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# STATISTICAL VALIDATION OF PATIENT VITAL SIGNS BASED ON ENERGY-EFFICIENT WIRELESS SENSOR NETWORK MONITORING SYSTEM

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## ABSTRACT

Vital signs taken from the patient's body has gained significant interest among researchers studying disease diagnosis. To achieve accurate diagnoses, the performance metrics of any proposed system must be satisfied. Two essential metrics can be found in such a system; the first metric is the measurement accuracy and the second one is the power efficiency. This paper aims to introduce accurate measurements and improve the power consumption of the proposed system. This study introduced a prototype of wireless vital signs monitoring system (WVSMS) for monitoring three vital parameters (i.e. heart rate, Spo2 and temperature) of patients inside/outside hospitals. A ZigBee wireless protocol was interfaced with the Arduino Pro mini based on ATmega 328p microcontroller to alert doctors in real time via a wireless sensor network (WSN) in emergency cases when a patient's vital signs rise to a critical level. The measurement accuracies of the heart rate, Spo2 and temperature are achieved relative to the consumer-ready devices based on statistical analyses, such as mean error, Bland-Altman and histogram. The power consumption of the WVSMS is improved by using duty cycle for the sleep/wake scheme. The experimental results revealed that the three vital parameters can be measured with high accuracy of 99.4%. In addition, the power savings of 84.5 % is achieved. Moreover, the WVSMS outperformed a similar system in terms of accuracy and power consumption.

**Keywords:** measurement accuracy, sensor, statistical analysis, wireless sensor network, ZigBee.

## 1. INTRODUCTION

Vital signs from patients are crucial in disease diagnosis. Medical parameters of patients, particularly temperature, heart rate, blood oxygen level ($SpO_2$), electrocardiogram (ECG), and breathing rate can be monitored by using sensors. These parameters can be transmitted wirelessly by using wireless sensor network (WSN) technologies. Thus, power consumption must be as small as possible for robust data delivery. In this study, we proposed wearable vital signs monitoring system (WVSMS) based on the ZigBee wireless technology. This device measure and monitor vital signals wirelessly. The ZigBee wireless technology is widely used for monitoring medical signals [1-3]because it has an efficient power consumption mechanism and is inexpensive[4, 5]. Vital signs can be measured and sent to caregivers by employing a wireless protocol for real-time patient monitoring, thereby enabling the caregivers to assist patients during risk cases.

Vital signs have been extensively researched. However, most studies [6-14] did not consider measurement accuracy. Megalingam *et al.* [15] designed a wheeled patient monitoring system that monitors multi health parameters, such as body temperature, heart rate, and oxygen level, and notifies healthcare professionals via a communication GSM module. The system can be implemented in hospitals and rehabilitation centers and is easily connected to a wheelchair. Miramontes *et al.* [4] developed and executed a health-monitoring system called PlaIMoS for receiving vital signals (i.e., ECG, temperature, heart rate, blood oxygen, skin response, fall detection, and respiration rate) from old people noninvasively in real time. The system uses Bluetooth, ZigBee, and Wi-Fi to send data in real-time on mobile operating systems. The system is small and inexpensive and has long battery life. However, the galvanic skin response lacks effectiveness. Watthanawisuth *et al.* [16] proposed implementation of WSN for real-time health monitoring systems based on ZigBee wireless technology. The system is implemented to monitor the pulse and $SpO_2$. The system is low cost, small, noninvasive, and comfortable for daily use and has low power consumption. However, the number of adopted sensors are few in their experiment. Yuce [17] designed and implemented a complete wireless body-area network platform to measure pulse rate, temperature, ECG, and electroencephalogram(EEG). The platform is extensively used in medical centers because it has a wide range, is cost-effective, has low power consumption, is flexible to the patients, improves quality of life, is highly efficient, and removes external interferences. However, the system is large and the sensor node uses wired connections with a central control unit.

Roh *et al.* [18] proposed a wearable wireless monitoring system that can evaluate the degree of depression on the basis of physiological signs via Smartphones. The system consists of a planner board with three electrodes, 16 registers for data management, low power front end, and nonlinear accelerometer. The system depends on certain filters to reduce heart rate signal noise. Experimental results compared the proposed system with commercial standard signals and indicated that the proposed system is lighter than commercial products. The proposed system did not consider any power reduction

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technique to reduce its power consumption. However, the proposed system consumes 100 mA. The system was convenient because of using android smart phone and depression scale accuracy of 71% is achieved.

Zhou *et al.* [19] used a modern low-power wearable small instrument for monitoring fall detection and heart rate. The device comprises a microcontroller (MSP430), three-axes digital accelerometer, filters, and a Bluetooth wireless module (CC2540). Experimental results extracted the standard deviation of adjacent peak-to-peak spacing and adjacent peak-to-peak amplitude as well as it shows a good consistency relative to Polar Electro. The power consumption of the proposed system is reduced to 290 µA based on standby power mode. The measurement accuracy of the system is 93.75%.

***Advantages:*** small size, detectsheartbeat problems in old people, more effective than POLAR RS100, and low cost and power consumption.

***Disadvantages:*** the system generates some errors in measurements during movement.

Ngu *et al.* [20] designed a Smart watch system that can establish communication with Smartphones to evolve a fall detection internet-of-things application. The system provides a reliable detection accuracy of 93.8%. The system consists of a Smart watch equipped with an accelerometer, Bluetooth Low Energy (BLE), and storage unit and is capable of data analysis. They used Weka (a Java package using for training and prediction of falls). Moreover, Java is used for the support of the Android access or host. Experimental results showed that the system has shortcomings between unexpected arm signals and real falls. Their proposed system draws 83.33 mA from the battery of the system and has no power reduction mechanisms. The measurement accuracy of the system is 93.8%.

