of time-domain reflectometry for the qualitative and quantitative assessment of fluids. A significant part of his current research is deeply rooted in RFID-related pursuits, spanning across a broad spectrum including antenna and system design, the seamless integration of sensors and RFID tags, innovative strategies for RFID-based robot navigation, and pioneering methods for tag characterization, optimization, and design. His collaborations extend to numerous research teams, delving into areas such as antenna arrays, the manufacturing of antennas, the role of 3D-Printing in electromagnetics, among others. Catarinucci authored over 200 papers in international journals and conferences, and four chapters in internationally recognized books. He is also the co-inventor of two patents, showcasing his commitment to practical and innovative applications in his field. In his professional journey, Catarinucci chairs the IEEE Technical Committee on Additively Manufactured Electronic Systems. He held the position of Vice President of Technical Activities at the IEEE Council on RFID (CRFID) for the 2022-23 tenure. As of now, he is the President-Elect of the IEEE Council on RFID for the 2-year term 2024-25.