***Advantage*s:** the system can work anywhere (easy to use), lightweight, noninvasive, and private.

***Disadvantage*:** the system is incapable of distinguishing unexpected arm gestures from real falls.

Rosa *et al.* [21] proposed a prototype to set walking weakness and fall risk of the elderly at home. They used a fall risk index based on various pattern recognition and gait parameters. The study used the BLE protocol to transfer data from the monitoring system to the smartphone. The system consists of a pressure sensor matrix, 6D accelerometer and gyroscope, flexible battery, and inductive charging. The data are transmitted via Wi-Fi or 3G to a PC or smartphone. The experimental results indicated that a similarity occurred between the risk of falls with maintained accuracy (i.e., 93.9%) and normal performance-based tests. The proposed project can decrease the current consumption to 50 mA (i.e., 20 h lifetime). However, the system has no power reduction mechanism.

***Advantage*s:** flexible, easy to use, and scalable.

***Disadvantages*:** (i) the data are not collected from all subjects because of limited multifunctioning of the prototype, (ii) transition and obstacle situations are not adopted in the work because the proposed system measurement emphasized steady-state gait positions, and (iii) a low number of volunteers tested the system.

He *et al.* [22] proposed an efficient framework based on tri-axial acceleration and gyroscope to test the variation between fall and normal activities. They used the Bluetooth WSN technology. The noise of accelerometer measurements was reduced by using Kalman filter. The framework consists of a Bluetooth device, tri-axial accelerometer, gyroscope sensors, and Android smartphone. The fall detection accuracy of 95.67% was estimated with Kalman filter. The entire system consumes approximately 142 mA and has no power reduction mechanism.

***Advantage*s:** lightweight, low cost, and suitable for elderly usage.

***Disadvantage:*** the proposed system consumes high power compared with other related work.

Magno *et al*. [23] presented a modified efficient power strategy for wearable wireless sensor node. The authors used the sleep/wake scheme with maintained activity recognition. The main components of the system are the processing-sensor unit, BLE (i.e., AMS002), RF 868 MHz radio (CC1110), accelerometer (BMC150), microcontroller (NXP LPC54102), nano power wake-up radio, and batteries of 200 mAh for slave node and 1000 mAh for master node. The experimental results proved the power consumption and system accuracy. The proposed system increases the lifetime of the sensor node to four times relative to that of a traditional one. Consequently, the power consumption can be minimized to 7.878 mA by using a specific technique, such as sleep/wake strategy. An accuracy of 97% was obtained.

*Advantag*es: efficient battery life and integration between hardware and software techniques.

Gharghan [24] designed and implemented a real-time remote monitoring system(RTRMS) for measuring the patient's temperature in/out hospitals by using a GSM modem and microcontroller. Their system is capable of sending warnings to caregivers via short message service when the temperatures of patients rise. The system consists of a GSM modem (SmartG100), microcontroller (PIC16F877A), temperature sensor (LM35), LCD, buzzer, power unit (rechargeable battery 7.2 V/1,000 mA). Experimental results indicated a close agreement between the proposed system and benchmark. The RTRMS reduced the current consumption to 3.087 mA. In this case, the RTRMS lifetime can be prolonged to 324 h prior to the charging cycle based on a sleep/wake scheme. The accuracy of the system is 99%.The proposed system provided surveillance for patients who are located in far places. In addition, the system can be used for patient monitoring in real-time when he/she is located at home. Moreover, the system was low cost because it uses the infrastructure mobile network. The system is also movable and power efficient, with high measurement accuracy. However, the system is slightly large.

Previous studies introduced certain limitations related to measurement that pose challenges in vital signs monitoring systems such as low measurement accuracy of

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the heart rate, $SpO_2$, and temperature parameters. In addition, some of these studies did not consider measurement accuracy. Moreover, some of them are presented a wired connection system that led to a restricted patient movement. These drawbacks motivated us to develop a prototype wireless sensor network measurement system with high accuracy.

The most significant vital signs that can be observed are temperature, heart rate, acceleration, ECG, and $SpO_2$ [2, 4, 16]. Among these vital signs, temperature, heart rate, and $SpO_2$ are three significant signals considered in the present work. Consumer-ready devices such as the Pic solution, Rossmax, and Finger Tip devices can measure temperature, heart rate, and oxygen level, respectively, by employing two sensors. One sensor detects heart rate and Spo2, and the other detects temperature. In this study, the WVSMS measurement accuracies were validated relative to the aforementioned benchmark devices. Validation was performed by using statistical analysis, such as error calculations (mean absolute percentage error [MAPE], mean absolute error [MAE], root mean square error [RMSE], and mean square error [MSE]), Bland-Altman test, and histogram test. The WVSMS consists of two transmitter and receiver nodes. The transmitter node includes two sensors (heart rate and $SpO_2$ embedded in one sensor and temperature sensor), Arduino Pro mini board, and ZigBee wireless standard (XBee S2C). The receiver node comprises an Arduino Uno board and ZigBee (XBee S2). The Arduino Uno board was interfaced with a laptop, where measured parameters can be viewed and process by using the Maker Plot software [25].

The contributions of the paper can be summarized as follows:

a) The paper presents a novel portable device (i.e., WVSMS) based on a wireless sensor network with low power consumption.
b) The paper compares the results that were obtained with consumer-ready devices that were used for patient monitoring system.
c) The performance validation of the proposed WVSMS is achieved through statistical analysis.
d) The accuracy of the proposed WVSMS is verified.

## 2. SYSTEM ARCHITECTURE

The proposed WVSMS is illustrated in Figure 1a. The system consists of a transmitter sensor node (sensor node) and a receiver node (coordinator node), as shown in Figures 1b and c. The transmitter sensor node comprises several components, as follows: a temperature sensor, heart rate sensor, and $SpO_2$sensor, Arduino Pro mini board, ZigBee module (XBee S2C), and two lithium batteries (3.7 V/2200 mAh). The receiver node consists of an Arduino Uno board, an XBee S2 module, and a laptop for the monitoring of vital parameter data in real time. The measured data were compared with those obtained through the benchmark system. Figures 2a, b, and c show the benchmark devices of temperature, heart rate, and $SpO_2$, respectively. The accuracies of the benchmark devices are ±0.2°C (temperature) [26], ±5 (heart rate)[27], and ±2% (Spo2)[28].

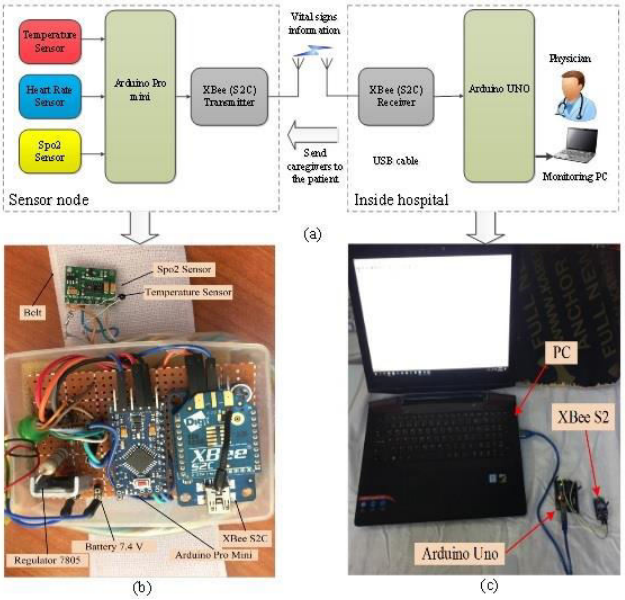


**Figure-1.** Proposed WVSMS (a) block diagram of the whole system, (b) hardware ofthe sensor node, and (c) hardware of receiver node.


**Figure-2.** Benchmark devices of (a) temperature, (b) heart rate, and (c) $SpO_2$.

## 3. HARDWARE IMPLEMENTATION

### 3.1 Temperature sensor

Temperature sensor based on negative temperature coefficient (NTC) thermistor (temperature sensitive resistors) is a semiconductor with high thermal resistance coefficients. The temperature of the human body is one of the most important parameters that indicate patient health. The NTC thermistor is widely used for measuring body temperature because it provides the highest variation of output voltage by temperature variation. However, the certainty of being extremely sensitive renders NTC to operate in a nonlinear mode. In this work, the NTC (10 KΩ) is used to control the size and reduce the power consumption of the proposed system. The NTC thermistor value decreases with increasing temperature value and vice versa. In our application, the NTC is connected to a 10 KΩ resistance as a voltage divider, as shown in Figure 3. The middle point (i.e., point A) between NTC and the resistor is used for sensing variations in output voltage on the basis of changes in temperature. The output voltage of point A

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($V_{out}$) is changed between 0 and 5 depending on the temperature of the patient. The temperature corresponds to the A/D converter of the Arduino microcontroller 0-1023 (10-bit resolution). The output voltage of the voltage divider can be translated to temperature in Celsius through Equation (1)[29].

$$\text{Temperature } (°C) = V_{out} * (100\,°C/V) \quad (1)$$

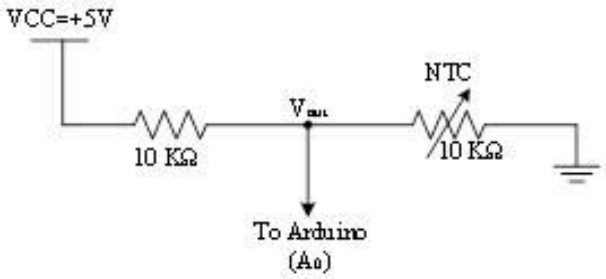


**Figure-3.** Circuit diagram of the NTC thermistor.

### 3.2 Pulse oximeter and heart rate sensor

The saturation percentage of oxygen in the blood ($SpO_2$) can be measured by a noninvasive method called pulse oximetry. The pulse oximetry principle is based on the blood absorption characteristics of light. A blood oxygen sensor (MAX30100) is used to obtain the blood oxygen value. This sensor consists of two LEDs (red and infrared) that emit light at different wavelengths. The light measured by a photodiode after it passes through the user's finger. The absorption of deoxyhemoglobin and oxyhemoglobin red and infrared light differently. The MAX 30100 can calculate the value of Spo2 based on Equation (2).

$$\text{Spo2} = 10.0002R^3 - 52.887R^2 + 26.817R + 98.293, \quad (2)$$

where R is the ratio between infrared and red light [16].In addition, this sensor also can be used to measure the heart rate based on Equations 3 and4.

$$Frequency = 10^6/(BPMT\_T\_COUNT * 10) \quad (3)$$

$$\text{Heart Rate} = \text{Frequency}/60 \quad (4)$$

Where *BPM_T_COUNT* represents total tick count.

Therefore, the frequency can be measured by applying Equation (3), and the heart rate can be computed based on Equation (4) [2].

### 3.3 Microcontroller

An 8-bit 16 MHz Arduino Pro Mini microcontroller is used in this study. The unit uses 32 Kbyte flash memory [30]. An analog to digital converter (A/C) is used, with seven-channel 10-bit resolution, 14 digital input/output pins with 6 that provide pulse width modulation, and an SPI interface. The converter operates at 5 V from a battery[31]. The Arduino can be programmed in a language, such as C++, with some simplifications and modifications, and the essential libraries of Arduino have been written in C and C++ [32]. In this study, the Arduino Pro Mini based on ATmega 328p microcontroller was programmed to forward the data from the three sensors to the XBee S2C module. The microcontroller transmits the data via the serial port to the XBee module at 9,600 bps. By contrast, the XBee S2C in the receiver circuit is used to receive data and send it to the laptop via Arduino Uno, as shown in Figure-1. The output of the microcontroller is displayed on the laptop using graphical user interface (GUI) software (MakerPlot).

### 3.4 Wireless protocol

ZigBee wireless protocol is a technology created for control and sensor networks based on the IEEE 802.15.4. The protocol can be used globally and is reliable and secure. ZigBee supports up to 65,000 nodes. ZigBee is easy to deploy with extremely long battery life and low cost. The data rate of ZigBee is 250 kbps, with 6 or 10 ms latency. Three basic types of XBee are available, namely, S1, S2, and S2C. Among these types, XBee S2C was selected in this study because of its low power consumption of 33 mA and long communication distance (1,200 m outdoors and 60 m indoors[33]) compared with XBee S1 and XBee S2. By contrast, S1 and S2 consume 50 and 40 mA, respectively. In addition, the S1 can cover a communication distance up to 100 m outdoors and 30 m indoors[34]. XBee S2 can reach 120 m outdoors and 40 m indoors[35]. The setup configuration of the ZigBee sensor node and coordinator node of the proposed system are shown in Figure-4.

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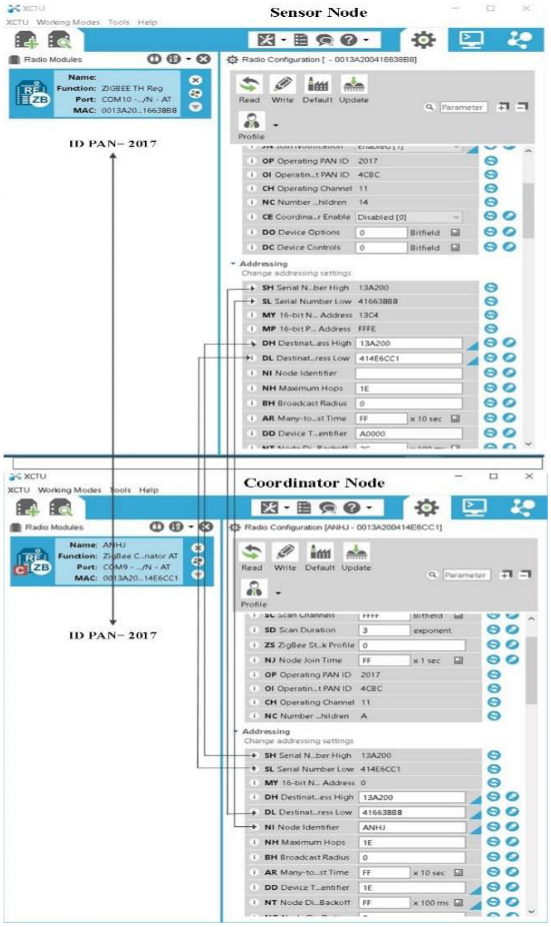


**Figure-4.** Setup configuration of ZigBee sensor and coordinator nodes.

## 4. MEASUREMENTS AND POWER CONSUMPTION ALGORITHM

Figure-5 illustrates the WVSMS algorithm. The proposed algorithm is built inside the Arduino Pro min board that uses the ATmega 328 microcontroller. The microcontroller measures the sensor data of the temperature, heart rate, and $SpO_2$. Then the microcontroller sends these data to the XBee S2C via serial communications, which in turn transmits all sensor information to the coordinator node. The power consumed by the sensor node is reduced by adopting a duty cycle (DC) of sleep/wake. Initially, all the components of the sensor node are in sleep mode until the microcontroller wakes up based on internal timer interrupt. The heart rate measurement relies on the number of beats per minute. The heart rate measurements of the benchmark (shown in Figure 2b) is acquired every 40 s. Therefore, this time is used in our proposed WVSMS in the measurements obtained with the heart rate sensor. In this case, the DC of 0.1333 (40 s/300 s) are considered for the two sensors (i.e., NTC thermistor and heart rate and $SpO_2$) and Arduino Pro Mini. Hence, the heart rate value can be measured for 30 s. This value can be multiplied by two to obtain the beats per minute. Based on this procedure, the active and sleep times of 40 and 260 s, respectively, are used.

When entire sensor data are acquired, the microcontroller sends a control signal to wake the XBee, which transmits data for 10 s and return to sleep mode for 290 s. Based on this strategy, the average current consumption (Equation 5) [24] of the sensor node can improve to 8 mA relative to a traditional system (i.e., without sleep/wake scheme, where the current consumption of the entire WVSMS is 88 mA), as shown in Table-1.

$$I_{avg} = DC * I_{active} + (1 - DC) * I_{sleep} \quad (5)$$

where DC is equal $\frac{t_{active}}{T_{total}}$ and $I_{active}$ and $I_{sleep}$ are the active and sleep or power down current consumption of each component of the WVSMS, respectively.

## 5. EXPERIMENT SETTING

A total of 1000 samples (temperature [334] samples, heart rate [333] samples, and $SpO_2$ [333]) were obtained from three vital parameters measured from 10 volunteers with an age range of 6–77 years and dual genders (i.e., male and female). The sensors were connected to the volunteers and started to transmit the data wirelessly from the sensor node to the coordinator node via the XBee S2C. The received data by XBee S2 were passed to the Arduino Uno that was connected to a laptop via USB cable. The received parameters are plotted on the LCD of the laptop by using MakerPlot software. The doctor monitors the plotted parameters of the patient that are displayed on a laptop in the monitoring room, and he/she can send for a caregiver in an emergency.

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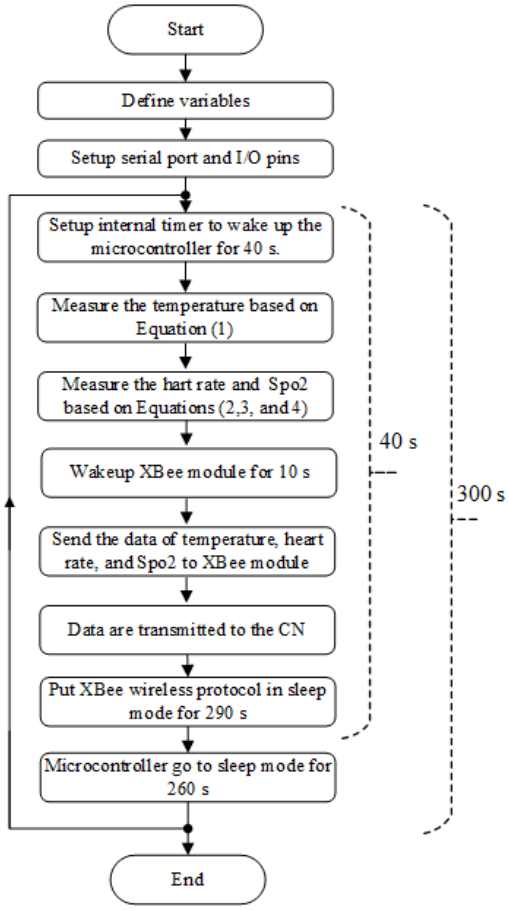


**Figure-5.** WVSMS algorithm flowchart.

## 6. MEASUREMENT PARAMETERS

The coordinator node of the WVSMS shown in Figure-6 receives the measured parameters, which were displayed on the LCD of the laptop using MakerPlot, as shown in Figure-7. The temperature, heart rate, and $SpO_2$ information are plotted in real time every 40 s. The MakerPlot displays the data in a GUI and saves these data in Excel file format [25]. The proposed device was validated by using a benchmark device and examining the saved data. Subsequently, the data of the two systems were plotted and compared. The results are shown in Figure-8a, b, and c, for temperature, heart rate, and $SpO_2$, respectively. The data obtained from the two systems were documented every 40 s for comparison. The results indicate mild differences between the two systems. The data obtained by the WVSMS system are validated by using performing statistical analyses.


**Figure-6.** Received data from the WVSMS receiver.

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**Table-1.** Current and time consumption of each WVSMS component.

| Parameter | Temperature sensor NTC thermistor | Heart rate and $SpO_2$ sensor | Arduino Pro Mini | XBee S2C |
|---|---|---|---|---|
| $I_{active}$/mA | 0.4 | 36.9 | 12.7* | 38 |
| $I_{sleep}$or $I_{power\ down}$/mA | Zero | Zero | 0.0058 | 0.58 |
| $t_{active}$/ s | 40 | 40 | 40 | 10 |
| $t_{sleep}$ or $t_{power\ down}$/s | 260 | 260 | 260 | 290 |
| $T_{total}$/s | 300 | 300 | 300 | 300 |
| Duty cycle ($t_{active}$ / $T_{total}$) | 0.1333 | 0.1333 | 0.1333 | 0.0333 |
| $I_{average}$/mA | 0.0532 | 4.9077 | 1.6936 | 1.2733 |
| $I_{average\_total}$= $I_{average\_NTC}$+ $I_{average\_Hreat\ rate\ and\ Spo2}$+ $I_{average\_Arduino\ Pro\ Mini}$+ $I_{average\_XBee\ S2C}$ = 8 mA<br>$I_{total\ in\ traditional\ case}$ = $I_{NTC}$+ $I_{Hreat\ rate\ and\ Spo2}$+ $I_{Arduino\ Pro\ Mini}$+ $I_{XBee\ S2C}$ = 88 mA<br>*without power LED and voltage regulator | | | | |

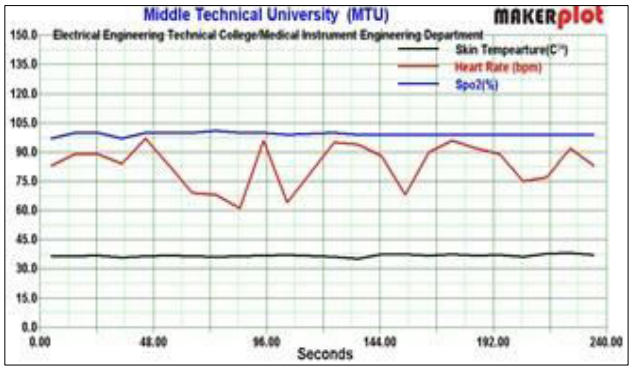
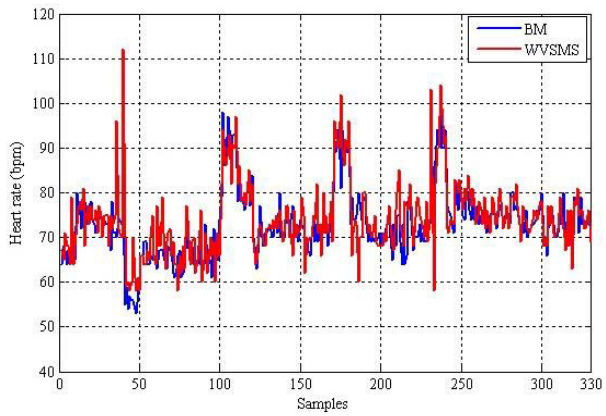
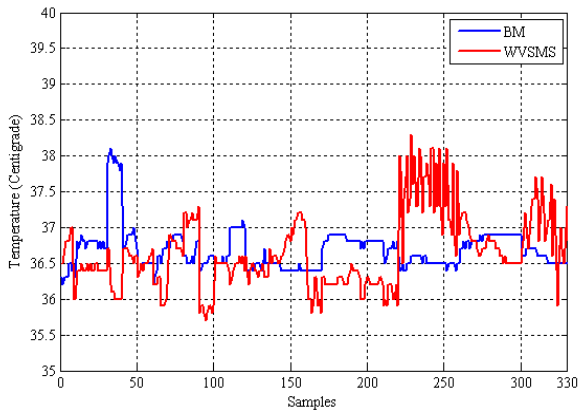


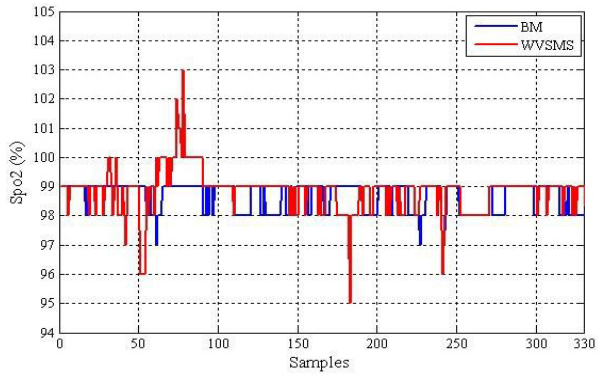

**Figure-7.** Data received by coordinator node and plotted by MakerPlot software.




(a)




(b)




(c)

**Figure-8.** Real-time measurements of (a) temperature, (b) heart rate, and (c) $SpO_2$for the WVSMS and the benchmark devices.

## 7. STATISTICAL RESULTS AND DISCUSSIONS

The three parameters of data were obtained using the WVSMS, which is based on the ZigBee wireless protocol. The proposed WVSMS was validated by examining and checking the benchmark device. The two systems were compared. The data obtained by the proposed WVSMS were examined through statistical

ARPN Journal of Engineering and Applied Sciences

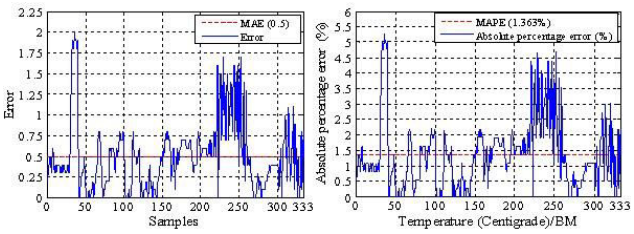


analysis (i.e., error test, Bland-Altman test, histogram test).

### 7.1 Error test

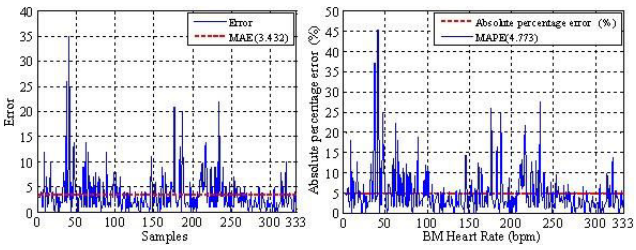
The error, mean absolute error (MAE), absolute percentage error (APE), and mean absolute percentage error (MAPE) in the temperature, heart rate, and $SpO_2$ measurements of the WVSMS with respect to those of the Benchmark are examined. Figures 9a and b, 10a and b, and 11a and b show the error and absolute percentage error for temperature, heart rate, and $SpO_2$, respectively. Figure-9a shows the error vary over the range from 0 °C to 2 °C with MAE of 0.5, whereas Figure 9b shows that the APE varies over the 0-5.263 percentage range. Figure-10a shows that error varies over the range 0 to 35 beat/minute with MAE of 3.432, whereas Figure 10b the APE varies over the 0-45.454 percentage range. Figure 11a demonstrates that the error varies over the 0–4.04 percentage range with MAE of 0.549, whereas Figures 11b shows that the APE varies over the 0–4 percentage range. The measurements of temperature and $SpO_2$ parameters revealed an acceptable

value of MAE. This result indicates means a close agreement between proposed WVSMS and benchmark devices. However, the measurements of the heart rate is diverged slightly from benchmark (i.e., Rossmax device). Table-2 presents the MAPE, MAE, MSE, and RMSE for three vital signs used in this paper.



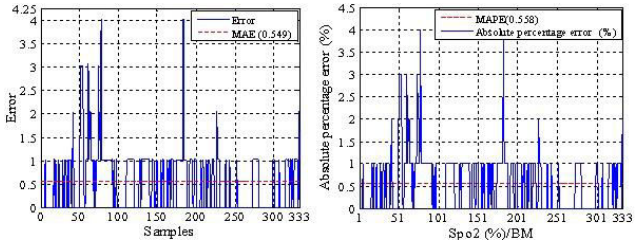

(a) (b)

**Figure-9.** Measurement error of temperature sensor (a) error with number of samples (b) absolute percentage error (%) relative to the BM.




(a) (b)

**Figure-10.** Measurement error of heart rate sensor (a) error with number of samples (b) absolute percentage error (%) relative to the BM.




(a) (b)

**Figure-11.** Measurement error of $SpO_2$ sensor (a) error with number of samples (b) absolute percentage error (%) relative to the BM.

**Table-2.** Values of MAPE, MAE, MSE, and RMSE of the three parameters.

| Parameters | MAPE | MAE | MSE | RMSE |
|---|---|---|---|---|
| Temperature (°C) | 1.363 | 0.501 | 0.424 | 0.651 |
| Heart rate (bpm) | 4.773 | 3.432 | 26.95 | 5.192 |
| Spo2 (%) | 0.558 | 0.550 | 0.772 | 0.879 |

### 7.2 Bland–Altman test

The Bland-Altman medical statistical analysis is commonly used to compare the measurements between

measured and reference values. The test was used for confirming the differences or similarity between our proposed WVSMS and the benchmark systems. Figures 12, 13, and 14 demonstrated a Bland-Altman plot of the alterations between the benchmark devices and the proposed system WVSMS for all three parameter data (temperature, heart rate, and $SpO_2$). For temperature, most (322/334) of the differences (i.e., errors) between the temperature data of the proposed system WVSMS and the benchmark device were within the $\bar{\mu} \pm 2\bar{\sigma}$ (96.4%) limits of agreement (- 1.32, 1.35). The mean difference (bias) of the temperature measurements between the proposed system WVSMS and the benchmark system was 0.01. The standard deviation of the difference is 0.667, and the width of the 96.4% bounds of agreementwas 2.67.

For heart rate, most (322/333) of the differences (i.e., errors) between the heart rate data of the proposed system WVSMS and the benchmark device were within the $\bar{\mu} \pm 2\bar{\sigma}$ (96.6%) limits of agreement (-11.26, 9.06). The mean difference (bias) of the heart rate measurements between the proposed system WVSMS and the benchmark system was -1.1. The standard deviation of the difference was 5.08, and the width of the 96.6% bounds of agreementwas 20.32.

For $SpO_2$, most (327/333) of the differences (i.e., errors) between the $SpO_2$data of the proposed system WVSMS and the benchmark device were within the $\mu \pm 2\sigma$ (98.1%) limits of agreement (-1.91, 1.52). The mean difference (bias) of the $SpO_2$measurements between the proposed system WVSMS and the benchmark system was

ARPN Journal of Engineering and Applied Sciences



-0.2. The standard deviation of the difference was 0.858, and the width of the 98.1% bounds of agreementwas 3.43.

In studies [36-39], when the data were within the 95%, this situation indicated the limits of agreement. Thus, this study is comparable to previous research. Small temperature, heart rate, and $SpO_2$ data wereoutside the limit of the agreement lines; they are shown as diamonds in Figures 12, 13, and 14, respectively. The Bland–Altman plots indicate an excellent agreement between WVSMS and benchmark systems. Figure-14 shows that fewer points are distributed between the limit of agreements because of significant matching between the two systems.

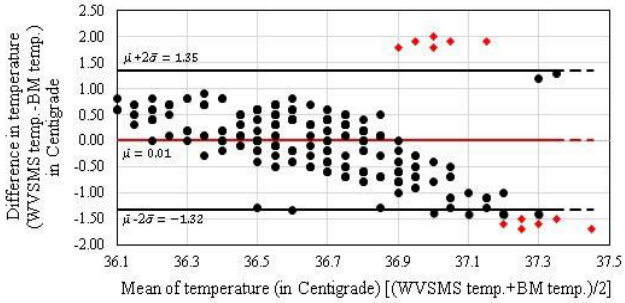



**Figure-12.** Bland-Altman plot for temperature.

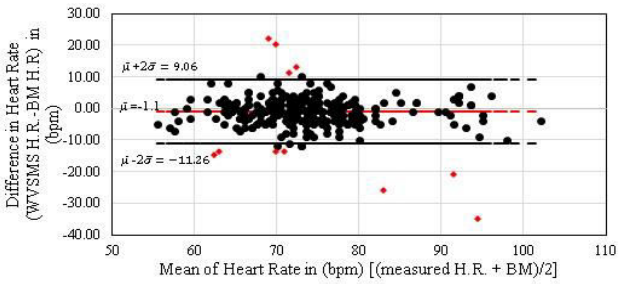



**Figure-13.** Bland-Altman plot for heart rate.

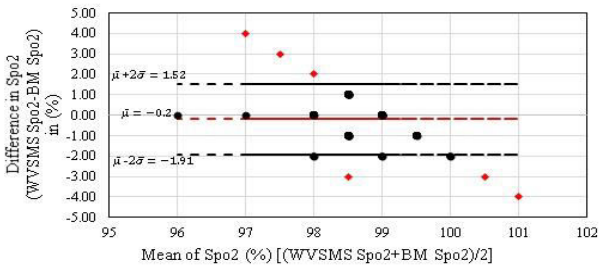



**Figure-14.** Bland-Altman plot for Spo2.

### 7.3 Histogram test

Histograms are a common graphical demonstration of a frequency distribution and feature representation [40]. A histogram comprises neighboring rectangles; the *x-axis* represents the bases of the rectangles that show the successive class boundaries and the *y-axis* represents heights of the rectangles that illustrate the frequencies class [41]. Low bars specify fewer points in a class, whereas high bars indicate extra points. Therefore, we determined whether the data measured by the proposed system WVSMS are compatible with the benchmark systems. The histogram of the temperature data (Figure-15) shows peaks of 118 and 99 points in the 36.603 and 36.519 °C classes for the BM and the WVSMS, respectively. The histogram of the heart rate data (Figure-16) illustrates peaks of 77 and 73 points in the 77.853 and 73.961(bpm) classes for the WVSMS and the benchmark system, respectively.The histogram of the Spo2 data (Figure-17) display peaks of 224 and 217 points in the 99.314 and 99.229 (%) classes for the WVSMS and the benchmark system, respectively. These results prove that the data measured by the proposed system WVSMS are comparable with those measured by the benchmark systems.

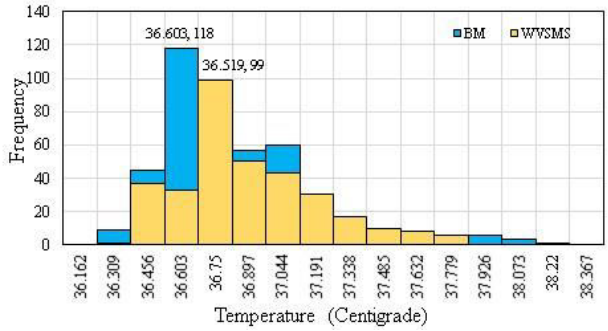



**Figure-15.** Histogram of the temperature data from the proposed system WVSMS and the benchmark system.

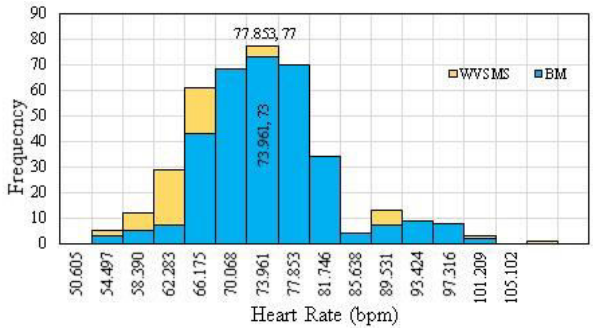



**Figure-16.** Histogram of the heart rate data from the proposed system WVSMS and the benchmark system.

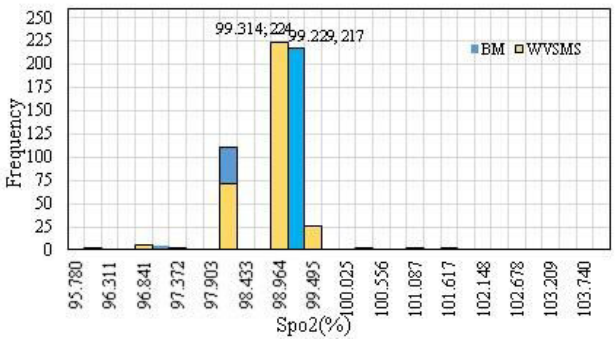



**Figure-17.** Histogram of the Spo2 data from the proposed system WVSMS and the benchmark system.

ARPN Journal of Engineering and Applied Sciences



## 8. COMPARISON RESULTS

The results of the proposed WVSMS can be compared with previous studies in terms of measurement accuracy and power consumption. First, the measurement accuracy is considered for comparison. Then, the power consumption is compared with similar related studies. The overall accuracy of the WVSMS are approximately 99.4% (i.e., temperature [99.9%], heart rate [98.5%], and $SpO_2$ [98.6%]). The entire measurement accuracy of the WVSMS is more accurate than that in previous research [3, 18-24] and outperformed them as shown in the bar chart of Figure-18. The *x-axis* is the application of each study, and the *y-axis*is the measurement accuracy.

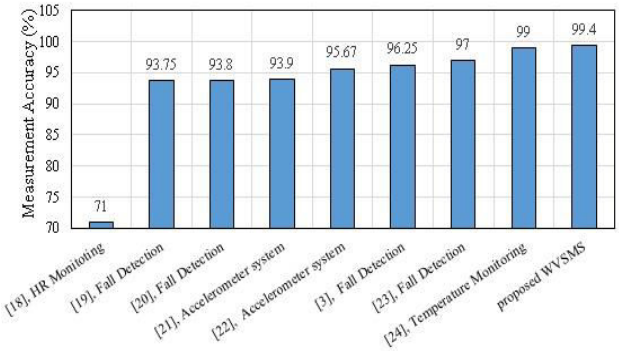



**Figure-18.** Bar chart comparison of the accuracy with previous studies.

Six dependable existing studies [7, 12, 13, 42-44] similar to the present study in terms of medical uses are measured with different patient's parameters (e.g., temperature, heart rate, and $SpO_2$) are considered for comparison with proposed WVSMS. These studies have used different wireless protocols such as ZigBee, GSM modem, and Bluetooth to communicate the vital signs of the patients. Our proposed WVSMS based on duty cycle of the sleep/wake algorithm of ZigBee (XBee S2) outperforms these other studies in terms of power consumption; its power consumption is 8 mA, as shown in Figure-19. The current consumption of the current work is 88 mA in the traditional mode. Based on these consumption values, the proposed WVSMS overtook the conventional WVSMS (i.e., without sleep/wake algorithm) by 91%. Consequently, the battery lifetime of the WVSM can be extended to 275 h (11.45 d) using a rechargeable lithium-ion battery 7.2V/2200 mAh based on duty cycle of sleep/wake strategy. However, the battery life is 25 h (1 d) for traditional WVSMS. The estimated battery lifespan for different battery capacities based on the current consumption of the proposed WVSMS with and without sleep/wake algorithm is shown in Figure-20. The figure shows a significant improvement of current consumption of the proposed WVSMS using sleep/wake scheme relative to the conventional WVSMS.

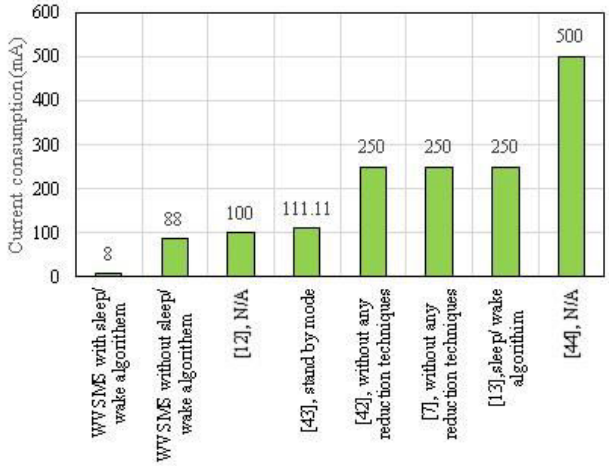



**Figure-19.** Bar chart comparison of the current consumption with previous studies.

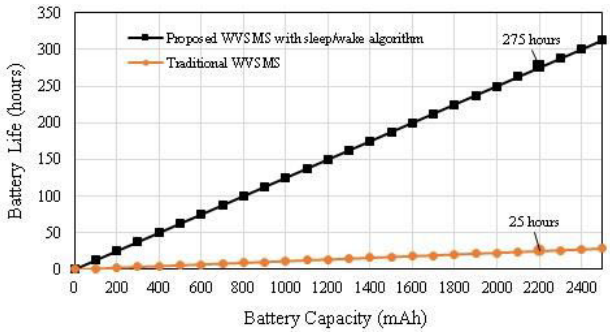



**Figure-20.** Estimated battery lifetime with respect to battery capacity.

## 9. CONCLUSIONS

This paper introduces the design and use of the wireless vital signs monitoring system that is based on the ZigBee wireless protocol. The proposed WVSMS includes two sensors used to measure three parameters (temperature, heart rate, and Spo2), an Arduino Pro Mini for transmitter, Arduino Uno for receiver, and two XBee S2C units, one for transmitter and the other for receiver. This study guaranteed a close agreement between the measured data acquired by the proposed system WVSMS and the benchmark systems. Few differences were observed between the two compared systems. The results of the statistical analyses (i.e., MAPE, MAE, MSE, RMSE, histogram, and Bland–Altman) provided powerful evidence of the validity of the WVSMS. The power consumption is significantly improved relative to the traditional WVSMS. Furthermore, the WVSMS was superior to that of the previous studies in terms of power consumption and measurement accuracy. Future work will focus on reducing the power consumption of the WVSMS by using a certain algorithm to decrease current consumption. Future work will focus on using a standalone microcontroller. The XBee S2C can be used for reducing power consumption and prolonging battery life.

ARPN Journal of Engineering and Applied Sciences



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